Title: Transitions in County-Level Poverty in the Rural United States: A Comparison of LISA Techniques

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ABSTRACT

Although scholarship regarding spatial inequality has grown in recent years, past research has seen limited use of spatial statistics —let alone comparison between spatial statistical techniques. Comparing and contrasting the application and use of spatial statistics is valuable in research because it allows for more precise identification of spatial patterns, and highlights results that may be hidden when only using a single method. This study serves as a demonstration on how the use of multiple LISA statistics can benefit inequality related research. Analyzing changes in county level poverty in the Rural United States from 1990-2015 serves as a tool to demonstrate these techniques and this study examined how the geographic distribution of poverty has changed, and well as if there is evidence of diffusion effects. The three featured techniques utilized LISA (Local Indicators of Spatial Association) statistics. The techniques are Bivariate LISA, LISA Cluster Transitions, and LISA Diffusion Transitions, with the last technique specifically designed for this study. Each technique varies in how it reports the changes in the spatial structure of poverty. Bivariate LISA and LISA Cluster Transitions are complementary to each other —with the former technique providing a single global statistic while the latter is more easily interpretable. Diffusion Transitions show how the highest and lowest values of a variable may be spreading over time. The study also produces new findings regarding rural poverty, with poverty in Mountain-West and Rural Sun Belt counties on the rise. Analysis shows a diffusion effect for poverty in Southeastern metropolitan fringe counties.

Keywords: Spatial Inequality, Poverty, LISA, Diffusion, Rural, United States

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1. INTRODUCTION

        Understanding spatial inequality, in all forms, has become a cornerstone research topic in social science, especially in spatially oriented fields like rural and urban sociology. At its core, spatial inequality research is about understanding the unequal distribution of forms of disadvantage across neighborhoods, counties, or even entire nations (Lobao 2004; Lobao and Saenz 2009; Tickamyer 2000). Understanding spatial inequality goes beyond just a simple mapping out of the inequality of interest; research needs a demographic or critical perspective to understand the generative processes and how the clustering of inequality relates to external socio-economic forces (Lobao 2004; Logan 2012). Analyzing why these inequalities occur in the first place and how policy can address these issues should be a key focus of spatial inequality research (Lobao et al. 2007). Despite a recent increased interest in spatial inequality, a common theme is the relative underuse of spatial statistics in analysis, with even fewer studies that have compared and contrasted results from differing spatial statistical methods (Goodchild and Janelle 2010; Voss 2007). However, in the past ten years, two journals, Spatial Demography and Spatial Statistics, have launched, both of which focus on the theory and application of these useful methods. This indeed indicates that spatial statistical analysis techniques are growing in usage, however very few studies have compared and the contrasted the results from multiple spatial techniques. Comparative analysis via the application of related spatial statistics is ideal for more descriptive or exploratory research in spatial inequality. It also allows researchers to find results not shown if using only a single method, thereby potentially helping to identify the underlying distributive or generating forces. Therefore, this study will compare the results of three different, but related, spatial techniques as they relate to one dimension of inequality, poverty, from the period of 1990 to 2015 in the continental United States.

        Specifically, this study will serve as a demonstration of the advantages of using multiple techniques based on Local Indicators of Spatial Association (LISA). LISA analysis helps researchers to understand the clustering of the high and low values of a variable across an area —or technically the level of spatial autocorrelation in an area. There are a variety of ways to implement LISA statistics in research, each with their own advantages and disadvantages. Utilizing multiple LISA-based techniques allows researchers to triangulate the longitudinal changes in the spatial structural of a phenomenon of interest, via the comparison of each technique's results. The purpose of this method study is to demonstrate the advantages of each technique not to produce a definitive answer on what technique is best, but to understand the strengths and limitations of each as it relates to research on spatial inequality. The three techniques are Bivariate LISA, LISA Cluster Transitions, and LISA Diffusion Transitions. The first two

techniques examine how the clustering of a variable of interest has changed over time but differ in their calculations and their interpretations. Past work has used both in a variety of ways; recently Bivariate LISA was used to understand temporal changes in crime (Porter 2011); and LISA Cluster Transitions to understand changes in county level ethnic diversity (Martin et al. 2016). However, based on a comprehensive review of the literature, a single study has not used these two techniques together in complement; this study will demonstrate how these two techniques together can identify changes of a spatial structure in a more complex way. The third technique, LISA Diffusion Transitions, developed specifically for this study, is an adaptation of the LISA Cluster Transitions technique, helps maps and analyzes the geographic spreading of the highest and lowest values of a variable over multiple periods.

Within spatial inequality research, poverty has been one of the most recurring research topics (Goodchild and Janelle 2010; Logan et al. 2010); this study will continue that tradition and will explore how multiple LISA techniques can provide insights on the changing nature of poverty and regional clusters of inequality. Scholars have examined poverty at various scales, from individuals to families to geographic areas. When it comes to understanding regional inequality, counties are the preferred unit of analysis and there have been many studies looking at spatial structure of county level poverty and its impacts (Call and Voss 2016; Lichter and Johnson 2007). Understanding where extreme poverty persists over time has dominated research in this area. Past research has also worked to identify the spatial diffusion or concentration processes of poverty (Thiede et al. 2018). Future spatial inequality research need not limit itself to understanding diffusion and long-term clustering of elevated levels of poverty only; there is also a need to research the spreading of low poverty, and where low poverty sustains itself over time. Areas of low poverty have understandably received less scholarly attention; however, examining the spatial trends of more well off place has its own merits. Reaching spatial inequality requires the identifications of places of both comparative advantage and disadvantage (Tickamyer 2000). Studying only places that are worse potentially limits the generation of theory regarding the underlying distributive process (Logan 2012; Tickamyer 2000). Therefore, mapping low poverty clusters will also be an emphasis of this study.

The purpose of this research is threefold. First, this research will demonstrate the advantages of using multiple LISA techniques when analyzing the changing nature of given form of spatial inequality. Second, this research will provide new perspectives on the changing spatial structure of poverty in United States counties—particularly non-metropolitan counties—since 1990. The third purpose is to understand how the methodological and substantive

findings of the study are connected. When looking at county level poverty in the United States, the non-metropolitan, or rural, regions of the nation have experienced many dramatic changes over the decades (Sparks et al. 2013; Weber and Miller 2017). In response, there has been a plethora of research on nonmetropolitan poverty change. Although there has been research on poverty on the changing spatial structure of urban poverty, much of that research is at the neighborhood, not county level —for example Wilson (2012), and Iceland and Hernandez (2017). This local emphasis in urban poverty research limits the ability of this study to describe and put in context findings that occur in metropolitan counties; and focusing on metropolitan counties allows for direct comparisons with nonmetropolitan counties. In response to both past research trends, this study will primarily focus on rural or nonmetro poverty. This study finds many trends identified in previous research, specifically as they pertain to regions such as Central Appalachia and the Mississippi Delta. However, the multiple technique application challenges the current understanding of the clusters of poverty growth and decline in counties in the Rust Belt states and the Texas border region. These new perspectives are rooted in the underlying statistical differences of the LISA techniques. LISA Diffusion Transitions, as first developed for this study, is well suited for poverty research; and provides evidence for spreading processes on both high and low poverty in different rural regions. The produced insights into the comparative advantages of the three techniques overall is discussed later.

Two set of research questions—two methodological, and two related to poverty—are the focus of this research.

1. How can the three LISA techniques supplement each other in spatial inequality research?
2. What are the specific advantageous applications of each technique?
3. How has the spatial distribution of poverty in counties changes from 1990 to 2015?
4. Is there evidence for diffusion effects of high and low levels of poverty?

2. BACKGROUND

2.1 Spatial Inequality, Clustering, and its Measurement

Identifying regional or local clusters is a key element to understanding spatial inequality (Weeks 2004; Wei 2015). The geographic clustering of poverty, particularly when these clusters are long standing, is associated with many negative impacts. In the context of this study, research connects persistent rural clusters of poverty to negative childhood outcomes (Call and Voss 2016; Curtis et al. 2012). Rural poverty clusters are also related to negative health outcomes (Burton et al. 2013), with specific negative outcomes such as decreased life expectancy (Fenelon 2013)and opioid abuse (Rigg and Monnat 2015). These places of persistent poverty often have pronounced

populations of racial minority and other historically marginalized groups (Weber and Miller 2017). Economic dependence on farming and natural resource extraction also produces clustering of poverty (Curtis et al. 2015; Lobao and Meyer 2001). In short, clusters of inequality in rural areas often intersect many areas of societal disadvantage, thus making the identification of clusters via comparative techniques an important research area. Although clustering exists at a variety of geographic scales, examining mid-level units has inherent research benefits (Lobao 2004; Lobao et al. 2008). Primarily, using mid-level units can help identify the links between micro and macro level forces and helps researchers understand better the generative process of poverty or other inequalities. Rural research on spatial inequality has traditionally focused on the role of local power structures, such as oppressive racial or extractive industry regimes (Shucksmith 2012). This study's use of comparative techniques and its use of counties will ideally further synthesize the micro and macro causes of rural poverty in the United States.

To precisely quantify clustering and measure the exact changes in spatial structure over time, research must measure via spatial statistics both local and global spatial-autocorrelation. Spatial autocorrelation, as shown in Figure 1, is the degree to which the values of are variable are either clustered or dispersed over space (Anselin et al. 2006). Measuring changes in spatial autocorrelation —the focus of this study— is a robust and replicable way to see where comparative advantage or disadvantage localizes. One of the most popular methods of measuring spatial autocorrelation is the Moran's I (Anselin 1996; Anselin and Rey 2014). The Moran's I test is a measure of the linear relationship between a unit's value of a variable and the weighted sum of neighboring units' value of the same variable. The produced statistic of Moran's I, ranging approximately from -1 to 1, is often interrupted like the Pearson's R coefficient, with a value of 1 indicating perfectly clustered values(positive autocorrelations); -1 being entirely dispersed values (negative autocorrelations); and zero meaning that the value's geographic pattern is entirely random (no autocorrelation). Simply, the Moran's I allows one to understand precisely how grouped together high or low values are on a map. The methods section outlines the exact calculation of the Moran's I and its application via the three LISA techniques, but for now, there are three main advantages of using Moran's I via LISA in spatial inequality research.

Figure 1 about Here

First, the Moran's I provides an exact quantification of the level of clustering in the area of interest (Anselin 1995). Many past studies on cluster identification have relied on just describing clusters in a non-empirical way through choropleth maps of quantile or quantile categories of the variable of interest. The Moran's I produces a

single, or global, statistic which allows researchers to exactly measure and compare the level of spatial

autocorrelation between multiple variables or the same variable in multiple time periods. For example, if poverty at

the county level has a Moran's I value of .64 and county level percentage African American has a Moran's I of .51,

a researcher can definitively determine that poverty is more concentrated. Second, if used correctly, certain spatial

statistics, such as LISA and the Moran's I, can also combine spatial and temporal analysis (Curtis et al. 2015). This

combining of spatial and temporal analysis has a multitude of applications and allows researchers to understand

change more complexly and better identify any underlying or generative processes. A combined analysis can also

identify spatial diffusion processes (Martin et al. 2016). Diffusion in this application will generally refer to the

increase or decrease in size of clusters over time. In other words, diffusion measured via LISA is an exploration of

how longstanding clusters have changed and whether there is growth out from or contraction in towards central

points within clusters. Third, Moran's I, via LISA analysis, identifies outlier values or areas (Anselin 1996). For

example, LISA can identify a high poverty county surrounded by only low poverty counties. Identifying outliers

diagnoses exceptions to the regional patterns and may indicate that there is an unknown localized process that may

be producing disadvantages or advantages in a unique way. In other words, the socio-economic forces that maybe

driving changes in poverty to an outlier county's neighbors are not present or have different effects in the outlier

county. Identifying outliers may be helpful in determining what counties, or other spatial areas, need further analysis

or need case study research. All these advantages play out differently in the three LISA techniques; and a main goal

of this research is to demonstrate how each technique uses the inherent advantages of LISA and Moran's I to address

different research questions.

2.2 Changes in Rural America and Rural Poverty

A brief overview of the current issues surrounding rural poverty helps provide context on substantive

questions addressed by this study and the results brought up by the three techniques. There has been extensive

research on the changing spatial nature of poverty in the nonmetropolitan United States. For this study the terms

rural and non-metropolitan will be used interchangeable, something that is often done in the literature on various

rural issues in the United States (Isserman 2005)[1]. Nonmetropolitan counties serve as a surrogate for rural America,

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[1] The U.S. Office of Budget and Management define the terms nonmetropolitan and metropolitan. Nonmetropolitan counties, unlike metropolitan counties, do not contain a city with a population over 50,000 or do not have strong community ties to a nearby metropolitan county. Essentially, nonmetro is a residual definition for counties not designated as metro.

for better or worse (Isserman 2005; Wang et al. 2012). Overall, over the past decades, poverty has become more concentrated in the rural US, meaning that fewer counties experience elevated levels of poverty (Thiede et al. 2018). But at the same time, poverty is increasing in already high poverty counties (Lichter and Johnson 2007), potentially caused by an in-migration of even poorer residents who were priced out of their origin counties who are looking to move to a place with a lower cost of living which is often found in high poverty counties (Foulkes and Schafft 2010). In recent years, this trend has seen a reversal via additional rural counties joining the extreme poverty group (Thiede et al. 2018). Historically, remote rural communities were associated with the highest levels of poverty, often attributed to their isolation and dependence on extractive industries (Curtis et al. 2015; Duncan and Lamborghini 1994). Yet work that is more recent indicates that less remote, micropolitian, counties are now the places of extreme poverty (Thiede et al. 2017, 2018; Wang et al. 2012).

Historically regional variations in poverty level have existed, which the different LISA techniques will help to highlight. Regions such as Appalachia, the Mississippi Delta, and the Northern Great Plains are known for persistent poverty (Curtis et al. 2012; Lichter and Johnson 2007; Lobao and Saenz 2009; Thiede et al. 2017; Whitney Mauer 2017). Most of these poverty pockets are associated with diverse populations; usually a specific ethnic minority group (Weber and Miller 2017). These areas have long been counties with weak economic conditions featuring high unemployment and dependence on extractive industries (Call and Voss 2016; Curtis et al. 2015; Weber and Miller 2017). Evidence also suggests that agricultural dependence is associated with poverty at the county level, which may increase poverty in many Western and Midwest counties (Curtis et al. 2012).

The results of this study highlight three main demographic shifts in rural America. First, many counties in the amenity-rich West and South have been experiencing population growth (Cromartie 1998), which can have unintended consequences. In some communities, rural gentrification has resulted from newcomers buying up land and raising the cost of living, forcing out more impoverished long-term residents (Hunter et al. 2005; Nelson and Hines 2018). Rural gentrification may decrease poverty rates in destination counties but has the adverse effect of potentially increasing poverty in neighboring counties that absorb displaced poor individuals. Many natural-amenities counties are also rural retirement destinations. Usually located the southeastern and southwestern U.S., these destinations are usually places with higher poverty levels and often on the metropolitan fringe (Brown et al. 2011; Rowles and Watkins 1993; Stallmann and Jones 1995).

Second, rural America has experienced large gains in diversity over the past few decades, primarily via Hispanic immigration (Lichter 2012; Lichter and Johnson 2007; Sharp and Lee 2017). Much of this related research has focused on new immigrant destinations located in the rural Midwest, where there are meatpacking and agricultural jobs (Artz et al. 2010; Broadway 2007). Hispanics are also migrating to cities that are retirement and natural amenities destinations that offer jobs in construction, hospitality, or entertainment, potentially raising the poverty in some of these counties (Cromartie 1998; Nelson et al. 2009, 2010). However, Hispanic migration to these rural counties has significantly slowed since 2006, so it is unclear what the long-term effects of this migration will be. There is a spatial unstable relationship in how poverty and Hispanic concertation plays out (Sparks et al. 2013), with higher percentages of Hispanic associated with to higher poverty in the southeast and southwest but lower in poverty in the Midwest and northwest (Crowley and Lichter 2009; O'Connell and Shoff 2014).

Lastly, the Great Recession and further deindustrialization has played a role in poverty and population change. The Great Recession saw increases in food stamp usage (Slack and Myers 2014)), unemployment (Thiede and Monnat 2016), and poverty (Call and Voss 2016; Thiede et al. 2018). The Great Recession also limited the population and economic growth effects of natural amenities development (Rickman and Guettabi 2015).

A review of the literature has shown that clustering of inequalities, particularly poverty, has long-term negative effects on individuals. When it comes to rural poverty there has been several well-documented clusters of persistent poverty, and the factors influencing change in county level poverty are well known. There are two main gaps in knowledge of both spatial inequality research and rural poverty; how comparative spatial techniques can lead to an understanding of the generative process of poverty, and how county clustering of poverty changes when using multiple techniques. This study aims to fill those gaps.

3. METHODOLOGY

3.1 Global and Local Moran's I

The Moran's I has two forms, a global and a local Moran's I. The global Moran's I indicates the level of autocorrelation for the entire data set, while the local Moran's I values indicate the autocorrelation for each unit in the dataset (Anselin 1995). LISA is a mapping of these local Moran's I values, specifically the Moran's I scatterplot (Anselin 1996). In the local Moran's I scatter plots on the x-axis the values of the variable in each observation (X) and the y-axis graphs the lagged (summed) values of each observation's neighbors (Y). Z-scores are produced for these X and Y values and the origin of the scatter plot is set at the Z-Score of zero —the mean of the values (Figure

2). This graphing creates four quadrants, with observations in quadrant one being observations that have high values of the variable with high-value neighbors. In quadrant two, high value observations neighbored by low values; in quadrant three, low values neighbored by low values; and in quadrant four, observations with low values neighbored high values. For LISA analysis, observations with values above a significance threshold of 95% are part of significant clusters and then mapped (Martin et al. 2016). The four quadrants and the significance testing yields LISA values of High-High (Q1), High-Low (Q2), Low-Low (Q3), Low-High (Q4), and Non-Significant (p-value > .05)[2]. Observations in quadrants one and three indicate positive spatial autocorrelation in the data, while one can interpret observations in quadrants two and four as spatial outliers, meaning they do not follow the general pattern of their neighbors. LISA analysis is a useful way of visually representing what regions of observations, in this study, counties, feature positive spatial autocorrelation, or clustering of similar poverty values, and negative spatial autocorrelation, i.e. spatial outliers.

Figure 2 about Here

Moran's I can both measure univariate spatial autocorrelation and bivariate spatial autocorrelation, which is the clustering tendency between two different variables (Porter 2011). The Bivariate Moran's I summarizes the relationship between one value of a variable in a unit and the lagged values of a different variable for one's neighbors. Bivariate Moran's I is ideal for the comparison of the same variable but at two different time points. In this research the bivariate Moran's I will be used on poverty at multiple points, with poverty in the latter period being compared to the lagged value of poverty in the earlier period. The univariate, bivariate Moran's I, and Bivariate LISA all use the same scatterplot and LISA value scheme. This research will produce Moran's I values for poverty in individual years within the study period (1990, 2000, 2010, 2015), but also a Bivariate Moran's I for poverty for 1990-2015. LISA Cluster Transitions and LISA Diffusion techniques uses univariate LISA values, while the Bivariate LISA Technique uses bivariate LISA values.

This study uses a Queen 1 adjacency matrix, meaning neighbors are those who share borders, including corners[3]. Using a Queen 1 matrix removes neighbor less observations from the dataset and are not included in the calculations. Of the 3109 counties originally included in the sample, four were neighborless.

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[2] High-High clusters will be represented in dark red, High-Low clusters with light red, Low-Low clusters with Dark Blue, Low-High Clusters with Light Blue, and Non-significant and neighborless counties with yellow.
[3] For sensitivity purposes, an N-th nearest Neighbor matrix and Queen 2 matrix where also tested. All three matrixes produce similar clusters and similar Global Moran's I values.

3.2 Three LISA Techniques

The main demonstrative focus of this study is on the comparison of three LISA techniques: Bivariate LISA, LISA Cluster Transitions, and LISA Diffusion Transitions. The first, Bivariate LISA, maps local Bivariate Moran's I values. For this specific application, poverty in the later period, 2015, will be the observation variable, and poverty in the earlier period, 1990, is the lagged or neighboring value variable. This technique measures how related 2015 poverty values are to 1990 neighboring poverty values. In the produced map, High-High values represent a high 2015 county poverty value surrounded by a high 1990 poverty counties; High-Low represents High 2015 values surrounded by low 1990 values, and so on. Bivariate LISA has the advantage of the global bivariate Moran's I, which tells you the spatial autocorrelation for the entire dataset between 1990 and 2015. This method provides a precise way of understanding persistent poverty values and allows for identification of regional outliers over time. In this specific application, Bivariate LISA incorporates a time dependency component, meaning that one assumes that 1990 county level poverty should relate to county level 2015 poverty.

The second technique is the LISA Cluster Transition map. This technique groups counties by their changes or transitions from univariate LISA values from one period to the next. Essentially, LISA Cluster Transitions visually represents a traditional transition matrix. For example, a county that was High-High in both 1990 (high value surrounded by high values in the same period) and 2015 has the value 11 (alternatively HH, HH); a county that is Low-Low in both periods is 22 (LL, LL); and a county that moved from non-significant to High-High is 01 (NS, HH). Figure 3 provides a demonstration of two period LISA Transitions. All transitions have assigned values; however, the produced map generalizes to show only certain types of transitions. There are possible 92 transitions, most with little substantive meaning, therefore for this research the produced map will only display transitions between High-High, Low-Low, or non-significant —this limitation focuses the analysis and was done in previous research that use LISA Cluster Transitions (Martin et al. 2016). This limitation addresses where poverty is persistent over time and where it is changing over time. Although LISA Cluster Transitions lacks the easily interpretable single statistic of the prior technique, the global Moran's I, the method offers a potentially more simplistic way of representing how the spatial structure is changing. This technique also allows for the study of more types of county level changes between periods. For example, if a county was non-significant in 1990 but became High-High in 2015 it is identified with LISA Cluster Transitions, but not when using the Bivariate LISA Technique.

Figure 3 about Here

The last LISA technique, LISA Diffusion transitions, follows the same basic principles of the previous method, but instead incorporates poverty values of multiple years within the study period and only considers clusters that are that are consistently or become consistently High-High and Low-Low. Diffusion implies a longitudinal process so to understand changes that occurred from 1990-2015, this techniques uses 1990, 2000, 2010, and 2015 univariate LISA values. As with the LISA Cluster Transitions a county that is High-High in all four years has the value 1111, but a county that is High-High consistently starting in 2000 is 0111, and so on. This method allows for the identification of the potential diffusion or spread of high or low levels of poverty in the 25-year period. In theory counties that are High-High or Low-Low are the centers of high or low poverty, and from these central counties there is a spreading out of similar values to neighboring counties. A potential downside of this method is that it limits the visual representation of the fine detail or exact changes. This technique has also not been tested outside of this study, however as the results will soon show, this method does potentially show the spreading out of high and low poverty at the county level.

3.3 Data

The unit of analysis for this research is all counties in the conterminous U.S., i.e. lower 48 states, excluding neighborless observations (N= 3105). Change in poverty in non-metropolitan counties does not exist independently of poverty or economic conditions in the rest of the United States, and in recent years, there has been a push by rural scholars to think no longer of rural America as a separate economic and social system (Lichter and Brown 2011). Therefore, this study will use all counties, both metropolitan and nonmetropolitan, in its analytical sample, though it will focus primarily on poverty in rural areas. LISA statistics calculate clustering of poverty not only in counties relate to the values of their neighbors but also how these levels compare to the overall sample level; therefore only using non-metropolitan counties only would likely distort any potential findings. The 2012 OMB classifications are the basis for all references to metropolitan or nonmetropolitan (urban and rural) counties.

Data for this study comes from the IPUMS National Historical Geographic Information System and draws from the 1990 Decennial Census, 2000 Decennial Census, 2010 ACS 5-Year Estimates, and 2015 ACS 5-Year Estimates (Manson et al. 2018). All these years allow for complete data coverage of all nonmetropolitan counties. The key variable for this study is the percentage of the population of each county living in poverty, determined by the US Census designation. An individual is in poverty if their household income falls below an absolute threshold,

adjusted for the number of children in the household and the age of the householder. This study provides descriptive statistics (Table 1) and quintile maps of county level poverty (Figure 4) for 1990 and 2015 for reference purposes.

Table 1 about Here

Figure 4 about Here

4. RESULTS

4.1 Univariate and Bivariate Moran's I

There is strong spatial autocorrelation for poverty in all years. The univariate Moran's I for poverty is at its highest in 1990. The clustering of poverty in rural America decreased for two straight decades, reaching its lowest point in 2010 only to shift slightly upwards in 2015 (Table 2). These numbers do not state that poverty in the country is decreasing but that there is a decrease in the clustering. The significant decrease in Moran's I from 2000-2010 potentially reflects the economic impacts of the 2008 financial crisis, which may have had varying impacts on poverty in different regions, thus disrupting the previous spatial pattern. An alternative hypothesize is that the change from 2000-2010 is a further continuation of the decline from 1990-2000 which could be a reflection of a variety of factors such as increased immigration (Lichter 2013)and welfare reform (Edin and Shaefer 2015). Interestingly the mean poverty levels for each year (Table 1) experienced less inter-period change than the changes in the univariate Moran's I; indicating the spatial structure of poverty is changing much more dynamically than the actual level of poverty. In a more abstract sense, the spatial distribution of the inequality is changing more than the overall level of inequality.

Table 2 about Here

Shifting to examining the Bivariate Moran's I also produces interesting results. Like with univariate Moran's I, the bivariate value for 1990-2015 is high, meaning that the spatial pattern of county poverty levels in 2015 strongly correlates with the regional structure of county poverty levels in 1990. In other words, many counties retained poverty levels that were similar to their neighbors during this span and that many regions of the U.S. are likely long-standing clusters of high and low levels of poverty. The three LISA techniques identify these exact high and low clusters.

4.2 Bivariate LISA

The Bivariate LISA technique produces apparent regional clusters of continued high and low poverty during the study period (Figure 5). There are High-High clusters throughout the Mississippi Delta, the Black Belt

(Deep South), Central Appalachia, the Four Corners Region, Texas Borderlands, and Native American Reservation Counties in the Northern Great Plains. Most have high percentages of minority populations and are geographically remote (Weber and Miller 2017). Clusters of continued low poverty are located throughout the Midwest, New England, and parts of the Mountain-West. An unexpected finding is that rural areas of many Rust Belt states are clusters of relatively low poverty. Historically, these Rust Belt counties have experienced deindustrialization and joblessness a likely driver of county-level, poverty increases which makes these more moderate levels of poverty surprising (Thiede and Monnat 2016). An alternative explanation is that while deindustrialization hurts many localities in the region, it does not necessarily affect the level of poverty at the regional level.

Figure 5 about Here

A strength of the bivariate technique is that it can help to identify spatial outliers, or High-Low and Low-High clusters. In this study, Bivariate LISA has identified several groupings of counties where their 2015 poverty levels do not match the poverty levels of their neighbors in 1990. Several counties in the western United States are High-Low clusters, meaning these counties experienced a relative increase in poverty. Metro-adjacent northeastern and Sun Belt counties expressed similar results. All three groups of counties are places where natural amenities related growth has occurred (Cromartie 1998; Hunter et al. 2005). Many Rust Belt counties are also high-low clusters; this may be a reflection of counting de-industrialization in the region (Thiede and Monnat 2016). A number of counties and regional groupings are outliers in the opposite direction, indicating a decrease in poverty over time compared to high poverty neighbors. These outliers cluster primarily in the Border States, Northern Great Plains, and the South. All of these counties are in regions identified in the literature as persistent poverty (Lichter and Johnson 2007), yet for some reason these counties are going against the regional pattern. Identifying the specific causes of these county outliers may be a topic for future research.

4.3 LISA Cluster Transitions

A complimentary method to the Bivariate LISA is LISA Cluster Transitions and its produced map. When examining the transition matrix for changes between 1990 and 2015, the majority of counties kept a similar level of poverty between the two periods, 312 were High-High in both periods and 339 were consistently low-low (Table 3). Other counties of interest are those switching between non-significant and either High-High or Low-Low[4]. Although

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[4] Only one county, Dawson County, Texas, switched completely from High-High to Low-Low

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this technique lacks a global Moran's I value indicating the level of clustering over time, by using the transition matrix it is still possible to assess the overall level of continuity and change.

Many of the persistent high and low poverty clusters from the previous technique are identified as either High-High or Low-Low both periods in Figure 6. High clusters are in central Appalachia, the greater south, and four corners region. Persistent low clusters of rural counties are present in the Midwest. The strength of this technique is that it maps change from non-significance in 1990 to either High-High or Low-Low in 2015 —signifying a shift away from more moderate poverty values in many regions. Many parts of the Rust Belt and rural North East experienced increases in poverty, while many parts of the Great Plains and the Southwest experienced further poverty decline. This Great Plains poverty loss may be rooted in a long history of population loss via outmigration (Curtis White 2008; Johnson and Rathge 2006) or the increase of Hispanic population (O'Connell and Shoff 2014). There is one region where there is an undecided regional pattern of poverty change, the Mountain-West. Some counties in the region switched from non-significant to High-High while others switched to Low-Low. The Bivariate LISA Technique did not show this pattern of change in the Mountain-West. A potential explanation of the mixed pattern is by the linked migration of rich and poor due to natural amenities development (Nelson et al. 2010). The documented pattern of rural gentrification, inflow of low-wage workers, and displacement of poor populations into neighboring counties may increase poverty in some counties while decreasing poverty in others.

4.4 LISA Diffusion Transitions

The last LISA technique is LISA Diffusion Transitions, which unlike the two other techniques analyzes longitudinal stability and change over time over several periods. Longitudinal stability in this technique indicates counties that remained High-High or Low-Low through all periods or remained in these groups after joining them. Many counties are high-high clusters in all four years (Figure 7). One can potentially interpret these counties, primarily those in the South, as centers, or hearths, of high poverty. Previous scholarship has indicated that the Texas border region is a place of high poverty; however, the diffusion map does not compliment previous results (Weber and Miller 2017). Counties in Appalachia, the Southwest, and Indian Reservation Counties in South Dakota are places of consistent poverty, yet they lack the regional spreading that is present in the southern U.S. There is an apparent spread, or diffusion, of high poverty throughout the South that is most pronounced in Southern Georgia and

the Carolinas. A likely cause of this diffusion, compared to other high poverty regions, is population growth, specifically growth of relatively high poverty migrants. Many of these spreading poverty counties either are on the metropolitan fringe or are micropolitian counties, places where poverty has been growing in recent decades (Thiede et al. 2018).

Figure 7 about Here

There is an apparent diffusion of low poverty in the Midwest and parts of the West, which support similar findings from the previous techniques. In the Midwest, population decline and the immigration of Hispanics into the region may explain this diffusion (Crowley and Lichter 2009; Johnson 2011; Johnson and Rathge 2006; O'Connell and Shoff 2014). It is interesting that many southern diffusion counties are high population growth areas. A point of optimism is that the spatial diffusion of low poverty is more widespread than high poverty diffusion. In exact numbers, 210 counties experienced this transition into the Low-Low category, while only 109 counties experienced a High-High transition.

5. DISCUSSION

5.1 Comparison of Techniques

Spatial Inequality is often a complex phenomenon and as this study demonstrates the benefits of using multiple comparative spatial statistical techniques. Each of the three LISA techniques has their benefits and drawbacks, and in general benefit from combined use. The Bivariate LISA and LISA Cluster Transitions are very complimentary to each other; however, there are small differences between the two, which future researchers should recognize. Measuring changes in a given inequality, in this case poverty, via the bivariate technique has the benefit of the global Moran's I, which can summarize the spatial pattern for the entire set of data. LISA Cluster Transitions does have the corresponding transition matrix however, which can provide a researcher with a general level of understanding regarding the overall level of change from period to period, but it not as precise as the global Moran's I. With this study the bivariate Global Moran's I for 1990-2015 is .49, indicating strong spatial autocorrelation, while the transition matrix shows that 950 out of over 3105 counties were either High-High or Low-Low clusters in either period. Looking at the number of counties in each category in the matrix is a potential substitute for the global statistic. An additional strength of the Bivariate LISA is that it allows for the identification of places with negative spatial autocorrelation, i.e. spatial outliers. Many counties in Texas and the Rust Belt are outliers with this technique. LISA Cluster Transitions can also identify outliers, but it requires the awareness of the researcher to pick

outliers out of the regional clustering. Although in this application, the LISA Cluster Transitions were narrowed to only show certain types of changes the technique can map out any transition between two LISA values. This techniques versatility can identify the continuation of High-Low clusters across periods or Low-Low to Non-significance —thus identifying places of poverty or inequality increase, to name a few alternative mapping and identification strategies. Overall, even though LISA Cluster Transitions may lack the statistical robustness of the bivariate technique, together they can help to identify clusters that were not present in the other technique. For example, they provide differing results on the pattern of poverty over 25 years in the Mountain-West.

This study is also featured the LISA Diffusion transitions, a technique specifically designed for this study. In the most basic terms, LISA Diffusion is a way of mapping out long-term persistence and the spread of persistence of a given inequality. The immediate strength of LISA diffusion is that it assists researchers in looking at change and continuations over multiple periods or years; the other two techniques are limited to just two periods. Incorporating all periods into one map is beneficial and can lead to an understanding of potential diffusional processes, yet this technique can only examine the highest and lowest values of regional poverty patterns. Diffusion Transitions do not show all changes between different types of clusters from year to year. The main limitation of the technique, besides its externally untested nature, is that it is purely exploratory. Diffusion transitions relay on the researcher identifying and teasing out the underlying generative and distributive processes of the inequality. This exploratory nature can also be said of the two techniques, however the Diffusion Technique is exploring if the inequality is spreading out geographically from central clusters over a given time period. Despite this limitation, LISA Diffusion still allowed for the identification of a clear spreading of high and low poverty in two regions of the country.

5.2 New Findings in Rural Poverty

Using the comparative techniques, this study further supported findings from past research on rural poverty. Clusters of high poverty such as central Appalachia and the Mississippi Delta are present in all techniques are well documented in the literature (Lichter and Johnson 2007; Thiede et al. 2017; Weber and Miller 2017). There are four new findings produced in this research, all of which will require further validation via additional research. First, this study identified persistent low poverty clusters in the Midwest and Northeast. This is important because documenting places of comparative disadvantage is only one, part of research in spatial inequality (Tickamyer 2000); identifying clusters of comparative advantages is also needed. Second, although past research has identified the Texas border region as a persistent poverty region (Weber and Miller 2017); in both the Bivariate LISA and

LISA Cluster Technique the region was experiencing a decline in poverty. Past research has shown that the high concentration of Hispanics in the region was associated with higher poverty levels while in the Pacific Northwest and the Midwest increasing Hispanic populations indicate lower poverty levels (O'Connell and Shoff 2014). A possible explanation for the downswing in Texas border poverty is that the role of Hispanic concentration is shifting to resemble the more northern Pattern. The third contribution of this study is that multiple techniques find contradictory results in the poverty pattern in the Rust Belt and the Natural Amenities West. With the later natural amenities development is associated with rural gentrification, the in-migration of low wage workers, and the displacement of locals to adjacent counties, all of which can either shift the poverty level of a county in a positive or negative way (Hunter et al. 2005). Further research needs to explore the relationship between migration and poverty in the region. The last contribution is that LISA Diffusion transition identified the diffusion over time of high poverty in the Southeast and of low poverty in the Midwest.

5.3 Future Research and Conclusions

A limitation of this study is that it only analyzed and compared one indicator of poverty, the official poverty measure. Poverty as a spatial inequality is complex in its causes and its measurement. A fruitful avenue for future research would be the use the three-fold LISA technique approach to compare different forms of the same inequality. For example a spatial comparative study that compares the changes in unemployment, educational attainment, and the official poverty measure. Understanding how spatial structure of these inequality sub-components would help the researcher to understand the interrelated spatial nature of the factors and if there is any time order affects that can measures via LISA techniques. A potential avenue for future research is to map counties that have changed LISA cluster type many times, potentially in positive and negative directions. Understanding these patterned multidirectional changes from decade to decade may offer insights into unexplored social and economic processes. A final area of future research is further testing the LISA Diffusion technique for the measurement of other inequalities and at different spatial scales. In this study, LISA Diffusion was used to examine counties only; understanding diffusion at the census tract or neighborhood level will likely help researchers understand diffusion processes better and what are the inherent strengths and weaknesses of the technique. Overall, this study served as a demonstration of three LISA techniques and provided new insights into how the spatial structure of county level poverty has changed over a 25-year period. Bivariate LISA and LISA Cluster Transitions are complimentary techniques best used together. For example, the bivariate LISA is able to provide an

overview of the level of spatial autocorrelation while LISA Cluster Transitions can map a variety of change types not available with the bivariate technique. This study also provides evidence for a diffusion of high and low poverty in the Southeast and Midwest, respectively. Although the LISA Diffusion technique is untested elsewhere, it is likely that it can find use in many future research applications. The largest contribution of this study is that is serves as a demonstration of how multiple spatial techniques can supplement each other in spatial inequality research. Truly, understanding spatial inequality and its core phenomenon of clustering relies on identifying and theorizing about the generative and distributive process of a given inequality (Lobao 2004; Logan 2012; Weeks 2004). Using the three LISA techniques contributes to understanding the generative process of rural poverty and other inequalities by helping researchers identify outliers, time order affects, and diffusion out from areas of extreme advantage and disadvantage.

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TABLES

Table 1. Descriptive Statistics of Poverty in all Periods

Variable	Min	Max	Median	Mean	Std. Dev.
Poverty Percentage - 1990	.00	.62	.15	.16	.08
Poverty Percentage - 2000	.00	.57	.13	.14	.07
Poverty Percentage - 2010	.00	.54	.14	.16	.06
Poverty Percentage - 2015	.01	.53	.16	.17	.07

N = 3105

Table 2. Global Moran's I Values

Year	Univariate Moran's I	Years	Bivariate Moran's I
1990	.64	1990 – 2015	.49
2000	.60		
2010	.50		
2015	.51		

Table 3. LISA Cluster Transitions, 1990-2000, 2000-2010, 2010-2015, 1990-2015

1990	High-High	High-Low	Not Significant	Low-High	Low-Low	Total
			2000			
High-High	412	10	76	0	0	498
High-Low	9	22	9	0	0	40
Not Significant	60	10	1646	7	144	1867
Low-High	0	0	7	15	4	26
Low-Low	0	0	138	19	517	674
Total	481	42	1876	41	665	3105

2000	High-High	High-Low	Not Significant	Low-High	Low-Low	Total
			2010			
High-High	346	16	119	0	0	481
High-Low	6	20	16	0	0	42
Not Significant	83	8	1653	22	110	1876
Low-High	0	0	9	23	9	41
Low-Low	0	0	233	29	403	665
Total	435	44	2030	74	522	3105

2010	High-High	High-Low	Not Significant	Low-High	Low-Low	Total
			2015			
High-High	351	11	73	0	0	435
High-Low	9	22	13	0	0	44
Not Significant	61	16	1815	14	124	2030
Low-High	0	0	21	40	13	74
Low-Low	0	0	90	20	412	522
Total	421	49	2012	74	549	3105

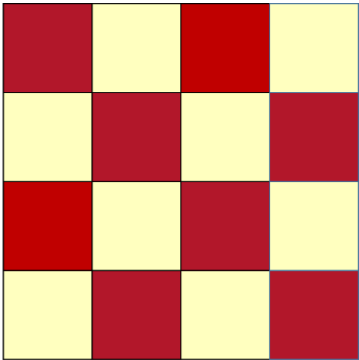| 1990	High-High	High-Low	Not Significant	Low-High	Low-Low	Total
			2015			
High-High	312	18	167	0	1	498
High-Low	5	13	22	0	0	40
Not Significant	104	18	1508	30	207	1867
Low-High	0	0	12	12	2	26
Low-Low	0	0	303	32	339	674
Total	421	49	2,012	74	549	3,105

FIGURES
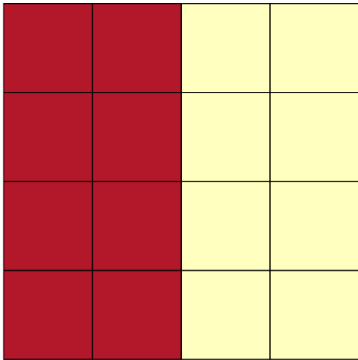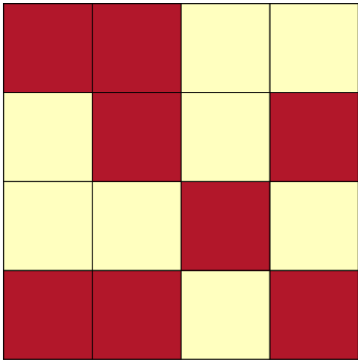
Positive Spatial Autocorrelation   No Spatial Autocorrelation   Negative Spatial Autocorrelation
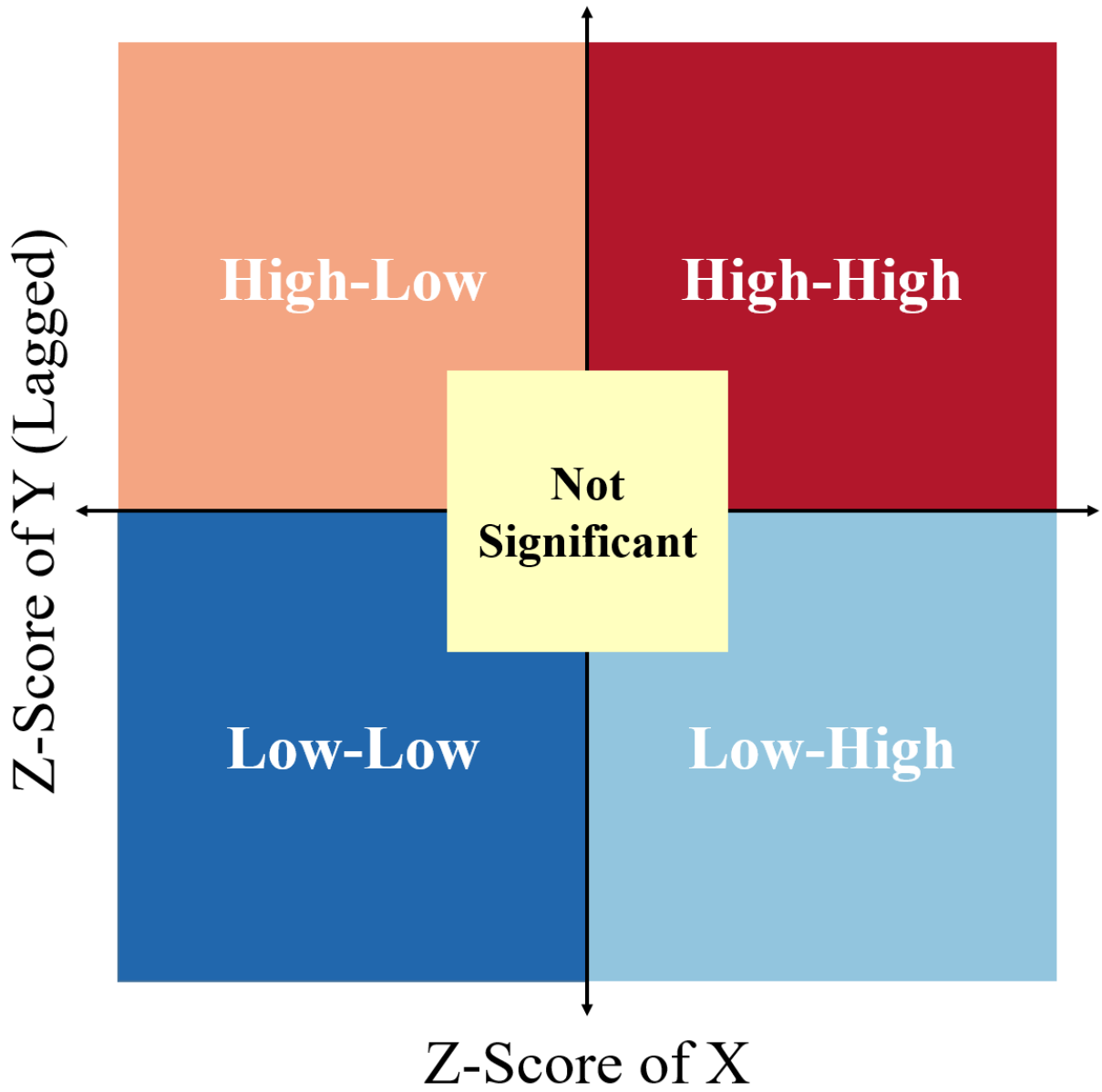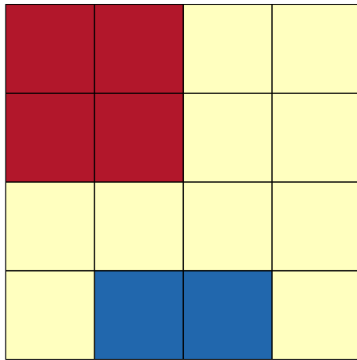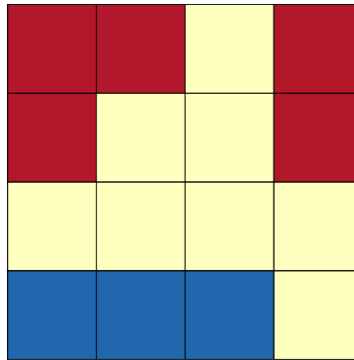
Figure 1 Example of Spatial Autocorrelation
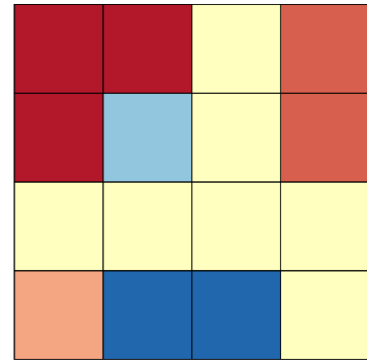
Figure 2 Example of Moran's I Scatterplot

Period 1

Period 2

Transition between Periods

High-High = 4
Low – Low = 2
Not-significant = 10

High-High = 7
Low–Low = 3
Not-significant = 8

High-High both = 3
NS to High-High = 2
High-High to Not-significant = 1
Low–Low both = 2
Low-Low to Not-significant = 1
Not-significant both = 7

Figure 3 Example of LISA Transition Matrix
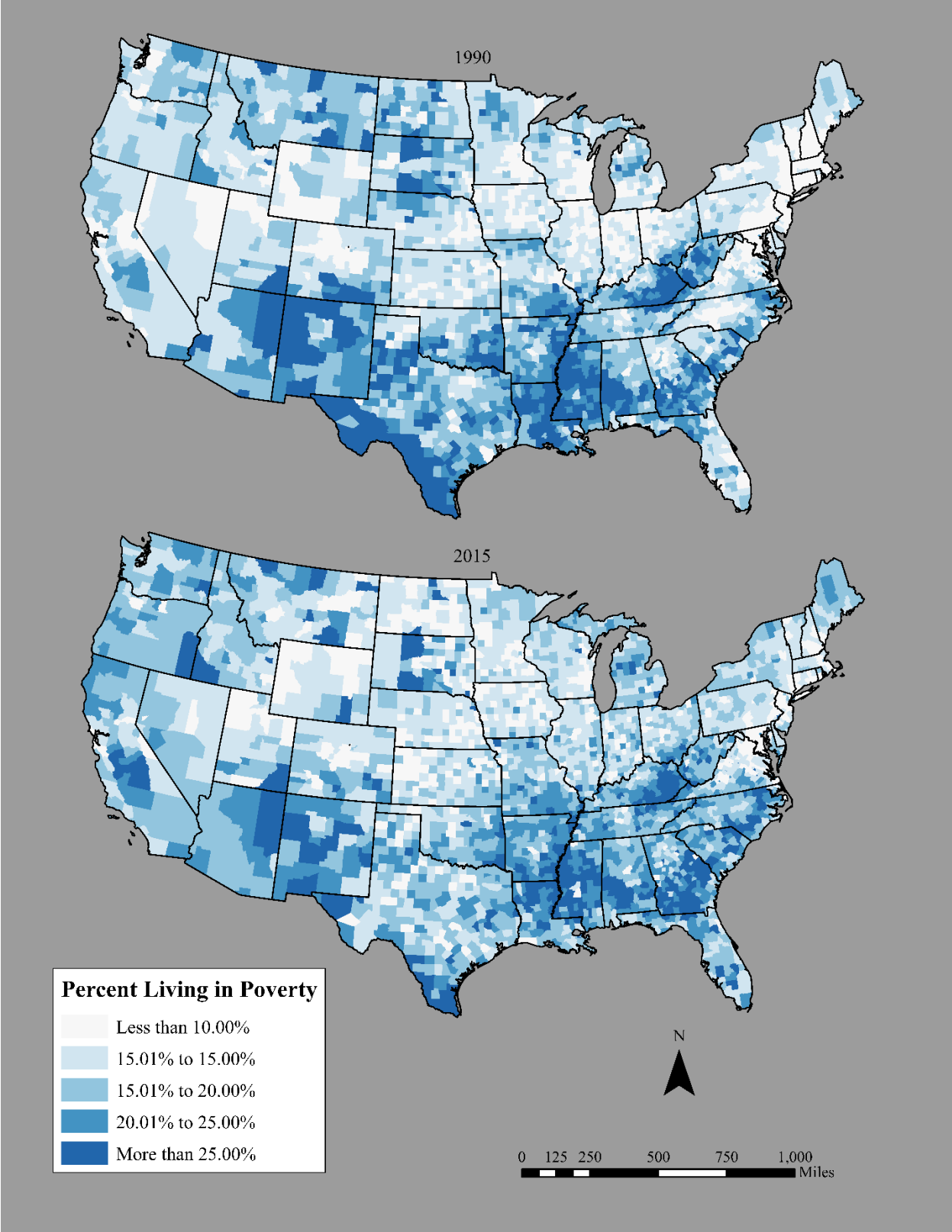
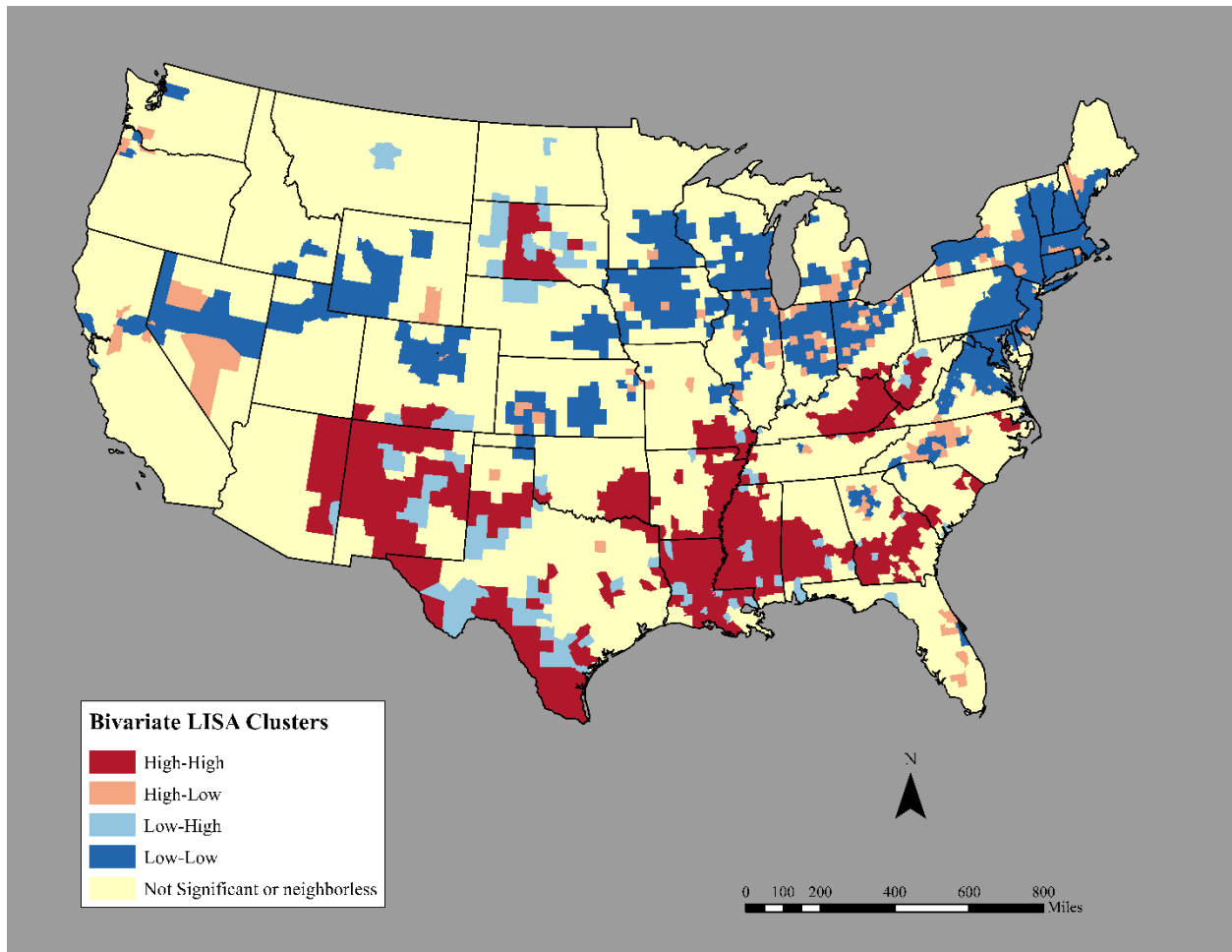*Figure 4. Poverty at the County Level, 1990 and 2015*
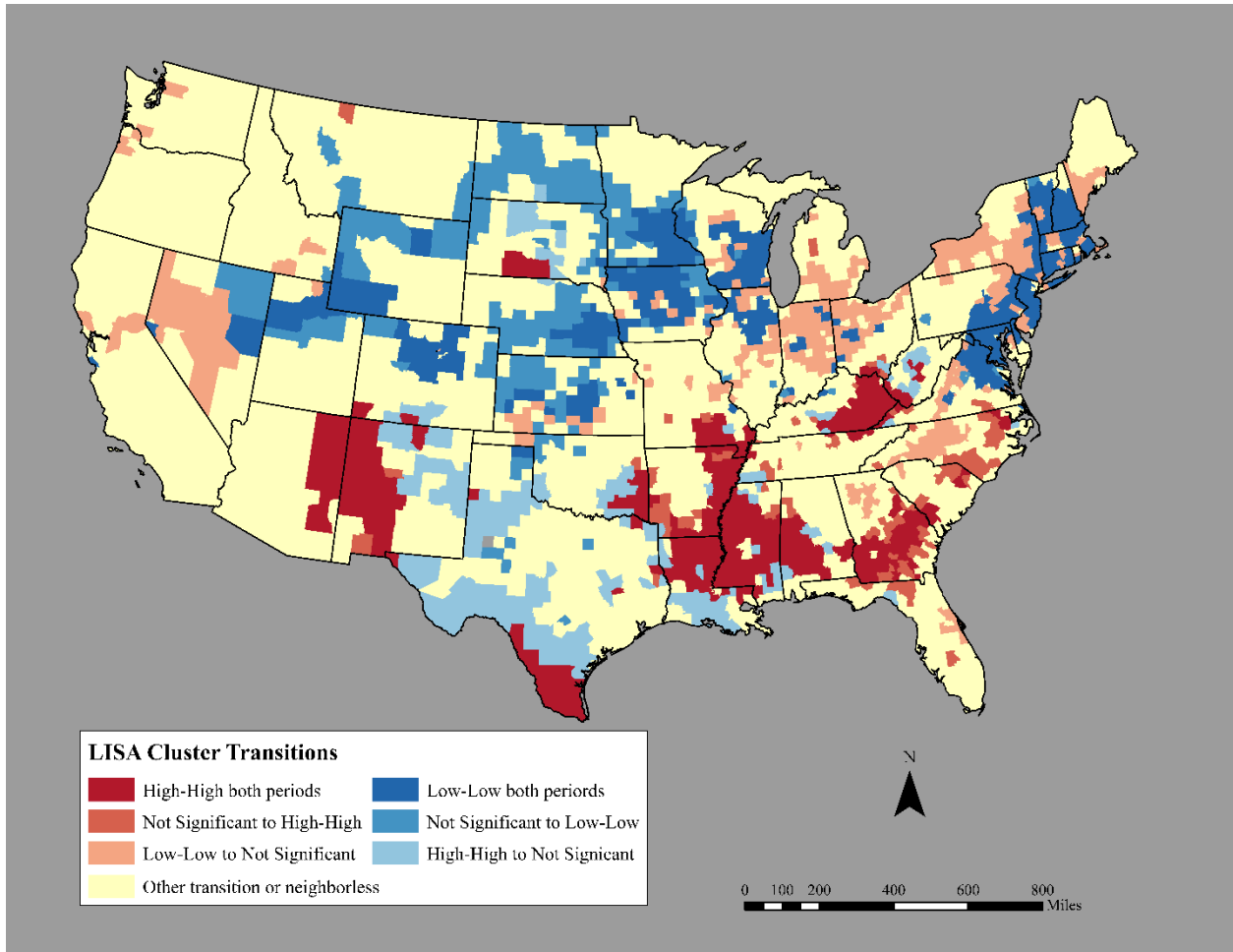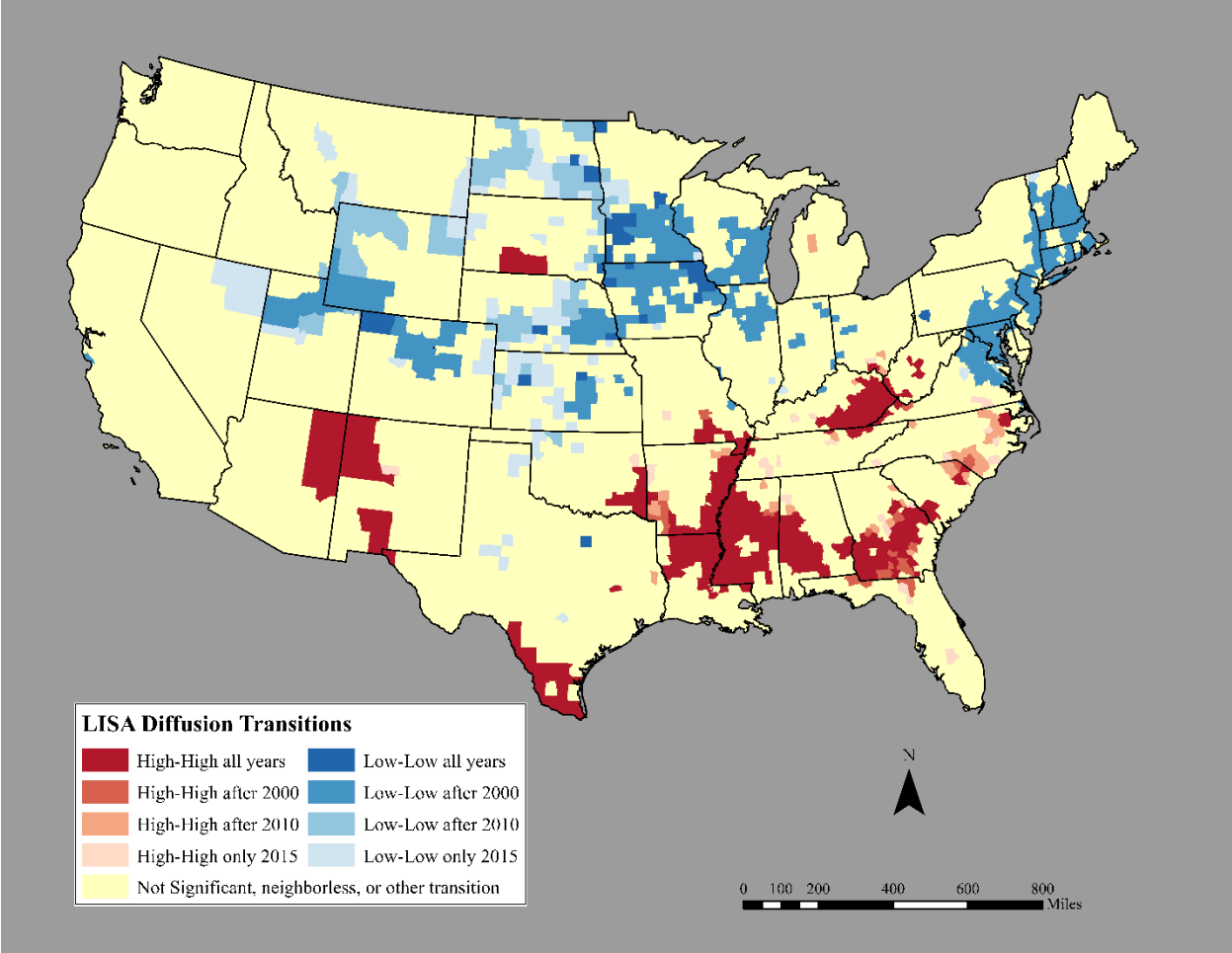
Figure 5 Bivariate LISA Map

Figure 6 LISA Cluster Transition Map

Figure 7 LISA Diffusion Transition Map