Essays on farmland values: a spatial econometrics perspective

by

Allan Pinto Padilla

M.Sc., Auburn University, 2020

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the
requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2023

Abstract

This dissertation seeks to evaluate the suitability of current statistical methods for identifying explosive unit root processes and to explore the spread of farmland values in a system influenced by temporal and cross-sectional interdependencies. The primary focus of the study is to examine the impact of agricultural and non-agricultural variables on farmland values at both the county level and in adjacent areas.

The study focuses on the analysis of farmland values in the 99 counties of Iowa from 1969 to 2014. It explores the influence of population density and income on those values. The econometric procedures developed by Ciccarelli and Elhorst (2018) are employed to examine the dynamics of farmland values in the region. The study reveals a positive relationship between population density and farmland values in Iowa. An increase in population contributes to higher farmland values due to increased alternative uses for farmland.

Using the multi-step procedure proposed by Aquaro, Bailey and Pesaran (2021), this study applies a heterogeneous spatial autoregressive model to analyze the Iowa farmland market, taking into account regional heterogeneity. The spatial parameters yield results that challenge prevailing economic theories of spatial dependence. A comprehensive framework is developed to capture the heterogeneous nature of farmland value spillovers, while simultaneously considering common factors in a manner that maintains generality.

The study also investigates the direct and indirect effects of income per capita and population density. Through this analysis, insights are gained regarding the influence of changes in neighboring population density and income per capita on farmland values within a particular county over a specified time period. The findings emphasize a dominant area ripple effect and core-periphery spillovers in urbanized areas. This dissertation makes a significant contribution by evaluating farmland dynamics and network effects in accordance with theories of new economic geography and spatial dependence.

Finally, this dissertation introduces and explains the “Kansas Property Tax Estimation Tool”,

including several illustrative examples. The tool is designed to enhance and streamline tax planning processes. Legislators, taxing districts, and land managers can utilize the Estimator to run various “what if” scenarios promptly, on any device. The tool offers sufficient flexibility to cater to the needs of taxing districts throughout the entire state, regardless of the device used (mobile or desktop).

Essays on farmland values: a spatial econometrics perspective

by

Allan Pinto Padilla

M.Sc., Auburn University, 2020

A DISSERTATION

submitted in partial fulfillment of the
requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2023

Approved by:

Co-Major Professor
Leah Tsoodle

Approved by:

Co-Major Professor
Allen Featherstone

Copyright

Abstract

This dissertation seeks to evaluate the suitability of current statistical methods for identifying explosive unit root processes and to explore the spread of farmland values in a system influenced by temporal and cross-sectional interdependencies. The primary focus of the study is to examine the impact of agricultural and non-agricultural variables on farmland values at both the county level and in adjacent areas.

The study focuses on the analysis of farmland values in the 99 counties of Iowa from 1969 to 2014. It explores the influence of population density and income on those values. The econometric procedures developed by Ciccarelli and Elhorst (2018) are employed to examine the dynamics of farmland values in the region. The study reveals a positive relationship between population density and farmland values in Iowa. An increase in population contributes to higher farmland values due to increased alternative uses for farmland.

Using the multi-step procedure proposed by Aquaro et al. (2021), this study applies a heterogeneous spatial autoregressive model to analyze the Iowa farmland market, taking into account regional heterogeneity. The spatial parameters yield results that challenge prevailing economic theories of spatial dependence. A comprehensive framework is developed to capture the heterogeneous nature of farmland value spillovers, while simultaneously considering common factors in a manner that maintains generality.

The study also investigates the direct and indirect effects of income per capita and population density. Through this analysis, insights are gained regarding the influence of changes in neighboring population density and income per capita on farmland values within a particular county over a specified time period. The findings emphasize a dominant area ripple effect and core-periphery spillovers in urbanized areas. This dissertation makes a significant contribution by evaluating farmland dynamics and network effects in accordance with theories of new economic geography and spatial dependence.

Finally, this dissertation introduces and explains the "Kansas Property Tax Estimation Tool",

including several illustrative examples. The tool is designed to enhance and streamline tax planning processes. Legislators, taxing districts, and land managers can utilize the Estimator to run various “what if” scenarios promptly, on any device. The tool offers sufficient flexibility to cater to the needs of taxing districts throughout the entire state, regardless of the device used (mobile or desktop).

Contents

List of Figures

List of Tables

Acknowledgements

I would like to begin by extending my heartfelt gratitude to my co-major professors, Dr. Leah Tsoodle and Dr. Allen Featherstone, whose guidance has been indispensable in the completion of this dissertation. I am incredibly thankful to Dr. Tsoodle for her unwavering support throughout my journey as an independent researcher, and for granting me the academic freedom to pursue my research interests with utmost dedication. Dr. Featherstone has been an incredible source of support, demonstrating immense patience and unwavering enthusiasm that has continuously inspired me. I would like to thank my committee members, Drs. Tian Xia, Nathan Hendricks, and Yoon-Jin Lee, for their insightful comments and contributions. I would also like to extend my gratitude to Dr. Paul J. Elhorst for the invaluable contributions to my research. His profound influence on my research approach and his integral role in shaping my development in the field of spatial econometrics are deserving of special recognition.

I would also like to express my gratitude to the participants at the 2022 Western and Agricultural & Applied Economics Association. Their invaluable feedback on earlier drafts of certain chapters significantly contributed to the improvement of this work. Additionally, I am deeply grateful to the Information Network of Kansas (INK) for their generous financial support, without which my graduate studies and conference participation would not have been possible.

Lastly, I want to express my heartfelt appreciation to my friends and family for their unwavering motivation and unwavering enthusiasm for my research. I cannot adequately express the depth of my gratitude to all of them for their stalwart support throughout my doctoral studies. Finally, this dissertation stands as a testament to the steadfast goodness of God and His perfection in the midst of my shortcomings.

1 Introduction

Farmland values depend on various factors, such as location, soil quality, topography, climate, water availability, and local market conditions. As a whole, farmland values in the United States have increased due to population growth, higher demand for agricultural products, and supportive government policies. However, regional variations in this trend exist, and some states are more sensitive to national changes than others. The Midwest states had a relatively higher increase from 2021 than others did, with value increases of 21.4% per acre in Iowa and 25.2% per acre in Kansas. Although there is an extensive body of literature using hedonic methods to model farmland values, few studies have employed spatial hedonic or panel hedonic models to understand value dynamics. Recently, researchers have increasingly applied neighborhood spillover effects to study farmland values (Huang et al. 2006 ; Burns et al. 2018).

1.1 Overview

Numerous studies have explored the dynamics of farmland prices over time, using various econometric models (Herdt and Cochrane 1966; Tweeten and Martin 1966; Reynolds and Timmons 1969; Van Dijk, Smit and Veerman 1986; Melichar 1979; Burt 1986; Featherstone and Baker 1987; Lloyd and Rayner 1990; Lloyd, Rayner and Orme 1991; Falk 1991). Those models aimed to capture the time-series movement of farmland prices and identify the key factors that affect their behavior. Other studies have analyzed factors affecting land values from a cross-sectional and time-series perspective, trying to explain the price variations among parcels of agricultural land (Danielson 1986; Palmquist and Danielson 1989; Xu 1990; Elad, Clifton and Epperson 1994; Kennedy 1997; Maddison 2000; Patton and McErlean 2003; and Tsoodle, Featherstone and Golden 2007). These findings suggest that farmland values and neighborhood characteristics vary over space and time. A limited number of studies have addressed the spatiotemporal relationship of farmland prices (Maddison 2009; Carmona and Rosés 2012; Yang, Ritter and Odening 2017; and Yang, Odening and Ritter 2019). This approach uses a less common spatial econometric model that includes a spatially lagged independent variable on the right-hand side of the equation.

1.1.1 Time Series Models of the Farmland Values Market

Waugh (1929) conducted the first study estimating the price of vegetables using a hedonic pricing model based on produce quality. In addition to examining the relationship between commodity prices and physical characteristics, he proposed a theory that the timing of the sale, as well as previous sales of the commodity, may also have an impact on current commodity prices. Herdt and Cochrane (1966) were among the first researchers to recognize that some variables affecting the land market today may have been generated several years ago Tweeten and Martin (1966) utilized a simultaneous equation model to analyze the reasons behind the significant rise in land prices from 1923 to 1963. The study acknowledged the impact of lagged variables on current land prices. Unlike other recursive models, they incorporated lagged dependent and independent variables. Estimated using ordinary, recursive, autoregressive least squares, the model was able to trace the reasons behind the increase in land prices since 1950.

Between the mid-1950s and 1970s, farmland values increased significantly, while annual net farm income was significantly lower than the annual increase in property values. This phenomenon is explained by the asset-pricing theory. One way to explain this phenomenon is through "time-varying risk premiums," which suggests that the risk premium associated with investing in assets can change depending on market conditions and investor sentiment. Melichar (1979) used data from 1954 to 1978 to analyze returns on farm assets and the rate of growth in their value. By applying a present value formula, the study found that changes in the present current return, annual growth rate, or discount applied to future returns could lead to a new equilibrium value of the present value of the asset. According to Melichar (1979), government programs and foreign demand had a more significant impact on agricultural returns in the 1970s than programs focused on promoting technological advances in agriculture. This perspective contrasts with the findings of Melichar (1977), who emphasized the importance of technology-focused programs. These divergent views underscore the complex and multifaceted nature of factors affecting agricultural returns, highlighting the need for continued research and analysis to gain a more nuanced understanding of these dynamics.

Chavas and Shumway (1982) employed a hedonic model to investigate crop prices in five of the nine crop reporting districts in Iowa between 1967 and 1977. Their results showed that adding time lags in prices, yields, and the consumer price index to the model explained approximately

99% of land price variation. By incorporating regional dummy variables and soil and climate quality measures, the study provided valuable insights into the complex factors affecting land prices in specific regions of Iowa.

Sandrey et al. (1982) conducted a study using a pooled and two-step OLS model to examine the farmland value trends specific to Oregon's agricultural subregions. Their findings suggested that structural changes occurred between 1969 and 1978, highlighting the importance of a disaggregated model with a lagged structure at the subregional level to capture regional and temporal diversities that influence agricultural land prices in Oregon.

Lloyd and Rayner (1990) utilized the fundamental principles of capital asset theory to examine the actual values of agricultural land, cash rent, and a constant rate of return from 1946 to 1988. According to their results, an increase in rent generates a corresponding increase in land prices, just as a new, higher level of inflation would raise land prices. Another noteworthy aspect of their model was its resolution to incorporate cash rent, intrinsic value derived from the rate of return of farmland, and a speculative (bubble) element to determine agricultural land prices.

In 1991, Falk investigated whether the constant expected returns version of the present value model could explain farmland prices, testing for restrictions imposed by the conventional present value model on the data. The results of Falk's vector autoregressive (VAR) model showed that the price of farmland and weighted cash rent tended to move in the same direction and were correlated. However, price movements were more volatile than rent movements. Similar to Featherstone and Baker (1987) findings, a set of exogenous variables were found to be responsible for price deviation from fundamental value in a nonstationary manner, known as a rational bubble.

1.1.2 Spatial Models of the Farmland Values Market

Geoghegan, Wainger and Bockstael (1997) introduced a new method for evaluating land use externalities in housing markets. The researchers created a spatial index using a spatial hedonic model to explain housing values within a 30-mile radius of Washington, D.C. By incorporating the perceived value of the range and distribution of land uses around houses, which included factors like diversity and fragmentation, Geoghegan et al.'s approach to hedonic modeling was a departure from the standard approach. This novel approach inspired subsequent studies to adopt spatial autoregressive (SAR) models and spatial error models (SEM) in their analyses.

Pace and Gilley (1997) incorporated the spatial configuration of observations into a spatial autoregressive model. The findings showed that the maximum likelihood estimates and signs obtained through the spatial autoregressive model differed from those obtained through ordinary least squares (OLS), resulting in a significantly higher degree of fit produced by the former.

Although the literature on time-series for hedonic models is extensive, it fails to account for in-parcel variation. Patton and McErlean (2003) were among the first studies to use parcel data to examine spatial effects in a hedonic pricing model of agricultural land transactions in Northern Ireland between 1996 and 1999. The researchers found evidence of spatial lag dependence and spatial heterogeneity in the agricultural land market, indicating that land prices are affected not only by their own location but also by neighboring areas. This implies that prices of individual plots are influenced by the prices of surrounding parcels, as land prices theoretically spill over spatially.

Huang et al. (2006) used county-level farm and off-farm data in Illinois between 1979 and 1999 to investigate the relationship between hog production and farmland values. Using a characteristic model that includes spatial and temporal dependencies, they found that farmland values decreased with plot size and distance from large cities, but increased with soil productivity, population density, and per capita personal income. Tsoodle et al. (2007) also employed a hedonic model, using data on all agricultural land sales in Kansas between 1996 and 2004 to estimate the market value of the land, considering urban influence and site-specific characteristics. They found that premiums for parcels near Wichita and Kansas City were slightly higher than would be expected based solely on their agricultural use.

In 2009, Maddison conducted a study that explored the impact of temporal and spatial lags when estimating farmland values. Maddison's study made a significant contribution by incorporating spatio-temporal relationships into the hedonic farmland values literature. The findings revealed that the price per acre of nearby land sold in the preceding six months, as well as the characteristics of the sold tracks, had an influence on farmland values. By including nearby properties and recent sales in the estimation model, there was an effect on the perceived value and statistical significance of farmland characteristics.

Geniaux, Ay and Napoléone (2011) used a spatial feature model to examine the land use conversion when land use regulation only utilize zoning at the inner-city level. Using data from the Bouches du Rhone region and 119 municipalities in France, the study used a mixed geographically weighted regression (MGWR) model and a two-stage approach to link agricultural land and developable land markets. The study used an optimal bandwidth as the spatial weight matrix and found that the optimal distance to the central business district and population were significant variables in determining the expected effects. Furthermore, the study showed that in the agricultural land market the optimal bandwidth was 10 km, as the agricultural market appears to be more homogeneous than the developable land market on a closer scale, which optimal bandwidth was sales closer than 20 km.

In 2019, Yang, Odening, and Ritter quantified the spatial diffusion of land prices by combining spatial econometric and market integration models. Their primary contribution was finding a dominant region between the 37 counties. This result indicated that farmland prices are influenced not only by spillover effects from neighboring counties, but also, to some extent, by land prices in one particular county, Cloppenburg County.

1.2 Spatial Data

Heteroscedasticity is a term used to describe an unequal distribution of variance, as explained by Dutilleul (1993). Spatial Heteroscedasticity, on the other hand, pertains to the variation between unit locations. It refers to the uneven distribution of units across space, as described by Anselin and Griffith (1988). Spatial dependence encompasses spatial autocorrelation, which is the correlation between observations based on distance Anselin (1988). Spatial autocorrelation exists when the value of one observation is affected or can be predicted by the value of its neighboring observations. According to Anselin's spatial autocorrelation theory, positive spatial autocorrelation exists when observations in close proximity to each other are more alike, but as distance increases, they begin to diverge. Conversely, when observations are closer and still differ, they exhibit negative spatial autocorrelation. In contrast to spatial autocorrelation, serial correlation, also known as autocorrelation, refers to the correlation between variables in the current period and variables from previous time periods. Spatial autocorrelation captures the degree of correlation of the same variable from previous time periods and spatially contiguous observations, which are two-dimensional and multi-directional. This spatial element is what sets it apart from autocorrelation (Anselin 1989; Bockstael 1996; and Florax and Nijkamp 2003)

Spatial autocorrelation can be present in both dependent and exogenous variables. In the case of dependent variables, it means that the value of a dependent variable at a particular location is influenced by the values of the neighboring locations' dependent variables. Meanwhile, spatial autocorrelation in the error term implies that an important spatially correlated variable was omitted from the analysis; or it can be caused by another spatially autocorrelated exogenous variable. Spatially heteroscedastic data can make ordinary least squares (OLS) estimates inefficient. Thus, classical econometric methods are used to separate spatial heterogeneity and spatial dependence, as explained by Anselin and Griffith (1988).

1.3 Modeling Spatial Data

To account for spatial dependence in the form of spatial autocorrelation, spatial econometric models incorporate an exogenous spatial interaction structure, known as the spatial weight matrix. This spatial weight matrix captures the relationships between observations in a spatial dataset. Two common spatial weighting specifications in the spatial econometric analysis are the adjacency-neighbor structure of the queen and rook contiguity. The queen contiguity neighborhood structure includes common vertices to define the neighborhood relationships between observations. The rook contiguity neighborhood structure only uses non-zero-length common edges. The difference between the specifications is minimal, especially for irregular polygons, such as political boundaries. The queen contiguity criterion is often preferred to account for potential inaccuracies in the electronic polygon files, especially if using state and county political boundaries. Griffin, Ibendahl and Mark (2015) observed that the spatial effect of the neighborhood on farmland values tends to increase as the order of adjacency increases. This effect is particularly evident when the definition of the neighborhood includes lower-order adjacencies.

In spatial econometrics, the spatial weight matrix, $\mathbf{W}$, is a matrix that represents the links between spatial locations. It is an $n \times n$ matrix, where n represents the number of locations, and each matrix element, w_{ij}, represents the spatial relationship between two locations, i and j. Typically, the matrix is constructed such that $w_{ii} = 0$ and $w_{ij} = 1$ if i and j are neighbors and $w_{ij} = 0$ otherwise. The performance of the spatial weight matrix and the estimation of the model is related to the connectivity of the $\mathbf{W}$ matrix. The connectivity of the $\mathbf{W}$ matrix is crucial because sparse or unspecified matrices can lead to larger estimation errors than dense or over-specified matrices. As pointed out by Florax and Rey (1995), the selection of the spatial weight matrix can have a substantial impact on the outcomes of spatial econometric analysis. Other weight matrices used in the literature include k-nearest neighbors, inverse distance, and correlation distance. Choosing the appropriate weight matrix is a crucial step in spatial econometric analysis.

1.4 Dynamic Spatial Durbin Model

Essay 2 focuses on a panel data framework and spatial panel models to study the dynamics of farmland values in Iowa. The methodology involves using cross-sectional averages as a measure of a common factor. By accounting for state effects driven by this common factor, the analysis reveals evidence of spatial dependence, indicating interdependencies among neighborhoods. The findings shed light on the presence of both positive and negative spillover effects.

The extended analysis goes beyond incorporating the common factor (cross-sectional averages) solely in the dependent variable and also includes it in the independent variable at both time t and $t-1$. By incorporating the common factor in both the dependent and independent variables, we aim to capture the influence of this shared factor on the relationships between variables over time.

This essay adds to existing research by evaluating the spatial and temporal aspects of farmland values at the county level for Iowa. The main advantages deriving from this result are that we consider the spatial dependence in the data set, specified spatial interaction types (spatial Durbin), and obtained more reliable estimated coefficients. The predictive power of variables affecting county-level farmland values improve by incorporating spatial dependence into the panel regression model. At the same time, the estimation of the independent variables become consistent. This analysis indicates the importance of considering spatial effects over time. Closer interaction between geography and farmland values should lead to a better understanding of the relationship between neighborhoods and values. The influence of farmland prices from county i into county j translates to time and space (Maddison 2009). This guides us to include the spatiotemporal lag of the dependent variable (weighted average value of farmland (USD)) as an explanatory variable. We include the characteristics of farmland values as additional explanatory variables to account for a limitation of the spatial model that presumes farmland price is affected by nearby land prices but not by the land's characteristics.

1.5 Estimation under Heterogeneous Spatial Autoregressive Model

Motivated by the rapid changes in farmland values over space and time, we derive a heterogeneous model of farmland values in 99 Iowa counties using a novel dynamic spatial panel model. The HSAR model presents a representation of farmland values diffusion with joint treatment of population density and income per capita. The model accounts for both forms of cross-sectional dependence, common factors and spatial dependence.

The spatial and system-wide diffusion multipliers obtained offer valuable insights into the impact of a disturbance in neighborhood farmland values on a specific county within a particular time frame. These multipliers provide a quantitative measure of how the variable shocks spread and affects the target county, providing meaningful information about the dynamics and propagation of farmland values across different areas. Based on our research findings, we observe that more populated areas exhibit a higher degree of spatial dependence. When examining cumulative dynamic multipliers related to changes in neighborhood farmland values, our findings indicate that more populated areas exhibit faster rates of adjustment. The higher population density in urban areas may transmit price information more efficiently than in rural areas.

1.6 Outline

The remaining chapters of the dissertation are organized as follows:

Essay 2 focuses on measuring the spatiotemporal diffusion of county-level farmland values from 1969 to 2014, utilizing the econometric procedures developed by Ciccarelli and Elhorst (2018). The role of various agricultural and non-agricultural factors are examined in relation to farmland values.

In Essay 3, a spatiotemporal model of farmland values in Iowa is developed, following the methodology proposed by Aquaro et al. (2021). The analysis employs cumulative spill-in and spill-out measures for exogenous variables of income per capita and population density, allowing for a directional analysis of spillover effects. The findings reveal a significant level of heterogeneity among counties, indicating substantial spatial dependence. The analysis indicates that the neighborhood spillover effects are stronger in subsequent periods than in the current period. This finding suggests that the influence of farmland value changes in one county on its neighboring counties becomes more pronounced over time. In other words, the impact of farmland value changes tends to spread and exert a stronger effect on neighboring areas in the future. This temporal dimension adds depth to our understanding of spillover effects and emphasizes the significance of considering the dynamic nature of these relationships in farmland valuation analysis.

Essay 4 introduces the "Kansas Property Tax Estimation Tool", including illustrative examples. The interactive R-shiny dashboard represents a pioneering effort in property tax estimation. The tool provides a user-friendly interface and real-time calculations, empowering local policymakers, such as public-school boards and municipalities, to easily conduct "what-if" analyses. Improved transparency among taxpayers, the Kansas Department of Revenue, and legislators is an additional benefit. Using the tool, legislators can easily assess the statewide, district-level, and county-level impact of proposed changes to the use valuation methodology on property tax revenues. Land managers can estimate taxes for future land acquisitions and budget accordingly, while tax districts can adjust mill levies to meet revenue goals.

Essay 5 concludes the dissertation by discussing the limitations of the research findings, presenting policy recommendations, and suggesting potential areas for future research exploration.

Chapter 2

2 Spatiotemporal Diffusion of Farmland Values across Iowa Counties: Dynamic Spatial panel Durbin Model with Common Factors and ESDA approaches

2.1 Introduction

Interest in the value of farmland has not waned, as evidenced by the increasing number of studies published in this area. The reduction of farmland used for agricultural production is partly a result of population growth and urban sprawl, as municipalities expand into rural areas. Since the 1980s, solar farms (Farja and Maciejczak 2021; Havrysh et al. 2022), windmills (Sampson, Perry and Tayler 2020), oil wells (Ogwang and Vanclay 2019), and other easements have competed with traditional production agriculture for farmland. The increasing global population and biofuel alternatives continue to play important roles in farmland values. Changing farmland values are an ongoing concern for stakeholders, including farmers, investors, real estate developers, economists, and policy makers.

An understanding of the geographic distribution of farmland values is an important facet to explore in the farmland market. County-to-county farmland value changes with indirect, spatial spillover, effects emphasize the importance of including spatial impacts in risk mitigation for investors and agricultural producers. This study focuses on accurately estimating county-to-county spatial dependencies and analyzing the economic drivers of farmland values.

A large number of studies have examined farmland values using hedonic pricing models in a spatial context. Wang (2013) used county-level data from the U.S. Census of Agriculture in Pennsylvania between 1982 and 2012. Their panel data consisted of 64 counties across seven periods. By applying the theory of spatial competition, Wang (2013) derived the spatial structure of farmland values and reported the spatial interdependence of farmland values across counties.

Griffin et al. (2015) examined the spatial autocorrelation among the lower 48 U.S. states using USDA-NASS data. The study discovered significant global spatial autocorrelation in farmland values between states and spatial autocorrelation in the percentage change in farmland values between states, regardless of the period. Their study only utilized state-level data and did not analyze county-level data or discuss any differences in data aggregated at different spatial scales. This research will expand on their research by examining county-level data.

Time series analysis is prevalent in examining farmland values, indicating temporal effects on farmland values. We expect that farmland values are also influenced by spatial effects. Thus, we conduct an exploratory spatial data analysis of county-level farmland values to determine the necessity of advanced spatial analysis. When feasible, county-level studies are compared to state-level studies to examine how the spatial scale impacts the analysis.

In 2021, production agriculture occupied approximately 85% (30.6 million acres) of Iowa's total land, making it a crucial sector of the state's economy. According to the United States Department of Agriculture National Agricultural Statistics Service (USDA-NASS), agricultural products such as corn, soybeans, hogs, cattle, and poultry play a crucial role in Iowa's economy. These commodities are among the most significant contributors to the state's agricultural sector and have a substantial impact on its overall economic wellbeing. During 2021, farmland values in Iowa increased 29% ($2,193), averaging $9,751 per acre compared to 2020. From 1969 to 2014, the state's farmland values rose from around $2,704 per acre to $7,940 per acre (inflation adjusted), while corn yield per acre increased from 96.49 to 178.14 bushels.

County-level data show patterns of economic growth and production. In 2014, O'Brien, Scott, and Sioux Counties had farmland values exceeding $10,000 per acre, while counties like Appanoose, Clarke, and Lucas had values below $5,000 per acre. Randomly selected years (1970, 1990, and 2010) were used to display the distribution of Iowa's county farmland values (Figure 2.1). From 1970 to 2010, farmland values in each county exhibited exponential annual growth. Scott and Sioux counties consistently demonstrated the highest farmland values, which were approximately twice as high as Adams and Davis. These variations in farmland value demonstrate spatial clustering. Figure 2.2 illustrates the aggregation of northern and southern counties based on their high and low farmland values, respectively. Figure 2.3 displays the average farmland values for select counties the period 1970-2014.

In this study, we examine the spatial impact of agricultural and non-agricultural influences on farmland values in 99 Iowa counties. Controlling for spatio-temporal effects through common factors, we analyzed spatial dependence using a spatially dynamic panel data model. Farmland values are estimated based on agricultural and non-agricultural variables at the county level from 1969 to 2014. Determining the spatial autocorrelation (correlation) between the agricultural and non-agricultural variables and farmland values is critical for understanding the direct and indirect effects of the independent variables.

Initially, we will determine if the results of the spatial autocorrelation in farmland values are consistent at a smaller spatial scale than the state level. Then we will test for the presence of spatial dependence in farmland values and specified exogenous variables. Next, we will interpret the direct and indirect impacts, in the short and long- run, of those spatial relationships. Finally, we will compare estimation results and cross-sectional dependence from a model with both space and time fixed effects and a model with common factors.

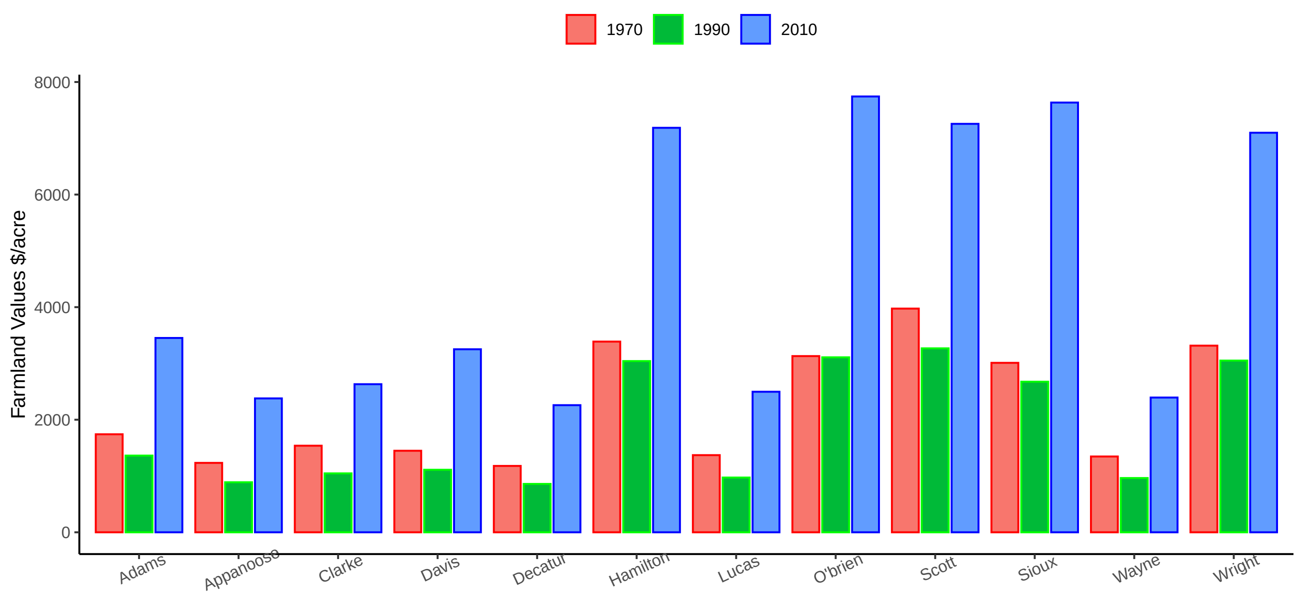

Figure 2.1: Farmland values for three random years for selected Iowa counties

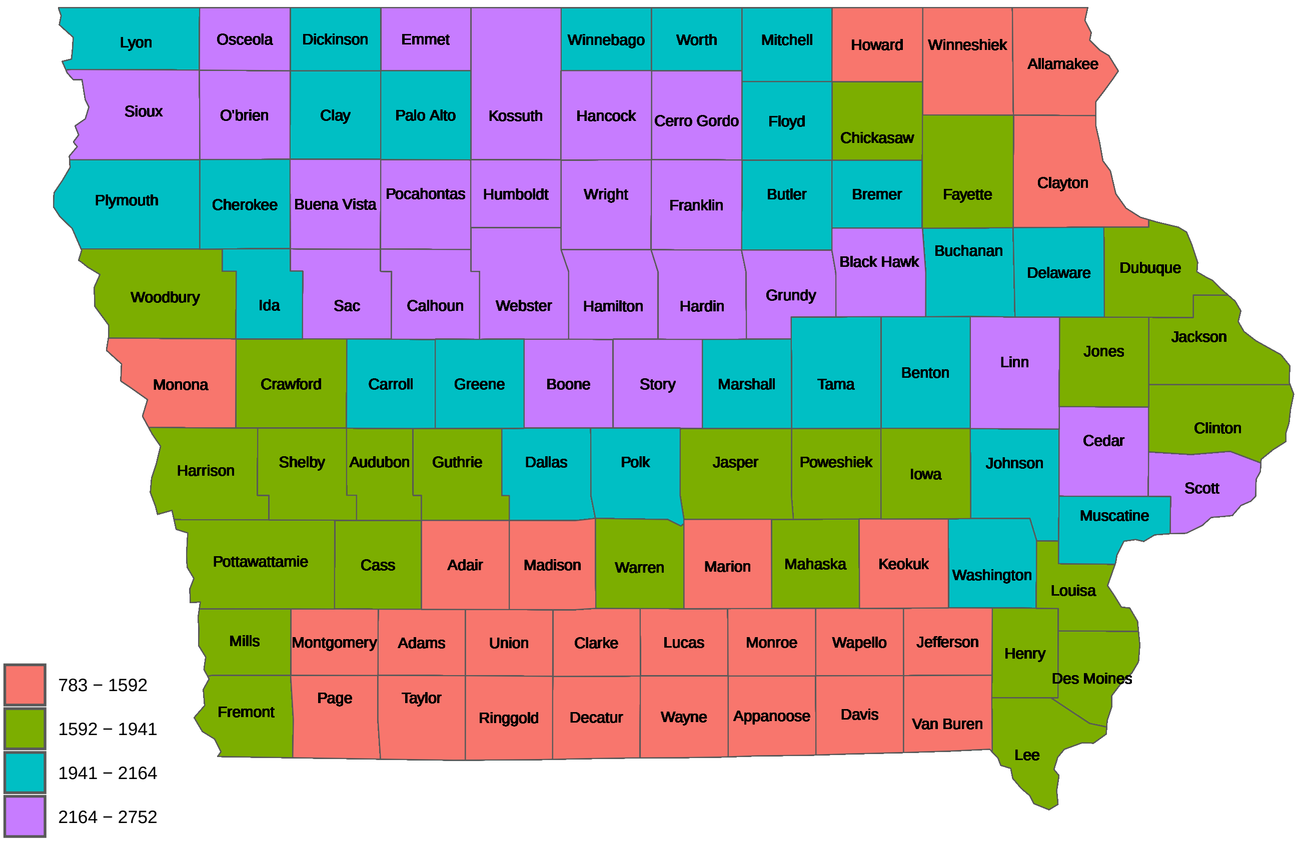

Figure 2.2: Average inflation-adjusted farmland values in Iowa between 1969 and 2014

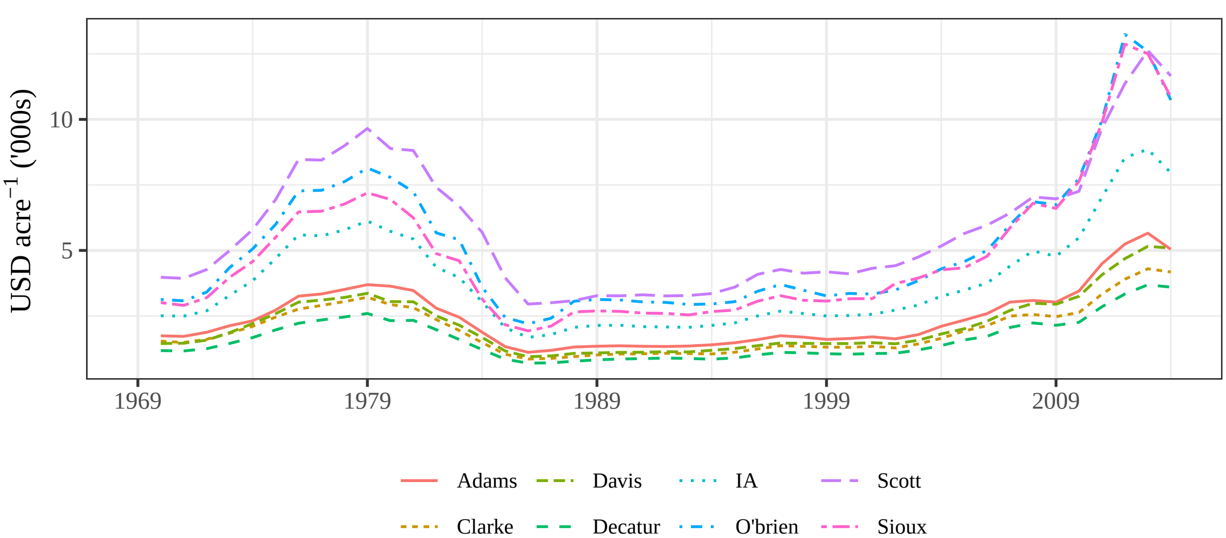

Figure 2.3: Farmland values, inflation-adjusted, selected Iowa counties, from 1969 to 2014

2.2 Farmland Value Literature

Over time, real farmland values in the United States have increased. However, regional variations in this trend exist, and some states are more sensitive to national changes than others are. According to the USDA- NASS, in 2022, the average value of U.S. farm real estate, which includes the value of all land and buildings owned by the farm, was $3,800 per acre. This marks an increase of $420 per acre (12.4%) from the previous year. The average value of US cropland rose to $5,050 per acre, an increase of $630 per acre (14.3%) from 2021, and the average value of pastureland increased by $170 per acre (11.5%), reaching $1,650 per acre in 2022. However, the Midwest regions had a relatively higher increase from 2021 than other states. Values increased 21.4% per acre in Iowa and 25.2% per acre in Kansas.

Many studies have focused on understanding the factors influencing farmland values. Several studies aim to help farmers make better risk management and investment decisions (Geoghegan et al. 1997; Shi, Phipps and Colyer 1997; Huang et al. 2006; Tsoodle et al. 2007). Some studies (Burt 1986; Featherstone and Baker 1987; Lloyd and Rayner 1990; Lloyd et al. 1991; Falk 1991; Lence 2014; Baker, Boehlje and Langemeier 2014; Henderson 2008) report a series of periods when neither the farmland market fundamentals, e.g., the value of land, interest rates, and cash rent, nor production factors, thoroughly explain the change in land values.

There is an extensive body of literature using hedonic methods to model farmland values. However, few studies have employed spatial hedonic or panel hedonic modeling to understand farmland value dynamics. Recently, researchers have applied neighborhood spillover effects to study farmland values (Huang et al. 2006; Burns et al. 2018). Farmland values exhibit a strong correlation over time and space. Several studies have addressed the time-dependence issue, focusing on serial dynamic effects to estimate trends and structural breaks in farmland values (Schurle et al. 2013). Other studies have focused on spatial autocorrelation in farmland values to detect clustering, global, and local spatial autocorrelation (Wang 2013).

Numerous studies have explored the dynamics of farmland prices over time, using econometric models. Some (Herdt and Cochrane 1966; Tweeten and Martin 1966; Reynolds and Timmons 1969; and Van Dijk et al. 1986) used simultaneous equation models, and others used asset-pricing models (Melichar 1979; Burt 1986; Featherstone and Baker 1987; Lloyd and Rayner 1990; Lloyd et al. 1991; Falk 1991). Traill (1979) used single equations. Those models aimed to capture the time-series movement of farmland prices and identify the key factors that affect their behavior, such as crop prices, interest rates, and government policies.

Other studies have analyzed factors affecting land values from a cross-sectional and time-series perspective (Danielson 1986; Palmquist and Danielson 1989; Xu 1990; Elad et al. 1994; Kennedy 1997; Maddison 2000; Patton and McErlean 2003; and Tsoodle et al. 2007). These findings suggest that farmland values and neighborhood characteristics vary over space and time. A limited number of studies have addressed the spatiotemporal relationship of farmland prices (Maddison 2009; Carmona and Rosés 2012; Yang et al. 2017; and Yang et al. 2019). This approach uses a less common spatial econometric model that includes a spatially lagged independent variable on the right-hand side of the equation.

2.2.1 Time Series

Chavas and Shumway (1982) investigated crop prices in Iowa using a hedonic model with time lags and regional dummy variables. The study highlighted the influence of major production commodities on land values. Sandrey et al. (1982) examined farmland value trends in Oregon's agricultural subregions, emphasizing the importance of disaggregated models to capture regional and temporal diversities.

Lloyd et al. (1990, 1991) applied capital asset theory to examine agricultural land values and land price expectations. They incorporated cash rent and inflation to determine land prices. Falk (1991, 1992) investigated the explanatory power of present value models on farmland prices, finding that investor sentiment had a greater impact on price changes than variables intrinsically relevant to the asset's fundamental values. Featherstone et al. (1993) analyzed the discount received by financial institutions during the 1980s financial crisis and indicated that certain characteristics influenced land prices. Some of these characteristics included land quality, road surface, cropland, improvements on the farm, irrigation, and others. Tsoodle et al. (2007) estimated land values and the "option" value based on agricultural productivity and the inclusion of a negative exponential specification. Their hybrid hedonic model considered production characteristics, total number of acres, percent of non-irrigated, irrigated, improved pasture acres, proximity of land to metropolitan areas, and other in-site characteristics. These studies collectively provide insights into the factors influencing farmland prices, including land quality, timing, technological advances, investor sentiment, inflation rate, interest rate, regional characteristics, and productivity.

2.2.2 Spatial

Studies have also addressed spatial heterogeneity and spatial effects in hedonic pricing models. Geoghegan et al. (1997) introduced a novel approach to hedonic modeling by incorporating a spatial index to explain housing values around Washington, D.C. This approach led to subsequent studies adopting spatial autoregressive models. Boisvert et al. 1997) analyzed farmland values and cash rents in the Lower Susquehanna River Basin, finding positive correlations with productivity, spatial orientation, and environmental vulnerability. They did not incorporate the spatial component in their model. Pace and Gilley (1997) did incorporate spatial configuration into a spatial autoregressive model to resolve incorrect signs and spatial autocorrelation in residuals. Their model yielded a higher degree of fit than an ordinary least squares.

The literature on time-series for hedonic models is extensive and has helped explain the movement of agricultural land prices over time. However, it fails to account for in-parcel variation. Several studies have attempted to address spatial heterogeneity by estimating a hedonic price for each sub-market or by jointly estimating separate coefficients for each sub-market using traditional spatial regime models (Xu 1990; Elad et al. 1994; Kennedy 1997; and Tsoodle et al. 2007). Patton and McErlean (2003) were among the first studies to use parcel data to examine spatial effects in a hedonic pricing model of agricultural land transactions in Northern Ireland between 1996 and 1999. Their research compared results from the hedonic model with spatial regime (sub-markets) and a spatial lag hedonic model. They found evidence of spatial lag dependence and spatial heterogeneity in the agricultural land market, indicating that land prices are affected not only by their own location but also by neighboring areas. This implies that prices of individual plots move with the prices of surrounding parcels in a region.

Huang et al. (2006) investigated the relationship between hog production and farmland values in Illinois, considering spatial and temporal dependencies. They found that farmland values varied based on plot size, distance from cities, soil productivity, population density, and per capita personal income. Carcamo and Roses (2012) analyzed the Spanish land market using land sales data, revealing distinct regional markets shaped by local economic and institutional factors. They found that land prices were influenced by productivity and local demand rather than by land size or ownership concentration. Yang et al. (2017) investigated the market efficiency and spatial convergence of agricultural land prices in Lower Saxony, Germany. They found similarities in land price dynamics across clusters of counties but rejected spatial market integration and the law of one price. In 2019, Yang et al. quantified the spatial diffusion of land prices in Lower Saxony, Germany. They identified a dominant region, Cloppenburg County, which influenced farmland prices not only through spillover effects from neighboring counties but also to some extent on its own. These studies contribute to the understanding of spatial effects, market integration, and factors influencing land values in various regions. The incorporation of spatial considerations and the exploration of regional heterogeneity enhance the accuracy and applicability of hedonic models in assessing land prices.

2.2.3 Common factors

Spatial dependence in farmland values, observed in the form of spatial autocorrelation, can emerge from shared business cycle effects, where county changes follow national or state changes in these factors, creating a system-wide phenomenon (Maddison 2009). However, spatial autocorrelation may also be caused by local interactions between smaller regions and counties, the effects of which are propagated in space and time. Hence, it is critical to test and control for both strong and weak cross-sectional dependencies when using cross-sectional cropland data (Kuersteiner and Prucha 2020; Bailey, Holly and Pesaran 2016). Regional data models that incorporate serial dynamics, spatial dependence, and merging of common factors have been used to examine house prices (Holly, Pesaran and Yamagata 2011; Bailey et al. 2016), regional unemployment differences (Vega and Elhorst 2016), and cigarette consumption (Ciccarelli and Elhorst 2018).

Using the change in the house price at the regional level in the UK, Holly et al. (2011) provided a method for analyzing the spatial and temporal diffusion of shocks in a dynamic system. The analysis was approached from the perspective of cross-sectional dependence. In a regional context, the proximity of one region to another is not necessarily limited to geographic proximity. It may also include economic measures of distance (Conley 1999; Pesaran, Schuermann and Weiner 2004) or social distance (Conley and Topa 2002). The literature defines these “common factors” as the cross-sectional averages of the dependent variable. Strong cross-sectional dependence is expected to be accounted for by including common factor terms in the model (Bailey et al. 2016; Vega and Elhorst 2016; Ciccarelli and Elhorst 2018).

2.3 Data

2.3.1 Dependent variable

The data used in this analysis are publicly available and consist of annual county-level farmland values in Iowa. Iowa State University (ISU) Extension and Outreach have collected county-level data for farmland values via survey since 1950. These values are the average nominal farmland value per acre for the 99 Iowa counties. Data obtained from ISU is adjusted for inflation using the Consumer Price Index (CPI), with 2015 as the reference year. Focusing solely on Iowa could result in border edge issues, where counties on the state border are impacted by excluded neighboring states. This boundary, or spatial edge, effect arises due to spatial dependencies beyond the geographic boundaries of the data, as noted by Anselin (1989).

2.3.2 Explanatory variables

Explanatory variables included in the model are corn yield in bushels per acre, acres planted to corn, jobs in the agricultural sector, population density, and per capita personal income. Data were accessed from ISU, U.S. Department of Agriculture National Agricultural Statistics Service (NASS) Quick Stats (USDA NASS 2017), and the Bureau of Economic Analysis (Bureau of Economic Analysis n.d.). All variables included in this analysis are available at the county level, so data aggregation is not required. In 2015, USDA-NASS began grouping counties where corn yield or acreage planted to corn was relatively low. Therefore, for this analysis, we will focus on data ranging from 1969 to 2014.

With corn being a vital crop for Iowa's economy, we expect that acreage planted to corn ($Acreage$) will impact the value of farmland. Corn acreage may offer insights into the effects of factors like weather on the region. Drought conditions in half of the counties may discourage planting corn and encourage planting potentially less profitable crops. Less profitable crops would influence producers' expectations of the profitability of that farmland. Additionally, corn acreage may provide some information about the broader agricultural sector. Higher corn acreage may indicate a focus on row crop agriculture, with a lower risk income stream, than livestock production. We expect acreage planted to corn to positively impact the value of farmland per acre.

Fluctuations in corn yield in bushel acres $^{-1}$ ($Yield$) directly impact farmland values through the expected future income stream from the land. Empirical evidence (Boisvert, Schmit and Regmi 1997), shows a positive correlation between corn yields and farmland values, with corn yield serving as a proxy for land productivity. Based on this understanding, we hypothesize that productivity, as measured by corn yield, has a positive effect on farmland values. Since corn yield requires significant inputs, like fertilizers, pesticides, and machinery, changes in corn yield can also influence other economic activities within the local economy.

Including farm sector jobs ($Jobs$) as an explanatory variable for farmland values provides a comprehensive proxy for the agricultural sector's economic health. Empirical evidence suggests a positive relationship between farm employment and farmland values. Farm employment serves as a proxy for the importance and intensity of agricultural production in the local economy, but it should be used alongside other indicators. We hypothesize a positive relationship between farm sector jobs and farmland values at the county level in Iowa.

Income Per Capita ($Income$) is a measure of the average income earned by individuals in a county and serves as an indicator of the region's overall economic health, beyond the agricultural sector. Similar to farmland values, Income is adjusted for inflation. Income per capita plays a role in determining the level of investment in agriculture. Studies have shown that an increase in per capita income is correlated with higher values of cultivated land and farmland (Cotteleer, Stobbe and Kooten 2008).

Population density ($PopDens$) refers to the number of people residing in a specific area, typically expressed as the number of individuals per square mile in each county. It serves as a proxy for the potential competition for land use within a region. Population density reflects the level of urbanization within counties. As population densities rise, there is pressure to convert agricultural land to residential or commercial uses, reducing the supply of farmland and subsequently driving up its value. Empirical evidence from studies (Boisvert et al. 1997; Huang et al. 2006; and Schlenker, Hanemann and Fisher 2006) consistently shows a positive correlation between population density and the value of cultivated land. Thus, we hypothesize a positive relationship between population density and farmland values.

2.3.3 Data sources

We use a panel dataset, containing the values for 99 counties between 1969 and 2014, to analyze the effects of agricultural and non-agricultural variables on farmland values in Iowa (Figure 2.2) accessed from ISU. Acreage planted to corn and corn yield measured as bushel $acres^{-1}$ were accessed from the USDA-NASS Quickstats. Population, jobs generated by the farm sector, and income per capita were accessed from the Bureau of Economic Analysis (Bureau of Economic Analysis n.d.).

The descriptive statistics for the variables in the model are presented in Table 2.1. To address heteroscedasticity and the dependence in the regression model specification, this research used a logarithmic transformation of the explanatory variables (Yu, Sang and Huan 2022). Taking the natural logarithm of variables will mitigate any potential biases or inconsistencies that may arise due to heteroscedasticity and model specification. The relationship between the values of the independent variable and the variance of the dependent variable is assumed to be uniform. This transformation helps stabilize the variables' variance and allows for a more robust analysis of their relationship with the dependent variable.

Table 2.1: Descriptive statistics of all variables.

Variables	min	25^{th}	median	mean	75^{th}	max
FarmlandValue	699.887	2303.276	3085.358	3803.016	4870.072	13241.370
Acreage	5200.000	89400.000	124700.000	123967.901	158000.000	336400.000
Yield	18.300	106.400	129.200	128.876	153.600	206.600
Jobs	421.000	921.000	1180.000	1301.571	1623.000	3474.000
Income	117679.838	348560.380	510616.322	996750.340	809694.123	22102400.842
PopDens	9.157	21.495	29.255	50.970	41.393	803.238

To validate the absence of multicollinearity, a correlation analysis between all logarithmic variables was conducted. We found that the core independent and control variables exhibited low correlation (Table 2.2). We also calculated the variance inflation factor (VIF) for the independent variables and found that all VIF values were below three, indicating no multicollinearity among the independent variables.

Table 2.2: Correlation analysis of all logarithmic variables

	FarmlandValue	Acreage	Yield	Jobs	Income	PopDens
FarmlandValue	1					
Acreage	0.501	1				
Yield	0.255	0.321	1			
Jobs	0.06	0.421	-0.319	1		
Income	0.44	0.275	0.662	-0.471	1	
PopDens	0.201	0.169	0.071	0.242	0.165	1
VIF	NA	2.048	1.912	2.653	2.721	1.216
CD	464.565	287.139	382.956	453.991	470.096	128.321
PW	0.983	0.608	0.811	0.961	0.995	0.272

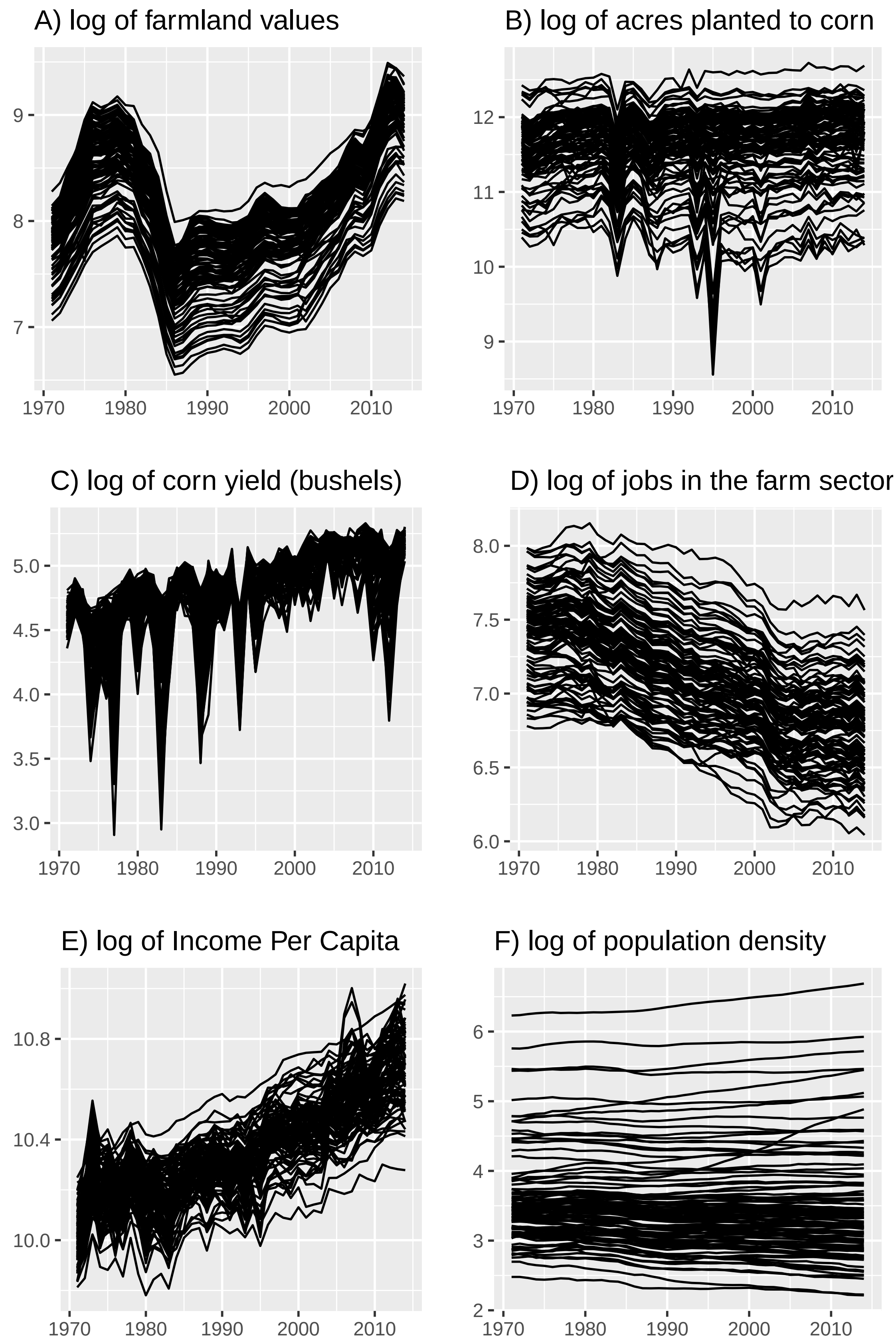

Figure 2.4: Farmland values and explanatory variables for 99 Iowa counties

2.3.4 Theoretical considerations

Initially, the study of farmland prices was motivated by the perception that land values were disproportionate to income and, therefore, not in equilibrium. Previous models employed in this field often assumed a static framework, implicitly assuming rapid adjustments to a long-run equilibrium. However, it is crucial to consider the time paths of adjustments for fundamental variables such as returns and interest rates, as these may provide part of the explanation for changes in farmland values. The dynamics of the market and the expectations of market participants contribute to trends in farmland values. These factors can result in the land price following a positive or negative trend over time. In this study, the theoretical model employed is the capitalization model. The model used in this study approximated the structure of the capitalization model by incorporating a second-order lag on farmland value. The model was extended to include the weighted average of farmland values in neighboring counties at both the current time and lagged periods. This extension allows for the consideration of spatial dependencies and interactions between farmland values in adjacent counties, providing a more comprehensive understanding of the factors influencing farmland values.

2.3.5 Model Specification Regression model

Ordinary Least Square (OLS) is used in conducting exploratory regression analysis. When the underlying assumptions hold, OLS provides unbiased and efficient estimates of the regression coefficients, particularly when the data does not exhibit spatial dependence in the form of spatial autocorrelation. The regression model is:

$$LFLV_{it} = \beta_0 + \beta_1 Acreage_{it} + \beta_2 Yield_{it} + \beta_3 Jobs_{it} + \beta_4 Income_{it} + \beta_5 PopDens_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (1)$$

where all variables are defined as natural logarithms. This specification allows one to interpret coefficients as elasticities. Parameters μ_i and η_t represent individual and time effects for each county, respectively. Individual effects for each county in the sample are related to explanatory variables and are fixed over time. Omitting the individual effect may result in bias estimates, if the fixed effect is correlated with the explanatory variable. The time effects control for time-specific events that affect all counties in a given period.

2.3.6 Spatial econometric models

A first-order queen-adjacency neighbor list, $q1$, is defined for the 99 counties in Iowa. Links are the connections between the Iowa counties. The number of links increases as the order of contiguity increases. The percentage of non-zero weights are the proportion defined by the neighborhood with connections. The minimum number of links was non-zero, indicating no counties had no neighbors in the data. The first-order queen contiguity has a total of 588 non-zero links, a percentage of non-zero weights of 6. The average, minimum, and maximum number of links were 6, 3, and 8, respectively. The q1 neighbor list has the highest spatial autocorrelation. Thus, $q1$ implies that a county's farmland value directly affects its neighboring counties' values. Row-normalized, first-order queen adjacency weight matrices were defined for the remaining diagnostic tests.

In analyzing spatial phenomena, it is common for studies to utilize a sparse binary contiguity (BC) matrix rather than a dense inverse distance matrix. This choice is particularly prevalent when examining diffusion processes, as highlighted in a comprehensive study by (Ciccarelli and Elhorst 2018). They reviewed 29 marketing studies that employed spatial econometric methods and observed that most researchers opted for the BC matrix as their preferred spatial representation. This preference underscores the widespread adoption of the BC matrix, especially in studies focusing on the analysis of diffusion processes.

According to Montero, Fernández-Avilés and Laureti (2021), spatial dependence can be modeled in several ways based on the relationship between dependent and independent variables. There are three models used to estimate spatial panel data models (Elhorst 2014a). The Spatial Autoregressive (SAR) model assumes that the spatially weighted average value of nearby regions has a partial influence on the dependent variable, along with the standard explanatory variables that have a direct impact. The spatial autorregressive lag model helps capture the spatial dependence in the data and model the direct and indirect effects of the independent variables on the dependent variable. The Spatial Error Model (SEM) assumes that at least one important spatially correlated variable is omitted from the regression, but it does not account for the indirect effects of spatial autocorrelation. According to the SEM model, unobserved shocks in one specific region are not affected by unobserved shocks in neighboring regions. The Spatial Durbin Model (SDM) is a statistical model incorporating spatially weighted independent variables as explanatory variables. Unlike the SAR and SEM models, the SDM model considers both the dependent and independent variables' spatial lagged effects, including spatial dependence in both variables. In the SDM, the dependent variable, y_{it} is modeled as a function of spatially lagged dependent variables, spatially lagged independent variables, and a stochastic error term. The SDM parameters are typically estimated using maximum likelihood or generalized method of moments (GMM) estimation techniques.

Direct and indirect effects

According to LeSage and Pace (2009), in the presence of spatial dependence in a model, the coefficients of the explanatory variables may not be sufficient to describe the marginal effect. Therefore, to correctly interpret the results of the spatial regression model, the coefficients of the Spatial Lag Model (SLM) explanatory variables are broken down into direct, indirect, and total effects. The direct effect captures the change in the explanatory variable on the i^{th} observation of the dependent variable. Indirect effects capture the feedback effects through the neighborhood structure. In contrast, the total effect captures the effect on each observation of changing the k^{th} explanatory variable by one unit across all observations. Decomposing the SDM coefficients increases the understanding of the effect of explanatory variables on the dependent variable in a spatially dependent setting. Direct, indirect, and total effects equations are explained in the Appendix section.

2.3.7 Empirical model

In exploratory spatial data analysis, tests are conducted to examine both global and local spatial autocorrelation. Global spatial autocorrelation assesses the relationship between individual observations and the degree of similarity between neighboring regions. Local spatial effects, on the other hand, measure the degree of spatial correlation at each particular location. To assess spatial autocorrelation, farmland values and percentage changes in farmland values are examined at a county level.

Given the political boundaries of counties, this study utilized a neighborhood structure based on contiguity. The spatial effect of the neighborhood increases as the order of adjacency increases, with lower orders, also included in the neighborhood definition. A queen contiguity neighborhood structure was chosen, including neighbors with a vertex or a border. In contrast, the alternative rook contiguity only considers shared sides of non-zero length. Although there may be minimal differences in practice, irregular polygons (such as political boundaries) can cause inaccuracies. Using the queen criterion compensates for such errors in the polygon files. The 1^{st}, 2^{nd}, and 3^{rd} orders of queen contiguity were employed, with 1^{st} order defined for regions sharing a boundary or corner, and 2^{nd} and 3^{rd} order defined as sequential adjacencies of neighbors and neighbors of neighbors, respectively. For 2^{nd} and 3^{rd} orders, immediate neighbors were excluded from their matrices. For example, even though Arizona shares only a corner with Colorado, they are considered neighbors. To illustrate the connectedness of counties, a map was generated, using Story County, Iowa as a reference point (Figure 2.5).

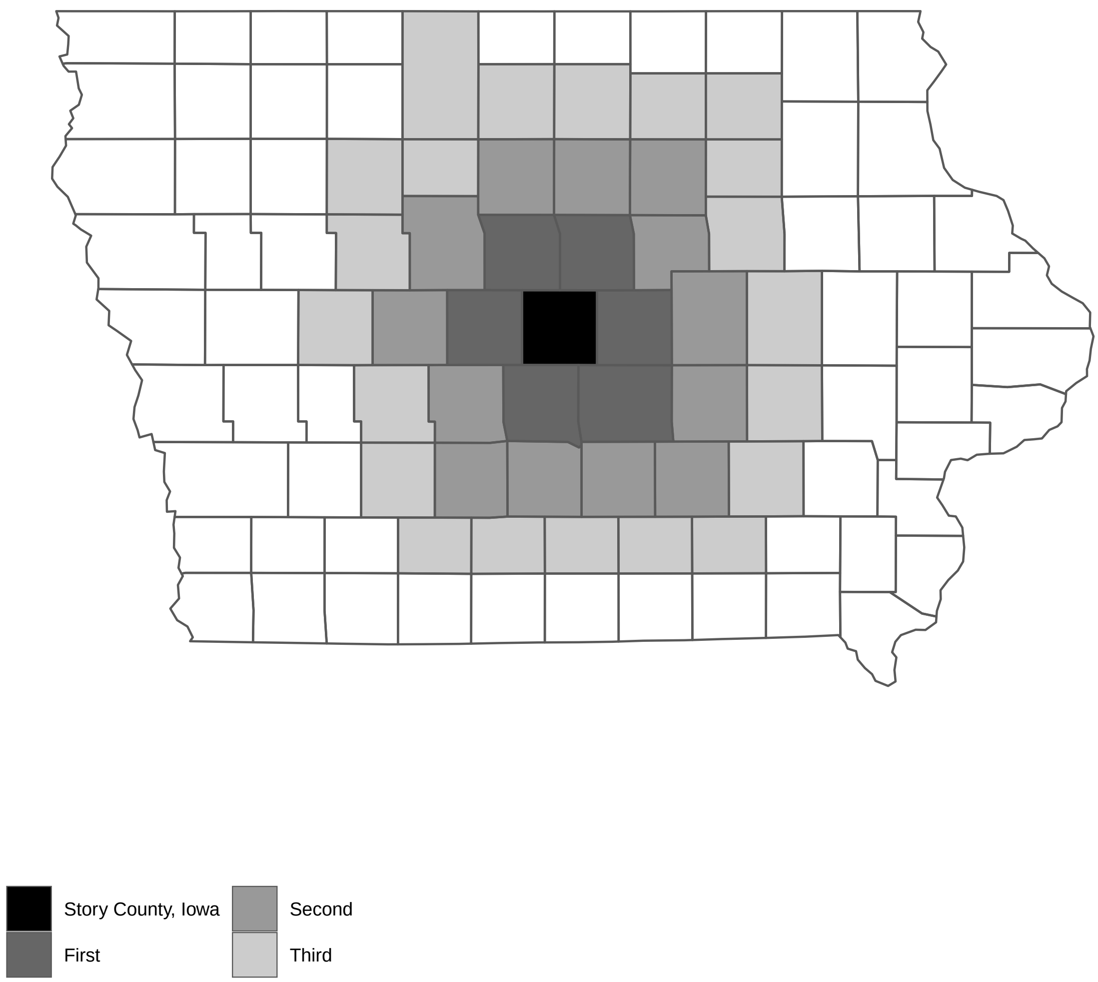

Figure 2.5: First three queen contiguity orders for counties relative to Story County, Iowa.

Spatial diagnostics were conducted on farmland values, with both global and local spatial autocorrelation assessed. To evaluate global spatial autocorrelation, the global Moran's index (I) was calculated (Equation 2). The degree of spatial correlation at each specific site was measured using the Moran's local autocorrelation index (LISA) (Equation 3). The global Moran's (I) was estimated for farmland values and percent change in farmland values for the 99 Iowa counties.

As noted by Schabenberger and Gotway (2017), the Moran's index can be loosely interpreted as a correlation coefficient. It is a spatial correlation coefficient that is not strictly bound between $[-1, 1]$, but rather between $\frac{1}{\wedge_{n-1}}$ and $\frac{1}{\wedge_{(1)}}$, where $\wedge_{(n-1)}$ and $\wedge_{(1)}$ are the minimum and maximum eigenvalues of $\mathbf{W}$. A value of 0 indicates spatial randomness, values less than 0 suggest negative autocorrelation or dissimilarity between objects, and values greater than 0 indicate positive autocorrelation or similarity between objects.

The Moran's I test statistic for spatial autocorrelation (Anselin 1988; Cliff and Ord 1981) uses equation 2

$$I = \frac{n}{\mathbf{W}_{ij}} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \overline{x})(x_j - \overline{x})}{\sum_{i=1}^{n}(x_i - \overline{x})^2} \tag{2}$$

The equation for calculating Moran's index is based on an $n \times n$ spatial weight matrix $\mathbf{w}_{ij}$ that represents the links between spatial units i and j, as well as an $n \times 1$ value of the variables in these units, denoted by x_i and x_j. The arithmetic mean value of the analyzed variable for all spatial units is represented by $\overline{x}$. The interpretation of positive Moran's index values is that high (low) values tend to have neighbors with high (low) values. Negative values indicate that high- and low-valued observations occur as neighbors. Finally, a spatially random distribution is indicated by a Moran's index value that is not statistically different from zero, as noted by Schabenberger and Gotway (2017), Anselin (1988), and Cliff and Ord (1981).

$$I_i = \frac{x_i - \mu}{\sigma_n^2} \sum_{j=1}^{n} w_{ij}(x_j - \mu) \tag{3}$$

where σ^2 is the variance of farmland values in region n; x_j is the observed value of variable X in region i, where $i = 1, ..., n$, and μ is the average of n regions. Local correlations and extreme spatial values are identified by Moran's Local Autocorrelation Index (LISA).

2.3.8 Spatial econometric analysis

The dynamic spatial panel data model with common factors is

$$LFLV_{it} = \rho \sum_{j=1}^{N} W_{ij} LFLV_{jt} + \tau LFLV_{it-1} + \eta \sum_{j=1}^{N} W_{ij} LFLV_{j,t-1} + X_t \beta + W X_t \theta$$
$$+ \Gamma_1 \overline{LFLV}_t + \Gamma_2 \overline{LFLV}_{t-1} + \sum_{k=1}^{K} \prod_{k} \overline{X}_{kt} + \mu_i + \xi_t \iota_N + \epsilon_t \tag{4}$$

The dependent variable is a column vector of observations at time t, meaning one observation for each unit of farmland values in the 99 Iowa counties over the period 1969-2014. The parameters τ, ρ, and η are the time, spatial, and spatiotemporal autoregressive coefficients, respectively. All other variables and coefficients are as previously explained. The model described is formally known as the dynamic spatial Durbin model, because it includes of both the traditional explanatory variables and the spatial weighted average effect of those explanatory variables, X and WX, respectively, in equation (4) (Elhorst 2014). The weak cross-sectional dependence, or local spatial dependence, is meant to be explained by the variables previously described. To account for the strong, or global common factor dependence, the averages of the dependent variable were included.

As discussed, LeSage and Pace (2009) explain that when spatial dependence is present in the model, the coefficients of the explanatory variables might not be sufficient to describe the marginal effect. Therefore, to properly interpret the results of the spatial regression model, the coefficients of the explanatory variables from DSDM were decomposed into the direct, indirect, and total effects. The change in the i^{th} observation of x_k on y_i is captured by the direct effect. Through the neighborhood structure, the feedback effects are captured by the indirect effects. The influence on each observation from changing the k^{th} explanatory variable by one unit across all observations is captured by the total effects.

2.4 Results

This study includes an exploratory spatial data analysis of county-level farmland values, focusing on reporting Moran's **I**. The results are presented in four sections. First, summary statistics and spatial weight definitions are provided. Second, the results of the Local Indicator of Spatial Association (LISA) significance and cluster maps are presented. Third, the results are compared to those reported by Griffin et al. (2015), who used state-level data over a relatively long time series but with a coarser geographic scale. Fourth, the results of Moran's **I** on residuals of four models are discussed. Fifth, the estimation results of non-spatial panel are presented and tested against LM lag and error, and robust versions to determine which model is more appropriate for the spatial analysis. Finally, the study includes the results of dynamic spatial panel model with short and long-term effects are more detailed explained.

2.4.1 Summary statistics

Table 2.3 presents descriptive statistics for the 1^{st}, 2^{nd}, and 3^{rd} order queen contiguity weight matrices for county-level data. The average number of links for the first three orders of queen contiguity were 6, 16.26, and 29.29 for Iowa counties. The percentage of non-zero weights is the proportion defined by the neighborhood with links. In all six cases, the minimum number of links was non-zero, ensuring that each observation had at least one neighbor and there are no isolates. The average number of links is 6 for 1^{st} order queen contiguity, with a maximum of eight; the 2^{nd}, and 3^{rd} order contiguity are much more connected at the county-level on average.

Table 2.3: Statistics, spatial weight definitions, first three queen contiguity orders, for Iowa counties

	99 Iowa Counties		
Order of Contiguity	1^{st}	2^{nd}	3^{rd}
Number of non-zero links	588	1610	2900
Percentage of non-zero weights	6	16	30
Average number of links	6	16	29
Minimum number of links	3	7	14
Maximum number of links	8	22	44

2.4.2 Global spatial autocorrelation

Moran's **I** test was conducted on farmland values and their percentage change for Iowa cropland. The spatial correlations of 1^{st}, 2^{nd}, and 3^{rd} sequential adjacency for all years are presented in Figure 2.6, and the standard deviations are shown in Appendix 1 Figure A1.

County-level farmland values exhibit spatial autocorrelation, with stronger autocorrelation observed at the 1st order of contiguity, similar to farmland values at the state-level presented by Griffin et al. (2015). This suggests that neighboring regions have a greater positive or negative impact on farmland values. As contiguity order increases, the spillover effect decreases but remains present. Figure 2.6 illustrates spatial correlations among farmland values and percentage change in farmland values at the 1^{st}, 2^{nd}, and 3^{rd} orders of contiguity for each year. Moran's I values at the 1^{st} order of contiguity were consistently high, ranging from 0.75 to 0.85 (Figure 2.6a). The Moran's I values for county-level farmland value percentage change show more variability than the Moran's I of farmland values over time (Figure 2.6b). The spatial autocorrelation patterns persist consistently across all orders of contiguity. The spatial autocorrelation of percentage change shows similar patterns and oscillations across the 1^{st}, 2^{nd}, and 3^{rd} orders of contiguity, and in some years, the percentage change values were more correlated than farmland values. The Moran's **I** value for both farmland values and percentage change peaked in 1971, followed by a decline, and a slow increase until 1986.

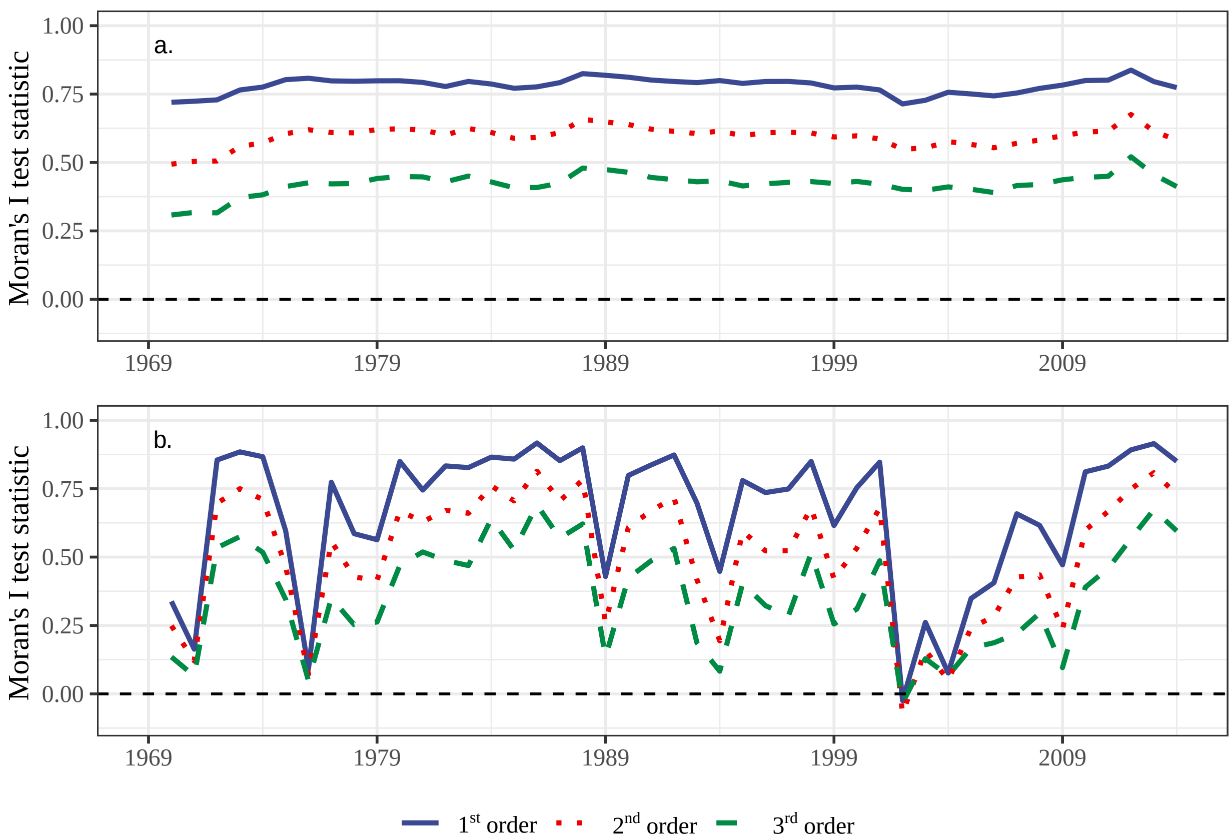

Figure 2.6: Moran's I test statistic, (a) farmland values and (b) percentage change, Iowa counties, 1969-2014

2.4.3 Exploratory spatial data analysis: Moran's I test statistics

Residuals of an OLS model, farmland values, and percentage change in farmland values were evaluated for global spatial autocorrelation using the first-order queen contiguity matrix. The null hypothesis of no spatial autocorrelation was rejected in all 45 years for farmland values but was rejected only for specific years for percentage change in farmland values and OLS residuals (Figure 2.7). Moran's **I** test statistics for annual farmland values varied from 0.71 (2002) to 0.84 (2012) with the null of no spatial autocorrelation being rejected for all years. The Moran's **I** for the residuals

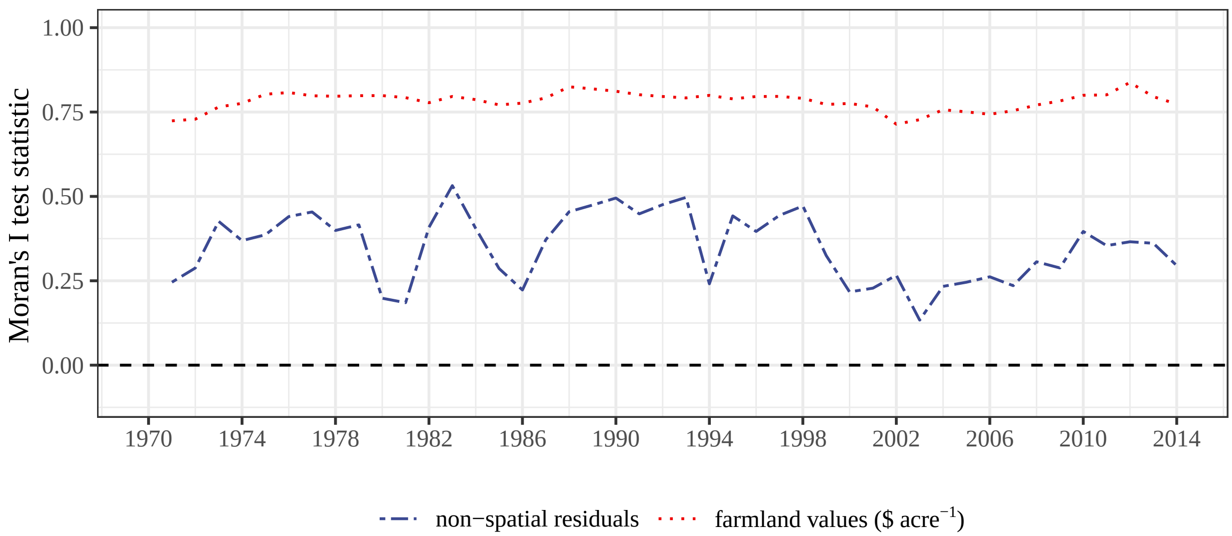

Figure 2.7: Moran's I test statistics, random variables and space-time recursive residuals, 99 Iowa counties, 1970-2014

2.4.4 Local Indicator of Spatial Association (LISA)

Evidence from Global Moran's **I** revealed that farmland values are spatially autocorrelated from the periods of 1969 to 2014. However, a deeper analysis is required to determine what counties are positively or negatively spatially autocorrelated. To assess the spatial autocorrelation of farmland values at the county level, this study calculated the local indicator of spatial association (LISA). LISA maps were generated for each dataset and clustered based on the significance level.

Figures 2.8 displays the randomly selected years of 2000 and 2014 for farmland values and percentage change of farmland values, respectively. Colorless regions had a statistically insignificant local autocorrelation. In the 2000 period, farmland values (Figure 2.8a) revealed two relatively large clusters: the High-High (HH) cluster formed by 31 counties and the Low-Low (LL) cluster formed by 21 counties. No outliers, HL or LH, were present on the map. Percentage change in farmland values (Figure 2.8c) displayed three clusters, with the largest being a HH cluster formed by 24 counties, the second largest a LL cluster formed by 18 counties, and the last one another LL cluster formed by four counties. The LL cluster of 18 counties also had two outliers (LH) in the group. Some counties experienced a switch from HH to LL or LL to HH in the clustering of farmland values (Figure 2.8a) and percentage change in farmland values (Figure 2.8c).

In 2014, farmland values (Figure 2.8e) revealed two large clusters. The High-High (HH) cluster formed by 28 counties neighboring Nebraska and South Dakota, and a Low-Low (LL) cluster formed by 19 counties neighboring Missouri. There was also a one-county cluster of HH and one outlier (LH) adjacent to the HH cluster. Percentage change in farmland values (Figure 2.8g) displayed two significant clusters. The largest was a HH cluster formed by 27 (Northwest) counties, and the other was a LL cluster of 37 (Southeast) counties. Similar to farmland values, there was a switch for some counties from LL to HH in percentage change of farmland.

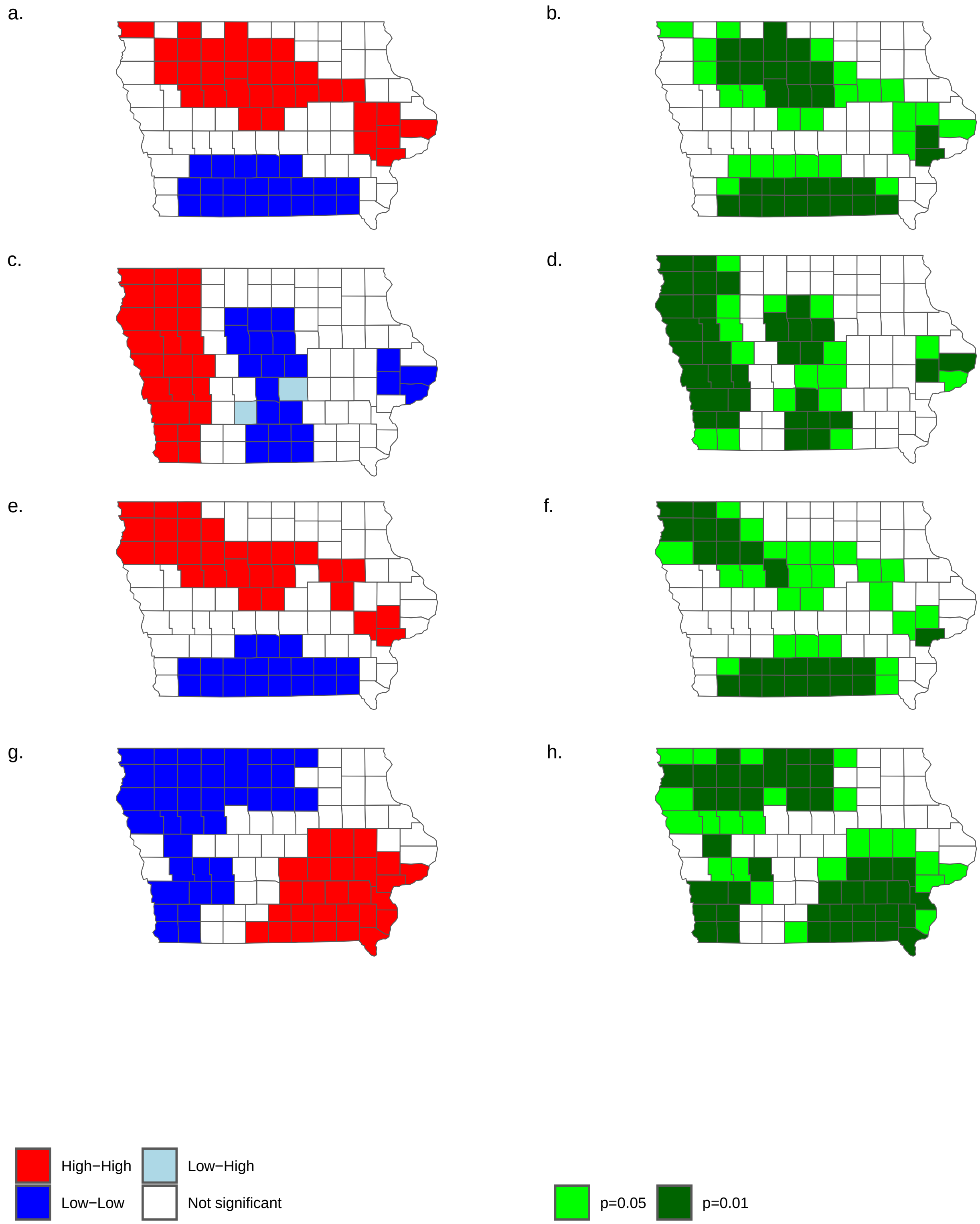

Figure 2.8: Significance maps (LISA) and LISA Cluster Map, related to farmland values (a., b., e., and f.), and their respective percentage change (c., d., g., and h.) for Iowa counties, 2000 (a., b., c., and d.) and 2014 (e., f., g., and h.)

2.4.5 Empirical Estimations

Results for the non-spatial panel data models are reported in Table 2.4. Pooled OLS, individual fixed effects, time fixed effects, and two-way fixed effects are listed in columns (1) to (4), respectively.

The classic LM tests indicate rejection of the null hypothesis of no spatially lagged dependent variable and the null hypothesis of no spatially autocorrelated error term at the 1% significance level, with some exceptions. When both individual and time-period fixed effects are included in the model specifications, the null hypotheses are not rejected or no spatial autocorrelation is found.

When using the robust LM tests, the hypothesis of no spatially lagged dependent variable continues to be rejected at a 1% significance level for the Pooled OLS and individual fixed effect models. When considering only time-fixed effects, the hypothesis of no spatially lagged dependent variable is rejected at a 1% significance level. The hypothesis of no spatially autocorrelated error term is rejected at a 10% significance level. The inclusion of two-way fixed effects in the model leads to the rejection of the hypothesis of no spatially autocorrelated error term at a 5% significance level. The hypothesis of no spatially lagged dependent variable is not rejected at any significance level.

These findings indicate that the SAR model with time fixed effect is a more suitable specification than the non-spatial model. This conclusion is supported by consistent evidence across different models, showing a rejection of the null hypothesis of no spatial lag. However, the results regarding the hypothesis of spatially autocorrelated error terms are inconclusive and require further analysis for definitive conclusions. To assess the joint significance of the individual fixed effects and time-period fixed effects, a Hausman test is conducted to compare the fixed effects and random effects models. The results of the Hausman test (243.25, with 6 degrees of freedom, p=0.000) suggest that the fixed effects model is the more appropriate specification for the panel data.

Table 2.4: Ordinary Least Square (OLS) Results

	Pooled OLS	Individual FE	Time FE	TWFE
Acreage	0.541***	0.845***	0.416***	0.013
	(30.862)	(21.344)	(60.737)	(1.584)
Yield	-0.191***	-0.320***	0.259***	0.059***
	(-6.501)	(-11.333)	(16.533)	(8.787)
Jobs	-0.261***	0.500***	-0.158***	0.020*
	(-13.599)	(11.835)	(-15.859)	(1.773)
Income	0.409***	1.735***	0.543***	0.152***
	(21.053)	(30.132)	(20.171)	(9.928)
PopDens	0.097***	0.877***	0.072***	0.048***
	(10.724)	(12.435)	(21.222)	(4.223)
σ^2	0.187	0.143	0.022	0.004
R^2	0.349	0.304	0.750	0.053
Durbin-Watson	0.293	0.391	2.034	2.094
LM spatial lag	7458.6***	9158.7***	21.172***	33.957***
RLM spatial lag	168.61***	1197.2***	6.290***	3.578**
LM spatial error	8756***	8260.8***	17.912***	31.296***
RLM spatial error	1465.9***	299.3***	3.030*	0.916
Regional FE	No	Yes	No	Yes
Time-period FE	No	No	Yes	Yes

FE = Fixed Effect

*p<0.1; **p<0.05; ***p<0.01.

T-value are reported in parentheses.

Spatial panel regression

After conducting tests to investigate the presence of spatial dependence, including spatial lag and error, we have determined that non-spatial panel models are inadequate for analyzing the factors influencing farmland values in the 99 counties of Iowa. Consequently, we have shifted our focus to spatial models.

We used Pesaran's (2015a) CD-test to examine cross-sectional dependence based on the farmland value patterns across the 99 counties during the period 1969-2014 (N=99, T=46). The test yielded a result of 464.565, with an average pairwise correlation coefficient of 0.98. These values are statistically significant, indicating the necessity to account for cross-sectional dependence. Additionally, when examining stationarity using the Cross-sectional Augmented Dickey-Fuller (CADF) test (excluding common factors), we observed a negative t-value of -0.028 for $\tau\prime$, leading us to reject the hypothesis of stationarity.

Table 2.5 presents the results of the model specifications in equation 4. The results of four simpler model specifications are presented in the Appendix (Table B1) to compare with commonly used alternatives from previous studies. The results presented in Table 2.5 demonstrate the effectiveness of controlling for strong and weak cross-sectional dependence by including the common factors of farmland values at time t and $t-1$. In this model, we observe a CD-test statistic of -2.250. The t-value of -2.156 for the CADF test and -6.557 for the stationarity condition ($\delta + \tau + \eta - 1 < 0$) provide evidence to not reject the hypothesis of stationarity, indicating no need to favor a unit root.

These findings followed the approach developed by Vega and Elhorst (2016), which offers a unified framework for considering serial dynamics, weak cross-sectional dependence, and strong cross-sectional dependence. This approach builds upon the two-stage estimation procedure introduced by Bailey et al. (2016). According to this framework, it is crucial to control for the cross-sectional averages of the dependent variable at both time t and $t-1$, to avoid model misspecification. These results align with the findings of Ciccarelli and Elhorst (2018), who emphasized the inclusion of the cross-sectional averages of the independent variable at time t and $t-1$, as well as the dependent variable at time t.

Korniotos (2010) interprets the coefficients of the temporal and space-time lags of the dependent variable (farmland values$_{t-1}$ and weighted farmland values$_{t-1}$) as measures of the internal and external habit persistence. In this case, the information is an upcoming trend of increasing/decreasing farmland values. Table 2.5 contains the results of the Dynamic Spatial Durbin model with common factors at time t and $t-1$. The coefficient on the temporal farmland values lagged one year is significant at the 1% level. This means that, in Iowa, the farmland values in the current period are positively affected by farmland values in the previous year. The coefficient for the spatial lag of farmland values is negative and significance at the 1% level. Thus, the current farmland values in Iowa are negatively affected by the farmland values in neighboring counties. These results align with the spatial dependence in the form of spatial autocorrelation, shown in Figure 2.6. However, spatiotemporal dependences are negative and significant at the 1% level. Hence, it can be concluded that local farmland values are decreased due to previous year's farmland values in adjacent counties, and local farmland values are highly dependent on neighboring counties farmland values.

The coefficients for acreage planted to corn and corn yield (bushels per acre) are statistically significant at the 1% level. Acreage planted to corn has a negative sign; this means if acreage planted to corn increases by 1%, farmland values will decrease by 0.026%. The coefficient on yield suggests that if bushels per acre increases by 1%, then farmland values will increase by 0.038%. These results imply that the impact of each of these variables on farmland values is small.

The socioeconomic variables included in this model show the expected relationships to farmland values. The coefficient of income per capita suggests that a 1% increase in personal income per capita results in an increase in farmland values by 0.014%. We expected this to be a positive relationship, as shown in prior studies (Boisvert et al. 1997; Huang et al. 2006; Schlenker et al. 2006; Maddison 2009; and Sheng, Jackson and Lawson 2018). The positive coefficient for population density, significant at the 10% level, indicates that an increase in population density can attribute to an increase in farmland values. We expected this positive relationship because increased population density increases the competition to convert farmland to commercial or residential development.

Table 2.5: Results for selected model

	Model-CF
Acreage	-0.026***
	(-5.934)
Yield	0.038***
	(11.503)
Jobs	0.005
	(0.783)
Income	0.014*
	(1.639)
PopDens	0.012*
	(1.797)
W*Acreage	0.016***
	(2.651)
W*Yield	-0.032***
	(-7.427)
W*Jobs	-0.003
	(-0.452)
W*Income	-0.013
	(-1.193)
W*PopDens	0.016
	(0.889)
FLV_{t-1}	0.862***
	(102.630)
W^*FLV_t	-0.130***
	(-4.969)
W^*FLV_{t-1}	-0.115***
	(-3.740)
corr-R^2	0.994
CD-test	-2.250
CADF-test	-2.1563
$\tau + \eta + \rho$	-0.154
	(-6.557)

*p<0.1; **p<0.05; ***p<0.01.
T-values are reported in parentheses.

Direct, Indirect, Total, Short-term and Long-term Effects

To compare the coefficients of a non-spatial model with those of a dynamic spatial Durbin model with lag dependencies, it is necessary to compute an unbiased measure of the marginal effects of the spatial explanatory variables (LeSage and Pace 2009). Those marginal effects take into account both direct and indirect effects through spatial interactions and simultaneous feedback in the model structure. The direct effect differs from the coefficient estimates, β, because of the spatial autoregression process between dependent variables observed at different cross-section units. The direct, indirect, and total effects of each explanatory variable are reported in Table 2.6. The differences between the estimates of Table B1 and those of Table 6 are because of the feedback effects. The results in Table B1 include the impacts passing through neighboring counties and back to the county itself, also known as spillovers. The indirect effect includes the impacts from the spatially lagged dependent variable ($\rho \sum W_{ij} Y_{jt}$), and the impacts from the spatially lagged value of the explanatory variable ($\sum W_{ij} X_{jt\gamma}$).

The findings presented in Table 2.6 indicate consistent and significant direct effects of the explanatory variables on farmland values in both the short-term and long-term. This suggests that the influence of these independent variables remains stable within individual counties and their surrounding areas. Moreover, the long-term impact of these variables is found to be stronger, indicating the presence of a cumulative effect over time. These results support the idea that the relationship between the independent variables and farmland values strengthens and becomes more pronounced over the long-term, potentially leading to cyclical patterns of cumulative impact.

Table 2.6 reports the estimated short-term and long-term effects derived from the coefficient estimates of Table 2.5 using Equation 4. The coefficient for total acreage in the short-term is -0.009 and in the long-term is -0.065. If acreage planted to corn increases, farmland values will decrease. Generally, the price per acre of farmland decreases as the size of the parcel increases. Both coefficients are also statistically significant. The analysis reveals an interesting pattern regarding the relationship between acreage planted to corn and farmland values. The own effect of acreage is found to be negative and statistically significant. A 1% increase in acreage planted to corn within the same county leads to a short-term decline in farmland values by 0.027% and a long-term decline of 0.195%. However, there is also a significant, positive spillover effect of acreage. This suggests that an increase in acreage planted to corn in neighboring counties has a positive impact on own-county farmland values. Specifically, the spillover effect amounts to a short-term increase of 0.018% and a long-term increase of 0.130% in farmland values. This spillover effect can be interpreted as a substitution effect, where the increase in acreage planted to corn in neighboring counties partially offsets the negative impact on farmland values caused by the own effect. In other words, the presence of neighboring counties with higher acreages planted to corn creates a substitution effect that mitigates the downward pressure on farmland values within a county. Another factor that may contribute to the negative relationship between acreage planted to corn and farmland values may be sustainable land management practices. Focusing solely on continually planting corn, without considering sustainable land management practices, may lead to soil degradation and nutrient depletion. These conditions would devalue the asset's income production in the future.

The analysis reveals a positive relationship between land productivity, proxied by yield, and farmland values. In the short-term, an increase in corn yield of 1 percentage bushel per acre is associated with a 0.035 increase in farmland values. Similarly, in the long-term, a 1 percentage bushel per acre increase in yield leads to a more substantial increase of 0.455 in farmland values. These findings indicate that higher productivity of land, as measured by corn yield, positively influences farmland values. This relationship reflects the market's recognition of the increased potential for profitable agricultural activities and thus a higher expected return from the farmland. The own effect of bushels is found to be positive and statistically significant, indicating that an increase in corn yield within the same county leads to a short-term increase in farmland values of 0.038 and a long-term decline of 0.278. The results also show a significant, negative spillover effect of yield. This suggests that an increase in corn yield in neighboring counties has a negative impact on own-county farmland values. Specifically, the spillover effect amounts to a short-term decrease of -0.005 and a long-term decrease of -0.023 in own-county farmland values. These findings are similar to the study of Huang et al. (2006), which reported a significant and positive relationship between farmland values and corn bushels per acre.

The total personal income per capita elasticity is significant and positive in the short and long run. In the short-term, it is 0.012, and in the long-term, it is 0.09. If income increases, then own-county farmland values increase. The spillover effect of income is statistically insignificant and negative. Income per capita is used as a proxy in the model for economic growth. Economic growth is often linked to improvements in infrastructure and buyers' willingness and ability to pay. These factors can enhance the profitability of the farming operations, improving the outlook of future income streams from the land. This result is consistent with findings of Boisvert et al. (1997); Huang et al. (2006); Schlenker et al. (2006); Maddison (2009); and Sheng et al. (2018).

The coefficient for population density indicates that, in the short-term, a 1% increase in population density is associated with a 0.0011% increase in farmland values. In the long-term, the increase is more substantial at 0.080%. The direct effect in the short-term of an increase in population density within the same county leads to a 0.012% increase in farmland values. In the long-term, there is a significant positive effect of a 0.087% increase in farmland values. However, there is a negative spillover effect of population density on farmland values. If the population density increases in neighboring counties, then own-county farmland values decrease.

The positive effect of population density or urbanization on farmland values is consistent with expectations. Local increases in population may involve the conversion of agricultural land into residential, commercial, and industrial uses. These alternative uses increase the competition for farmland, putting upward pressure on farmland values. It is essential to consider that the specific dynamics of each region and the interplay of various factors can influence the relationship between population density and farmland values. This result is consistent with findings of Boisvert et al. (1997); Huang et al. (2006); Schlenker et al. (2006); Maddison (2009); and Sheng et al. (2018).

Table 2.6: Short and Long-term Estimation Results of Dynamic Spatial Durbin Model-Common Factor, C_t,C_{t-1}

	Direct	Indirect	Total	Direct	Indirect	Total
W*Acreage	-0.027***	0.018***	-0.009*	-0.195***	0.130***	-0.065*
	(-5.763)	(3.182)	(-1.869)	(-5.344)	(2.851)	(1.780)
W*Yield	0.038***	-0.005***	0.035***	0.278***	-0.023	0.253***
	(11.339)	(-4.841)	(10.747)	(9.428)	(-0.569)	(4.937)
W*Jobs	0.004	-0.001	0.004	0.032	-0.002	0.030
	(0.703)	(-0.675)	(0.705)	(0.701)	(-0.239)	(0.708)
W*Income	0.013*	-0.002	0.012*	0.098*	-0.008	0.090
	(1.640)	(-1.532)	(1.651)	(1.642)	(-0.469)	(1.558)
W*PopDens	0.012*	-0.001*	0.011*	0.087*	-0.008	0.080*
	(1.789)	(-1.653)	(1.787)	(1.779)	(-0.080)	(1.692)

*p<0.1; **p<0.05; ***p<0.01.
T-value are reported in parentheses.

2.5 Conclusion

Research on the spatial correlation of farmland values at the county level is limited, despite its role as an important investment in agricultural operations. Previous studies have primarily focused on farmland values at the state-level, with Wang (2013) being the first to investigate spatial correlation at the county-level. Building on the work of Griffin et al. (2015), we highlight the importance of understanding the spatial correlation between farmland values and percentage changes at the county level. This knowledge is critical for agriculture stakeholders and real estate investors seeking to manage risk and make informed decisions in the farmland market.

The main motivation behind the current study is to investigate the spatial relationships among farmland values in 99 Iowa counties. The spatial relationships among the variables are generally consistent with previous literature. The results of the empirical estimation of the DSDM-CF confirm that income per capita, and population density have significant, positive total impacts on the farmland values of Iowa counties.

Spatial correlation is identified at the county level, as demonstrated by local clusters in farmland values and their respective percentage changes across different time periods. Given the spatial relationships found, there is potential for producers to substitute knowledge about price movements across space. For example, if data are lacking in a particular county, neighboring counties could provide valid substitutes. It also shows how land values can be aggregated into coarser geographic units.

The role of agricultural and non-agricultural factors on farmland values was estimated. Investment in more efficient management practices, adopting advanced technologies, and sustainable agricultural practices can optimize productivity and improve the overall profitability of farmland. The increased profitability will be reflected in higher farmland values. The findings have revealed that spatial and temporal dependences have played a significant role in influencing farmland values at the county level in Iowa. The temporal accumulation effect, which refers to the impact of past values on current values, has enhanced the valuation of farmland in Iowa. This suggests that past farmland values significantly influence current farmland values, and this influence has grown over time.

Moreover, the spatiotemporal dependence, which combines both spatial and temporal effects, has significantly impacted the farmland values at the county level in Iowa. This indicates that the interplay of spatial and temporal effects is important in determining farmland values. Accounting for spatiotemporal relationships appears to improve the overall prediction ability for variables impacting the value and statistical significance of the characteristics of farmland. This result is not surprising given that some aspects of farmland are spatially correlated. The spatiotemporal model also appears to better control for hard-to-model, but conceptually important, local influences such as development potential. Including the spatiotemporal nature of farmland data is important in empirical studies to more accurately capture the impact of exogenous variables.

This essay adds to existing research by evaluating spatial and temporal aspects of farmland values at the county level for Iowa. This study considered the spatial dependence in the data set, specified spatial interaction models (spatial Durbin), and obtained reliable estimated coefficients. At the same time, the estimation of the independent variables became consistent. This analysis indicated the importance of considering spatial effects over time when examining the association between the neighborhood of farm and non-farm characteristics within the farmland market. Closer interaction between geography and farmland values should lead to a better understanding of the relationship between neighborhoods and values. By including the characteristics of farmland values as additional explanatory variables, we intended to account for another limitation of the spatial model that presumes that farmland price is affected by nearby land prices but not by the land's characteristics.

Chapter 3

3 Estimating Spillover Effects in Iowa Farmland Values: A Heterogeneous Spatial Autoregressive Panel Approach

3.1 Introduction

Understanding the geographic distribution of farmland values can help landowners and farm operators develop risk management strategies and allocate resources. The distribution of farmland values does not affect the state's agricultural production; however, the distribution of economic activity and land use does influence local regions. This essay focuses on estimating spatial dependence of farmland values between regions, and the economic drivers of farmland values. County farmland values do tend to move with national farmland values; however, the extent to which a region's values respond to changes in the national rate can be heterogeneous.

Aquaro et al. (2021) proposed to measure strong and weak cross-sectional dependencies, known as common factor and spatial dependencies, to estimate the spatial lag coefficients subject to heteroskedastic errors. This research used their proposed approach to measure the heterogeneity in spatiotemporal dynamics of farmland values for 99 Iowa counties over the period 1969-2021. The availability of data since the 1960s and early 70s makes comparisons across time periods an advantage of the dataset.

Research that tests and accounts for cross-sectional dependence has been increasing. Cross-sectional dependence can arise from a number of reasons. This essay proposes to explain the differences in farmland values by using a dynamic spatial model with common factors. The model accounts for serial dependence across the data in each region over time and accounts for global common factors and local spatial dependence across the observations at each point in time. The model includes common factors that cover simpler spatial econometric models and provides an excellent tool to describe diffusion processes for agricultural data. This essay is the first to investigate the spatial disparities of farmland values and studying the cyclical sensitivity of those values, using county-level data.

3.2 Literature Review

Three types of statistical models that dominate the farmland value literature are spatial econometrics, time series, and spatio-temporal models. Time series models have been used to estimate trends in farmland values (Engsted 1998; Falk 1991). Spatial econometric models evaluate either spatial lag or spatial error processes in hedonic pricing models. Spatial effects have been evaluated in farmland values and rents, using a hedonic pricing model in a spatial context (Boisvert et al. 1997; Huang et al. 2006; Cotteleer et al. 2008; Maddison 2009; Schilling, Sullivan and Duke 2013; Wang 2013). A spatial econometric model, used less frequently in the literature, consists of a spatially lagged independent variable on the right-hand side. Pesaran (2006) proposed an approach to estimate the cyclical sensitivity of a variable by using cross-sectional averages of the variable, also known as common factors or aggregate shocks. Attention has become focused on recognizing characteristics that distinguish one form of cross-sectional dependence from the other. These two forms of cross-sectional dependence, common factor and spatial dependence, are also viewed as strong and weak cross-sectional dependence, respectively, (Chudik, Pesaran and Tosetti 2011).

Topics such as housing prices, unemployment rate, and cigarette consumption are among the regional studies that have used serial dynamics, spatial dependence, and common factors (Holly et al. 2011; Bailey et al. 2016; Vega and Elhorst 2016; Ciccarelli and Elhorst 2018; and Aquaro et al. 2021). In 2021, Aquaro et al. were the first to use regional house price data to model serial dynamics, spatial dependence, and common factors. Their research was followed by studies on regional unemployment differences (Vega and Elhorst 2016) and the diffusion of cigarette consumption (Ciccarelli and Elhorst 2018).

Using changes in the real house prices at the regional level in the UK, Holly et al. (2011) provided a method for analyzing the spatial and temporal diffusion of shocks in a dynamic system. The analysis was approached from the perspective of a spatial dimension that manifests in the form of cross-sectional dependence. In a regional context, the proximity of one region to another is not necessarily limited to spatial proximity but is based on economic measures of distance (Conley 1999; Pesaran et al. 2004) or social distance (Conley and Topa 2002).

Based on spatial competition theory, Wang (2013) derived the endogeneity of spatial structure and reported the existence of spatial interdependence of farmland value across counties in Pennsylvania. Wang's final panel data set consisted of 64 counties across seven time periods. Wang found that by estimating a spatial autoregressive model, space-time relationships and spatial heterogeneity can be controlled for using a spatial panel feature-pricing model. Ye and Wu (2011) used a fixed effect model with spatial error autocorrelation to determine the impact of the socioeconomic factors on the homicide rate in Chicago. They stated that analyzing fixed-effects panel regression models with spatial dependence improved model predictive power.

Several approaches have facilitated the analysis of spatial and temporal dependencies in economic data, enabling researchers to obtain meaningful insights into the underlying patterns and mechanisms driving economic phenomena. Aquaro et al. (2021) further developed the model introduced by Bailey et al. (2016) to include explanatory variables and called it a heterogeneous spatial vector autoregressive (HSAR) model. The HSAR model incorporates fully heterogeneous spatial parameters. This model captures spatial dependence directly, through contemporaneous dependence among individual units and their neighbors, and indirectly, through potential cross-sectional dependence in the regressors. By considering both forms of spatial dependence, the HSAR model provides a comprehensive framework for analyzing the spatial dynamics of panel data.

3.3 Data

The data include farmland values for the period 1969-2021 in 99 counties in Iowa. The timeframe is interesting because of the persistence of clusters of high and low farmland values, as well as changes in the composition of those clusters, at the county level. In addition, data are available since the early 1970s and 1980s allowing comparisons of recessions and recoveries from recent economic developments. These data are publicly available, annual, county-level farmland values in Iowa collected in a survey by Iowa State University (ISU) Extension and Outreach from 1960 through today. Average nominal and inflation-adjusted values were acquired from

Iowa State University (ISU). Since 1941, the ISU survey has been conducted annually. The state farmland average directly relies on data gathered through the survey. The county-level estimates are computed differently. The estimates are a combination of data collected from the U.S. census and the Iowa State survey. See the Appendix for more details.

Income per capita is used as an indicator of the overall economic well-being of a region, extending beyond the agricultural sector, drawing on the assumption that economic growth plays a pivotal role in shaping land use and value. We calculated the per capita annual income in constant dollars, using 2014 as the base year. Previous studies, such as Huang et al. (2006), have demonstrated a positive correlation between per capita income and the value of cultivated land. Additionally, Schlenker et al. (2006) found a strong link between higher income per capita and farmland values in U.S. counties, highlighting the influential role of income levels on farmland values. Moreover, Cotteleer et al. (2008) suggest that variables like per capita income will impact land values. Based on these findings, we predict a positive relationship between personal income per capita and farmland values at the county level.

Population density is the number of individuals residing in a specific area, measured as the number of people per square mile in each county. Population density serves as an indicator of urbanization levels within counties. As population densities increase, there may be mounting pressure to convert agricultural land into residential or commercial uses, reducing the supply of farmland and subsequently driving up its value. Empirical studies (Boisvert et al. 1997; Huang et al. 2006; Schlenker et al. 2006; Maddison 2009; and Sheng et al. 2018) provide evidence supporting a positive correlation between population density and cultivated land value. Thus, we expect a positive relationship between population density and county farmland value.

Movement of specific Iowa county and state farmland values are shown in Figure 3.1. Over the past seven decades, they have moved together. This figure shows the bubble that occurred in farmland values in the late 1970s. During that time, inflationary expectations were the economic aspects attributed to the increase in farmland prices. The bubble of the 1970s and 1980s reached a peak from 1977 through 1979. The farmland price to cash rent ratio (P/rent) also reached a high from 1977 to 1979 of just over 20 compared to the average of 17.9 from 1960 to 2013. Baker et al. (2014) found that farmland prices in 2013 were higher than they were before the agricultural crisis of the late 1970s or 1980s.

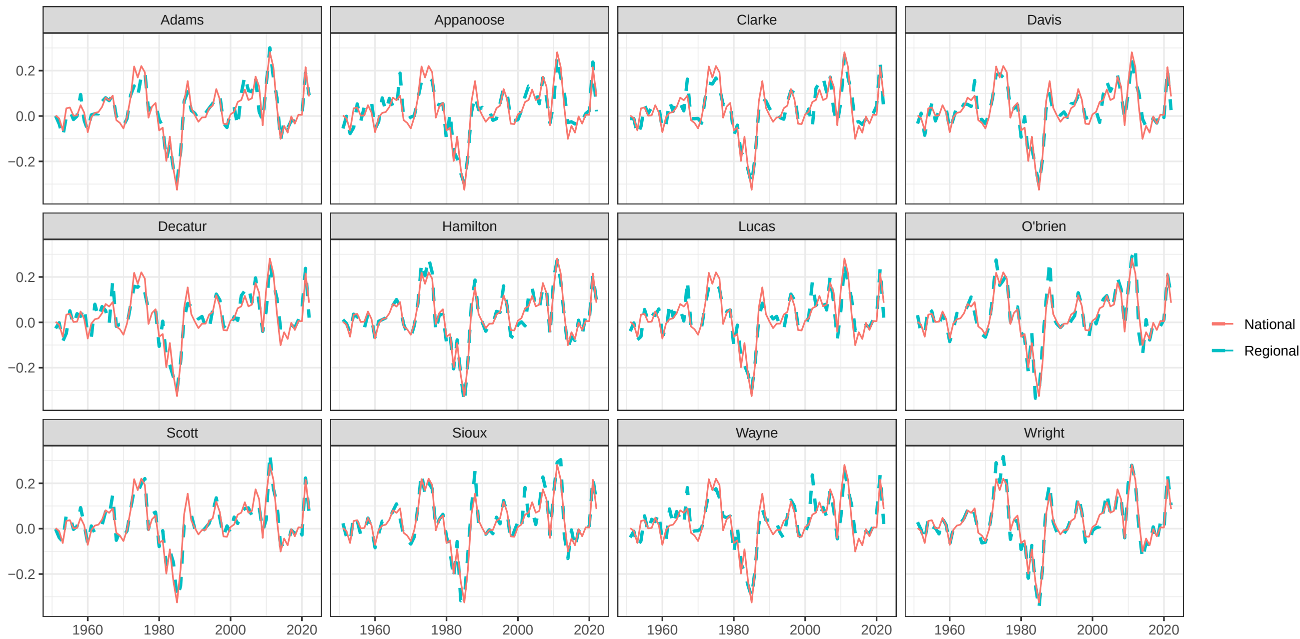

Figure 3.1: Iowa counties compared to State of Iowa farmland values, 1951-2020

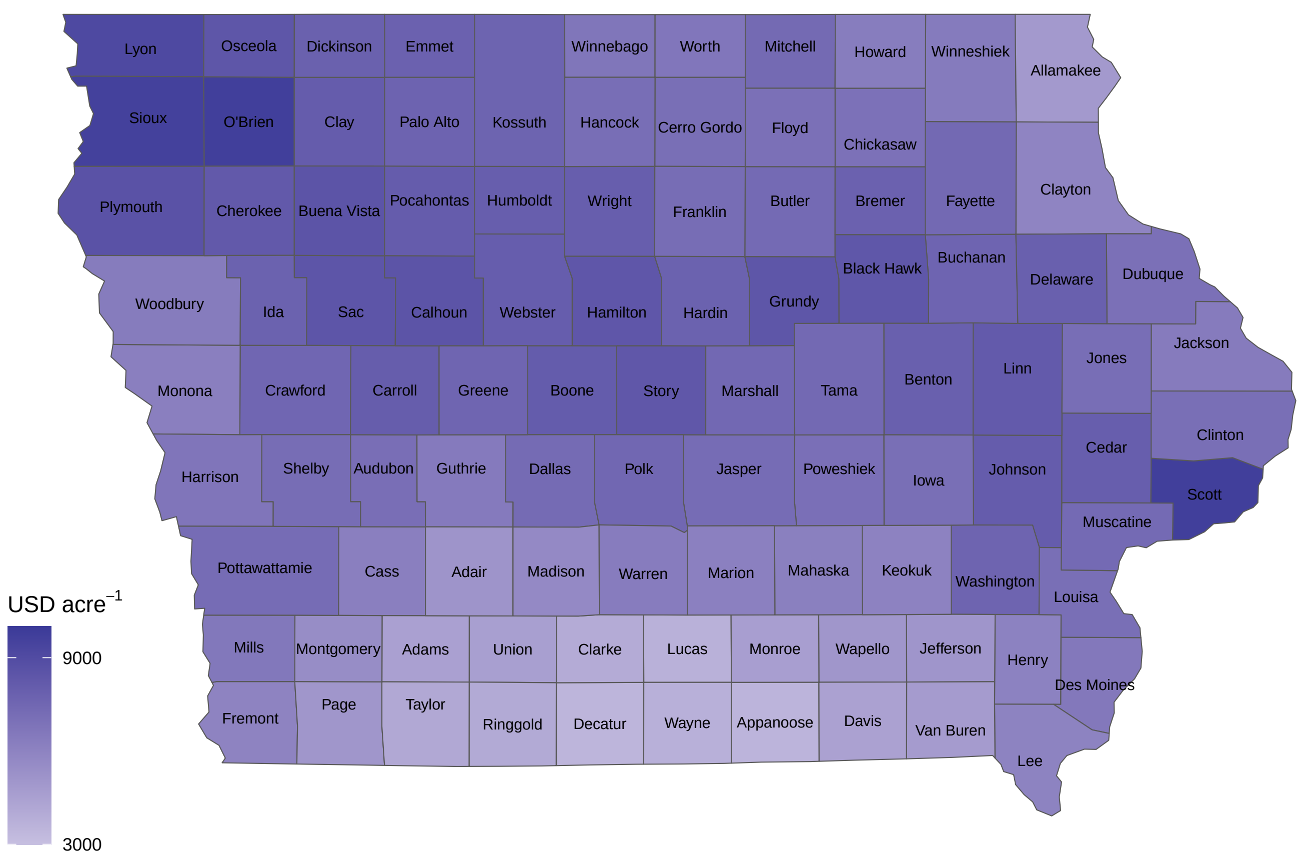

Figure 3.2: Spatial distribution of Iowa farmland values 2020

3.4 Econometric Model

3.4.1 Cross-sectional dependence

Testing for the existence of cross-sectional dependence and the magnitude of the data is a necessary step ahead of estimation. According to Pesaran (2015), the cross-sectional correlation test (CD) works well for large T and small N, but not the opposite. Since our sample of N = 99 and T = 52 fit in the large T case, we apply the standard CD tests. For our sample of farmland values at the county level, we obtained $CD = 521.808$ and $CD_{local} = 74.658$, and an average pairwise correlation coefficient of 0.895. With highly statistically significant test outcomes, we can conclude that cross-sectional dependence exists at the county-level for farmland values.

Before estimating the spatial model with heterogeneous coefficients, it is necessary to purge the data of common sources of their dependence, as suggested by BHP (Bailey et al. 2016). To do that, we defactored farmland values (FLV_{it}), population density (PD_{it}), and income per-capita (I_{it}), using residuals from OLS regressions. The defactored regional farmland value (population density and personal income per capita) is given by the residuals from equation 5, as follows

$$\hat{e}_{rt} = lv_{rt} - \hat{\gamma}_{0r} - \hat{\gamma}_{ir} lv_{Nt} \tag{5}$$

3.4.2 The Heterogeneous Spatial Autoregressive Model

A two-stage methodology that accounts for spatial dependence and common factors was first introduced by (Bailey et al. 2016). Vega and Elhorst (2016) proposed a methodology that simultaneously accounts for spatial dependence and common factors. Aquaro et al. (2021) further developed the model to include explanatory variables, calling it a heterogeneous spatial vector autoregressive (HSAR) model. This essay follows Aquaro's procedures, using the HSAR model for farmland values allowing for spatiotemporal effects in land value fluctuations. The first stage is the de-factoring of all the variables.

After extracting the common factor effects of the dependent variable, that defactored residuals is used in the second stage and assumed net of aggregate fluctuations. Thus, we proceed to model the defactored regional farmland value as

$$FLV_{it} = \alpha_i + \beta_i^{PD} PD_{it} + \beta_i^I I_{it} + \tau_i FLV_{i,t-1} + \psi_{0i} \sum_{j=1}^{N} w_{ij} FLV_{jt} + \psi_{1i} \sum_{j=1}^{N} w_{rj} FLV_{jt-1} + \varepsilon_{it} \quad (6)$$

where FLV_{it} denotes the farmland values for each county, at a particular point in time t. The parameters β_i^{PD} and β_i^I are the slope coefficients for population density and personal income per capita, respectively. The parameters τ, ψ_{0i}, and ψ_{1i} are associated with the time lagged, space lagged, and time and space lagged dependent variable, respectively. By including time lagged of farmland values the strong correlation over time is addressed. The space lagged as well as space and time lagged of the dependent variable are included to address spatial dependence. The average effect of other units on unit i at time t are captured by w (spatial weights), which is the i^{th} row of the $N \times N$ spatial weight matrix $\mathbf{W}$. ε_{it} is an independent and identically distributed error term for i and t with zero mean and constant variance σ^2. Different from Vega and Elhorst (2016) the coefficients of time, space, and space-temporal lagged are the unit-specific. The model includes in the spatial and temporal autoregressive coefficients as well as full heterogeneity.

From equation 7, the data generating process can be written as

$$FLV_t = (I_N - \psi W)^{-1} \left(\alpha + \sum_{k=1}^{K} B^k x_t^k + \varepsilon_t \right) \quad (7)$$

The reduced form from equation 8, to consider the partial derivatives associated with a change in population density or income per capita (kth) variable vectors.

$$\partial y / \partial x^{K\prime} = (I_N - \psi W)^{-1} B^k \quad (8)$$

The equation 9 is an $N \times N$ matrix. Through this matrix the HSAR estimates how a change in a specific county's kth characteristic could impact own-county farmland values, plus (potentially) farmland values of all other counties, with the strength of these other-county impacts dependent on the levels of spatial dependence for all counties. This particular spatial effect is calculated using the main diagonal $\psi = diag(\psi_1, ..., \psi_N)$, and magnitude of $B_k = diag(\beta_1^k, ..., \beta_N^k)$. This results in an $N \times 1$ vector of impacts from changing each counties kth characteristic.

Once the parameter estimates from running the HSAR model are collected, then the direct and indirect effects can be computed. A $N \times N$ matrices summarizing these effects across cross-section units and for each of the exogenous variables that have been included in the model is generated. Average and cumulative effects are just averages/summations of columns/rows of these matrices. The model assumes that $\hat{\psi}_{0i} + \hat{\psi}_{1i} = \Psi_i$. Thus, the direct/indirect effects are computed using the following formula:

$$\frac{\partial \pi_{t+h}}{\partial x_{jl,t}} = [\phi^h (I_N - \Psi_0 W)^{-1} e_j] \beta_{jl} \tag{9}$$

A unit change in $x_{jl,t}$ can be calculated though the average marginal direct and indirect effects:

Average marginal direct effects

$$D_N(h,l) = \frac{1}{N} \sum_{i=l}^{N} \frac{\partial \pi_{i,t+h}}{\partial x_{il,t}} \tag{10}$$

Average marginal indirect effects

$$ID_N(h,l) = \frac{1}{N(N-1)} \sum_{i \neq j}^{N} \frac{\partial \pi_{i,t+h}}{\partial x_{jl,t}} \tag{11}$$

3.4.3 Interpreting the HSAR model estimates

The analysis draws upon the findings of LeSage and Chih (2016), who derived the marginal effects for the HSAR model. The reduced form of the HSAR model can be represented as a matrix of partial derivatives in an $N \times N$ format.

$$\frac{\partial y_t}{\partial y\prime_{t-1}} = (I_N - \psi_0 W)^{-1} (\Delta + \psi_1 W) \tag{12}$$

The expression above captures the relationship between the persistence of farmland values in a specific county and its influence on both the change of farmland values within that county and neighboring counties. The diagonal elements of the matrix represent own-partial derivatives. These elements quantify how the persistence of farmland values in a particular county directly influences the change of farmland values within that same county in the current time period.

The off-diagonal elements of the matrix, the cross-partial derivatives, capture the spillover impact, showing how the dynamics of one county's farmland values influence the farmland value changes experienced in neighboring counties.

To account for the variations among counties, we adopt the methodologies proposed by LeSage and Chih (2016), where each diagonal element of the matrix estimates the direct impact of farmland values in each county. The sum of the off-diagonal elements in each row yields a vector representing the county- specific indirect effects, capturing the spillover effects of farmland values from county i to others. By calculating the cumulative sum of the off-diagonal elements in each row, we obtain a vector that represents the county-specific cumulative spill-in effects. These effects illustrate how variations in farmland values in neighboring counties, j (where $j \neq i$), generate a spill-in impact on the farmland values of county i. The cumulative sum of the off-diagonal columns yields the cumulative spill-out effects, indicating the impact of changes in farmland values in county i on neighboring counties j (where $j \neq i$). These effects measure how variations in farmland values within county i influence the farmland values of neighboring counties.

3.5 Results

3.5.1 Cross-Sectional Dependence (CD) in Farmland Values

The CD statistic proposed by Pesaran (2004, 2015) assesses the level of cross-sectional dependence in farmland values. The results are summarized in Table 3.1. Before defactoring, the average pairwise correlation of farmland values was 0.895. The CD value was determined to be 521.808, significantly exceeding the critical value of 1.96 at a 5% significance level. Thus, we rejected the null hypothesis of weak dependence, finding the presence of strong cross-sectional dependence. Common effects at the county, regional, or state level could be the reason for cross-sectional dependence. Estimating the exponent of cross-sectional dependence, α, using the approach outlined by Bailey et al. (2016), yielded an estimated value of 0.996, with a standard error of 0.04. Both results indicate strong cross-sectional dependence, suggesting that traditional spatial methods are inappropriate and prone to severe bias. After defactoring, the CD test on the residuals showed a substantial decrease from 521.808 to -1.471. The pairwise correlation also significantly decreased from 0.895 to -0.021. The exponent of cross-sectional dependence also decreased. These results demonstrate a sufficient level of cross-sectional dependence, enabling the utilization of spatial techniques to account for the remaining weak cross-sectional dependence.

Table 3.1: CD Test and Cross-sectional Exponent Measures before and after De-factoring Farmland Values

Variable	$\hat{\rho}_{ij}$	CD	α
FLV_{it}	0.895	521.808 (0.986)	0.996
ε_{it}	-0.021	-1.471 (-0.003)	0.892

3.5.2 HSAR county specific estimates

It is possible to estimate the HSAR and detect the spillover effects in farmland values in the 99 Iowa counties, without filtering the influence of the state. However, the results suffer from the interactions of state and local influences and can be misleading. Therefore, we estimated the HSAR with the state influence filtered. Consistent with previous research on spatial diffusion and pattern behaviors, our analysis employed binary contiguity (BC) based on the first-order queen contiguity. The BC matrix is sparse, and every county has neighboring counties, ensuring no isolated counties. The selection of BC is particularly relevant when examining diffusion processes, as emphasized in Ciccarelli and Elhorst (2018).

Figure 3.3 displays the total spatial parameter estimates ($\hat{\psi}_{0i} + \hat{\psi}_{1i}$), and Figure 3.4 displays the spatial lag parameter estimates ($\hat{\psi}_{0i}$). Figure 3.5 displays the spatiotemporal lag parameter estimates ($\hat{\psi}_{1i}$), and Figure 3.6 displays the autoregressive parameter estimates ($\hat{\tau}_i$) for counties in Iowa. Across all figures, counties colored in blue correspond to positive spatial, spatiotemporal, and temporal parameter estimates, while counties colored in red correspond to negative parameter estimates. Darker shades of blue or red indicate more sizable impacts, while lighter shades indicate impacts closer to zero in absolute terms.

Figure 3.3 illustrates the estimates of total spatial effects. On average, spatial (time t and $t-1$) effects across the whole state of Iowa net out to a value of -0.04 (0.74). However, it is evident from Figure 3.3 that there are significant differences in these effects across individual counties. Forty-five counties have positive total spatial lag coefficients, of which 11 are statistically significant. Fifty-four counties have negative total spatial lag coefficients, 14 of which are significant. Overall, these total spatial lag coefficients point to the existence of important spillover effects in some of the 99 Iowa counties farmland values market.

Clustering of the total spatial lag effect is clearly observed in Figure 3.3. We can identify a distinct pattern of negative total spatial lag effect, starting from Ringgold in the South and extending diagonally to Winneshiek in the Northeast. Another line of negative effect emerges from Muscatine and stretches up to Cherokee. Positive total spatial effects also form noticeable clusters, such as the one encompassing Harrison in the west and extending to Pocahontas in the north. Another cluster is formed by Winnebago, Worth, Cerro Gordo, Floyd, and Mitchell in the Northern region. The majority of counties either share a border or a corner with other counties of the same total spatial effects sign, indicating that a county with a positive sign have a border or corner with another county exhibiting a positive spatial total effect.

For instance, Allamakee County (highlighted in dark blue) in the Northeastern corner exhibits a significantly positive total spatial effect. Moving from top to bottom, a positive pattern can be observed, extending down to Warren and Lee in the Southeastern corner. According to the Iowa Regional Economic Analysis Project, the agricultural, forestry, fishing, and hunting sectors contribute substantially to the Gross Domestic Product (GDP) of Allamakee's economy, accounting for approximately 14% and ranking second after private industries. Clayton County, which is a direct neighbor of Allamakee County and exhibits a positive total spatial effect, shows that agriculture contributes 17% to the county's economy. In contrast, Union County shows a considerable negative total spatial effect. Agriculture accounted for only 1% of Union County's GDP in 2021. Similarly, agriculture only contributed 3% to the 2021 GDP of Clarke County, which is a direct neighbor of Union County and also exhibits a negative spatial effect.

Webster is located in the central North side of the state. Counties like Calhoun, Greene, Hamilton, Humboldt, and Pocahontas surround Webster. Agriculture contributes 33, 24, 31, 25, and 39%, respectively, to their economy. According to the Iowa Department of Natural Resources, the north-central region of the state consists of high relief among major river valleys, with agriculture being important to the economy of those counties.

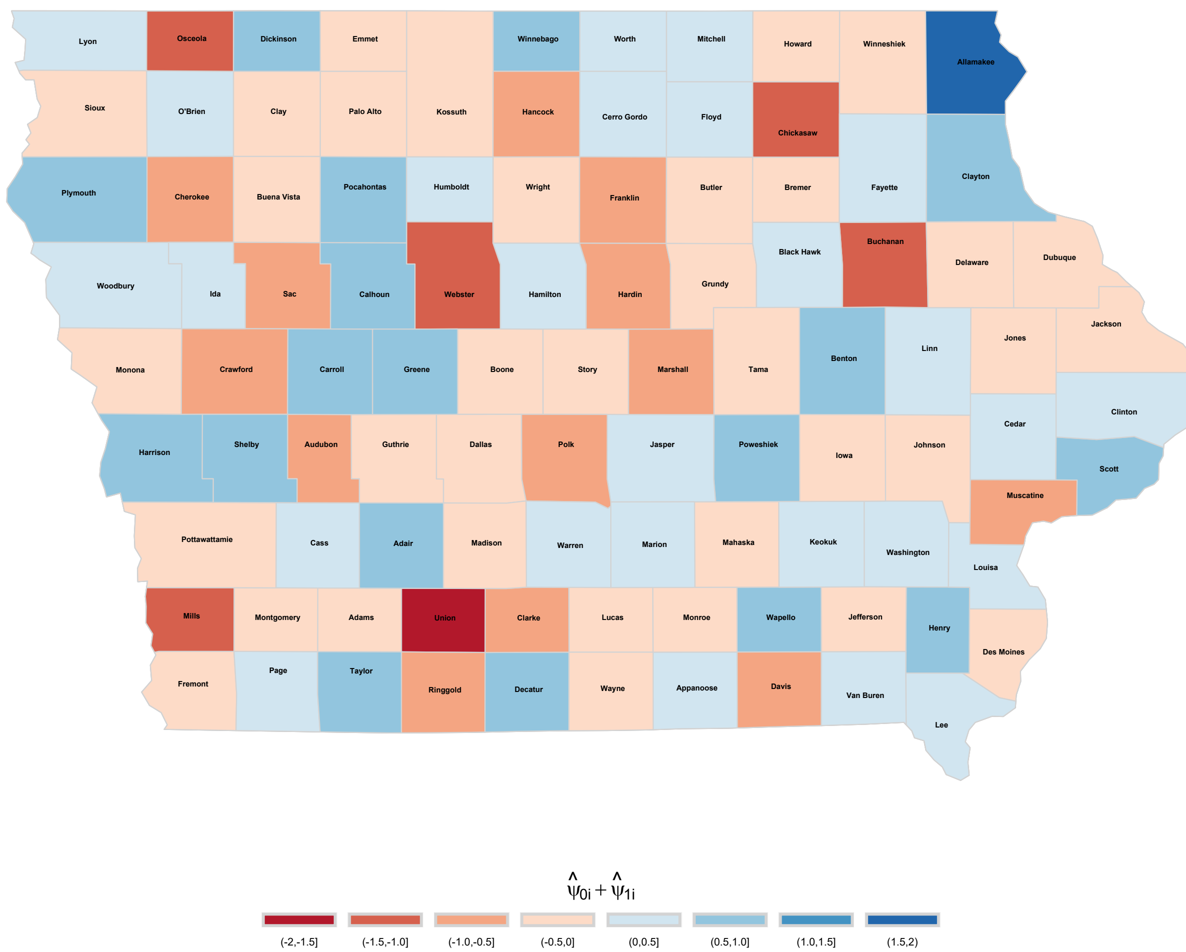

Figure 3.3: Total spatial parameter estimates $(\psi_{0i} + \psi_{1i})$ for 99 Iowa counties.

Figure 3.4 displays the spatial estimates at the current time period. Almost all counties show a darker color, positive or negative, than shown in Figure 3.3. Webster and Allamakee are consistent with dark shades of red and blue, respectively. Counties like Buena Vista, Cherokee, Osceola, and Sioux in the left corner shifted from light-medium red to a dark shade of red. Plymouth and Dickinson shifted from a medium shade of blue to a darker shade. Similar to Figure 3.3, almost all counties share a border or a corner with a county showing same-sign impacts. For example, Plymouth shares a corner with O'Brien, and both have positive spatial lag estimates. Sioux shares corners with Osceola and Cherokee, all showing negative spatial lag estimates. However, Decatur is a one county cluster of positive spatial lag estimate. Decatur reported a GDP of $234,102 in 2021, with agriculture contributing 6% to it. In 2021, farmland values there increased 24% from 2020.

Spatial lag estimates capture the spatial dependence between neighboring locations at the same time point. Negative spatial lag estimates suggest a negative relationship between the variable of interest in the focal location and its neighbors' values, indicating spatial autocorrelation with neighboring locations having lower values when the focal location has a high value (Figure 3.4).

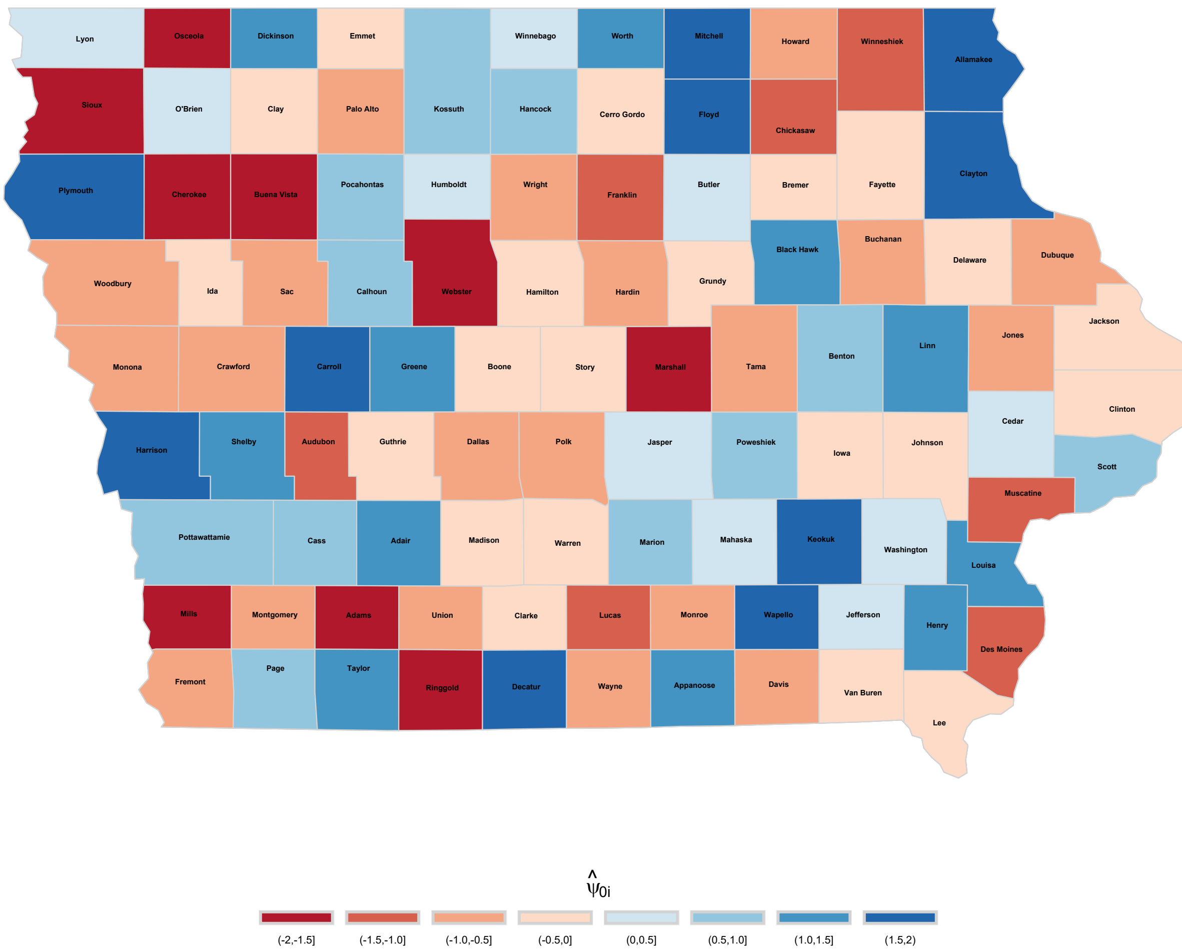

Figure 3.4: Effect of neighboring county farmland values on own county farmland values at current time (ψ_{0i}) for 99 Iowa counties

Spatiotemporal lag estimates capture both spatial and temporal dependencies between farmland values at different locations and time points (Maddison 2009). If we observe positive spatiotemporal lag estimates, it means that when the farmland value in a given county is high, the neighboring locations at different time points also tend to have higher values. This suggests a positive relationship between the focal location and its neighboring locations in terms of farmland values. In other words, there is a spatial dependence where higher farmland values in one county are associated with higher farmland values in neighboring counties at different time points.

Given the nature of farmland markets and farmers behaviors, the temporal aspect of spatiotemporal lag estimates comes into play because farmers consider expected future income generated from the farmland when valuing it at different time points. This expectation means that the relationship between farmland values extends beyond spatial proximity alone. The positive spatiotemporal lag estimates indicate that not only are neighboring locations spatially related, but they also exhibit a temporal pattern. This suggests that the values of farmland in neighboring locations tend to follow a similar trend over time.

Figure 3.5 displays the spatiotemporal lag estimates of the 99 Iowa counties. In contrast to Figure 3.4 (spatial lag coefficients), the spatiotemporal lag coefficients show that the positive pattern is bigger and almost all extreme values are lighter shades in Figure 3.5. Fifty-seven counties show a positive spatiotemporal lag, rather than the 60 that had a positive spatial lag; forty-two show a negative spatiotemporal coefficient, compared to 39 that had a negative spatial lag.

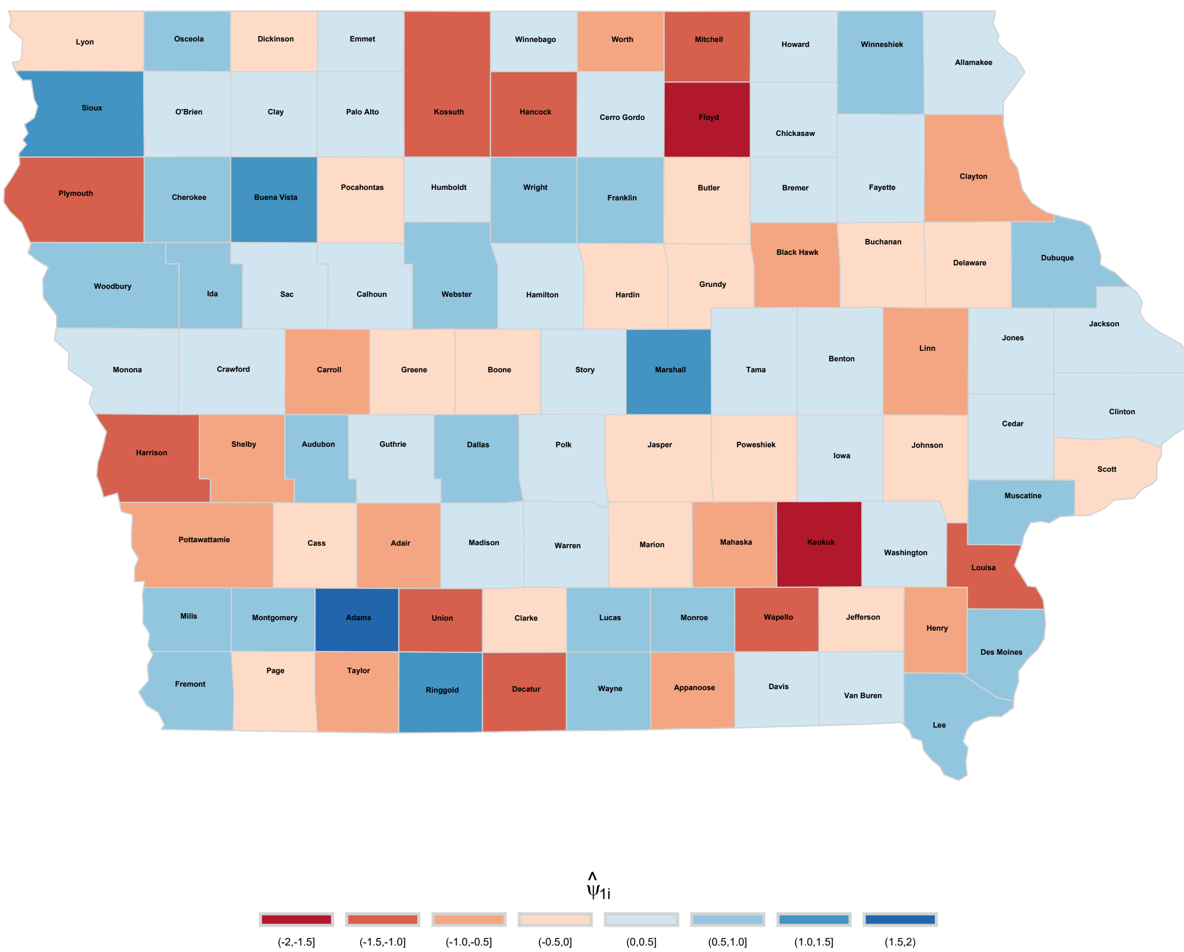

Figure 3.5: Effect of neighboring county lagged farmland values on own county farmland values at current (ψ_{1i}) for 99 Iowa counties

Figure 3.6 displays the temporal coefficients (τ), which are all positive and significant. Participants in the land market, heavily weight the value of land from the last period (Maddison 2009). Even though all counties showed a positive temporal lag dependency, a major cluster of dark blue can be seen. The intrinsic value theory, also known as the earnings capitalization theory suggests that farmland values reflect past farm income. This theory posits that the market value of farmland is determined by its ability to generate income in the future. According to the Intrinsic Value Theory, investors and market participants evaluate farmland based on past income or earnings streams. The historical profitability and income generation of the farmland is used as a basis for estimating its future income potential. The theory assumes that the market value of farmland is driven by the expectation of earning a reasonable return on investment, taking into account the income history as an indicator of future earning potential.

Under this theory, if farmland has a track record of consistent and strong income generation, it is expected to have a higher market value. Conversely, if the historical earnings from farming activities on the land have been poor or unstable, it may result in a lower market value. The past income performance serves as a measure of the land's potential to generate future income. The Intrinsic Value Theory considers the historical earnings of farmland, but it does not necessarily mean that the past income solely determines the market value of farmland. Nonetheless, the theory highlights the significance of past farm income as a factor in determining the market value of farmland.

Counties, including Cherokee, Osceola, Sioux, Mills, Ringgold, and Webster from Figure 3.4, as well as Keokuk and Floyd from Figure 3.5, exhibit a temporal lag dependency that is close to zero and positive. Allamakee, Benton, Calhoun, Cedar, Humboldt, O'Brien, and Winnebago are the counties for which spatial, spatiotemporal, and temporal lags were always positive. O'Brien, Osceola, and Calhoun were among the counties with highest farmland values, with O'Brien having the highest value in the years of 2012, 2015, 2016, 2018, 2019, and 2021.[1]

[1]Note that this are not the highest farmland values in the data set, but the highest values in that year. For example, the highest farmland value in the entire dataset in fact is O'Brien with $13241 per acre in 2012. However, the second, third, and fourth highest farmland values are Sioux 2012, Scott 2013, and O'Brien 2013 with $12871, $12623, and $12594, respectively.

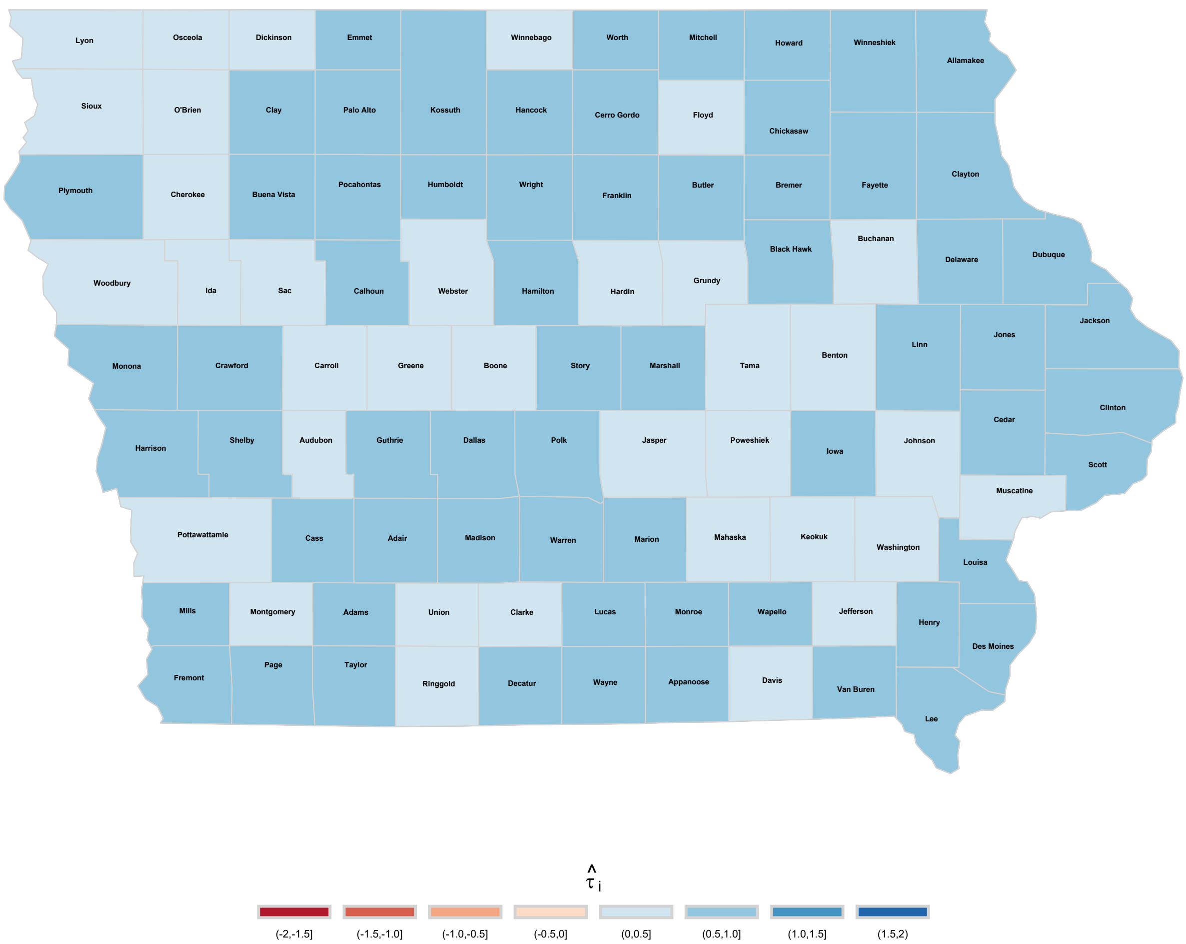

Figure 3.6: Effect of own lagged farmland values on current farmland values (τ) for 99 Iowa counties

The county-specific estimates of the elasticities of farmland values to population density and real per capita income are shown in Figures 3.7 and 3.8, respectively. The contemporaneous population density had a statistically significant positive impact on farmland values in 28 counties. Of these, more than 23% coincided with counties that had positive estimates for the total $(\hat{\psi}_{0i} + \hat{\psi}_{1i})$ spatial lag coefficients in Figure 3.3. Another 18% coincided with counties reporting a negative total spatial lag estimate, and the other 58% had a sign switch. The positive relationship in the 28 counties indicates that as population density increases farmland values increase. In 37% of the counties, population density had a positive relationship with farmland values. About 21% of the 99 counties showed a negative relationship between population density and farmland values. About 21% of the 99 counties showed a negative relationship between population density and farmland values. Scott, Linn, Johnson, and Woodbury have highest population density levels and show a positive relationship to farmland values. The counties with negative estimates are spread evenly across the state. According to the Data USA (2014), violent crimes in Polk County grew 59.9% per 100,000 population from 2014 to 2021. Previous research had demonstrated that crime hot spots negatively affect housing sales and prices (Lynch and Rasmussen 2001).

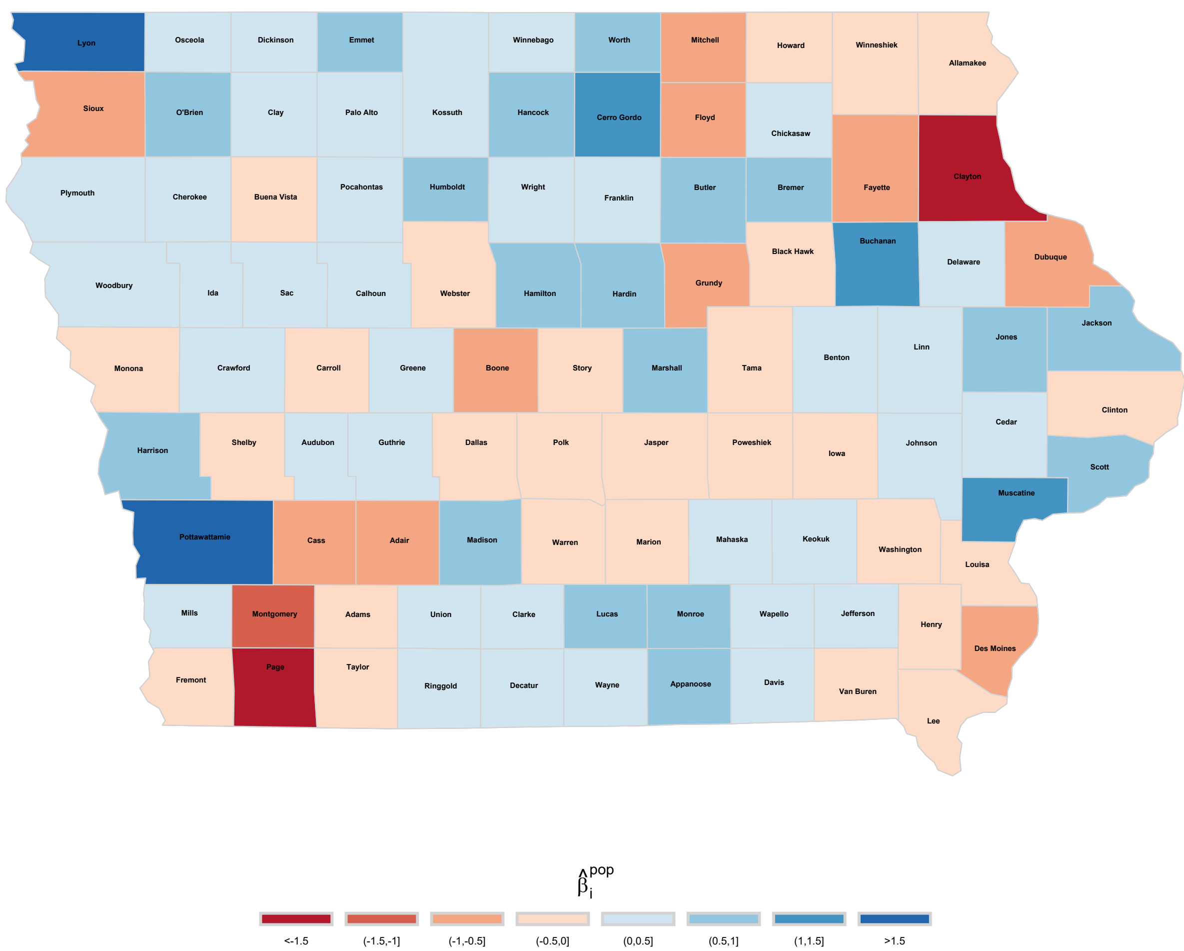

Figure 3.7: Spatial elasticities of farmland values to population density growth estimates (β_i^{PD}) for 99 Iowa counties

Figure 3.8 displays the contemporaneous elasticities of farmland values with respect to a change in real income per capita ($\hat{\beta}^{inc_i}$) for counties in Iowa. Sixty-three counties showed a positive relationship between income and farmland values; the estimates were statistically significant for 19 of those counties. Thirty-six counties showed a negative relationship between income and farmland values, with a statistically significant relationship in nine of those counties. More than 28% of the counties with positive contemporaneous elasticities coincided with counties that also had positive estimates for the total ($\hat{\psi}_{0i} + \hat{\psi}_{1i}$) spatial lag coefficients. Sixteen counties reported positive estimates for contemporaneous elasticities for population density and income per capita and coefficients for total spatial lag. Cedar County had the highest positive contemporaneous estimated elasticities of farmland values to income per capita (Table B2). If income per capita increases by 1%, it leads to a 0.557% increase in farmland values in Cedar County. Sioux, Adams, Dallas, Monona, Webster, Polk, Montgomery, and Iowa showed negative relationships for the three estimates. Montgomery County had the highest negative contemporaneous elasticity of farmland values to income per capita. If income per capita increased by 1%, then farmland values in Montgomery County decrease by 0.424% (Table B2). In Polk and Dallas counties, 62.9% and 62.2% of the households, respectively, paid taxes in the category of $3000 and more, compared to the national average of 41% (Data USA 2014). Devadoss and Manchu (2007) found that i property taxes negatively affected farmland values using county-level data in Idaho.

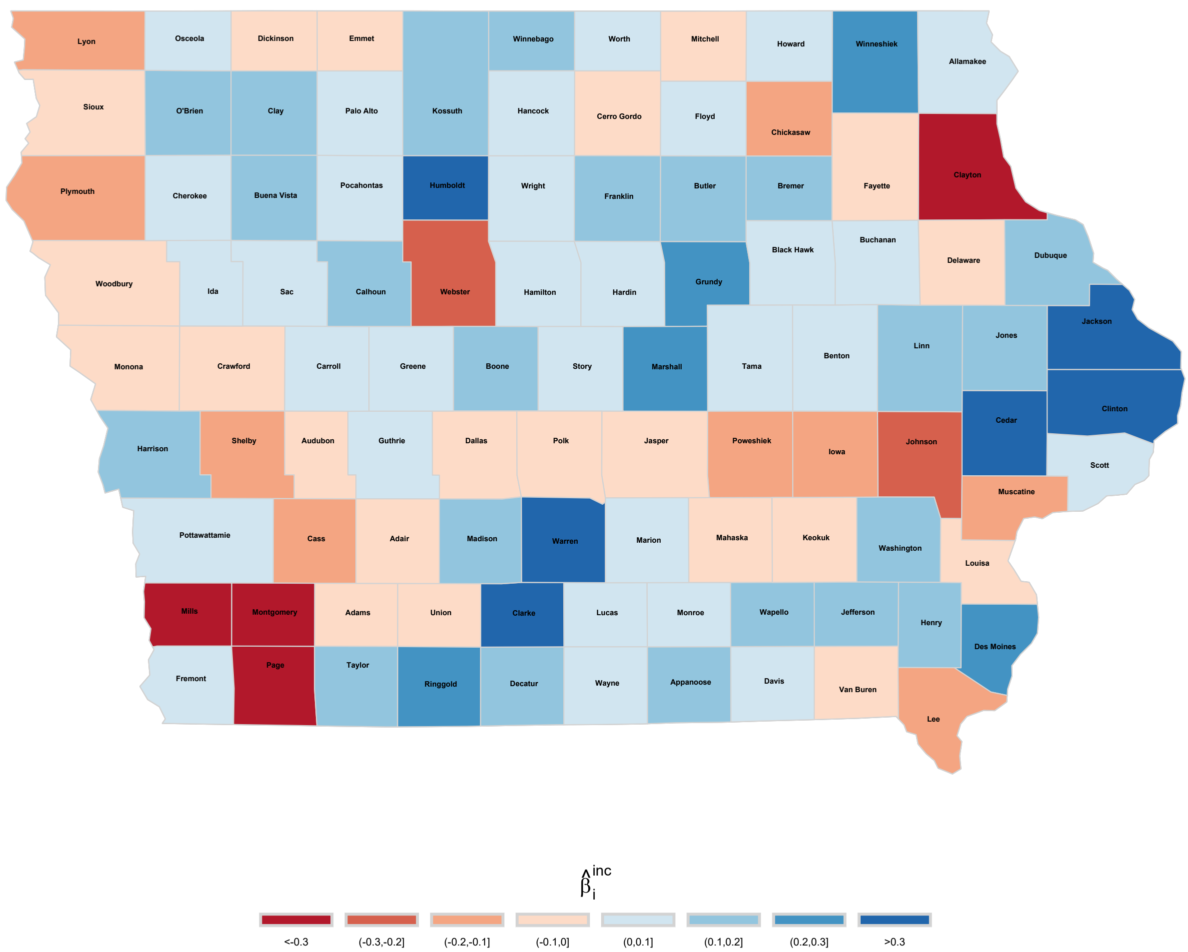

Figure 3.8: Spatial elasticities of farmland values to income per capita growth estimates (β_i^I) for 99 Iowa counties

3.5.3 Direct and Indirect spatial effects at different horizons

Following Debarsy, Ertur and LeSage (2012), Aquaro et al. (2021) extended the spatial autoregressive (SAR) model. Aquaro's extension made it possible to use the spatiotemporal model from Equation 7 for impulse response analysis of the effects of county-specific shocks (ε_{it}) to the exogenous variables. Figure 3.9 illustrates the direct effects on county farmland values at different time horizons (0, 3, and 6 years), following a one percent change in either the population density or income per capita within the same county. The indirect effects were divided into spill-out and spill-in components (Figures 3.10 and 3.11, respectively). These figures show the relative importance of these effects over time and space.

The main diagonal of the $N \times N$ matrix captures the own-partial derivatives, representing how a change in population density or income per capita would directly impact each county's farmland values. Significant impacts on farmland values resulting from changes in population density and income per capita variables, whether within the same county or neighboring counties, are primarily concentrated within each region. The effects between regions are comparatively minimal, consistently accounting for less than 0.3% of the direct effects. Direct effects outweigh indirect effects for both population density and real income per capita variables across all 99 counties. However, the ratio of indirect to direct effects remains relatively consistent for each county. Nevertheless, substantial variation exists across regions, indicating heterogeneity.

Forty (36) of the 99 counties had a negative direct effect of population density (income per capita). Twenty counties had a negative direct impact on farmland values from both population density and income per capita. Direct effects tended to be larger in more densely populated counties, such as Webster, Clayton, Cass, Adair, Page, and Montgomery. A 1% shock to population density and income per capita had a diminishing direct effect on farmland values, starting in year 3. In essence, the impact became less intense after three years. Consistent with theory, we found a greater long-run elasticity of farmland values to both population density and income per capita. The direct effect of population density was larger than that of income per capita in time zero. The direct effect of the population density shock was still present in the long run (horizon 6 in this analysis), but most of the counties had fallen into the positive or negative category closer to zero. Thus, the effect of the population density shock appeared to have nearly died down to zero in the long-run. The same held for the income per capita shock.

However, Cedar, Clinton, and Allamakee counties stayed in the same upper category (> 0.074) through all horizons (0, 3, and 6).

These results suggest that a 1% increase in population density in Hardin County would lead to a short-run increase in farmland values by 1% but a long-run decrease in farmland values of 0.11%. Since the income per capita elasticity is positive for 63 counties, then, overall, increases in county-level per capita income led to increased farmland values. In the short run a 1% increase in income per capita in Cerro Gordo County led to a .55% increase in farmland values but almost died out in the long run, at 0.0056% increase. The observed phenomenon of increasing income leading to decreasing farmland values in certain counties may seem counter intuitive, based on theory. However, the specific dynamics of each county can influence the relationship between income and farmland values. Cerro Gordo and Mills counties exhibited different responses to changes in income per capita. Other factors, such as population density, urbanization, or specific agricultural practices, may be exerting a stronger influence on farmland values in some counties, offsetting the expected positive impact of increased income.

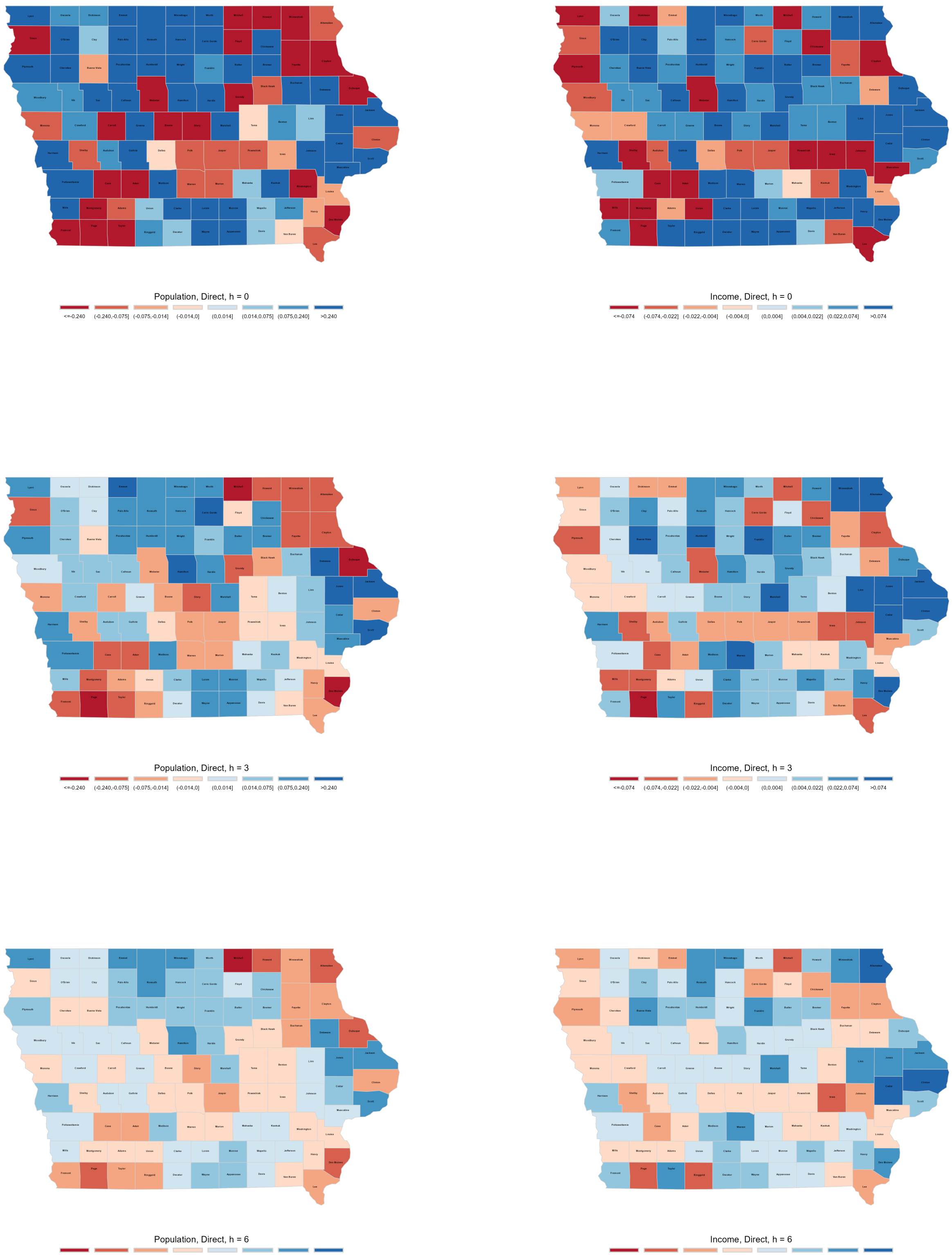

Figure 3.9: Direct effects for Iowa counties at time horizons h = 0, 3, 6 years after a one percent change to own county population or real income growth at time t.

Figure 3.10 illustrates the spill-out indirect effects. These effects encompass both contemporaneous spatial spillovers and the diffusion that occurs over time. Given that the estimates for the spatial dependence parameter, ψ_{i0}, hover closer to the upper and lower bounds, it is likely that these effects have a significant magnitude. Only around 10 counties exhibit minimal or zero spatial dependence.

The spatial spill-out can be interpreted as the impacts on counties neighboring the originating county. The off-diagonal elements of the $N \times N$ matrix, $\partial y_2/\partial x_1^{PD}, \partial ..., y_N/\partial x_1^{PD}$, capture how changes in population density or income per capita in region i impact farmland values on neighboring region j. The presence of spatial spillover and diffusion effects aligns with the phenomenon commonly referred to as "cross-border land shopping" or "cross-border land investment."

The indirect effects of population density on farmland values are positive and different from zero up to a time horizon of 6 years in 32 of the 99 counties (Figure 3.10); the positive sign is consistent with Huang et al. (2006). The indirect effect estimates tell us that a positive change in own-county population density will lead to increased farmland values in neighboring counties, which is consistent with Abelairas-Etxebarria and Astorkiza (2012). When the direct effect died down to zero or close to zero in the long runand the cumulative spill-out effects were positive, we saw that cross-border land investment may offset the cumulative negative own-county farmland elasticity effect in the long run.

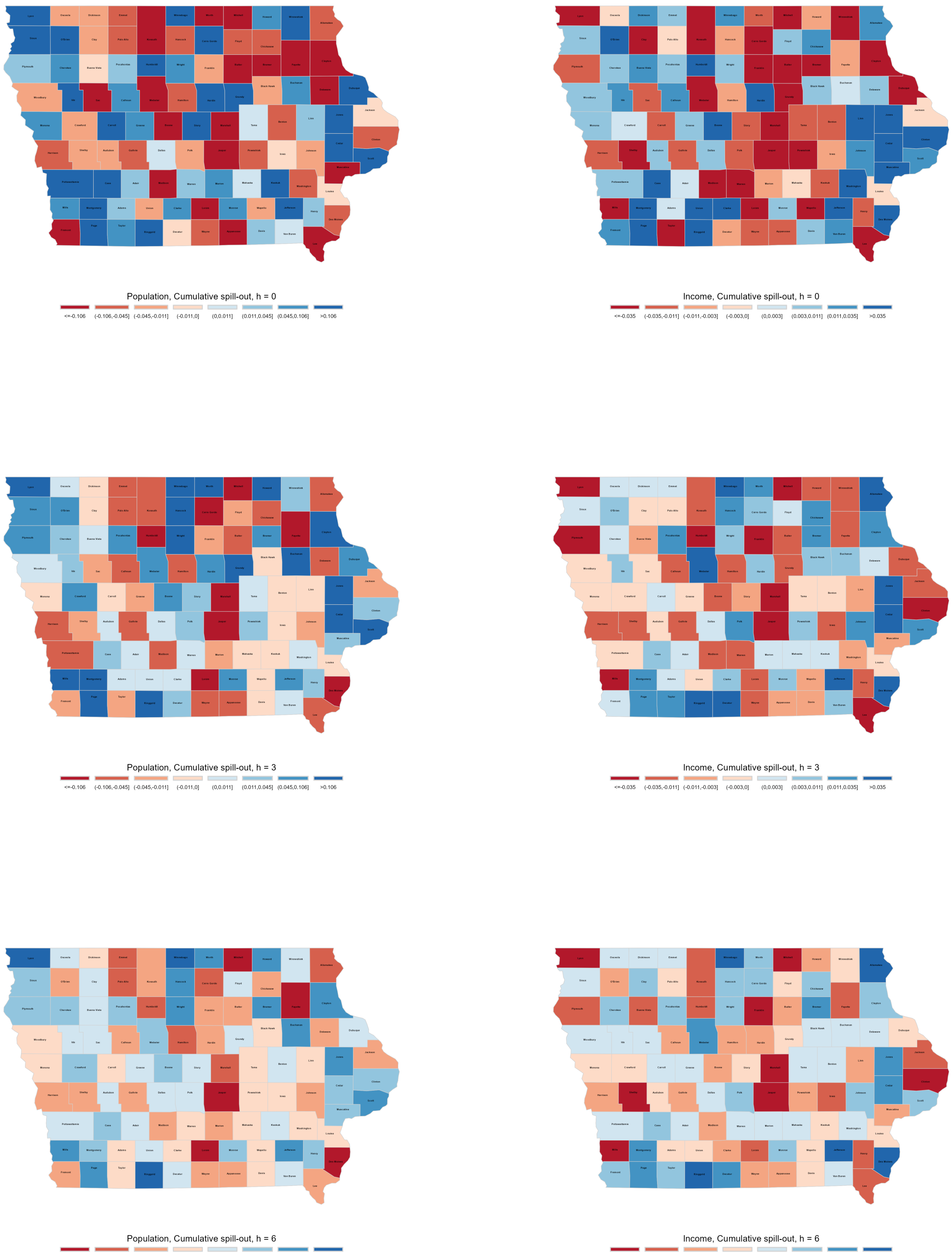

Figure 3.10: Spill-out effects for Iowa counties at time horizons h=0,3,6 years after one percent to own county population or real income growth at time t.

According to LeSage and Chih (2016), the spatial spill-in effects are the off-diagonal elements of the N $\times$ N matrix showing how a change in the kth explanatory variable value in regions neighboring county j impacts farmland values in county i. Figure 3.11 shows the spill-in effects for Iowa counties at time horizons h = 0, 3, 6 years after a one percent change to neighboring population or real income growth at time t. The spill-in effects exist but were smaller than the spill-out effects; these results agree with Abelairas-Etxebarria and Astorkiza (2012). This suggests that increases in neighboring county-level population density or income per capita exert a minimal influence on own-county farmland values. Several counties experienced a negative spill-in effect in own-county farmland values in response to an increase in neighboring county's population density. For example, Franklin County had a negative spill-in effect on farmland values with the increase in population density of Butler, Cerro Gordo, Floyd, Grundy, Hamilton, Hancock, Hardin, and Wright. However, the effect started to die out in the long run, h= 6.

In general, the spill-in effect for income per capita is smaller than that of population density. The highest positive and negative spill-in effects were in Clayton and Marshall with 0.33 and -0.23 at h=0, respectively. Kossuth County farmland values experienced a positive spill-in effect with an increase in income per capita in Emmet, Hancock, Humboldt, Palo Alto, Pocahontas, Winnebago, and Wright at h=0. That effect was negative by h=3 and was more negative by h=6. This means that the increase in neighboring counties' income per capita could create a short-run increase in Kossuth farmland values and an increasingly negative impact over time.

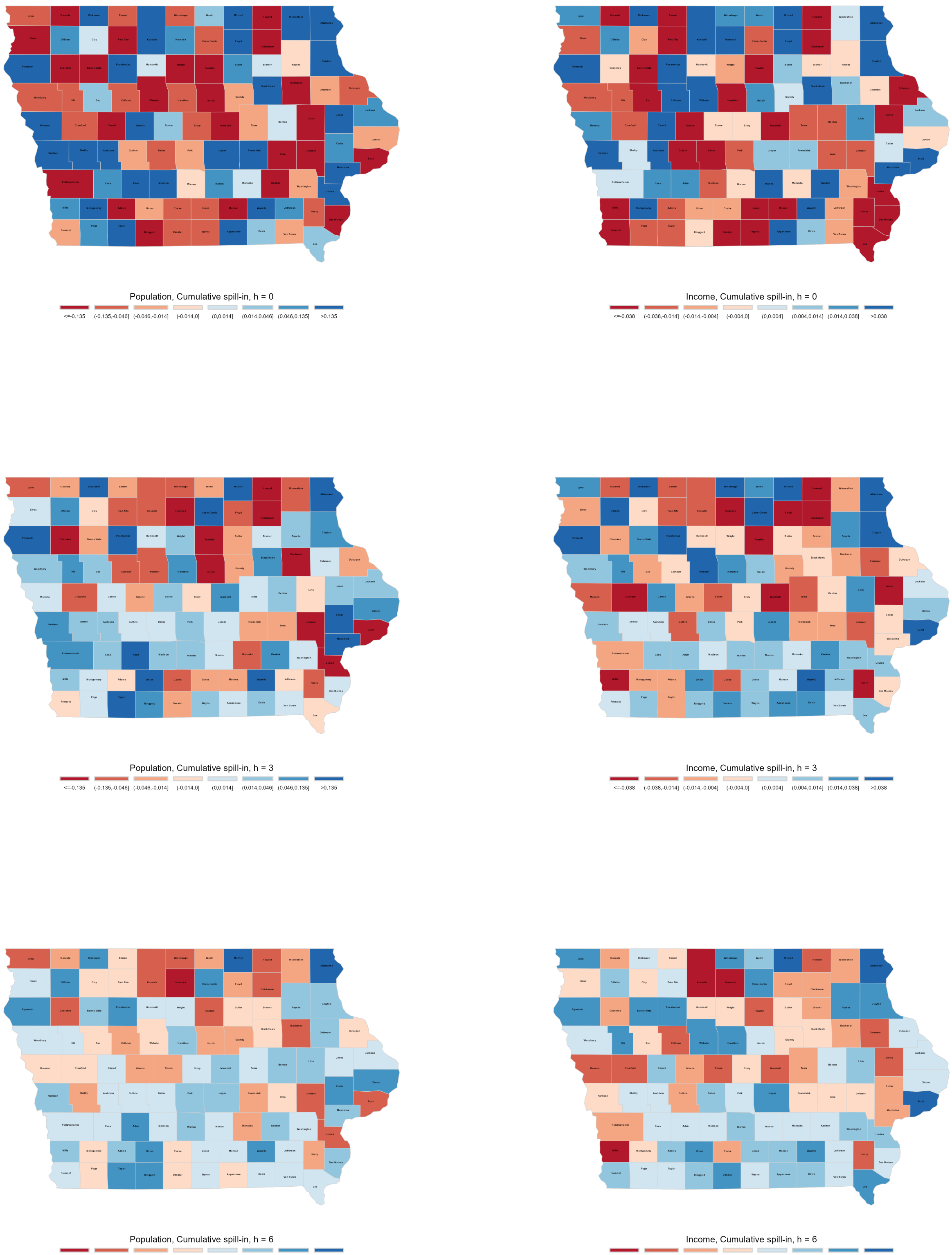

Figure 3.11: Spill-in effects for Iowa counties at time horizons h=0,3,6 years after a one percent change to neighboring population or real income growth at time t.

3.6 Discussion

Contemporaneous spatial dependence in farmland values was captured by the estimated parameter $\hat{\psi}_{i0}$. The inclusion of $\hat{\psi}_{i1}$ allowed for the consideration of space-time lagged values of changes in farmland values. The incorporation of $\hat{\psi}_{i1}$ accounts for the influence of neighboring values observed in the previous period on the current-period dependent variable. Changes in farmland values in a particular area can lead to various changes in neighboring values and vice versa. These relationships can be positive or negative, indicating the presence of complementary or substitute effects between different counties.

The findings from Table B2 provide strong evidence of both temporal and spatial effects on farmland values across counties. The temporal effects in all counties and the spatial effects in most counties were significant at the 1% level. These results indicate that changes in farmland values are influenced not only by past property price growth within the same county, but also by changes in neighboring farmland values in the contemporaneous and/or past year. The estimates for contemporaneous spatial effects were less precise than the temporal and space-time lagged values. The data-driven method used in this analysis allowed for the parsing of negative and positive spillover effects. Both spill-in and spill-out effects were significant and similar in magnitude, indicating that neighboring farmland values can influence each other positively or negatively.

The analysis revealed that the spillover effects of farmland values are not easily defined by county boundaries. Instead, there are significant variations within regions, with some counties being more affected than their neighboring counties. Even after accounting for common factors, the spatial effects on farmland values in some counties were significant but scattered in a non-uniform manner. This finding challenges the notion of a ripple effect hypothesis, which suggests a more uniform pattern of spatial effects.

It is worth noting that the diffusion of farmland values may require a longer timeframe to become evident. Therefore, it could be beneficial for future research to incorporate dynamic multipliers to assess whether a delayed effect becomes apparent. This approach would allow for a more comprehensive understanding of the temporal dynamics involved in the spillover effects on farmland values. There is evidence of significant spillover effects with a greater magnitude observed in O'Brien County and its surrounding areas. This suggests that the influence of farmland value changes extends beyond immediate neighboring areas and has a more pronounced impact in this particular region.

3.7 Conclusions

Previous literature included spatial dependence and weak cross-sectional dependence to explain regional farmland values in a continuous dynamic framework. Frequently, previous literature has not considered strong cross-sectional dependence, leading to an overestimation of spatial relationships between areas. In this research, we used the model proposed by Aquaro et al. (2021) to measure the cyclical sensitivity of farmland values accounting for serial dynamics, spatial dependencies, and communal factors. This paper addresses this issue by estimating a spatio-temporal HSAR model of annual farmland values across the 99 counties in Iowa from 1960 to 2021. Accounting for common factors, the study showed county-level spatial relationships. We then examined the spillover effects of income per capita and population density on farmland values in 99 Iowa counties.

By incorporating an explicit measure of spatiotemporal spillovers, the model allowed the estimation of the magnitude and persistence of spillovers. This enables a comprehensive understanding of the impact and dynamics of these spillovers. Unlike the general space-time dynamic model, there is no imposition of restrictions. The dynamic space-time model encompassed contemporaneous and time and space diffusion effects in future periods. The contemporaneous effect signified pure spatial impacts. The inclusion of the time and space diffusion effects in future time horizons made it challenging to differentiate between the two. However, when consistent with the model and sample data, it was possible to separate the spatial, temporal, and diffusion impact magnitudes. This separation enabled a more precise analysis of the individual contributions of these factors.

The findings revealed a high level of heterogeneity among counties, indicating significant spatial dependence. Removing the influence of national and regional factors, it became apparent that O'Brien County exhibits a strong temporal and spatial dependence. Variation in spatial dependence across counties highlighted the inadequacy of delineating the farmland market solely by county boundaries. The analysis revealed a complex interaction between spatial and temporal dynamics among the counties. Specifically, it indicated that there were stronger neighborhood spillover effects over time in subsequent periods compared to the current period. This finding suggests that the influence of farmland value changes in one county on its neighboring counties becomes more pronounced over time. In essence, the impact of changes in farmland values tends to spread and affect neighboring areas more strongly in the future. This temporal dimension adds depth to our understanding of the spillover effects and highlights the importance of considering the dynamic nature of these relationships.

It is important to note that the method used in this analysis may lead to the detection of erroneous pairwise relationships between counties. Regarding the ripple effect hypothesis, these findings suggest a more nuanced spatial impact than theory implies. Areas with higher levels of economic activity, exhibit stronger spillover effects. However, it is possible that the ripple effect operates over a longer timeframe than what this study explored. Future research could incorporate dynamic multipliers to further investigate this hypothesis.

In summary, this study highlights the importance of accounting for cross-sectional dependence in analyzing spillover effects in farmland values. The findings demonstrate heterogeneity across counties, emphasizing the need to consider spatial relationships beyond county boundaries. The study identifies positive and negative spillover effects between counties and suggests avenues for future research, including alternative approaches to multiple testing and exploration of the ripple effect hypothesis using dynamic multipliers.

Chapter 4

4 Kansas Property Tax Estimator Tool Guide

4.1 Introduction

In 2021, we started building the Kansas Property Tax Estimation Tool with a goal of transparency for the Kansas Department of Revenue's agricultural land valuation methodology, governed by Statute KS 79-1476. According to the statute, agricultural land value will be estimated using the use value appraisal method, instead of the market value appraisal methodology used for other types of properties. Appraising the property in its current use, rather than its highest or best use, is intended to remove market influences that are unrelated to agriculture from the agriculture land valuation process. The Kansas Legislature and the Kansas Department of Revenue (KDOR) Property Valuation Division (PVD) collaborated with agricultural economists from Kansas State University to develop the use valuation methodology for agricultural land in the state of Kansas; this method follows the income capitalization theory. This method is used to calculate an estimated appraised land value for all soils in Kansas.

The Kansas Property Tax Estimation Tool will enhance and ease tax planning. We envision that this tool will be useful to all stakeholders in the property tax market. Legislators, taxing districts, and land managers can run many "what if" scenarios in a timely manner by using the Estimator. This tool will allow enough flexibility to be useful throughout the entire state for all taxing districts on any device, mobile or desktop. An indirect benefit of the tool will be an increased level of transparency among taxpayers, KDOR, and legislators. Legislators can see how proposed changes to the use valuation methodology will impact property tax revenues for the entire state, for their district, or simply for their home county. However, the tool will not just be useful in the legislative process. Land managers can estimate taxes for future land purchases and/or budget for potential legislative changes. Tax districts will be able to determine how much to change their mill levies to meet revenue goals. In short, the tool will be useful to all parties involved in property taxation.

The tool is designed to be interactive. It incorporates soil productivity and land uses (irrigated, non-irrigated, and pasture) in a manner similar to the current property tax legislation. The tool inputs and calculations will change if the landscape of the property tax legislation changes. Making the tool interactive in this manner enables it to be sustainable in perpetuity.

An offshoot impact of this project may be the development of additional tools for other revenue departments to enable strategic planning in Kansas, down to the tax district level. Creating this initial tool will allow for an informal beta test of estimation tools for the state. This kind of testing enables the state to work out the kinks on a smaller scale. Once perfected, the process can be replicated and tailored to specific governmental departments. The interactive web dashboard is developed so that it can be deployed and accessed from the K-State AgManager.info, INK, PVD, and other State of Kansas websites via embedded HTML code.

The Kansas property tax estimation tool follows the income capitalization method. In the tool, income is estimated by broader groupings of land class, rather than by individual soils. This is the main difference between the tool calculation and the valuation methodology used by PVD. The Natural Resource Conservation Service (NRCS) groups land into classes, depending on its productivity. NRCS land classes are used in the Tool to calculate estimated income. Land class and 8-year average Landlord Net Income (LNI), as calculated using the PVD methodology, is assigned to each soil. The Tool sums the product of acres per soil and LNI per soil. This sum is divided by the total number of acres in the Land Class to arrive at the LNI by Land Class.

One of the main advantages of an interactive R-shiny dashboard is that it has more efficient calculations and analyses than spreadsheets. We have chosen to develop the Kansas Property Tax Estimation Tool using R, a cutting-edge statistical software environment. R provides real-time interactive business intelligence through a web dashboard, making it an ideal platform for this tool. R is widely recognized as mainstream open-source software, extensively utilized for statistics education at universities, data science in the private sector, peer-reviewed academic research publications, and the deployment of business intelligence web dashboards, using R Shiny.

Over two decades ago, the State of Kansas invested significant resources to develop a precise and detailed methodology to estimate the value of agricultural land. However, comprehending this methodology requires expertise not only in mass appraisal methods but also in the agricultural industry. Our Tool aims to simplify the valuation process, making it more accessible to individuals without specialized knowledge. By providing this tool, we hope to clarify the valuation process and enhance understanding among users.

One of the key benefits of the Tool is its ability to allow users to adjust the major components of the valuation formula. This feature empowers users to comprehend and evaluate the impact of changes on their property valuations. For taxing districts, the tool facilitates the determination of more accurate mill levies to achieve predetermined revenue levels. Furthermore, legislators can utilize the tool to swiftly assess the relative effects of modifications to the use valuation methodology on agricultural land valuations.

The primary objective of this essay is to introduce and present the interactive Tax Tool Shiny app dashboard. This tool is specifically designed for land managers, policymakers, and taxing districts. The essay will provide a systematic guide, detailing the development process of the Tax Tool Shiny app, and demonstrate its capabilities across various scenarios.

4.2 Data

The Tool uses PVD precomputed data and variables. Data needed in the calculations are provided by the United States Department of Agriculture's Natural Resource Conservation Service (NRCS), Farm Service Agency (USDA-FSA), National Agricultural Statistics Service (NASS), Risk Management Agency (RMA), and the Land Use Survey Office (LUSO) in the Department of Agricultural Economics, Kansas State University. The Tool does not recalculate the variables that are used in the LNI calculation for PVD, so a brief description of each variable and the estimation process is necessary. For brevity, only the methodology used in the calculation of non-irrigated LNIs is discussed.

The Kansas Soil Rating for Plant Growing (KS_SRPG) is one of the main components used to calculate the LNI for PVD. The Natural Resources Conservation Service (NRCS) developed the KS_SRPG system to rank the productivity of each soil mapping unit on a scale of zero to 100. Weighted average productivity for an area is computed by summing for the county of the products of acreage by soil mapping unit and the KS_SRPG. That weighted average KS_SRPG is used to index the KS_SRPG for each soil mapping unit. The interpretation of the indexed productivity is that average soils have an indexed value of 1.00 and above (below) average soils have an indexed value over (under) 1.00. The indexed value is multiplied by the average LNI calculated for the county, giving above (below) average soils above (below) average income, as would be expected[2].

The ratio of acres planted to a crop relative to the total acres planted in an area, crop mix percentage, is calculated using only crops representing 5% or more of the total acres planted for a county. Each soil mapping unit in a county has the same percentage of crop mix. Crop production costs and crop revenue are weighted using this percentage. Average crop mix percentages at the county level were calculated using Albright, Featherstone, and Cole's method of moving averages (AFC MOMA) to calculate an 8-year average.

Yield per acre, crop production divided by acres planted (except alfalfa, which uses acres harvested), also uses 8-year averages calculated using the AFC MOMA to calculate yield. To incorporate fallowing practices, we calculate an 8-year average percentage of one-half of fallow acreage and an 8-year average percentage of continuous cropping acreage. Those percentages are multiplied by their respective yields to calculate an 8-year average fallowed wheat yield. Other crops are not fallowed; they are the AFC MOMA yields for 8-years.

The monthly average price paid to farmers for the crops at the state level were weighted with the percentage of the crop sold per month. The annual price for each crop is the sum of these weighted monthly prices. Like the previous variables, prices use the 8-year AFC MOMA; this price reflects the average price paid to landowners, weighted to reflect the time of the year when most crops are sold. Prices for all crops, except alfalfa and sunflower, are calculated on the Crop Reporting District level. Prices for alfalfa and sunflower are statewide.

The landlord's share of line-item crop expenses is determined by the most recent Non-Irrigated Farm Lease Arrangement Survey. Production costs per acre represent the cost of multiple inputs, including fertilizers, herbicides, pesticides, harvesting, natural gas fuel oil, machinery, and seeds. The landlord's share of each of these expenses is multiplied by the per acre cost of the respective expense.

The use value methodology includes a management fee of 10% that is consistent with typical rates charged by Kansas farm management firms to the landlord. The management fee is the

[2]This is Crop Reporting District for Irrigated, Native, and Tame Pasture land.

product of the 10% and weighted gross landlord income to account for related business and management decision costs. The rate is validated by Kansas State University's management fee survey conducted every four years since 1990. Any government program payments are excluded from the PVD LNI methodology. After a brief description of all necessary variables, the valuation methodology used by PVD will be presented. Calculation steps are taken from the Kansas Department of Revenue Home Page (ksrevenue.gov).

The lease arrangement for non-irrigated land that occurs most often for the nine crop reporting districts in Kansas is 1/3 crop share to the landowner, except in districts North Central-40 and Northeast-70. The 40% crop share for the landlord was the most common in those districts.

Average landlord's gross income is calculated by multiplying the average yields, prices, crop mix, and the landlord's crop share. By weighting the average landlord's gross income by the crop mix percentage for each crop, the landlord's weighted gross income for each crop is calculated. The total average landlord's weighted gross income for the county is the sum of the weighted gross income per crop. The landlord's share of the production expense for each crop is summed to arrive at the landlord's average total production costs.

The total landlord's gross income is indexed using the indexed productivity values for each soil type in the county. This provides a gross income for each soil mapping unit. The county average production costs and 10% management fee are deducted from gross landlord income to get the LNI for each soil mapping unit. As a result, each soil mapping unit has a Landlord Net Income (LNI). The "Kansas Property Tax Estimation Tool" does not calculate the LNI. It is provided by PVD. However, it is imperative to understand the calculations and parameters included in the system of equations.

Data or variables used in tax estimation are: County name, MUNAME (Mapping Unit Name), MUSYMBOL (Mapping Unit four digit code), County number, CountyMU (County number and MUSYMBOL), ACREPCT (% total of acres), LNI (pre-calculated following the statute and PVD directives), Crop Reporting District (10-90), Land USE ("Irrigated," "Non-Irrigated", "Native Pasture", "Tame Pasture"), WELL DEPTH (50,100,200,300. . ., 700 if irrigated, 0 otherwise) and Land Class (productivity). The Mapping Unit is the NRCS term for each soil. Any reference to mapping unit is a reference to the individual soils.

4.3 User interface (UI) and server side

Before explaining all the computational issues encountered while constructing the app, a brief explanation of the UI and server is needed. Pinto Padilla and Griffin (2023), explains how the creation and presentation of Extension work through Shiny Apps could not only enable the hosting of data online but also deliver a real-time result. Thus, results and data presented on a Shiny Apps are kept up-to-date with the latest information, reflecting coordinated updates by PVD, INK, and Kansas State University. They also explained the two principal components of the Shiny App. The app consists of two distinct parts: the back end (server side) and the front end (user interface/UI). Each component is powered by its own set of code. On the server side, reactive expressions are utilized to generate outputs that are displayed on the UI. Essentially, the server side handles all the calculations and analytics, while the UI side presents the results to enhance the user experience. Specific code and explanation of the app creation will be given as we move further into the app core. Steps

The main objective behind performing a priori computation and data management is to ensure that once the tool is launched and updated data become available, the code remains accessible and user-friendly. This approach allows for easier data updating and replication by individuals with basic knowledge and skills. However, due to the specific nature of data collection and presentation, some preliminary data management steps are necessary.

The step-by-step process of creating and utilizing the app will be explained in detail later. It is important to note that the app is designed to enable users to generate all the required information dynamically. This means that the user will have the ability to select one or multiple land uses and classes at any given time. Consequently, it becomes crucial to simultaneously handle the uploading, management, calculations, and cleaning of the data to ensure a seamless and accurate final presentation.

4.4 First version.

The initial version of the code was designed to handle multiple files simultaneously, performing filtering, management, and calculation of the necessary variables. However, it faced certain issues limiting the user to selecting only one type of land at a time. This preliminary code suffered from being too generalized.

One of the challenges encountered was importing the data into R-Shiny. Since each district had different file names based on the land use, exporting the data proved to be difficult. To address this issue, several reactive expressions and conditional statements, such as if_else(), were utilized. In R-Shiny, a reactive expression utilizes widget inputs and returns a value, updating it whenever the original widget changes. Each land use had its own reactive code.

The primary challenge was to bring the relevant data into R-Shiny. The code was created to paste several words together to create the name of the file. For example, if the user selected the county “Cheyenne” and the land use “Native”, the code was designed to concatenate the values of “10”, “NW”, and “-NAT”. The resulting file name that the program used to import the data was “read_excel(”10NW-NAT.xlsx”)“.

The issue with the initial code was that it attempted to call all files for the selected county without considering whether the files actually existed or not. For example, if the selected county was Cheyenne or district 10, the code would try to retrieve data for all land uses, including irrigated. However, in some cases, certain districts may not have data available for specific land uses of irrigated or tame pasture. As a result, the code would encounter errors or crashes when attempting to access non-existent files.

To address this issue, a more specific or detail-oriented code was developed to incorporate checks to verify the availability of data files for the selected county and land use combination before attempting to access them. This way, it can ensure that only valid and existing files are called, preventing errors or crashes. By implementing proper conditional statements or data validation techniques, the code can handle cases where certain districts may lack data for specific land uses, providing a more robust and reliable execution.

4.5 Second version

After encountering several issues with the more general code in the first version, a more detailed and specific code was developed. The code involved a thorough examination of the data to determine which districts and counties had the necessary information for tax calculations. This detailed code utilized conditional statements, particularly using if_else(), to filter and display the appropriate options based on the selected land use and county.

For example, if Allen County was selected, only non-irrigated, native, and tame land uses were displayed as selectable options. Conversely, if Barber County was selected, the options included irrigated, non-irrigated, and native land uses. Similar steps were taken to filter the well-depth options based on the selected county and the condition of having irrigated as the land use. As per PVD directives, LNIs are not calculated for irrigated and tame pasture soils for some counties. Extensive lines of code were implemented to ensure that the app accessed the correct data file for tax calculations. The code was designed to bring in one file at a time, filter the data, calculate the tax estimates, and present the results to the user.

However, when the results were presented to the tax expert and the Property Valuation Division (PVD), several new issues arose. The first new issue involved implementing a floor for the appraised value in the app. The appraised value is calculated as LNI (Landlord Net Income) divided by the capitalization rate. The floor values are set at $10 for all land uses and soils. The code now calculates the appraised value from the provided LNI, and then apply the floor checks and replaces values where necessary to ensure that the appraised value meets the floor requirements. This issue was fixable with the same code since the "error" or inaccuracy in the calculations were generated after the tool called in the correct file.

A second error proved to be more challenging to resolve. It related to setting a floor value for the irrigated land use. The value for irrigated land use cannot fall below the value of the corresponding non-irrigated (dryland) soil. The issue arose because the detailed code was designed to call and process one file at a time, filtering, calculating, and presenting the tax estimate. However, when a new file was called and processed, the program would delete or replace the previously stored data with the new data, resulting in the loss of the previous calculations and making it difficult to set and compare the appropriate floor value for irrigated land use.

4.6 Third version

To resolve the second error, we created a "master file" that consolidated all land uses into a single file. This master file was crucial in addressing the issue and ensuring accurate calculations. In terms of computational steps, the code was modified to call and process this master file, enabling the calculation of weighted LNI for all land uses simultaneously. Once the estimates were obtained, a comparison was made between the value for irrigated land use and the values for dryland uses. If the value for irrigated land use was greater than the value for dryland use, the original value was used to calculate the tax estimates. However, if the value for irrigated land use was less than the values for dryland use, the app utilized the higher value among the dryland use to calculate the tax estimates.

The intention behind creating the master file and modifying the codewas to minimize the need for manual intervention once the app was launched. The code for generating the master file was designed to be efficient and streamlined, requiring minimal steps to generate the file.

4.7 Creating the master file.

The main objective of developing the tool using R-Shiny instead of MS Excel was to minimize human error and create a more automated process. The goal was to reduce the need for manual intervention and make the tool self-sufficient. However, due to the constraints related to the required floor values on the (LNI/cap rate) calculation, additional human labor became necessary. To address this, an extra code was created to generate a master file that consolidates the data for all districts and counties into a single file. This code was designed to streamline the process for the user.

The code functions by calling each district file, retrieving all the sheets at once, compiling them into individual files per district, merging the districts' files into a master file, and saving it in a designated folder. The master file is then later accessed by the Kansas Property Tax Estimation Tool. This step simplifies the overall process by generating a single file that can be readily used by the tool, reducing the need for repeated file access and data retrieval.

4.8 Calculated variables

The masterLNI file, created using data by PVD and other data sources, includes several variables such as "COUNTY", "MUNAME", "MUSYMBOL", "LNI", "DISTRICT", "USE", and "DEPTH". Using these variables along with the variables input by the user, the tool calculates various other variables.

One of the calculated variables is the Estimated Income ($ per Acre). This is derived by calculating the weighted LNI for each land class and summing them up into a single variable called "currentLNI" by Land Class. The "Appraised Value ($ per Acre)" is calculated by dividing the currentLNI by the cap rate that the user inputs into the dashboard. It is important to note that a floor value of $10 has been set for the estimated income. If the calculated estimated income is less than $10, it is adjusted to be $10. Additionally, for irrigated land use, the floor value is set to be the value of dryland. This ensures that the estimated value of irrigated land is not lower than the value of dryland, even if it is greater than the $10 floor.

After calculating the appraised value, the next step is to determine the “Assessed Value ($ per Acre)”. By multiplying the estimated appraised value per acre by the assessment rate of 0.30. The assessment rate represents the percentage used to determine the assessed value of each class of property assigned by KDOR.

The next calculation is the “Estimated Tax ($ per Acre)”. This value is obtained by multiplying the assessed value by the mill levy input by the user. The mill levy represents the tax rate that is utilized to determine the property tax amount collected by each taxing district. It may be determined by dividing the total funding required for the taxing district by the assessed property value in the district. By applying the mill levy to the assessed value, the property tax amount can be estimated to reflect the funding needs of the local community to provide essential services and infrastructure. The final variable calculated by the tool is the “Estimated Total Tax”. This value is obtained by multiplying the tax per acre by the total acres input by the user. By multiplying these two values, the app determines the total estimated tax amount based on the specified variables entered by the user.

4.9 How does the app work?

The Tax Tool is an interactive R-Shiny website that comprises three main tabs, each serving a distinct purpose. The first tab is an interactive Map. The map allows users can explore geographical data related to taxes. Users can navigate the map, zoom in or out, and interact with different counties, school districts, and soil types within the state of Kansas to visualize tax-related information. The second tab is a data Explorer tab that gives users access to the comprehensive data exploration tool. They can input specific parameters, such as land use, well-depth, or land class, and retrieve relevant tax data. The Data Explorer empowers users to analyze and calculate tax-related information, based on their specific requirements. The last tab displays the team information. It serves as a source of information about the Tax Tool team.

Users can find details about the team members, their roles, and contact information. This section provides transparency and facilitates communication between users and the developers of the Tax Tool.

To illustrate how to use the Tax tool, a set of examples and scenarios are developed for several counties, land use, land classes, well-depth, and acres across the state of Kansas. Every year, the Property Valuation Division (PVD) of the Kansas Department of Revenue (KDOR) and other public institutions receives several questions regarding land taxes. The intent of the tool is to improve the understanding of the property taxation process. Users can access the tool from an internet connected browser from laptop or smartphone. The information provided by this tool is intended to increase transparency in the taxation process.

4.10 Interactive Map

Figure 4.1 illustrates the "Interactive Map" tab, showcasing its features from left to right. The first set of icons located in the top-left corner consists of a "+" and "-" symbol, enabling users to zoom in and out, allowing for a closer examination of specific regions within Kansas. Additionally, the house icon serves as a navigation tool to return to the initial location.

On the top-right corner, there are two layer control options in the form of check-boxes. These options allow users to select or deselect the display of counties and school districts. Both layers are enabled by default, but users have the flexibility to enable or disable either one according to their preference.

Below the layers control, users will find a draggable box called the county explorer. This box provides demographic information for each selected county. By default, the graph displays the state average. In the center of the map, the state of Kansas is highlighted in a white-transparent color. When a county or school district is selected, a bubble containing the respective name will pop up. Both the map and the county explorer box are interactive and linked to the table within the "Data Explorer" tab. The combination of these interactive features provides users with a seamless and connected experience, allowing them to explore data through the map, county explorer, and data table in the "Data Explorer" tab.

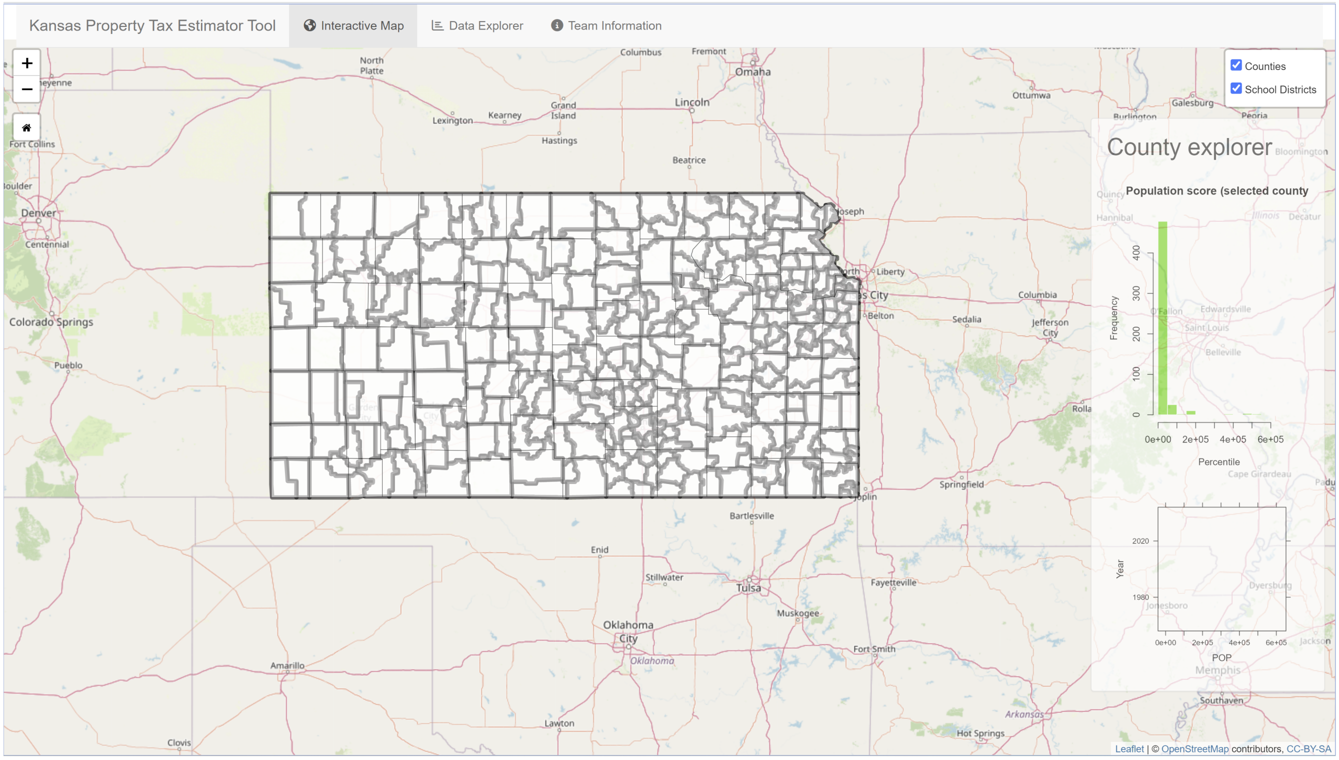

Figure 4.1: Interactive Map Tab

4.11 Data Explorer

Figure 4.2 showcases the "Data Explorer" tab, presenting its components and functionalities. Starting from the top-left corner, the first select box is labeled "County." This box allows users to either select a county from a drop-down list or manually input the county name. Users can only select one county at a time.

Next, we have the "Land Use:" box, which is also a write and select drop-down list. However, the available options in this box are dependent on the county selected by the user. There is no default option, and the selection of a county is necessary to display the corresponding land use options. The four land use types available are native, tame, non-irrigated, and irrigated. The land use options are specific to each county, ensuring that only valid choices are presented. For instance, Allen County may only have data or options for non-irrigated, native, and tame land uses, while Barber County could have data or options for all four land use types. This approach avoids presenting land use options that lack the necessary data for accurate tax calculations, ensuring a smooth and user-friendly experience.

The subsequent box is labeled "Well-depth:". The availability of well-depth options is linked to the land use selection. Non-irrigated, native, and tame uses do not have the well-depth variable, and therefore this box remains hidden for those land use selections. When users select "irrigated" as the land use, the well-depth options will be displayed. Similar to the land use options, the available well-depth options are specific to the selected county. For example, Barber County may offer well-depth options of 50, 100, 200, 300, and 400, while Clay County may only have options for 50, 100, 200, and 300. This tailored approach ensures that users are only presented with relevant options for their specific county. The lease arrangement for non-irrigated land that occurs most often for the nine crop reporting districts in Kansas is 1/3 crop share to the landowner, excepting NC-40 and NE-70. The 40% crop share for the landlord was the most common in those districts. The next box is the "Land Class:" selection, which is dependent on the prior selections of county, land use, and well-depth (if applicable). This box presents a drop-down list of all available land classes based on the user's previous selections. Lastly, we have three open boxes that allow users to input the amount of acres, cap rate, and mill levy associated with the selected county, land use, well-depth, and land class. These boxes are flexible and can be filled with the user's desired values.

The "Submit" button serves the purpose of sending the selected information to the server. Once received, the server will filter and calculate the taxes based on the chosen county, land use, well-depth, land class, acres, cap rate, and mill levy. This allows for the accurate computation of taxes tailored to the specific selections made by the user.

The "+ Add" button enables the user to add one row at a time, allowing for the calculation of multiple acres for different land uses, well-depths, and land classes. This feature accommodates scenarios where the user needs to calculate taxes for various combinations of these parameters. The "Delete row" button allows the user to remove a selected row in case they made an error while selecting or inputting the required information. This provides a way to correct any mistakes and ensure accurate calculations. The "New" button resets the page and clears all the information. It provides the option to start over if needed, allowing the user to make fresh selections and calculations.

Regarding the "Bookmark. . ." feature, it functions similar to the bookmark feature found in web browsers. Users can save the URL or web address of the current page for future reference or easy access. By bookmarking the page, users can quickly return to it without having to manually enter the URL. This feature is especially useful when users have specific calculation questions or need to refer to their selections at a later time. They can bookmark the page and reach out to any team member via email with their questions or concerns.

By incorporating these interactive and conditional selection options, the Data Explorer tab offers users a customized experience, guiding them to make relevant choices and input the necessary information for accurate tax calculations.

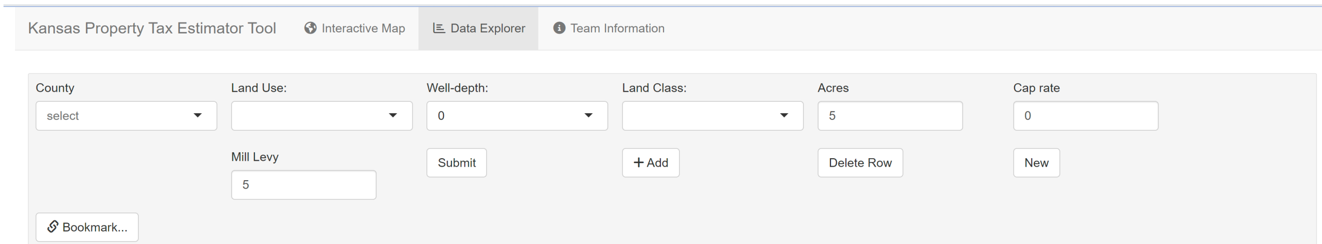

Figure 4.2: Data Explorer Tab

4.12 Team Information

Figure 4.3 illustrates the “Team Information” tab, which provides an overview of its components and functions. Starting from the top-left corner, the app displays the contact information of each team member, along with their respective university websites for further exploration. By clicking on the name of a team member, such as “Terry W. Griffin” or “Leah Tsoodle,” the user will be redirected to their individual university websites, where they can access detailed information about their research, extension activities, and other relevant topics related to farm management and land use valuation.

To facilitate communication, the app also offers the convenience of directly contacting team members via email. By clicking on email addresses such as “twgriffin@ksu.edu”, “ltsoodle@ksu.edu”, or “Allan F. Pinto”, the user’s email client will automatically open with the selected team member’s university email address already filled in. This function streamlines the communication process.

After the team’s contact information, the app displays the website URL for some data sources relevant to the Tool. One of these sources is the Information Network of Kansas (INK), which funded this project. The second data source is the Kansas Department of Revenue. The last data source is Kansas State University AgManager website, which serves as the host for the “Kansas Property Tax Estimation Tool”. AgManager is a comprehensive online resource provided by Kansas State University’s Department of Agricultural Economics. It offers a wealth of information, tools, and resources related to agricultural management, economics, and policy.

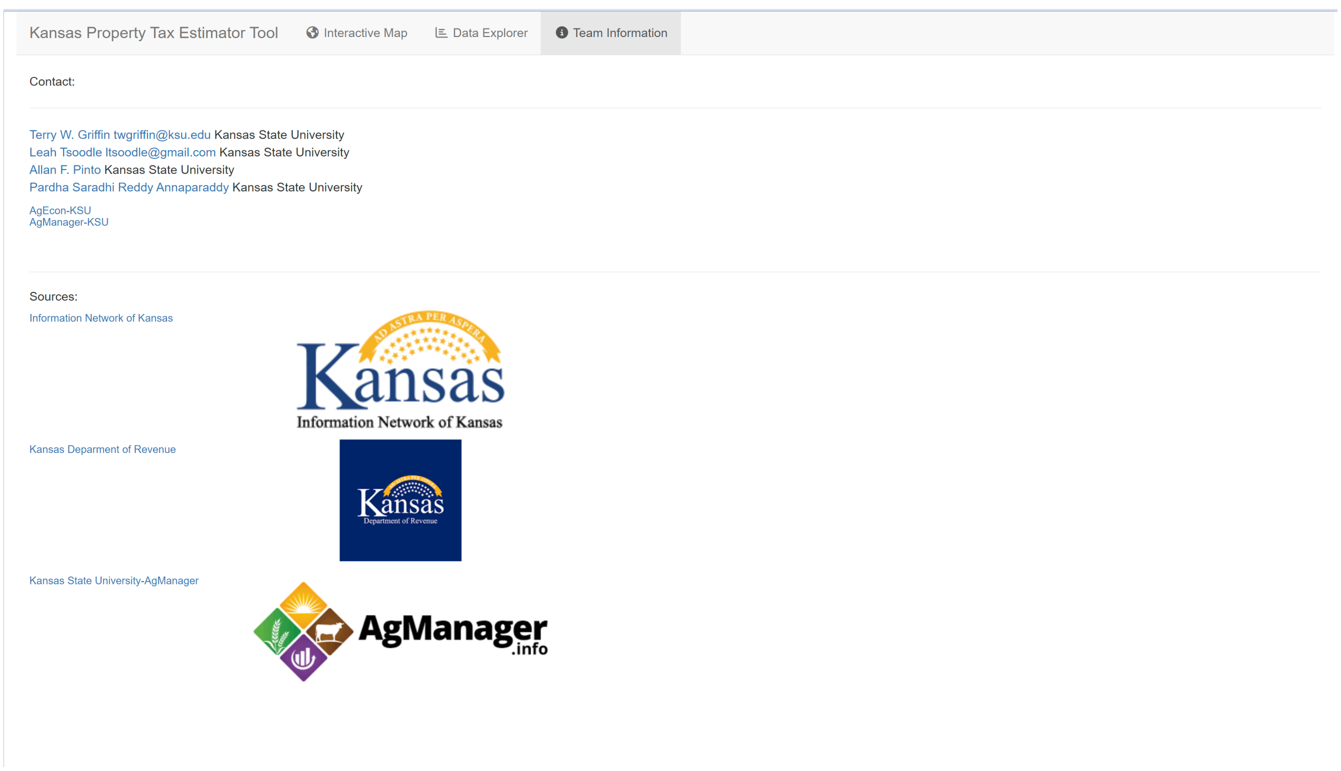

Figure 4.3: Team Information Tab

4.13 Tool scenarios

Several scenarios will be presented to demonstrate the user experience with the app.

4.13.1 Single county-single land use-single land class

In the first scenario, a landowner in Barber County is calculating taxes for a single land use and land class. Figure 4.4 showcases the estimated "Tax" for the selected county. The user selects Barber County, "NONIRRIGATED" as the land use, "0" as the well-depth (default for dryland), land class "2", "60" acres, a "20" Cap rate, and a "10" Mill Levy. Based on these selections, the app calculates the following variables. The estimated income ($ per acre) of $26.8658, appraised value ($ per acre) of $134.3288, assessed value ($ per acre) of $40.2986, tax ($ per acre) of $0.403, and the total estimated tax of $24.1792. This means that a landowner in Barber County, given the selected variables, will owe approximately $24.1792 for their 60 acres of land. Recall that in section 3.4, we discussed the calculation and definition of estimated income, appraised value, assessed value, tax per acre, and tax total. These variables are essential in estimating the property tax liability for the selected property.

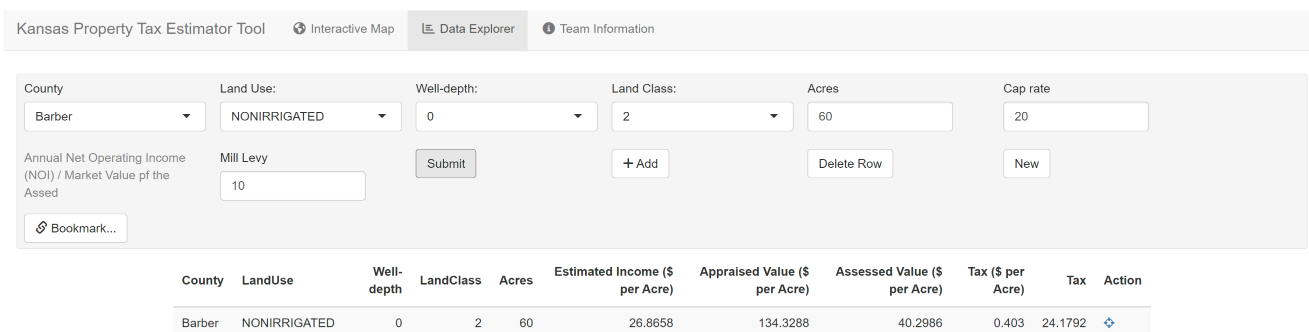

Figure 4.4: Single county-single land use-single land class scenario

4.13.2 Single county-single land use-multiple land class

In the second scenario, we consider a landowner in Barber County who is calculating taxes for a single land use (NONIRRIGATED) and multiple land classes. Figure 4.5 illustrates the estimated "Tax" for this selected county. The user specifies Barber County, NONIRRIGATED as the land use, a well-depth of 0 (default for dryland), land class 2, 60 acres, a cap rate of 20, and a mill levy of 10.

Based on these selections, the app calculates several variables. The estimated income per acre is determined to be $26.8658, the appraised value per acre is $134.3288, the assessed value per acre is $40.2986, the tax per acre is $0.403, and the final estimated tax for the specified acreage is $24.1792. If the user changes the land class to 3, the app recalculates the variables. The new estimated income per acre becomes $11.5395, the appraised value per acre is $57.6974, the assessed value per acre is $17.3092, the tax per acre is $0.1731, and the final estimated tax for the given acreage is $10.3855.

Similarly, when the user selects other land classes, the app performs the calculations for all the aforementioned variables and presents the corresponding results. This scenario demonstrates how the tool can adapt to different land classes within the same land use, allowing users to obtain accurate tax estimates based on their specific property characteristics.

In section 4.11, it was explained that the interactive map and the table in the data explorer are connected. Figure 4.6 illustrates how this connection works. After the user selects and inputs all the necessary information, and the app generates and displays the results, an additional functionality becomes available.

Under the "Action" column in the table, there is a "crosshairs" icon. When the user clicks on this icon, it automatically takes them back to the "Interactive Map" tab. The map then zooms in and centers on the selected county. However, in this scenario, a pop-up bubble appears on the map, displaying the tax amount, land class, and land use from the selected row in the table. The histogram in the data explorer also updates to display the information specific to the selected county, rather than the state average. This enhanced interactivity between the map, table, and histogram allows users to explore the tax information in a more localized and detailed manner. This feature enables users to easily navigate between the map and table and visualize the tax information for specific counties, based on the data entered.

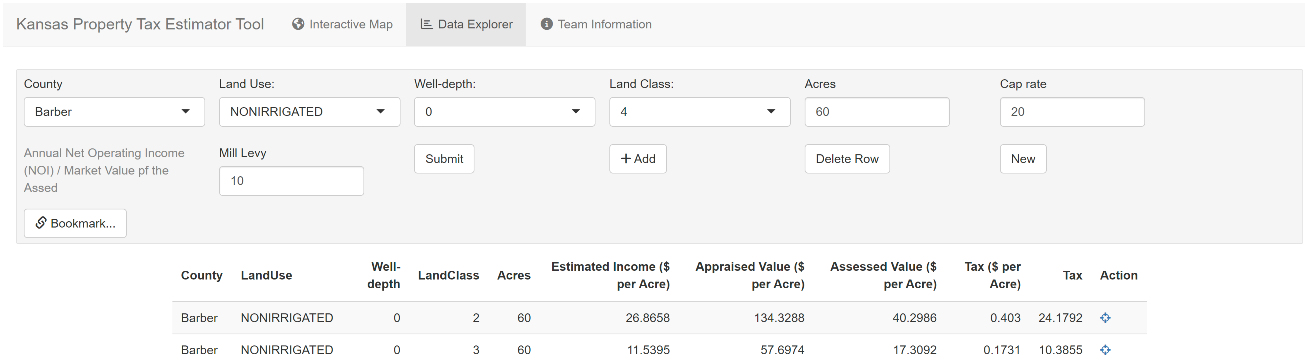

Figure 4.5: Single county-single land use-multiple land class scenario

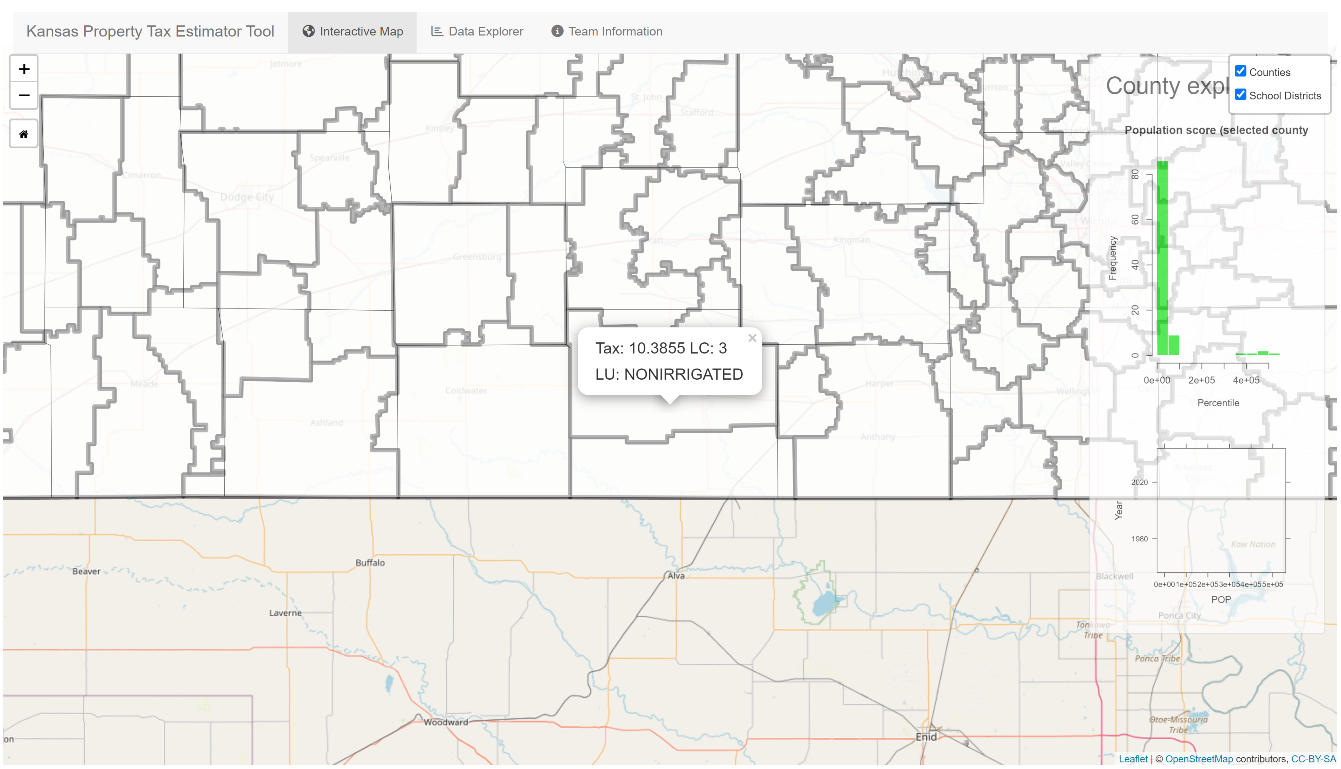

Figure 4.6: Connection between Interactive Map and Data Explorer table

4.13.3 Single county-multiple land use-multiple land class

In the third scenario, we consider a landowner in Barber County who is calculating taxes for multiple land uses and multiple land classes. Figure 4.7 shows the estimated “Tax” for this selected county. The user specifies Barber County, selects “NONIRRIGATED” as the land use, sets a well-depth of 0 (default for dryland), chooses land class 2, specifies 60 acres, sets a cap rate of 20, and provides a mill levy of 10. These values are the same as in the previous scenario.

However, the difference in this scenario is that the user has added an additional land use, “IRRIGATED”, and specified a well-depth of 100 feet. The app takes into account all the new selections and calculates the results accordingly. The user has also added the “TAME” land use.

There are two noteworthy results in this example. First, the irrigated land use has the highest estimated income, appraised value, assessed value, tax per acre, and total tax. This is expected as irrigated land typically has higher values compared to other land uses. Second, the appraised value for the “TAME” land use in Barber County is less than the floor value. In such cases, the app uses the floor value of $10 to estimate the tax, ensuring consistency in the calculation process.

The app displays the selected county, land use, well-depth, and land class. This display allows the user to keep track of their calculations and ensure they have included all the necessary information in their tax sheet. This feature provides transparency and helps the user stay organized and informed throughout the tax estimation process.

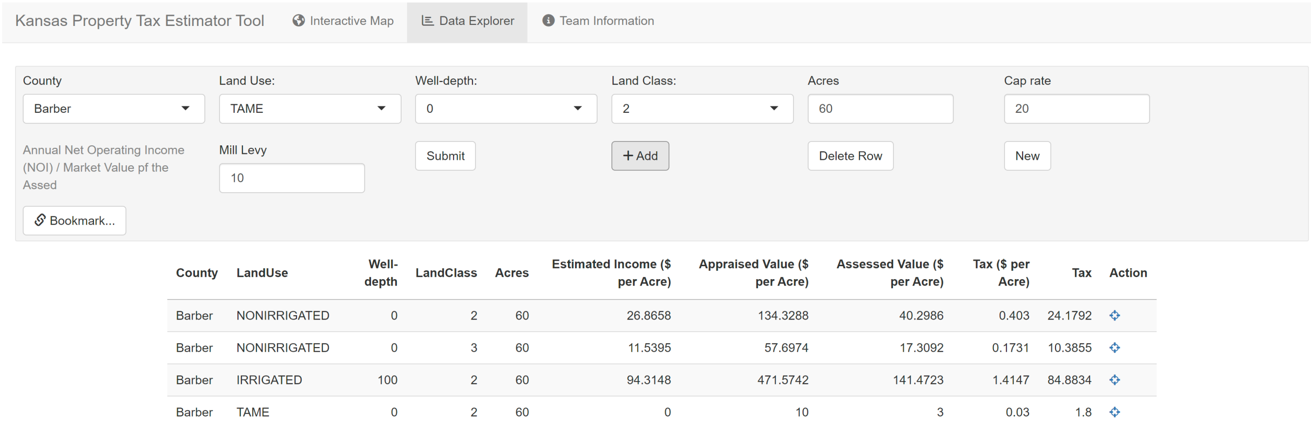

Figure 4.7: Single county-multiple land use-multiple land class scenario

4.13.4 Multiple county-multiple land use-multiple land class

In the last scenario, we consider a landowner or a school district in Barber and Pratt counties. Figure 4.8 shows the estimated "Tax" for the selected counties. The app takes the selected variables and values input by the user and calculates the tax for the first county. It then proceeds to calculate the tax for the second county. The app can continue this process for any additional counties that the user selects. While Figure 4.8 displays results for two counties for simplicity, it is important to note that the user can select as many counties, land uses, and land classes as desired. The app will calculate and present the results for each selected county, ensuring a comprehensive tax estimation process.

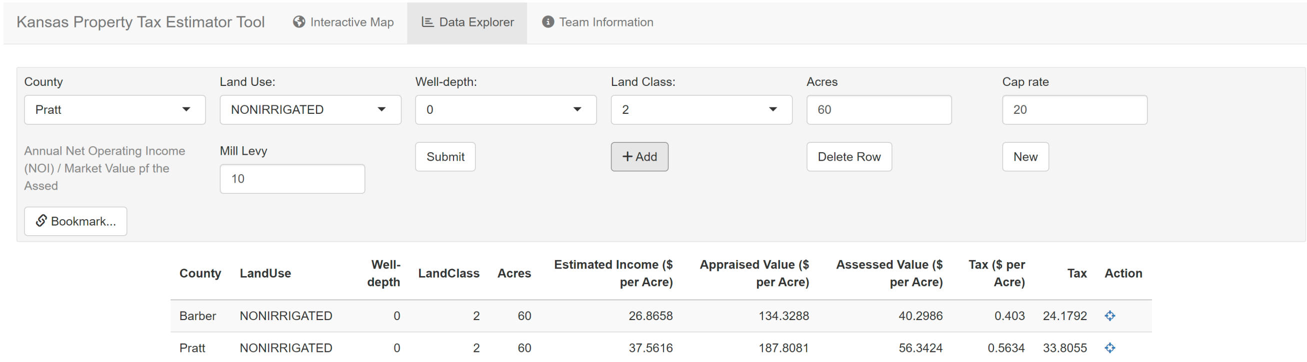

Figure 4.8: Multiple county-multiple land use-multiple land class scenario

4.14 Conclusions

The interactive R-shiny dashboard represents a pioneering effort in the field of property tax estimation. This project aims to benefit all stakeholders involved in the property tax arena. The Kansas Property Tax Estimation Tool is a valuable resource that enhances transparency and simplifies the property tax estimation process for all stakeholders involved. The primary goal of the Tool is to give producers and taxing entities a simple way to estimate their tax obligations and enhance the transparency in the property taxation process. By providing a user-friendly interface and real-time calculations, the tool empowers policymakers, such as public-school boards and municipalities, to perform "what-if analyses" and estimate the potential impact of changes to millage rates. Overall, the objective of this project is to enhance the transparency of state property taxation process and equip decision-makers with the necessary tools to make informed choices. To ensure widespread adoption and understanding of the tool, the project team will offer educational materials and training events in the future.

When using the tool, users can estimate and forecast their tax liabilities with ease, enabling them to make informed decisions. The app allows users to calculate the tax for their specific land, reducing the burden and complexity of the tax calculation process. The tool also offers the ability to save calculations and generate a unique URL for future reference. Users can easily access their saved calculations and compare scenarios. The app provides a direct means of communication with the team members, allowing users to seek assistance or clarification on specific questions or concerns.

One of the key advantages of the tool is its accessibility. Users only need an internet-connected device, such as a laptop, tablet, or smartphone, to access and utilize the tool. The calculations are performed on the server, minimizing the computational requirements on the user's device. This feature is particularly beneficial for rural areas with limited connectivity, as it reduces reliance on wireless capacity. In the agricultural realm, where mobile electronic devices have become essential tools, the availability of the tool on various devices ensures that farmers and landowners can easily access and utilize it. This accessibility promotes widespread usage and understanding of the property taxation process, fostering improved communication and engagement. Individual taxpayers and land managers can leverage the tool to plan and model the impact of market changes, enabling them to make informed decisions and adapt to future scenarios.

The open-source nature of the tool allows for future contributions and expansion, as individuals and organizations have the ability to download or fork the code to replicate or build upon the existing tool with their own enhancements. This flexibility enables the tool to be replicated and modified to calculate taxes in other states, accommodating their unique specifications and requirements. By sharing the code, the tool can be adapted and customized, extending its reach and impact to a broader range of regions and jurisdictions.

To maximize the tool's reach, a comprehensive promotional strategy will be implemented to inform the public and potential users about its availability. The tool will be accessible through various platforms, including the Information Network of Kansas (INK) website, ensuring easy access and utilization by policymakers, local public-school boards, municipalities, and other interested parties. The tool's "what-if analysis" capability empowers policymakers to estimate the impact of potential changes to millage rates, facilitating informed decision-making.

Overall, the Kansas Property Tax Estimation Tool is poised to have significant policy implications by increasing transparency, improving communication, and providing decision-makers with real- time tools to estimate the potential impact of tax-related decisions.

Through its user-friendly interface and accessibility, the tool aims to enhance understanding, engagement, and strategic planning in the realm of property taxation.

Chapter 5

5 Concluding Remarks

In this dissertation, various data-driven techniques are employed to analyze the dynamics of farmland values in 99 Iowa counties. The following is a brief overview of the three chapters, as well as the limitations of the study, suggestions for policy changes, and potential areas for future research.

Farmland values in Iowa are influenced by various factors, including population density, agricultural and non-agricultural factors, and urbanization. Chapter 2 identifies agricultural and non-agricultural factors driving farmland values in the 99 Iowa counties between 1969 and 2014, using the econometric procedures devised by Ciccarelli and Elhorst (2018). The study on the dynamics of farmland values in the Iowa counties suggests that the relationship between population density and farmland values in Iowa is positive.

In the third chapter, a two-stage procedure proposed by Aquaro et al. (2021) is utilized to estimate a heterogeneous model of farmland values diffusion. The outcomes reveal that policies implemented at the regional or county level may cause an increase in the disparity of farmland value changes across counties. This is due to clusters of areas being more prone to the impacts of farmland value growth in neighboring areas.

It is important to note that the proposed method may require further refinement to address limitations and potential biases. For example, the approach assumes that the spatial effects are stationary over time, which may not be the case in reality. Additionally, the method does not take into account potential endogeneity issues or the impact of unobserved factors. Future research could explore alternative weighting schemes or incorporate additional variables to improve the accuracy of the estimates. It may also be beneficial to conduct sensitivity analyses to assess the robustness of the results to different modeling assumptions. Further research is needed to execute a suggested data-driven technique. Currently, the HSAR estimates derived from the data-driven weights can be ascribed to either the adjacency matrix or the HSAR estimates that exhibit a considerable number of negative values. Overall, the proposed data driven method has the potential to provide valuable insights into the spatial dynamics of farmland values.

The Kansas Property Tax Estimation Tool Guide aims to improve and simplify tax planning processes. We develop the tool using R to offer real-time interactive business intelligence through an R-Shiny web dashboard R is widely recognized as mainstream open-source software and is extensively utilized in various sectors. By providing this tool, we hope to enhance the understanding of land valuation in Kansas. One of the key advantages of the Tax Tool is its ability to allow users to adjust the major components of the valuation formula. This feature empowers users to understand and assess the impact of changes on their property valuations. For taxing districts, the tool facilitates a more accurate determination of mill levies to achieve predetermined revenue levels. Additionally, legislators can utilize the tool to quickly evaluate the effects of modifications to the use valuation methodology on land valuation. The Tax Tool represents a significant step forward in property tax estimation, offering enhanced accuracy and transparency for all stakeholders involved. It provides a user-friendly interface and the capability to perform various “what-if” analyses, enabling better tax planning and decision-making processes.

References

Abelairas-Etxebarria, P., and I. Astorkiza. 2012. "Farmland prices and land-use changes in periurban protected natural areas." *Land use policy* 29(3):674–683.

Anselin, L. 1988. *Spatial Econometrics: Methods and Models.* Dordrecht: Springer Science & Business Media.

Anselin, L. 1989. "What is special about spatial data? Alternative perspectives on spatial data analysis (89-4)."

Anselin, L., and D.A. Griffith. 1988. "Do spatial effecfs really matter in regression analysis?" *Papers in Regional Science* 65(1):11–34.

Aquaro, M., N. Bailey, and M.H. Pesaran. 2021. "Estimation and inference for spatial models with heterogeneous coefficients: An application to US house prices." *Journal of Applied Econometrics* 36(1):18–44.

Bailey, N., S. Holly, and M.H. Pesaran. 2016. "A two-stage approach to spatio-temporal analysis with strong and weak cross-sectional dependence." *Journal of Applied Econometrics* 31(1):249–280.

Baker, T.G., M.D. Boehlje, and M.R. Langemeier. 2014. "Farmland: Is it currently priced as an attractive investment?" *American Journal of Agricultural Economics* 96(5):1321–1333.

Bockstael, N.E. 1996. "Modeling economics and ecology: The importance of a spatial perspective." *American Journal of Agricultural Economics* 78(5):1168–1180.

Boisvert, R., T.M. Schmit, and A. Regmi. 1997. "Spatial, productivity, and environmental determinants of farmland values." *American Journal of Agricultural Economics* 79:1657–1664.

Bureau of Economic Analysis. "Bureau of Economic Analysis." Available at: %7Bhttps://www.bea.gov/%7D.

Burns, C., N. Key, S. Tulman, A. Borchers, and J. Weber. 2018. "Farmland Values, Land Ownership, and Returns to Farmland, 2000-2016."

Burt, O.R. 1986. "Econometric modeling of the capitalization formula for farmland prices." *American Journal of Agricultural Economics* 68(1):10–26.

Carmona, J., and J.R. Rosés. 2012. "Land markets and agrarian backwardness (spain, 1904–1934)." *European Review of Economic History* 16(1):74–96.

Chavas, J.-P., and R. Shumway. 1982. "A pooled time-series cross-section analysis of land prices." *Western Journal of Agricultural Economics*:31–41.

Chen, W.Y., F.Z.Y. Hu, X. Li, and J. Hua. 2017. “Strategic interaction in municipal governments’ provision of public green spaces: A dynamic spatial panel data analysis in transitional china.” *Cities* 71:1–10.

Chudik, A., M.H. Pesaran, and E. Tosetti. 2011. “Weak and strong cross-section dependence and estimation of large panels.”

Ciccarelli, C., and J.P. Elhorst. 2018. “A dynamic spatial econometric diffusion model with common factors: The rise and spread of cigarette consumption in italy.” *Regional Science and Urban Economics* 72:131–142.

Cliff, A.D., and J.K. Ord. 1981. *Spatial Processes: Models & Applications*. Pion Limited.

Conley, T.G. 1999. “GMM estimation with cross sectional dependence.” *Journal of econometrics* 92(1):1–45.

Conley, T.G., and G. Topa. 2002. “Socio-economic distance and spatial patterns in unemployment.” *Journal of Applied Econometrics* 17(4):303–327.

Cotteleer, G., T. Stobbe, and G.C. van Kooten. 2008. “A spatial bayesian hedonic pricing model of farmland values.” No. 44137, European Association of Agricultural Economists. Available at: https://ideas.repec.org/p/ags/eaae08/44137.html.

Danielson, L.E. 1986. “Using hedonic pricing to explain farmland prices.” *SRDC series-Southern Rural Development Center (USA)*.

Data USA. 2014. “Data USA.” Available at: https://datausa.io/profile/geo/mills-county-ia#economy.

Debarsy, N., C. Ertur, and J.P. LeSage. 2012. “Interpreting dynamic space–time panel data models.” *Statistical Methodology* 9(1-2):158–171.

Devadoss, S., and V. Manchu. 2007. “A comprehensive analysis of farmland value determination: A county-level analysis.” *Applied Economics* 39(18):2323–2330.

Dutilleul, P. 1993. “Spatial heterogeneity and the design of ecological field experiments.” *Ecology* 74(6):1646–1658.

Elad, R.L., I.D. Clifton, and J.E. Epperson. 1994. “Hedonic estimation applied to the farmland market in georgia.” *Journal of Agricultural and Applied Economics* 26(2):351–366.

Elhorst, J.P. 2014. “Spatial panel data models.” In *Spatial econometrics*. Springer, pp. 37–93.

Engsted, T. 1998. “Do farmland prices reflect rationally expected future rents?” *Applied Economics Letters* 5(2):75–79. Available at: https://doi.org/10.1080/758523507.

Falk, B. 1991. "Formally testing the present value model of farmland prices." *American Journal of Agricultural Economics* 73(1):1–10. Available at: https://onlinelibrary.wiley.com/doi/abs/10.2307/1242877.

Farja, Y., and M. Maciejczak. 2021. "Economic implications of agricultural land conversion to solar power production." *Energies* 14(19):6063.

Featherstone, A.M., and T.G. Baker. 1987. "An examination of farm sector real asset dynamics: 1910–85." *American Journal of Agricultural Economics* 69(3):532–546. Available at: https://onlinelibrary.wiley.com/doi/abs/10.2307/1241689.

Featherstone, A.M., B.W. Schurle, S.S. Duncan, and K.D. Postier. 1993. "Clearance sales in the farmland market?" *Journal of Agricultural and Resource Economics*:160–174.

Florax, R.J.G.M., and S. Rey. 1995. "The impacts of misspecified spatial interaction in linear regression models." In L. Anselin and R. J. G. M. Florax, eds. *New Directions in Spatial Econometrics*. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 111–135. Available at: https://doi.org/10.1007/978-3-642-79877-1_5.

Florax, R.J., and P. Nijkamp. 2003. "Misspecification in linear spatial regression models." *Tinbergen Institute Discussion Papers* (2003-081):3.

Geniaux, G., J.-S. Ay, and C. Napoléone. 2011. "A spatial hedonic approach on land use change anticipations." *Journal of Regional Science* 51(5):967–986.

Geoghegan, J., L.A. Wainger, and N.E. Bockstael. 1997. "Spatial landscape indices in a hedonic framework: An ecological economics analysis using GIS." *Ecological Economics* 23(3):251–264.

Griffin, T.W., G. Ibendahl, and T.B. Mark. 2015. "How spatially clustered are state-level farmland values?" *Journal of the American Society Farm Managers and Rural Appraisers* 2015:103–112.

Havrysh, V., A. Kalinichenko, E. Szafranek, and V. Hruban. 2022. "Agricultural land: Crop production or photovoltaic power plants." *Sustainability* 14(9):5099.

Henderson, J. 2008. "Will farmland values keep booming?" *Economic Review* 93(2):81–104.

Herdt, R.W., and W.W. Cochrane. 1966. "Farm land prices and farm technological advance." *American Journal of Agricultural Economics* 48(2):243–263.

Holly, S., M.H. Pesaran, and T. Yamagata. 2011. "The spatial and temporal diffusion of house prices in the UK." *Journal of urban economics* 69(1):2–23.

Huang, H., G.Y. Miller, B.J. Sherrick, and M.I. Gómez. 2006. "Factors influencing illinois farmland values." *American Journal of Agricultural Economics* 88(2):458–470. Available at: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-8276.2006.00871.x.

Kennedy, G.A. 1997. "An empirical analysis of the louisiana rural land market."

Kuersteiner, G.M., and I.R. Prucha. 2020. "Dynamic spatial panel models: Networks, common shocks, and sequential exogeneity." *Econometrica* 88(5):2109–2146.

Lence, S.H. 2014. "Farmland prices: Is this time different?" *Applied Economic Perspectives and Policy* 36(4):577–603.

LeSage, J., and R. Pace. 2009. "Introduction to Spatial Econometrics. Boca Raton: CRC Press."

LeSage, J.P., and Y.-Y. Chih. 2016. "Interpreting heterogeneous coefficient spatial autoregressive panel models." *Economics Letters* 142:1–5.

Lloyd, T.A., and A. Rayner. 1990. "Land prices, rents and inflation: A cointegration analysis." *Oxford Agrarian Studies* 18(2):97–111.

Lloyd, T.A., A. Rayner, and C.D. Orme. 1991. "Present-value models of land prices in england and wales." *European Review of Agricultural Economics* 18(2):141–166.

Lynch, A.K., and D.W. Rasmussen. 2001. "Measuring the impact of crime on house prices." *Applied Economics* 33(15):1981–1989.

Maddison, D. 2000. "A hedonic analysis of agricultural land prices in england and wales." *European Review of Agricultural Economics* 27(4):519–532.

Maddison, D. 2009. "A spatio-temporal model of farmland values." *Journal of Agricultural Economics* 60(1):171–189. Available at: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1477-9552.2008.00182.x.

Melichar, E. 1979. "Capital gains versus current income in the farming sector." *American Journal of Agricultural Economics* 61(5):1085–1092.

Melichar, E. 1977. "Some current aspects of agricultural finance and banking in the united states." *American Journal of Agricultural Economics* 59(5):967–972.

Montero, J.-M., G. Fernández-Avilés, and T. Laureti. 2021. "A local spatial STIRPAT model for outdoor NOx concentrations in the community of madrid, spain." *Mathematics* 9(6):677.

Ogwang, T., and F. Vanclay. 2019. "Social impacts of land acquisition for oil and gas development in uganda." *Land* 8(7):109.

Pace, R.K., and O.W. Gilley. 1997. "Using the spatial configuration of the data to improve estimation." *The Journal of Real Estate Finance and Economics* 14:333–340.

Palmquist, R.B., and L.E. Danielson. 1989. "A hedonic study of the effects of erosion control and drainage on farmland values." *American journal of agricultural economics* 71(1):55–62.

Patton, M., and S. McErlean. 2003. "Spatial effects within the agricultural land market in northern ireland." *Journal of Agricultural Economics* 54(1):35–54.

Pesaran, M.H. 2015. "Testing weak cross-sectional dependence in large panels." *Econometric reviews* 34(6-10):1089–1117.

Pesaran, M.H., T. Schuermann, and S.M. Weiner. 2004. "Modeling regional interdependencies using a global error-correcting macroeconometric model." *Journal of Business & Economic Statistics* 22(2):129–162.

Reynolds, J.E., and J.F. Timmons. 1969. "Factors affecting farmland values in the united states, agricultural experiment station bulletin 566." *Ames, Iowa: Iowa State University.*

Sampson, G.S., E.D. Perry, and M.R. Tayler. 2020. "The on-farm and near-farm effects of wind turbines on agricultural land values." *Journal of Agricultural and Resource Economics* 45(3):410–427.

Sandrey, R.A., L.M. Arthur, R.A. Oliveira, and W.R. Wilson. 1982. "Determinants of oregon farmland values: A pooled cross-sectional, time series analysis." *Western Journal of Agricultural Economics*:211–220.

Schabenberger, O., and C.A. Gotway. 2017. *Statistical Methods for Spatial Data Analysis.* CRC press.

Schilling, B.J., K.P. Sullivan, and J.M. Duke. 2013. "Do residual development options increase preserved farmland values?" *Journal of Agricultural and Resource Economics* 38(3):1–17. Available at: https://ideas.repec.org/a/ags/jlaare/165931.html.

Schlenker, W., W.M. Hanemann, and A.C. Fisher. 2006. "The impact of global warming on US agriculture: An econometric analysis of optimal growing conditions." *Review of Economics and statistics* 88(1):113–125.

Schurle, B., A.M. Featherstone, C.A. Wilson, and D. Crosson. 2013. "Land prices during periods of rapid change." *Journal of American Socieity Farm Managers and Rural Appraisers* 76:61–73.

Sheng, Y., T. Jackson, and K. Lawson. 2018. "Evaluating the benefits from transport infrastructure in agriculture: A hedonic analysis of farmland prices." *Australian Journal of Agricultural and Resource Economics* 62(2):237–255. Available at:

https://onlinelibrary.wiley.com/doi/abs/10.1111/1467-8489.12243.

Shi, Y.J., T.T. Phipps, and D. Colyer. 1997. "Agricultural land values under urbanizing influences." *Land economics*:90–100.

Traill, B. 1979. "An empirical model of the UK land market and the impact of price policy on land values and rents." *European Review of Agricultural Economics* 6(2):209–232.

Tsoodle, L.J., A.M. Featherstone, and B.B. Golden. 2007. "Combining hedonic and negative exponential techniques to estimate the market value of land." *Agricultural Finance Review*.

Tweeten, L.G., and J.E. Martin. 1966. "A methodology for predicting US farm real estate price variation." *Journal of Farm Economics* 48(2):378–393.

USDA NASS. 2017. "NASS - Quick Stats." Available at: https://quickstats.nass.usda.gov/.

Van Dijk, G., L. Smit, and C. Veerman. 1986. "Land prices and technological development." *European Review of Agricultural Economics* 13(4):495–513.

Vega, S.H., and J.P. Elhorst. 2016. "A regional unemployment model simultaneously accounting for serial dynamics, spatial dependence and common factors." *Regional Science and Urban Economics* 60:85–95.

Wang, H. 2013. "The spatial structure of farmland values: A semiparametric approach." No. 150330, Agricultural; Applied Economics Association. Available at: https://ideas.repec.org/p/ags/aaea13/150330.html.

Waugh, F.V. 1929. "Quality as a determinant of vegetable prices: A statistical study of quality factors influencing vegetable prices in the boston wholesale market." In *Quality as a determinant of vegetable prices: A statistical study of quality factors influencing vegetable prices in the boston wholesale market*. Columbia University Press.

Xu, F. 1990. *An econometric study of contributions of parcel characteristics to agricultural land values in washington: A hedonic approach*. PhD thesis. Washington State University.

Yang, X., M. Odening, and M. Ritter. 2019. "The spatial and temporal diffusion of agricultural land prices." *Land Economics* 95(1):108–123. Available at: http://le.uwpress.org/content/95/1/108.abstract.

Yang, X., M. Ritter, and M. Odening. 2017. "Testing for regional convergence of agricultural land prices." *Land Use Policy* 64:64–75.

Ye, X., and L. Wu. 2011. "Analyzing the dynamics of homicide patterns in chicago: ESDA and spatial panel approaches." *Applied Geography* 31(2):800–807.

Yu, H., P. Sang, and T. Huan. 2022. “Adaptive box–cox transformation: A highly flexible feature-specific data transformation to improve metabolomic data normality for better statistical analysis.” *Analytical Chemistry* 94(23):8267–8276.

Appendix 1

Below is the decomposition process of the short-term direct, indirect, and total effects.

Direct effects:

$$[(I - \rho W)^{-1}(\beta_k I_N + \theta_k W)]^{\bar{d}} \tag{13}$$

Indirect effects:

$$[(I - \rho W)^{-1}(\beta_k I_N + \theta_k W)]^{\overline{rsum}} \tag{14}$$

Total effects:

$$[(I - \rho W)^{-1}(\beta_k I_N + \theta_k W)]^{\bar{d}} + [(I - \rho W)^{-1}(\beta_k I_N + \theta_k W)]^{\overline{rsum}} \tag{15}$$

Below is the decomposition process of the long-term direct, indirect, and total long-term effects.

Direct effects:

$$[((1 - \tau)I - (\rho + \eta)W)^{-1}(\beta_k I_N + \theta_k W)]^{\bar{d}} \tag{16}$$

Indirect effect:

$$[((1 - \tau)I - (\rho + \eta)W)^{-1}(\beta_k I_N + \theta_k W)]^{\overline{rsum}} \tag{17}$$

Total effects:

$$[((1 - \tau)I - (\rho + \eta)W)^{-1}(\beta_k I_N + \theta_k W)]^{\bar{d}} + [((1 - \tau)I - (\rho + \eta)W)^{-1}(\beta_k I_N + \theta_k W)]^{\overline{rsum}} \tag{18}$$

I denotes the identity matrix. The operators $\bar{d}$ and $\overline{rsum}$ compute the average row sum of a matrix's average diagonal and off-diagonal elements, respectively. These operators compute a matrix of spatial weights that is a fundamental building block of spatial regression models. According to Elhorst (2014) and Chen et al. (2017), these operators help to quantify the spatial dependence structure of the data.

The Z-score, which represents the standard deviation of Moran's I, indicates whether the null hypothesis of no spatial clustering can be rejected. For farmland values, the null hypothesis was rejected for all years and for all orders of contiguity, as shown in Figures A1.a, A1.b, and A1.c, Appendix 1. However, for the percent change in farmland values, the null hypothesis was rejected only in specific years and consecutive orders, as shown in Figures A1.d, A1.e, and A1.f. A Z-score greater (less) than 1.96 (-1.96) is considered statistically significant at the 0.05 level.

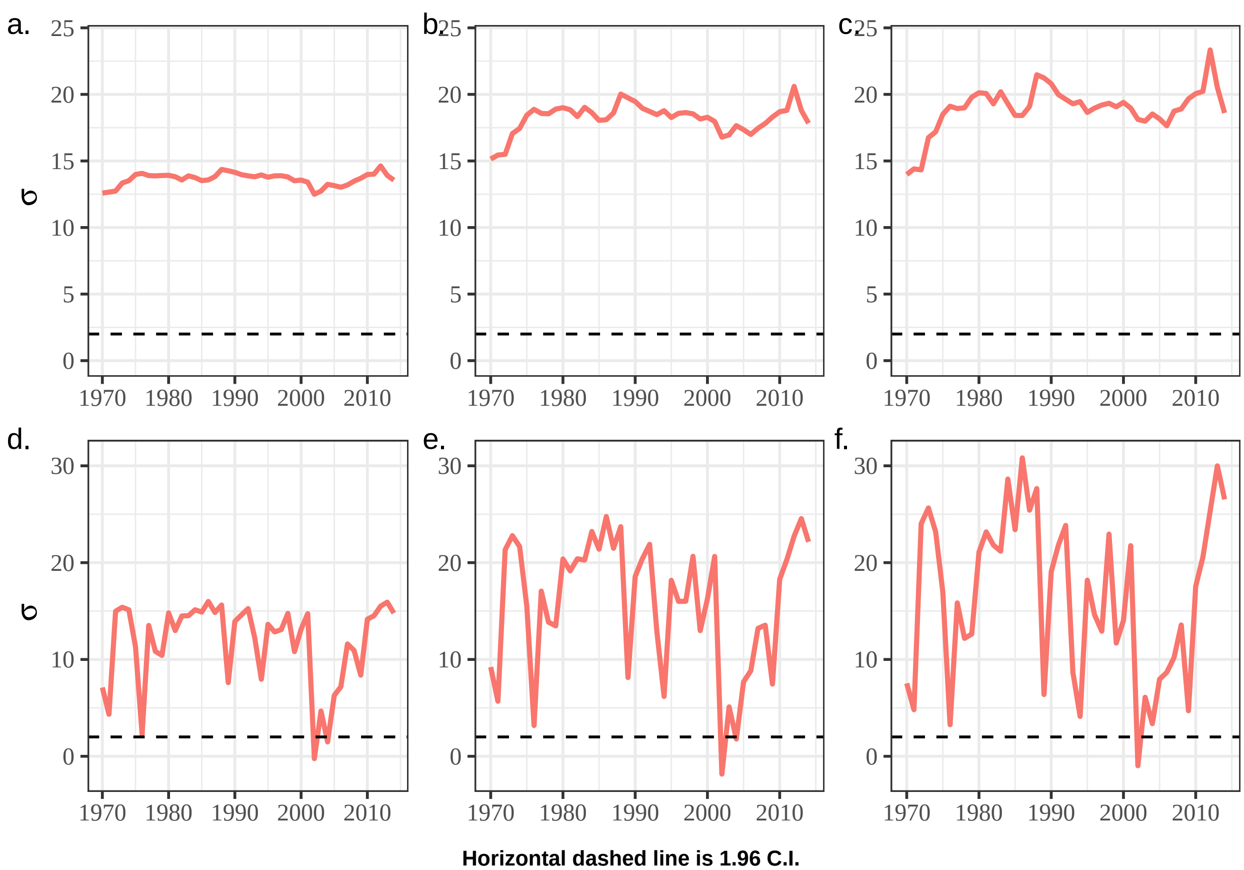

Figure A1: Moran's test statistic standard deviation, 1^{st}, 2^{nd}, and 3^{rd} order contiguity for farmland values (a., b., c.) and percentage change (d., e., f.), Iowa counties, 1969-2014

Model 1 represents the dynamic spatial panel data model without common factors ($\Gamma = \prod = 0$) but incorporates time-period fixed effects, which aligns with the conventional approach prevalent in spatial econometrics literature. In this model, the spatial weight matrix W is formulated using a binary contiguity (BC) matrix. However, it is evident that non-stationarity poses a challenge in this model specification. Moving forward, we will elaborate on the shortcomings of these simpler models and elucidate why the proposed model specification is more robust and comprehensive.

Upon utilizing the binary contiguity (BC) matrix in model 1, we observe that the sum of the three coefficients is less than 1, specifically 0.872. Additionally, the associated t-value of -5.411 for $\tau + \delta + \eta - 1$ suggests that the hypothesis of stationarity cannot be upheld, favoring the presence of a unit root instead.

The reasoning behind these findings lies in the fact that the inclusion of time period effects as controls is insufficient to sufficiently account for the non-stationarity resulting from the diffusion process. In other words, the effects captured by the time period fixed effects fail to adequately address the dynamics of the diffusion process, leading to the rejection of the stationarity hypothesis.

The CD-test (Cross-sectional dependence test) conducted on the residuals of model 1 yields a value of 0.257. Model 3, on the other hand, represents a dynamic spatial panel data model with controls for common factors of farmland values at time t. This model generates unit-specific coefficients to the common factor Γ_1, rather than using a common coefficient for all units like model 1. Including both time dummies and the common factor would lead to perfect multicollinearity.

There is a rationale behind controlling for a single common factor at time t only, rather than including it for both time t and time $t-1$. One reason is to limit the number of parameters to be estimated. The model already comprises 99 unit-specific intercepts μ, and each additional common factor would necessitate estimating another set of 99 parameters. To prevent an overly large number of parameters, it may be preferable to exclude additional common factors at time $t-1$.

The results demonstrate that this approach proves highly effective in achieving model stability. However, the sum of the coefficients τ, δ, and η amounts to 0.357, which remains significantly smaller than 1. Additionally, the CD-test performed on the residuals of this model yields a value of -1.788. These outcomes indicate that the model inadequately accounts for both weak and strong cross-sectional dependence.

By considering only the cross-sectional average of farmland values at time $t-1$ in the analysis, we observe that the results are comparable to when only time t is included, as demonstrated in model 3. The corresponding t-values for model 2 and model 3 are -0.721 and -0.265, respectively. These t-values indicate that the stationarity condition is not met. Moreover, the CD-test statistic significantly increases to 25.833, indicating that the model fails to effectively address strong cross-sectional dependence.

In model 4, we control for the cross-sectional averages of both the dependent and independent variables at time t. The specific variables analyzed include acreage planted to corn, bushels per acre, jobs generated by the farm sector, personal income per capita, and population density. However, the parameter estimates and test statistics for model 4 are similar to those of model 2, indicating that this model also falls short in effectively capturing both weak and strong cross-sectional dependence. Additionally, it is worth noting that model 4 contains a total of 608 coefficients, raising concerns of potential multicollinearity.

Table B1: Estimation results for Dynamic Spatial Durbin Model-Common Factor

Common-Factor	NO	C_t	C_{t-1}	C_t,X_t
Acreage	-0.006	-0.011**	-0.011**	0.011*
	(-1.319)	(-2.316)	(-2.214)	(1.816)
Yield	0.045***	0.040***	0.041***	0.039***
	(11.995)	(10.696)	(10.462)	(9.410)
Jobs	0.007	0.005	0.013*	0.009
	(1.052)	(0.659)	(1.871)	(0.712)
Income	0.016*	0.031***	0.048***	-0.019
	(1.851)	(3.285)	(5.032)	(-1.530)
PopDens	0.011	0.010	0.018**	-0.011
	(1.577)	(1.181)	(2.411)	(-0.340)
W*Acreage	0.005	0.004	0.012	0.009
	(0.492)	(0.630)	(1.592)	(0.646)
W*Yield	-0.001	-0.041***	-0.062***	0.013
	(-0.088)	(-8.335)	(-11.962)	(1.273)
W*Jobs	0.001	0.001	-0.007	-0.026
	(0.088)	(0.092)	(-0.829)	(-0.876)
W*Income	-0.020	-0.006	0.021*	-0.079***
	(-1.005)	(-0.515)	(1.643)	(-2.676)
W*PopDens	0.014	0.028	0.067***	-0.159**
	(0.711)	(1.418)	(3.307)	(-1.965)
FLV_{t-1}	0.875***	0.776***	0.898***	0.564***
	(105.947)	(88.143)	(93.697)	(51.649)
W*FLV_t	-0.001	0.335***	0.912***	0.107***
	(-0.004)	(17.254)	(129.756)	(4.605)
W*FLV_{t-1}	-0.002	-0.754***	-0.659***	-0.554***
	(-0.060)	(-76.281)	(-26.307)	(-48.081)
corr-R^2	0.722	0.994	0.945	0.996
CD-test	0.257	-1.788	25.833	-2.695
CADF-test	-0.2877	-0.7213	-0.2645	-0.8901
$\tau + \eta + \rho$	-0.127	-0.001	0.151	-0.001
	(-5.411)	(-33.647)	(5.672)	(-37.913)

*p<0.1; **p<0.05; ***p<0.01.

T-values are reported in parentheses.

Appendix 2

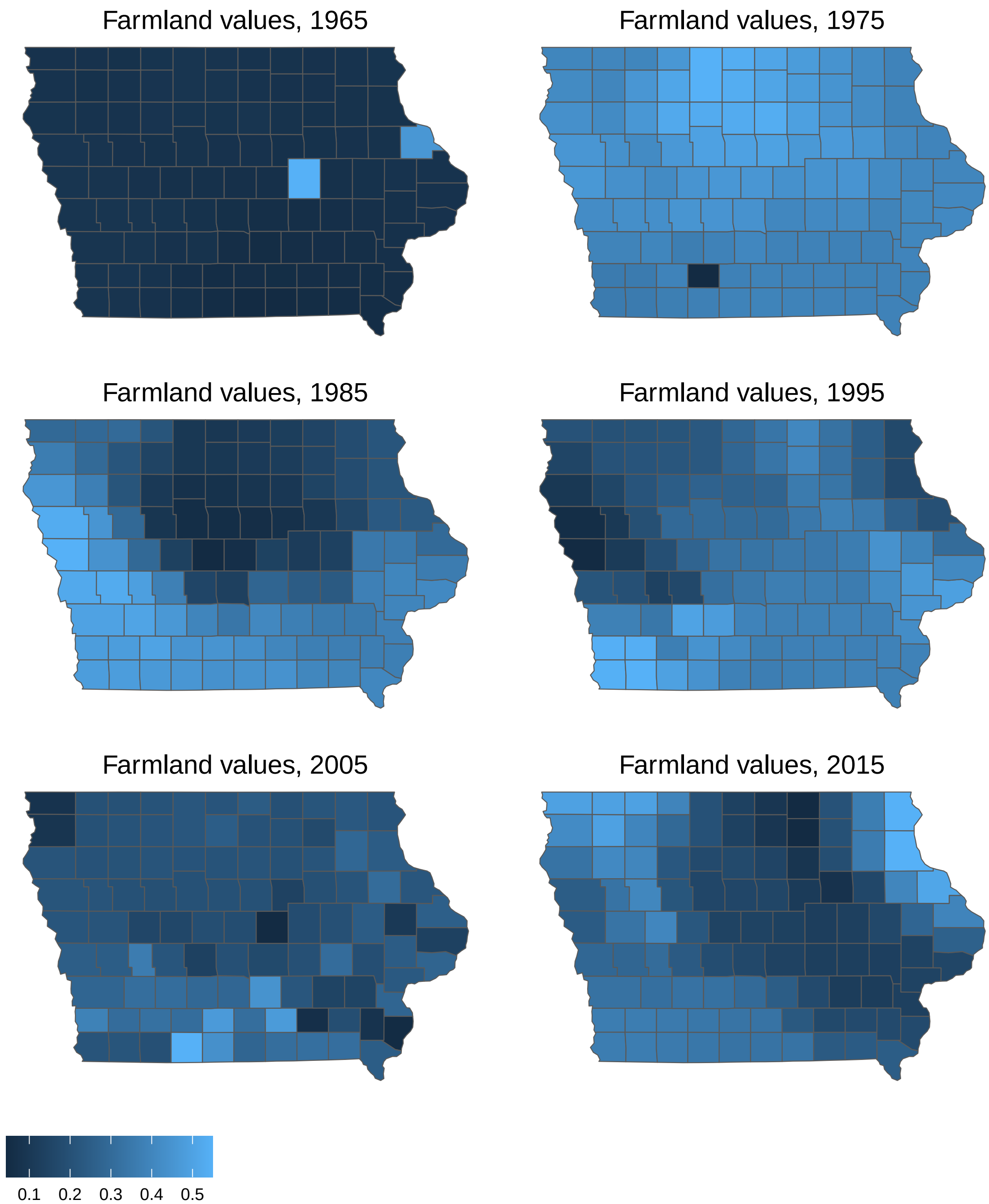

Figure A2: Iowa counties farmland values rates selected years

Table B2: Serial dynamics and spatial dependence, Iowa counties

County	Wy0	Wy1	Wy0Wy1	y1	pp	ic
Adair	1.399	-0.579	0.819	0.640	-0.674	-0.093
	0.313	0.360	0.422	0.099	0.189	0.089
Adams	-1.729	1.650	-0.079	0.626	-0.163	-0.014
	1.538	1.035	0.670	0.107	0.120	0.044
Allamakee	1.877	0.089	1.966	0.862	-0.147	0.092
	16.959	7.290	9.727	0.787	1.844	0.894
Appanoose	1.001	-0.728	0.273	0.565	0.844	0.111
	4.456	2.139	2.382	0.161	1.131	0.110
Audubon	-1.469	0.929	-0.540	0.493	0.161	-0.052
	0.593	0.333	0.433	0.211	0.145	0.112
Benton	0.589	0.002	0.591	0.316	0.208	0.052
	0.418	0.329	0.254	0.160	0.186	0.119
Black Hawk	1.359	-0.993	0.366	0.543	-0.091	0.045
	0.340	0.334	0.285	0.118	0.232	0.048
Boone	-0.068	-0.374	-0.442	0.484	-0.663	0.140
	1.185	0.880	0.384	0.104	0.253	0.167
Bremer	-0.080	0.004	-0.075	0.665	0.709	0.177
	0.423	0.403	0.411	0.084	0.277	0.094
Buchanan	-0.915	-0.323	-1.238	0.297	1.464	0.028
	0.484	0.318	0.402	0.137	0.267	0.105
Buena Vista	-1.605	1.387	-0.219	0.730	-0.021	0.190
	1.287	1.001	0.425	0.096	0.253	0.101
Butler	0.299	-0.318	-0.019	0.569	0.548	0.152
	0.421	0.446	0.157	0.101	0.303	0.093
Calhoun	0.597	0.151	0.748	0.578	0.274	0.116
	0.602	0.453	0.252	0.092	0.158	0.065
Carroll	1.546	-0.887	0.659	0.283	-0.500	0.083
	0.410	0.314	0.272	0.145	0.528	0.085
Cass	0.543	-0.233	0.310	0.727	-0.560	-0.156
	0.818	0.574	0.368	0.081	0.302	0.186
Cedar	0.092	0.131	0.224	0.700	0.369	0.557
	0.375	0.350	0.309	0.084	0.288	0.182
Cerro Gordo	-0.131	0.415	0.284	0.649	1.024	-0.074
	1.007	0.449	0.623	0.109	0.950	0.106
Cherokee	-1.613	0.635	-0.979	0.375	0.450	0.038
	1.126	0.717	0.542	0.092	0.133	0.033
Chickasaw	-1.156	0.152	-1.004	0.580	0.428	-0.122
	0.573	0.694	0.324	0.094	0.232	0.095
Clarke	-0.236	-0.396	-0.632	0.472	0.291	0.308
	0.909	0.547	0.469	0.129	0.251	0.105
Clay	-0.411	0.109	-0.302	0.599	0.050	0.183
	0.253	0.228	0.270	0.098	0.259	0.145
Clayton	1.589	-0.866	0.723	0.514	-1.991	-0.380
	1.225	1.011	0.351	0.092	0.524	0.152
Clinton	-0.093	0.292	0.199	0.767	-0.152	0.472
	1.238	1.079	0.457	0.070	0.507	0.212
Crawford	-0.675	0.127	-0.548	0.599	0.173	-0.004
	0.729	0.280	0.781	0.105	0.227	0.058
Dallas	-0.617	0.607	-0.010	0.695	-0.008	-0.013
	0.760	0.591	0.355	0.114	0.083	0.236
Davis	-0.923	0.413	-0.509	0.449	0.040	0.012
	0.352	0.331	0.203	0.130	0.105	0.063
Decatur	1.841	-1.237	0.604	0.503	0.055	0.152
	0.508	0.440	0.528	0.163	0.223	0.117
Delaware	-0.202	-0.074	-0.276	0.777	0.476	-0.008

	0.553	0.432	0.412	0.098	0.649	0.069
Des Moines	-1.055	0.950	-0.104	0.727	-0.677	0.266
	0.361	0.360	0.112	0.089	0.438	0.144
Dickinson	1.011	-0.153	0.858	0.402	0.131	-0.085
	0.609	0.470	0.465	0.133	0.165	0.124
Dubuque	-0.734	0.576	-0.158	0.682	-0.899	0.194
	0.213	0.191	0.181	0.080	0.469	0.136
Emmet	-0.497	0.381	-0.116	0.768	0.710	-0.018
	0.330	0.297	0.296	0.070	0.192	0.092
Fayette	-0.018	0.255	0.238	0.577	-0.984	-0.070
	3.423	1.463	2.059	0.222	0.276	0.094
Floyd	1.994	-1.792	0.202	0.244	-0.805	0.057
	4.343	3.141	1.319	0.254	0.909	0.282
Franklin	-1.285	0.689	-0.597	0.739	0.087	0.166
	1.566	1.171	0.491	0.088	0.218	0.062
Fremont	-0.854	0.777	-0.078	0.677	-0.380	0.068
	2.015	1.342	0.867	0.114	0.294	0.095
Greene	1.030	-0.157	0.874	0.331	0.409	0.024
	0.264	0.238	0.252	0.176	0.334	0.037
Grundy	-0.186	-0.250	-0.435	0.430	-0.738	0.203
	0.249	0.277	0.243	0.149	0.283	0.084
Guthrie	-0.414	0.129	-0.285	0.525	0.331	0.091
	0.156	0.137	0.166	0.104	0.127	0.064
Hamilton	-0.257	0.370	0.113	0.778	0.629	0.096
	1.226	0.908	0.378	0.081	0.423	0.076
Hancock	0.504	-1.240	-0.736	0.648	0.666	0.063
	0.510	0.585	0.561	0.112	0.226	0.095
Hardin	-0.892	-0.077	-0.969	0.498	0.955	0.065
	1.233	1.135	0.277	0.089	0.586	0.074
Harrison	1.991	-1.309	0.681	0.669	0.561	0.141
	0.717	0.412	0.794	0.146	0.287	0.068
Henry	1.353	-0.729	0.624	0.719	-0.075	0.108
	0.997	0.942	0.429	0.163	0.279	0.116
Howard	-0.643	0.211	-0.431	0.745	-0.449	0.073
	2.697	1.480	1.303	0.103	0.438	0.079
Humboldt	0.070	0.037	0.107	0.610	0.992	0.382
	0.495	0.258	0.406	0.073	0.204	0.063
Ida	-0.323	0.705	0.382	0.289	0.243	0.043
	0.340	0.354	0.266	0.171	0.157	0.071
Iowa	-0.478	0.387	-0.091	0.731	-0.020	-0.151
	0.535	0.588	0.235	0.109	0.263	0.089
Jackson	-0.182	0.100	-0.082	0.733	0.663	0.394
	0.413	0.369	0.210	0.087	0.311	0.173
Jasper	0.322	-0.238	0.084	0.429	-0.177	-0.044
	1.236	0.458	0.830	0.128	0.399	0.240
Jefferson	0.084	-0.108	-0.025	0.389	0.123	0.128
	0.335	0.253	0.103	0.107	0.116	0.037
Johnson	-0.333	-0.154	-0.486	0.456	0.407	-0.274
	0.329	0.323	0.255	0.112	0.178	0.153
Jones	-0.696	0.467	-0.229	0.824	0.540	0.164
	0.943	0.846	0.342	0.107	0.441	0.254
Keokuk	1.995	-1.595	0.400	0.457	0.233	-0.021
	1.694	1.036	0.908	0.098	0.305	0.116
Kossuth	0.950	-1.166	-0.216	0.796	0.359	0.131
	0.900	0.555	0.602	0.092	0.184	0.096
Lee	-0.499	0.549	0.049	0.625	-0.252	-0.190
	0.134	0.109	0.097	0.103	0.225	0.069
Linn	1.070	-0.764	0.307	0.752	0.036	0.186
	0.403	0.343	0.217	0.098	0.101	0.081
Louisa	1.094	-1.054	0.040	0.635	-0.019	-0.006

	1.443	1.280	0.409	0.094	0.177	0.132
Lucas	-1.098	0.963	-0.136	0.514	0.902	0.093
	0.417	0.411	0.281	0.134	0.322	0.095
Lyon	0.420	-0.084	0.336	0.163	1.683	-0.126
	0.292	0.224	0.231	0.132	0.420	0.108
Madison	-0.465	0.287	-0.178	0.593	0.518	0.106
	0.225	0.190	0.160	0.111	0.164	0.113
Mahaska	0.101	-0.561	-0.460	0.491	0.043	0.000
	0.939	0.536	0.454	0.150	0.416	0.100
Marion	0.525	-0.340	0.185	0.555	-0.221	0.023
	0.185	0.167	0.084	0.122	0.210	0.096
Marshall	-1.995	1.381	-0.614	0.640	0.532	0.287
	0.706	0.665	0.328	0.087	0.294	0.161
Mills	-1.608	0.599	-1.010	0.599	0.481	-0.389
	0.601	0.501	0.508	0.151	0.127	0.276
Mitchell	1.661	-1.246	0.415	0.706	-0.763	-0.077
	0.556	0.437	0.401	0.110	0.196	0.046
Monona	-0.518	0.236	-0.281	0.543	-0.203	-0.012
	0.426	0.403	0.279	0.138	0.237	0.060
Monroe	-0.966	0.819	-0.148	0.580	0.615	0.061
	0.604	0.655	0.248	0.126	0.528	0.096
Montgomery	-0.774	0.606	-0.168	0.456	-1.437	-0.425
	0.515	0.395	0.275	0.122	0.335	0.157
Muscatine	-1.412	0.741	-0.672	0.496	1.191	-0.124
	3.876	2.029	1.868	0.376	1.429	0.186
O'Brien	0.201	0.138	0.339	0.342	0.805	0.121
	1.406	0.441	1.070	0.124	0.430	0.100
Osceola	-1.993	0.983	-1.010	0.128	0.080	0.005
	0.776	0.459	0.519	0.162	0.435	0.038
Page	0.511	-0.436	0.075	0.640	-1.722	-0.356
	0.821	0.664	0.443	0.094	0.628	0.194
Palo Alto	-0.855	0.408	-0.446	0.679	0.293	0.004
	0.181	0.179	0.192	0.110	0.119	0.025
Plymouth	1.974	-1.267	0.707	0.649	0.284	-0.177
	1.459	0.694	0.926	0.092	0.272	0.148
Pocahontas	0.765	-0.190	0.575	0.602	0.362	0.050
	0.322	0.292	0.222	0.108	0.092	0.046
Polk	-0.687	0.178	-0.510	0.557	-0.099	-0.070
	1.099	0.507	0.649	0.098	0.079	0.047
Pottawattamie	0.648	-0.792	-0.144	0.406	1.873	0.013
	0.561	0.396	0.322	0.087	0.246	0.094
Poweshiek	0.959	-0.288	0.671	0.428	-0.171	-0.167
	2.149	1.912	0.485	0.135	0.477	0.579
Ringgold	-1.981	1.478	-0.503	0.471	0.202	0.223
	22.482	9.744	12.766	0.996	0.702	0.804
Sac	-0.865	0.323	-0.542	0.403	0.497	0.029
	0.648	0.506	0.360	0.135	0.132	0.054
Scott	0.954	-0.215	0.739	0.530	0.986	0.057
	0.555	0.467	0.480	0.125	0.246	0.149
Shelby	1.423	-0.682	0.741	0.675	-0.084	-0.168
	0.182	0.263	0.243	0.115	0.273	0.093
Sioux	-1.619	1.140	-0.479	0.476	-0.825	-0.022
	0.555	0.490	0.298	0.099	0.275	0.073
Story	-0.476	0.156	-0.320	0.617	-0.468	0.029
	1.657	0.845	0.878	0.177	0.390	0.121
Tama	-0.628	0.350	-0.278	0.487	-0.003	0.059
	0.222	0.182	0.196	0.130	0.151	0.068
Taylor	1.447	-0.830	0.617	0.749	-0.294	0.156
	1.104	0.601	0.651	0.092	0.286	0.131
Union	-0.997	-1.445	-2.442	0.088	0.038	-0.086

	1.532	1.449	1.122	0.197	0.692	0.288
Van Buren	-0.112	0.133	0.021	0.583	-0.007	-0.028
	0.254	0.181	0.136	0.086	0.223	0.062
Wapello	1.991	-1.334	0.657	0.713	0.065	0.136
	9.892	4.994	4.967	0.417	2.200	0.602
Warren	-0.060	0.171	0.110	0.711	-0.102	0.319
	0.317	0.372	0.300	0.087	0.134	0.168
Washington	0.482	0.010	0.492	0.363	-0.261	0.126
	0.236	0.198	0.208	0.111	0.319	0.099
Wayne	-0.887	0.751	-0.136	0.671	0.273	0.071
	0.791	0.481	0.438	0.129	0.418	0.131
Webster	-1.577	0.508	-1.069	0.417	-0.362	-0.213
	0.322	0.312	0.266	0.115	0.237	0.114
Winnebago	0.455	0.074	0.529	0.493	0.460	0.125
	0.583	0.348	0.505	0.075	0.206	0.070
Winneshiek	-1.125	0.698	-0.427	0.756	-0.346	0.207
	0.841	0.580	0.512	0.098	0.454	0.126
Woodbury	-0.717	0.747	0.030	0.348	0.108	-0.028
	0.656	0.438	0.490	0.133	0.180	0.047
Worth	1.261	-0.784	0.477	0.563	0.740	0.066
	0.466	0.433	0.426	0.089	0.238	0.036
Wright	-0.886	0.669	-0.217	0.654	0.424	0.027
	0.202	0.201	0.193	0.120	0.240	0.061