MEASURING THE SPATIAL DIMENSIONS
OF POVERTY IN OKLAHOMA

By

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OF POVERTY IN OKLAHOMA

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TABLE OF CONTENTS

LIST OF TABLES

Table | Page

LIST OF FIGURES

Figure Page

Figure Page

CHAPTER I

INTRODUCTION

Even though the World Bank reports that the percentage of people living in poverty has declined over the past several years (World Bank 2007), in absolute terms, the total number of people living in poverty continues to rise (Harper 2008). Despite the decline in overall poverty rates, it continues to be a worldwide problem that affects millions each day, especially in developing countries where monetary and environmental resources are lacking and conditions remain unstable. For many decades, social scientists, including sociologists, anthropologists, and political economists, have been studying social phenomena such as poverty. Yet, poverty was not at the forefront of geographic research until relatively recently.

In the 1970s, geographers began to recognize that, "in the many books of readings that have been published, social, psychological, political, historical, as well as economic aspects of poverty have been explored, but conspicuously absent is any consideration of a spatial or geographic dimension" (Morrill and Wohlenberg 1971, 6-7). Geographers, nevertheless, did acknowledge that poverty exhibited a spatial dimension. Richard Peet, for example, notes "the incidence of poverty…varies greatly from one place to another" (1972, 2). As late as the 1990s, however, studies of regional variations in poverty, especially in the United States, were still scarce in the geographic literature (Shaw 1996).

Recently, with the advances in geographic information systems (GIS), as well as developments of new quantitative methodologies aimed at targeting spatial variations of specific phenomena, geographers have begun to focus attention on the spatial dimensions of poverty in developing countries (see for example, Bigman and Fofack 2000; Hentschel et al. 2000; Elbers et al. 2004). Additionally, the spatial distribution of poverty in the United States has increasingly become a research focus (Duval-Diop 2006; Partridge and Rickman 2006, 2007). Even the United States Census Bureau has recognized the geographic nature of poverty, with a recent report on the concentration of high poverty rates in specific regions of the country (Bishaw 2005).

Within the framework of this current study, I intend to add to the growing literature concerning poverty analyzed from a geographic perspective by highlighting the problem of poverty within the state of Oklahoma. I not only focus on the spatial distribution of poverty across the state, but I also aim to identify several underlying factors that are affecting the poverty rate across the state. In addition, I will be concentrating on how the influence of these factors varies across the state in the hopes of isolating areas where location specific policies might be initiated that will better target poverty throughout the state. The introduction to this research will focus on defining poverty, illustrating the spatial distribution of poverty within Oklahoma, and establishing my research objectives as well as providing a justification for this study.

Poverty Defined

Because of infinite geographic differences in the world's populations, poverty cannot be defined the same in all parts of the world. For example, poverty among people in the United States is vastly different from poverty among people in sub-Saharan Africa because of differences in the composition of the population, the environment, and the financial and natural resources available. For this reason, no other figure in the analysis of poverty is more contested than the quantification of poverty itself. Diane Perrons (2004) offers a comprehensive analysis of the various methods employed in current research including the Gini coefficient and the Human Development Index, among others. Each of these measures supplies a different calculation of poverty based on various aspects of social and economic inequalities present.

For example, measuring poverty in terms of income inequalities is the basis for the Gini coefficient. The Gini coefficient utilizes the Lorenz curve, which is a representation of the distribution of wealth across an area (Perrons 2004). The Lorenz curve plots the percent cumulative population on the x-axis and the percent cumulative income of the population on the y-axis. A 45 degree line where $x = y$ would denote a situation where the wealth is perfectly equally distributed among the population. The Gini coefficient quantifies the deviation from perfect equality by calculating the area under the Lorenz curve (Figure 1). The Gini coefficient results in a number between zero and one, with zero representing absolute equality and one indicating absolute inequality. As an example, the Gini coefficient for the United States in the 1990s was 0.414 (Weeks 2005). In the Netherlands, a lower coefficient of 0.294 indicates that wealth in that country is more equally distributed among the population than it is in the U.S.

Going beyond measuring poverty solely on the basis of income, the Human Development Index (HDI), created by the United Nations, is an assessment of quality of life based on education levels and life expectancy at birth, as well as per capita economic measures (Perrons 2004, Harper 2008). The HDI is a comparative index with each country being given a ranking based on its level of development. In 2002, Norway was ranked as the most highly developed country in the world on the HDI scale, with the United States being ranked sixth (Perrons 2004, Table 2.6). At the low end of the HDI scale was Sierra Leone with an overall HDI of 173. In the developing world, the World Bank often combines methods of determining poverty by using measures of consumption, inequality, vulnerability, health, nutrition, and education (Coudouel, Hentschel, and Wodon 2002).

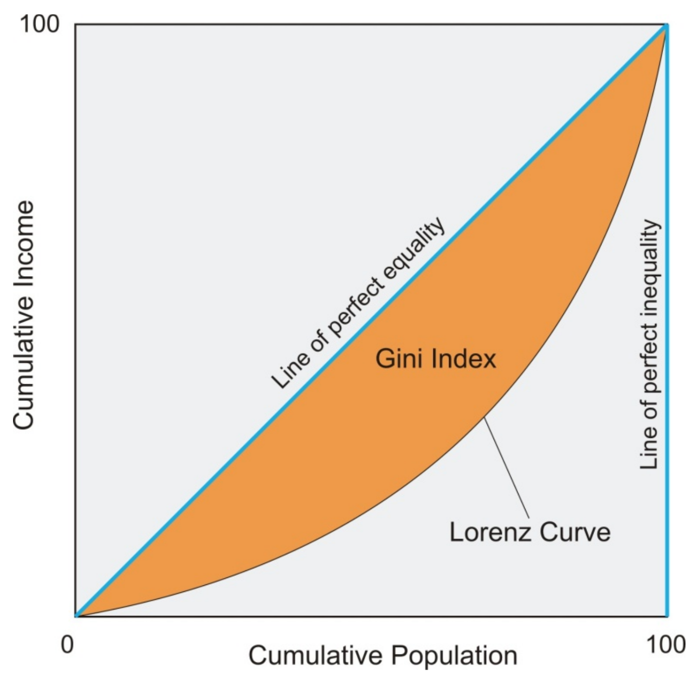


Figure 1. The Lorenz curve and Gini coefficient.

While poverty can be measured on a number of different levels, the current study utilizes poverty as defined by the United States Census Bureau, which determines poverty status among Americans based on income. The Census Bureau has established 48 different income thresholds that compare a family's total income to the number of family members present in the household (Table 1). If a family's total income does not meet the income bracket for the specified size of the family, then all members within that household are counted as living in poverty. These thresholds are adjusted every ten years to account for inflation with the Consumer Price Index (Bishaw and Iceland 2003). While this measure is the most common index used in studies on U.S. poverty, it has been highly criticized for several reasons. The conflicting nature of the Census Bureau's definition is best understood by examining the development of the measure as well as its modern usage.

Table 1. Poverty thresholds (in whole dollars): 1999

Size of family unit	Related children under 18 years								
	None	One	Two	Three	Four	Five	Six	Seven	Eight +
One person (unrelated individual)									
Under 65 years	8,667								
65 years and over	7,990								
Two people									
Householder under 65 years	11,156	11,483							
Householder 65 years and over	10,070	11,440							
Three people	13,032	13,410	13,423						
Four people	17,184	17,465	16,865	16,954					
Five people	20,723	21,024	20,380	19,882	19,578				
Six people	23,835	23,930	23,436	22,964	22,261	21,845			
Seven people	27,425	27,596	27,006	26,595	25,828	24,934	29,953		
Eight people	30,673	30,944	30,387	29,899	29,206	28,327	27,412	27,180	
Nine people or more	36,897	37,076	36,583	36,169	35,489	34,554	33,708	33,499	32,208

Source: U.S. Census Bureau, Current Population Survey (after Bishaw and Iceland 2003).

Economist Mollie Orshansky first calculated the original thresholds in 1963 while she was an employee of the Social Security Administration (Fisher 1992). Using data from the United States Department of Agriculture (USDA), Orshanksy developed the thresholds using figures that were based on a family's ability to purchase food. The adopted thresholds were based on the USDA's least costly food plan, which detailed the minimal amount of money needed to provide a family with a nutritionally adequate diet.

However, these measures were intended to reflect the amount needed only on a short-term basis when a family's funds ran low. As Harrel Rodgers (2006) notes, "…even the Department of Agriculture does not claim that any family could purchase an adequate diet for any significant period with the funds allowed by the economy budget" (20). Yet, the Census Bureau still uses these figures to calculate the poverty thresholds in the United States despite their being antiquated and impractical.

Rodgers (2006) provides additional reasons why these rates have been questioned by researchers. First, the Census Bureau does not calculate thresholds for different parts of the country based on regional costs of living. Second, it does not account for taxes citizens must pay or variations in the cost of health care across the country. Perhaps most telling, the Census Bureau does not report poverty status for the some of the most marginalized citizens including those living in mental hospitals, nursing homes, prisons, college dorms, on military bases, and the homeless. Thus, the estimates produced by the Census Bureau most likely severely underestimate poverty in the United States. Despite these limitations, many researchers still use the Census Bureau's calculations of poverty rates, and therefore it remains the most comparable statistic used for studies of poverty in America (Duval-Diop 2006). As such, I will also employ the Census Bureau's calculations for my research, while also using several recently developed techniques in order to better quantify poverty.

Spatial Distribution of Poverty

Figure 2 illustrates the spatial distribution of poverty among the counties of the United States based on the Census Bureau's 1999 measurements. Distinct pockets of higher than average poverty rates are evident in parts of the southwest, the southeast, the Appalachian region, and in the Mississippi Delta region. Also apparent in this figure is the dense cluster of counties with high poverty rates in the southeast corner of Oklahoma.

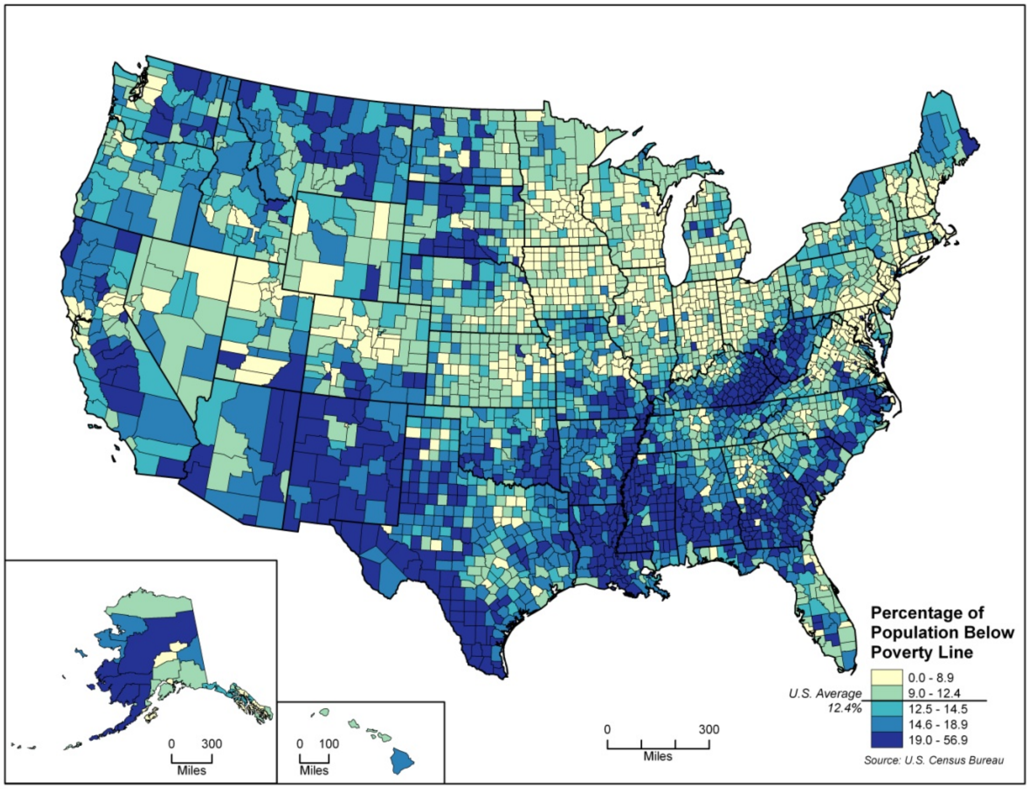


Figure 2. Spatial distribution of poverty among U.S. counties.

Oklahoma is indeed among the poorest states in the country in terms of the percentage of its citizens living below the poverty line. The state currently ranks 42nd in the nation with almost 17 percent of its population living in poverty, well above the national average of just over 12 percent (DeNavas-Walt, Proctor, and Smith 2008). When examined at the county level, poverty rates across Oklahoma vary greatly; however, there are a striking number of exceptionally poor counties clustered in the southern portion of the state, especially in the southeast corner (Figure 3). A greater amount of variation in the distribution of poverty across the state is evident when examined at the Census tract level, as seen in Figure 4. The differences are particularly evident in the two metropolitan areas of the state with higher poverty rates clustering in the northern portion of the Tulsa metro area while in Oklahoma City, poverty is more rampant in the central area, near the city's downtown.

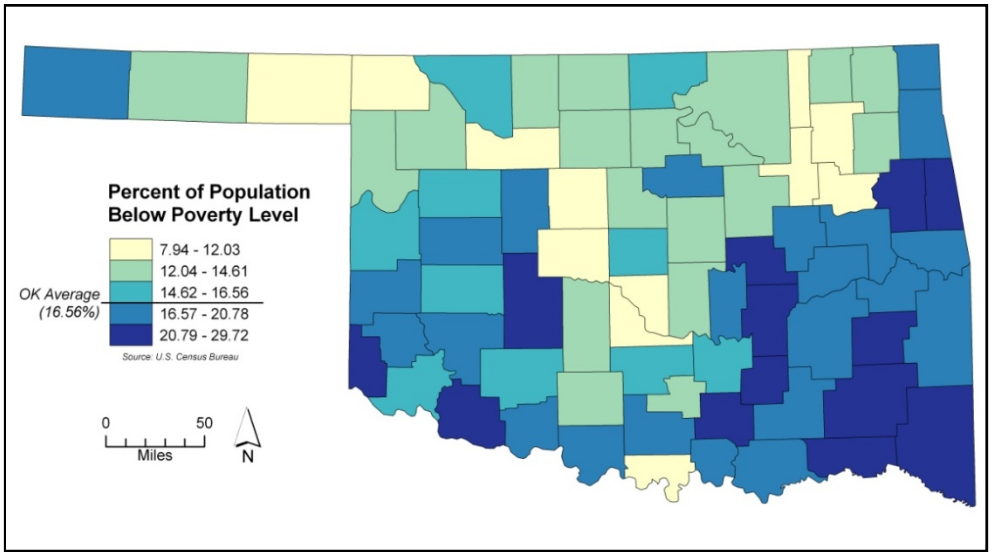


Figure 3. Spatial distribution of poverty among Oklahoma counties.

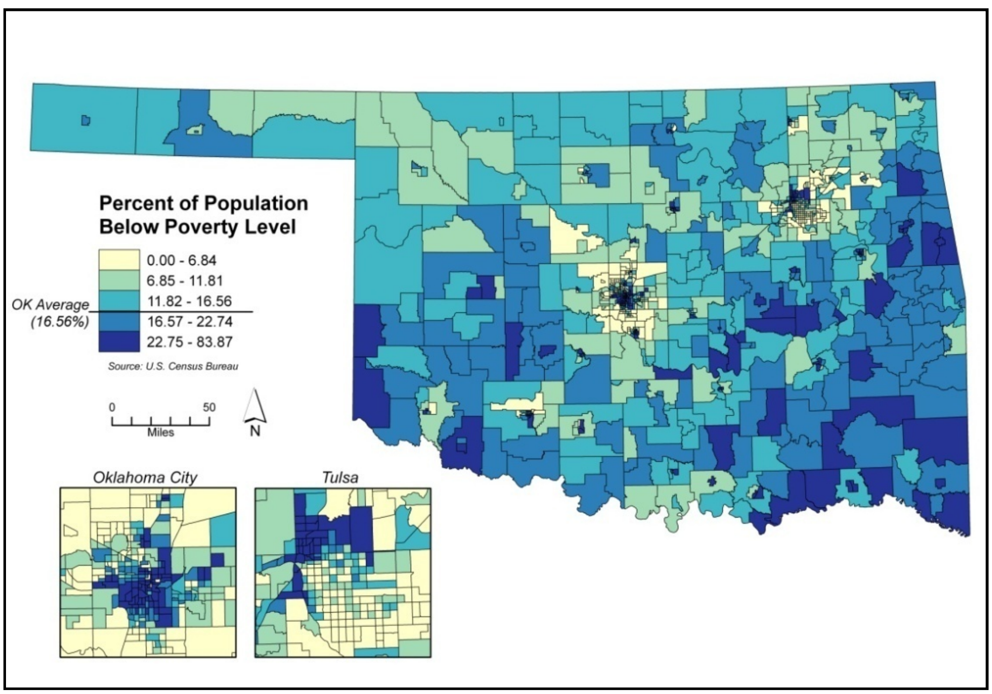
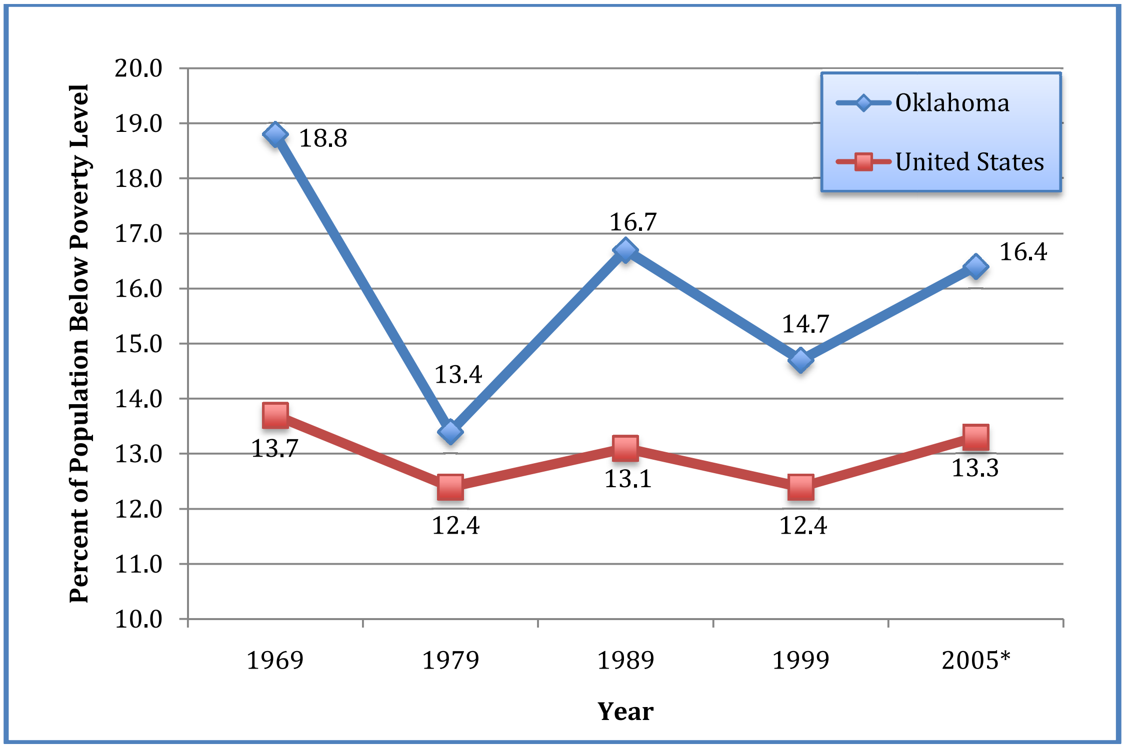


Figure 4. Spatial distribution of poverty among Oklahoma tracts.

Statement of the Problem

Although the study of poverty in the United States has been mainly focused on either general urban poverty (see for example, Sackrey 1973; Jencks and Peterson 1991; Jargowsky 1997), or poverty in rural areas (see for example, Hansen 1970; Tickamyer and Duncan 1990; Duncan and Coles 1999), there has been little written specifically about poverty in Oklahoma. One exception to this could be John Steinbeck's fictional novel, *The Grapes of Wrath*, which details the plight of Tom Joad and his family as they migrate from Oklahoma during the Great Depression in search of a better future in the west (Steinbeck 1939). While this novel is a work of fiction, it does provide a quasi-historical background for the presence of persistent poverty counties in Oklahoma. More importantly, it served as inspiration for sociologist Robert Maril's *Waltzing with the Ghost of Tom Joad: Poverty, Myth, and Low-Wage Labor in Oklahoma* (2000), the one scholarly work on Oklahoma poverty evident in the literature.

Maril (2000) provides a detailed explanation of the status of the poverty rate in the state since 1960 when the Census Bureau began officially measuring poverty. As illustrated in Figure 5, the poverty rate in the United States has been relatively steady since the late 1960s. The poverty rate in Oklahoma, however, has risen and fallen sharply over the last four decades, consistently remaining above the national average. Maril attributes the steep decline in Oklahoma's poverty rate between 1969 and 1979 to the mid-1970s oil boom, which vastly improved the state's economy. He notes that a significant bust in the oil industry followed, contributing to rising poverty rates in the 1980s.



* 2005 data based on U.S. Census Bureau estimates; source: U.S. Census Bureau 2005.

Figure 5. U.S. and Oklahoma poverty rates, 1969 - 2005.

While Maril's work provides an overall understanding of poverty within the state, he does not attempt to analyze the issue from a geographical perspective. In fact, he addresses the spatial distribution of poverty in Oklahoma in just two paragraphs toward the end of the book. He does state, however, that "we need strategies [to combat poverty] that are regional in scope, and we also need strategies that specifically address local problems" (2000, 145). The use of local regression modeling to study poverty in Oklahoma will provide this much-needed attention to these local problems. As no studies have yet been undertaken on the spatial dimensions of poverty in the state of Oklahoma, this current research seeks to add to the relatively sparse literature on the regional variations of poverty in the United States and additionally provide insight into the specific causes for these regional variations within Oklahoma.

Objectives of Study

As noted above, poverty in general is now recognized as a spatial problem. This is certainly true of poverty in Oklahoma where higher than average poverty rates cluster in specific regions of the state. In order to better understand this distribution, the objectives of my study are three-fold:

1. Determine which factors most influence the poverty rates across Oklahoma;
2. Develop a local regression model using geographically weighted regression (GWR) to determine if, and how, the influence of these factors varies across the state at both the county level and the Census tract level;
3. Determine the impact that federal and state funding for various programs has on poverty levels among Oklahoma counties, and determine whether there are programs that could be more beneficial in combating poverty in specific areas of the state.

Significance of Study

In light of the recent economic crisis facing many Americans today, the need to discover what factors might be most affecting the poverty rate in local areas has never been greater. Historically speaking, the United States has dealt with issues of inequality and poverty since its founding. The problems that plagued the country for decades after the Great Depression prompted President Lyndon B. Johnson, in his 1964 State of the Union Address, to declare an official "War on Poverty" (Johnson 1964). Johnson enthusiastically called for action against poverty at state and local levels. It is on these local levels that this current study seeks to make significant gains in understanding poverty within Oklahoma.

Across the United States, the USDA identifies persistent poverty counties as those for which the poverty rate has been greater than 20 percent in each of the past four censuses (Partridge and Rickman 2007). In Oklahoma, the fourteen counties that have the highest current poverty rates have been identified as persistent poverty counties (Figure 6). These counties have been listed in Table 2 in order from the highest current poverty rate to the lowest, along with their poverty rates from the past four censuses and an estimated poverty rate for 2007.

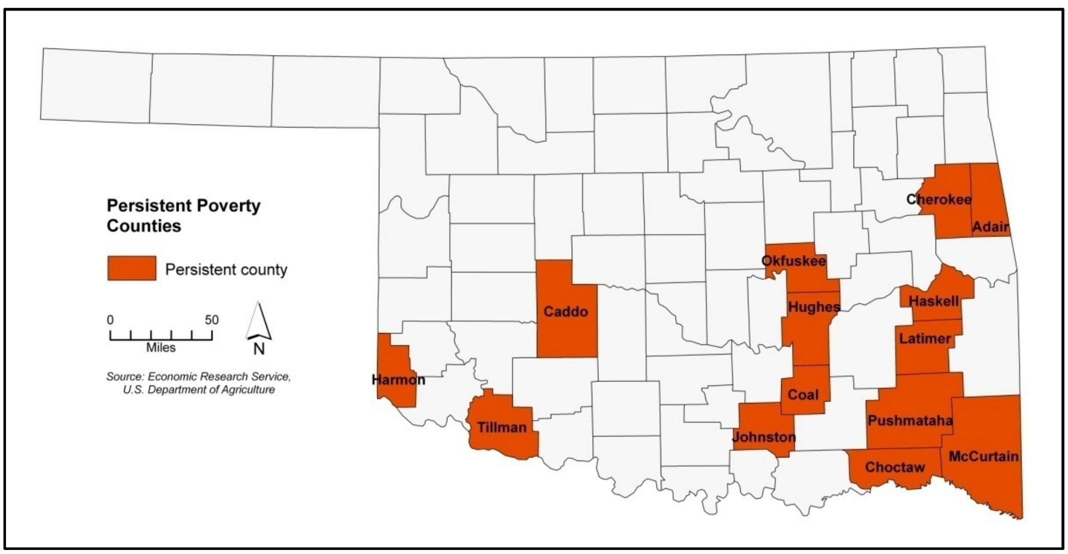


Figure 6. Persistent poverty counties in Oklahoma.

Table 2. Poverty rates in persistent poverty counties, 1959 - 2007.

County	1959[a]	1969[a]	1979[b]	1989[c]	1999[c]	2007[d]
Harmon	35.4	29.4	27.2	34.2	29.7	27.6
McCurtain	39.6	37.2	24.1	30.2	24.7	25.2
Choctaw	61.4	40.0	26.0	32.7	24.3	26.8
Adair	66.1	47.8	27.6	26.7	23.2	25.4
Pushmataha	60.8	45.5	26.7	30.2	23.2	22.4
Coal	52.9	37.3	25.1	27.4	23.1	24.4
Okfuskee	56.4	42.2	24.3	29.4	23.0	21.9
Cherokee	53.9	32.5	22.2	28.8	22.9	31.8
Latimer	54.9	35.5	25.4	23.3	22.7	18.7
Johnston	55.5	37.4	30.6	28.5	22.0	19.9
Hughes	50.2	34.7	24.4	26.9	21.9	25.7
Tillman	42.7	29.3	22.8	22.9	21.9	23.7
Caddo	43.3	27.6	21.6	27.8	21.7	19.6
Haskell	57.6	32.3	20.7	27.1	20.5	16.9

[a] U.S. Census Bureau 1975.
[b] U.S. Census Bureau 1983.
[c] USDA 2002.
[d] USDA 2008.

Examining these figures, the question becomes, if these counties have been in persistent poverty for the past forty years, why have government assistance programs thus far been ineffective at helping to alleviate poverty in these areas? The answer may well revolve around the types of assistance programs that have been implemented in these counties. With a clearer indication of which factors most affect the poverty rate in particular areas of the state, more programs could be offered that target the problems specific to these counties. These targeted programs may be the key to effective poverty relief throughout the entire state.

CHAPTER II

REVIEW OF LITERATURE

Introduction

To begin to understand the geographies of poverty in Oklahoma, I plan to isolate some of the underlying factors that perpetuate poverty in the state. Therefore, this review will focus on literature pertaining to the suspected causes of poverty, and the recently developed means for analyzing these causes. The first section of the review provides the background and theoretical framework for the study of poverty. Then, I address the methods for analyzing poverty, with an emphasis on recent techniques such as poverty mapping, geographic targeting, and geospatial statistics, such as spatial regression modeling. This last section places my study of poverty in Oklahoma within the broader context of recent analyses, and explores ways that my study can expand on these current methods.

Theoretical Approaches to Poverty

Despite decades of research on the subject by sociologists, anthropologists, economists, and more recently, geographers, poverty is still not easily understood. In order to comprehend why poverty is such a complex phenomenon, it is helpful to examine historical and current theoretical approaches to its study, particularly with regard to the suspected causes of poverty.

In the late 19th and early 20th centuries, many scholars believed that the primary causes of poverty included idleness, alcoholism, immorality, and reckless spending, characteristics which were often viewed as being within the individual's control (Dendy 1891). Elevating oneself out of poverty was merely a matter of having the desire and the will to do so. Only a few external causes, such as extreme illness or accidental injury, were recognized as possible reasons for a person's status among the poor. That said, some early researchers, like Lilian Brandt (1908) recognized the importance of not only identifying supposed causes of poverty, but also focusing on why certain factors are common. As she states, "knowledge of causes is indispensable to good work…whether in helping an individual or in improving social conditions" (1908, 646). Although the causality to which Brandt refers is difficult to predict, there are several modern quantitative techniques that allow the underlying factors contributing to poverty to be more readily studied.

In the 1950s, causality of poverty was attributed to cultural characteristics. Oscar Lewis, for example, proposes that those living in poverty could be likened to a true subculture within society, and that in order to understand poverty, this "culture" must be studied in relation to the individual member, the family, and the community, as well as the connection between the culture and the remainder of society (Coward, Feagin, and Williams 1974). Lewis's theory received critical attention, mostly from sociologists claiming a lack of empirical evidence that the shared traits of poverty exist among the poor; in fact, several analyses undertaken by sociologists found that vast differences do indeed exist among poor populations, thereby nullifying the entire concept of a poverty culture (Irelan, Moles, and O'Shea 1969). This theory was also condemned as a causal assumption, implying that the poor were responsible for their own circumstances (Roach and Gursslin 1967). However, in more recent years, the theory has also had many proponents, including Harvey and Reed (1996), who argue that by understanding the "culture of poverty" premise as true Marxist ideology, as was originally intended by Lewis, it could provide a solid framework for understanding the root causes of persistent poverty.

The Marxist ideology to which Harvey and Reed (1996) refer provides a strong basis for studies of inequality worldwide, especially within countries with capitalist economies, such as the United States. Karl Marx's theory on inequality states that not only is inequality unavoidable in capitalist societies, it is intrinsically produced and maintained through the mechanization of production and the system of wage labor present among the working class (Peet 1975). This in turn creates segments of the population in which poverty is rampant, but inevitable. Marxist ideology cannot only be applied to capitalist economies, but more recently it has been discussed in relation to developing countries increasingly subjected to market economies via globalization (Holton 2000; Lee and Smith 2004; Perrons 2004). Marxist ideology, therefore, provides a strong framework for many theories behind the causes of poverty worldwide, but particularly in the United States.

For example, Richard Peet (1975) combines a Marxist theory on poverty and inequality with a geographic perspective by examining the role of the natural environment on the persistence of poverty in certain areas. Peet states, "central to the idea of a geography of inequality is the realization that a person may only exploit the social resources of a limited section of space in order to ready himself for the labor market" (1975, 568). He asserts that similar to the Marxist philosophy of a hierarchy of social classes, there are also "…differentiated social resource environments in which each class reproduces itself" (1975, 569). Inherent in his argument is the idea that poverty persists in specific areas because that way of life is passed down from generation to generation. In this regard, Peet echoes the highly criticized theory of a "culture of poverty" that had been introduced by Oscar Lewis over a decade earlier.

Following on the heels of Richard Peet's work, the 1980s brought a renewed interest in Americans' perceptions of poverty, and especially its causes, throughout the country. Examining the factors that Americans perceived were responsible for poverty, sociologists discovered that given the choice between individualistic causes, in which people are considered responsible for their own economic status, and structural causes, whereby people are living in poverty due to forces they cannot control, Americans largely perceived poverty as the fault of the individual (Nilson 1981; Smith and Stone 1989; Wilson 1996). This is supported by the public's notion that poor people make the choice to remain in poverty because of the attractiveness of generous government funded welfare programs, an idea referred to as "new structural poverty" (Sanders 1991). Jimy Sanders (1991) shows that government welfare programs have not directly encouraged people to remain in poverty, but notes that, with a lack of empirical studies to definitively prove this, public perception of these programs continues to hold.

Though geographers have only recently joined the discussions concerning poverty, they have contributed by exploring poverty's spatial dimension. Geographers realize the importance of focusing not only on individuals, households, or even a "culture" of poverty, but also on the significance of understanding spatial factors at national, state, and community levels where poverty is widespread and persistent. A thorough understanding of these smaller areas of analysis, especially the underlying factors that influence the lives of the residents within them, is of vital importance if we are to propose and implement solutions to these societal problems (Johnson 2002).

Recognizing the importance of studying social issues at a regional scale, Peet (1972) expresses bewilderment at the lack of geographical inquiry into social problems. Peet states that these issues are indeed worthy of geographic study because "…the analysis of social problems fits both the spatial tradition and that of studying relationships between man and environment…" (1972, 5). Wendy Shaw (1996) contends that while studies of poverty have been prevalent in the more recent geographic literature, geographers in general have been hesitant to assign causality to poverty, choosing instead to focus their attentions on the mere spatial distributions of poverty across the country. She asserts that the main reason for this may be related to the complex set of conflicting theories surrounding the causes of poverty. Peet (1972) himself does not offer definitive causal reasons for poverty but only reiterates two main categories, in which either the individual or the environment is at fault.

According to Wendy Shaw (1996), fault is the basis for the categorization of both historical and current theories. Shaw, who extensively culls the literature in order to gather various theoretical approaches to poverty, assigns causes of poverty theories into five broad categories based on the perceived responsible party. There are: 1) no fault theories, in which general poor economic health or environmental causes are to blame, 2) individual/group responsibility theories, whereby human flaws are considered the culprits for an individual's poor status, 3) societal responsibility theories, which includes cultural discrimination toward specific groups of people, such as minorities, women, and the aged, 4) government/institutional responsibility theories, which include criticisms of the government welfare system, and 5) theories in which the responsible party is the economic system, including capitalism itself.

Using an historical perspective, Hernando de Soto (2000) provides a current analysis of the problem of poverty with regard to the presence, or more importantly the absence, of true capital, namely in the form of formal property. In his interpretation, the lack of legalized property rights in developing countries has kept them from competing in the global economy because without ownership of property, there is no way for citizens to generate any real capital for themselves. He states, "so long as the assets of the majority are not properly documented and tracked by a property bureaucracy, they are invisible and sterile in the marketplace" (2000, 211). Using the history of the United States as a case study, de Soto argues that the system of legalizing property rights developed in the U.S. allowed this country to advance to be the leading capitalist economy that it is today and that developing countries should follow suit if they are to better provide for their citizens.

Janet Kodras (1997) also acknowledges the importance of having a geographical, as well as an historical, perspective on poverty. She begins her analysis with the realization that since the Reagan era, the conservative political climate in the United States has strengthened the idea that poverty is the fault of the individual. Drawing on Marxist philosophies concerning the growth of capitalism, Kodras emphasizes that the recent economic transformation in the United States has only served to intensify poverty across the country. She notes, however, that this intensification has occurred in very specific geographic regions (for example in the Mississippi Delta region, the Dakota badlands, and parts of the Midwest) where the effects of the changing economy have been felt deeper than in other areas of the country. She succinctly summarizes, "…poverty is geographically produced, as changes in the market and the state emanating from national and global levels are differentially translated into the social order of particular locales, generating distinctive prospects for affluence or impoverishment" (1997, 70). This is certainly the case in Oklahoma, where poverty has not affected the counties in the same way throughout the state.

Attempting to understand poverty from a resource perspective, Charles Harper (2008) notes that followers of the late 18th century theorist Thomas Malthus would argue that population growth worldwide is the leading cause for the rise of poverty. Malthus considered that exponential population growth would cause severe shortages of the resources available to those populations, which would ultimately result in rampant disease and famine across the globe. Resurgence in these ideas has led many neo-Malthusians to posit that not only will population growth lead to worldwide poverty, but will also bring about severe environmental degradation as a result of the overuse of resources, which will in turn serve to perpetuate poverty. Converse to the neo-Malthusian argument, Harper (2008) points out the many theories praising population growth as a mechanism for technological innovation and improved world markets that may actually help to improve poverty on a global scale.

As shown in this discussion of the various theories concerning the causes of poverty, no single dominant theory guides researchers who are attempting to understand the exact reasons underlying poverty. What is clear, however, is that the way in which social scientists approach poverty from the onset will shape not only the understanding of the problem, but the interpretation of the possible solutions as well (Yapa 1996). Because poverty is a human condition, even approaching the data from a purely quantitative perspective must be done with caution. However, with the numerous quantitative techniques, in combination with advances in GIS technologies, more definitive approaches to understanding the root causes of poverty can be attempted. This research must be guided by first defining an accurate measure of poverty, as discussed in the previous chapter, which has proven to be a difficult task for researchers worldwide. Despite this problem, many recently developed techniques have enhanced the study of poverty throughout the world.

Recent Techniques for Studying Poverty

Poverty mapping and geographic targeting

A relatively new technique that is being applied to the study of poverty is poverty mapping. Poverty mapping uses GIS to map poverty rates across a geographic region. These maps are then used to visually identify specific areas within the region where poverty rates are higher than in the surrounding areas. As Hentschel et al. (2000) explain, “a poverty map is essentially a geographic profile of poverty...,” which can be used to locate areas in greater need of antipoverty policies and programs (161). For example, the mapped poverty rates among Oklahoma counties reveal a greater concentration of high poverty levels in the southern and southeastern portion of the state (Figure 2). Therefore, these areas are in need of stronger antipoverty programs. Thus far, this technique of poverty mapping has only been widely applied to poverty-stricken areas of the developing world, but it could prove to be effective at combating poverty in parts of the United States as well, as my current study hopes to illustrate.

Bedi, Coudouel, and Simler (2007) offer several reasons why poverty mapping has become a useful tool in the struggle to alleviate poverty. For instance, since these maps offer a visual reference, they can be easily read and interpreted by most people, from researchers and policy makers to the lay public. A temporal aspect can also be applied to study the rate of poverty change in an area over time. More importantly, these maps provide a means for analyzing the effectiveness of current antipoverty programs across an area, as well as addressing areas where stronger policies are warranted in order to further alleviate poverty. In the current literature, this focus is known as geographic targeting, and has been widely employed across the globe.

The most common type of methodology applied in poverty mapping and geographic targeting in the developing world is known as small area estimation. For this approach, variables common between both the country census and household surveys are used to approximate a model of consumption for the households of particular regions. Income levels for the region are then extrapolated from the model, again using data from the countrywide census, and these levels are used to estimate poverty levels at subnational and subregional divisions (Hentschel et al. 2000). This technique has been applied to studies in various parts of the world including Ecuador (Hentschel et al. 2000; Araujo 2007), Bolivia (Arias and Robles 2007), Bulgaria (Gotcheva 2007), Cambodia

(Fujii 2007), and Indonesia (Ahmad and Goh 2007), among others. While its usefulness is apparent at the onset, several issues with its application must also be addressed.

First, the maps themselves are subject to the limitations of the data used to gather information about poverty levels within an area (Bedi, Coudouel, and Simler 2007). In some developing countries, poverty figures can be difficult to accurately determine, and even in the case of the United States, we have already seen how the Census Bureau's calculation of poverty, which is the most frequently used figure for research, is skewed. Second, because the purpose of poverty maps is to illustrate variations in poverty rates across a region, the data must often be disaggregated in order to represent subnational and subregional areas. Cole (1981) emphasizes why this is the case when he notes that potential problems exist when data on poverty are aggregated on a worldwide, or even countrywide scale, since "…as aggregation proceeds, regional disparities appear to diminish" (1981, 68). Therefore, the focus must be on local levels of analysis rather than on global ones.[1] Several researchers have noted that this is indeed a problem that must be dealt with, and various means of disaggregating global data have been applied (Bigman and Fofack 2000; Fofack 2000; Hentchel et al. 2000). While the methods of disaggregation for geographic targeting have been questioned, Elbers et al. (2004) find that disaggregating data to the local level does indeed offer potentially more beneficial ways of identifying areas that are in greater need of antipoverty policies. One advantage of using the Census Bureau's figures in studies of poverty in the United States is that

[1] It should be noted that in geospatial statistics, "global" refers to aggregated data covering an entire study area, while "local" refers to the disaggregated data that is used to calculate the global value (Fotheringham, Brunsdon, and Charlton 2002). For example, the overall poverty rate for the state of Oklahoma is a global measure, while the poverty rate of each specific county within the state is a local measure.

these data are readily available at the state, county, tract, and block group level, so that smaller units of analysis can be easily examined.

A third important limitation of poverty mapping that Bedi, Coudouel, and Simler (2007) discuss is the critical idea that the spatial distributions illustrated on poverty maps can only be interpreted as general correlations between poverty and other mapped characteristics, such as geographic and socioeconomic factors, and should not be used to imply any type of causal relationship. The authors note that in order for these true relationships to be understood, additional studies, such as those using geospatial statistics, are needed. Building on this notion, I combine poverty mapping with statistical measures of local variability across Oklahoma. This method will provide a valid measure of some of the causal linkages between poverty and the underlying factors that affect it.

With these limitations in mind, it is important to understand why poverty mapping and geographic targeting have been so widely used within the last decade, and why they have become such valuable techniques in the fight against poverty. As Partridge and Rickman (2006) explain, there is currently a great deal of debate about whether or not government antipoverty programs are more effective when targeted towards poor populations in general, or instead whether these programs should be supplemented by policies which target the places where poverty rates are high. The authors detail the debates for and against these place-based policies, but through a thorough investigation of the spatial distribution of poverty among United States counties they conclude, "given the spatial dimensions of poverty, we cannot imagine an effective poverty-reduction program that does not aggressively address the place-based barriers that underlie the severe pockets of poverty" (Partridge and Rickman 2006, 272). By examining the implications that local effects, such as the natural environment and local economic structures, as well as the demographic characteristics of local populations, can have on the poverty and policies of specific places, Rebecca Blank (2005) also provides a persuasive argument on why place-based policies are necessary. However, in order to identify where and how these supplemental policies should be implemented to be the most effective, it is essential to have analytical models that will detect variation at the local level.

Geospatial statistics, global, and local regression modeling

With the development of more local measures of spatial variability (see Anselin 1995; Fotheringham, Brunsdon, and Charlton 2000, 2002), much of the recent literature on the geographic analysis of social issues focuses on the need to study poverty at a local level rather than via global means, which can be limiting. For example, global models can be useful for examining the pattern of an occurrence across an entire study area, but there may be pockets of variability *within* the study area that will not be expressed when studied globally. For these pockets of variability to be identified, local models are crucial (Anselin 1995; Fotheringham, Brunsdon, and Charlton 2000, 2002). While some researchers have not yet begun to employ these local spatial measures, many at least acknowledge their usefulness and necessity to truly understanding variability across a region (Petrucci, Salvati, and Seghieri 2003; Partridge and Rickman 2006; Holt 2007). The most recent studies on poverty have begun to utilize local techniques, such as geographically weighted regression (GWR), in order to analyze the underlying causes of poverty across regions (Duval-Diop 2006; Minot, Baulch, and Epprecht 2006; Partridge and Rickman 2007).[2] As these studies will be particularly useful in my research, which uses GWR in order to understand the spatial distribution and concomitant indicators of poverty across Oklahoma, I review the most recent literature utilizing these techniques below.

Petrucci, Salvati, and Seghieri (2003) begin their analysis of poverty in Ecuador with a discussion on the importance of poverty maps, but state that these maps should be used in combination with statistical methods in order to reveal "…the causal linkages between poverty and the variables that influence it" (2003, 1). Their main focus is therefore the development of a global regression model using data gathered from the World Bank and the Ecuadorian Census in order to understand the main causal factors of poverty across Ecuador. The results of their analysis show that both socioeconomic factors, as well as environmental factors, can be the root cause of poverty across the country.

The variable having the strongest influence on poverty in Ecuador is adult literacy rates, which the authors equate to education and the presence or absence of a diploma (Petrucci, Salvati, and Seghieri 2003). When examined with a global regression model, where no internal variation is measurable among the counties, I found that the lack of a high school diploma is also among the most common indicators of poverty among Oklahomans. Petrucci, Salvati, and Seghieri do recognize the need for a more localized model, but do not attempt to analyze the data in such a way. They state that, "it would be

[2] Geographically weighted regression (GWR) is the name of the technique as well as the title of a computer program developed by Fotheringham, Brunsdon, and Charlton (2000, 2002) that is used to measure and map local variations of phenomena across regions. It builds upon global regression techniques, but allows users to explore data at the local level by analyzing the effects that neighboring areas have on one another. GWR will be discussed in detail in the methodology section.

useful to develop poverty maps by conducting the statistical analysis at a degree of disaggregation below broad regions; otherwise it is assumed implicitly that, within a region, the model of consumption is the same for all households irrespective of which province, county, or community they reside in" (Petrucci, Salvati, and Seghieri 2003, 23). This study would certainly have benefited from the use of a local regression model, which might have highlighted the relative importance of different factors, such as education, housing characteristics, and land use, at more local levels (e.g., county or province level) across the country.

James Holt (2007) builds on the work of Petrucci, Salvati, and Seghieri, but goes one step beyond their study in his analysis of the spatial distribution of poverty across the United States. Holt recognizes that in addition to global modeling, measuring for spatial autocorrelation across regions can also yield significant results.[3] Like Petrucci, Salvati, and Seghieri, Holt recognizes that visual inspection of mapped variables, such as the poverty rate across the counties of the United States, does not allow for a true spatial interpretation of the distribution. He contends that statistical measures, combined with visualization techniques, should be applied in order to gain a valid geographical interpretation of the mapped variable (2007). Holt argues that measures of spatial autocorrelation can be one effective way of highlighting distinct clusters of poverty within the United States, but he also acknowledges that rather than relying solely on the global measure of spatial autocorrelation, a local form of the statistic, such as local Moran's *I*, provides a much more valuable geographic understanding of poverty, since it

[3] Spatial autocorrelation (SAC) refers to the degree of spatial dependence present in a dataset. In other words, are the values like each other and if so, is it because they are in close proximity? The most common means of measuring SAC is the use of the Moran's *I* statistic, for which there is a global and a local variant (Anselin 1995). SAC will be discussed in detail in the methodology section.

is these measures that highlight local variations of poverty clusters across the country (Holt 2007).

In order to create a map of high poverty and low poverty clusters across the United States, Holt (2007) uses county-level data from the Community Health Status Indicators database. He applies a measure of the local indicator of spatial association (LISA) statistic and combines these results (the z scores of the local Moran's I) with the poverty rate for each county. With clear positive spatial autocorrelation present, he demonstrates that the distribution of higher poverty rates is concentrated in the southern part of the country, just as the distribution of lower poverty rates is clustered in the northern part of the country; in order to describe this dichotomous relationship, Holt coins the term "continental poverty divide" (2007, 5). An important observation is that Oklahoma lies on the high poverty side of Holt's "continental poverty divide" (Figure 7).

Holt (2007) argues that the methods he applies have important implications, including aiding in the study of the potential underlying causes of the distributions of poverty that he has shown. However, as his article is merely the demonstration of a useful technique, Holt makes no attempt to quantify or discuss these possible underlying forces as they pertain to poverty in the United States. He does state the need for caution when examining causes using standard global techniques, as the presence of spatial autocorrelation violates the basic assumptions of global regression models. Holt argues that local regression models, such as GWR, are necessary in order to properly capture the local variations responsible for high poverty rates in specific parts of the country.

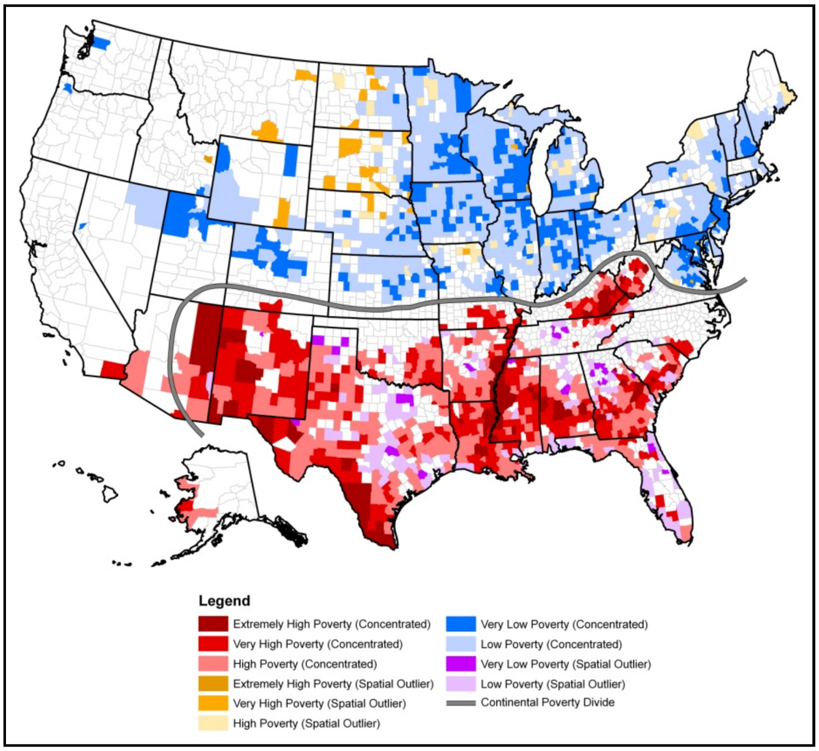


Figure 7. Poverty rates among U.S. counties showing continental poverty divide (reproduced from Holt 2007, 5 [Fig. 5])

Minot, Baulch, and Epprecht's (2006) analysis of poverty in Vietnam makes good use of a local regression model. The authors explain that the Vietnamese government currently employs geographic targeting to combat poverty in certain areas of the country. They emphasize that localized analyses may help "…to improve the targeting of these programs by adopting more precise estimates of poverty at the district and commune level…" (Minot, Baulch, and Epprecht 2006, ix). Thus, the main objectives of their study include examining the spatial distribution of poverty at local levels across the country, analyzing the relationship of various geographic determinants and poverty in both rural and urban areas, and using these results to make recommendations for area-specific antipoverty programs in Vietnam.

The authors list several geographic factors that may be helpful in determining the spatial distribution of poverty across Vietnam, including variations in elevation, soil type and land cover, slope of the land, distance to cities, and rainfall amounts. Analyzing these geographic variables using both a global model as well as a local model (GWR), Minot, Baulch, and Epprecht discover that the predictive power of the variables is indeed strengthened by use of the local model. Application of the global regression model results in 74 percent explanatory power of the chosen geographic determinants. Under the local model, however, the overall explanatory power is increased to 95 percent (R^2 ranges from 0.83 to 0.99 across the country) (Minot, Baulch, and Epprecht 2006). These results lead the authors to suggest areas in Vietnam where the government might intensify their current antipoverty programs in the hopes of further alleviating poverty in these areas. While this particular study is significant in illustrating the power and usefulness of local regression models in analyzing poverty, it is somewhat lacking in its analysis in that the authors use only geographic determinants to predict poverty and do not examine socioeconomic factors that may also be contributing to the variability of poverty rates across the country.

Dominique Duval-Diop's (2006) dissertation focuses on an analysis of poverty in the Mississippi Delta region of the United States, and also utilizes GWR in order to analyze not just the poverty levels across the region, but also the effectiveness of government poverty reduction programs in the region. Duval-Diop acknowledges that the Mississippi Delta is among the poorest areas of the United States and has recently been targeted by policymakers in the hopes of improving the impoverished status of this region's residents (Duval-Diop 2006). Her study builds upon the work of Bigman and

Fofack (2000), who state that geographic disparities in poverty can exist because regional differences in government spending perpetuate high poverty rates in certain areas.

This leads to the main research questions posed by Duval-Diop (2006) concerning the regional impacts that government funded antipoverty programs have had in the Mississippi Delta region, as well as understanding the underlying causes influencing poverty in the Delta region. In her regression models, she includes variables relating to educational attainment, demographics, and employment and income statistics, in addition to the variables relating to federal spending. She concludes that antipoverty programs are not applied evenly throughout the area, and she also finds the causal predictors of poverty are not distributed equally across the Delta region. In addition, Duval-Diop shows that the local model provides better explanatory power than the global model, especially in the central part of the Delta region. Most importantly, however, is her conclusion that the local models are more powerful overall and thus, "local results that differ substantially from the averages represented by the global regression models strengthen the case for policies and programs that are more sensitive to local differences" (2006, 104). This inference lends further validation to the use of local regression modeling over global modeling to establish effective place-based antipoverty policies.

As Duval-Diop was among the first to employ these local models to the study of poverty in the United States, Partridge and Rickman (2007) are justified to comment on the "…surprisingly little research on whether there is a role for place-based economic development policy in persistent pockets of American poverty" (202). Partridge and Rickman, further examining the possible implications of place-based policies, focus their study on counties in the United States where the poverty rate has been greater than 20 percent over the past three decades. These are the so-called "persistent pockets" of poverty. The authors contend that the use of local regression models is essential in capturing the variations in the underlying causes of poverty across a region, so that these factors might be appropriately addressed with specific policies and programs. Partridge and Rickman use the results of their study to conclude that place-based policies, in addition to policies that target specific groups of people, are indeed necessary to implement the most effective programs aimed at alleviating poverty.

Conclusion

As noted in this chapter, a relative paucity of current literature exists focusing on poverty in America specifically aimed at studying local variations among causal factors. These types of studies are needed in order to better target areas for poverty reform. By examining poverty among Oklahoma's counties using local regression modeling, including GWR, I hope to discover how local variations in socioeconomic factors, as well as geographic ones across the state, are contributing to high poverty rates in certain areas. Not only will this provide background for possible policy reform measures in the state, but it will also add to the current literature and expand the general knowledge of this underutilized technique.

The following chapter reviews the specific methodology that I will employ in this research, including an explanation of the variables and data sources that I will examine. I will also discuss the various geospatial statistical techniques that I will utilize, such as exploratory spatial data analysis and geographically weighted regression.

CHAPTER III

DATA AND METHODOLOGY

Variables and Data Sources

The variables used in this study are listed below in Table 3. Data for the variables were obtained from the United States Census Bureau's American Fact Finder website (www.factfinder.census.gov), from the Census Bureau's Consolidated Federal Funds Report, and from the Oklahoma Department of Human Services (OKDHS) website (www.okdhs.org). In order to satisfy the objectives for this study, data were gathered at both the county and census tract levels.

The dependent variable is the percentage of the total population living below the official poverty threshold as calculated by the United States Census Bureau in 1999. This is the latest year for which this figure was officially calculated. Although the Census Bureau has provided estimates of poverty rates for more recent years, these estimates can be somewhat unreliable and therefore the 1999 data are used for all calculations in this study. For the purposes of this research, the total number of people living below the poverty line is divided by the number of people for whom poverty is measured to obtain the percentage of people within each county/tract living in poverty. It should be noted that while the Census Bureau's measurement of poverty is flawed, as was discussed

Table 3. Variables: sources and descriptions

Variable	Description
Dependent Variable – Census 2000, Summary File 3	
Poverty (POV)	% of the population living below the poverty line in 1999
Independent Variables	
Education – Census 2000, Summary File 3	
NO_HS	% of the population 25+ years of age with no high school diploma
Ethnicity – Census 2000, Summary File 1	
AM_IND	% of the population who are American Indian
MINOR	% of the population who are of other minority groups[a]
HISP	% of the population who are Hispanic[b]
Age – Census 2000, Summary File 1	
MED_AGE	Median age
ELDER	% of the population 65+ years of age
Family Structure – Census 2000, Summary File 3	
FAM_SIZE	Average family size
FEM_HH	% of households headed by a single female
Income – Census 2000, Summary File 3	
PCI	Per capita income
Employment – Census 2000, Summary File 3	
UNEMPL	% of population 16+ years of age in the labor force who are unemployed
PRIM	% of population employed in primary industries[c]
SECOND	% of population employed in secondary industries[d]
TERT	% of population employed in tertiary industries[e]
QUAT	% of population employed in quaternary industries[f]
County/Tract Characteristics – Census 2000, Summary Files 1 (RURAL) and 3 (STABLE)	
STABLE	% of population 5+ years of age living in the same county for the past five years
RURAL	% of the population living in rural areas
Federal and State Expenditures – Census 2000, Consolidated Federal Funds Report[g] and OKDHS	
FED_AFS	Per capita federal agricultural and natural resources expenditures
FED_CRS	Per capita federal community resources expenditures
FED_HRS	Per capita federal human resources expenditures
FED_ISS	Per capita federal income security expenditures
FED_TOTS	Per capita total federal expenditures
DHS_FS	Per capita state expenditures for food stamps program
DHS_SUP	Per capita state expenditures for supplemental programs
DHS_TANF	Per capita state expenditures for TANF program
DHS_TOTS	Per capita total state expenditures

[a] Other minorities include Black/African American, Asian, Native Hawaiian/Pacific Islander, and other categories of "one race alone."
[b] The Census Bureau identifies "Hispanic" as an indication of cultural origins, which includes heritage, lineage, or country of birth.
[c] Primary industries include agriculture, forestry, fishing/hunting, and mining.
[d] Secondary industries include manufacturing and construction.
[e] Tertiary industries include service industries, transportation, communication, entertainment, healthcare and law.
[f] Quaternary industries include government, education, and professional occupations.
[g] Data gathered from USDA 2005.

earlier, and may under-represent actual poverty levels, it is the most commonly used figure for studies on poverty in the United States. It is also the figure that is used by policymakers to target poverty across the country (Duval-Diop 2006) and therefore is used in this study.

The independent variables can be roughly divided into four broad categories covering various demographic factors, employment, and county/tract characteristics, as well as federal expenditures per capita for various programs. It should be noted that the data for federal and state funded programs are only available at the county level. The variables concerning the population structure deal with education, ethnicity[4], age, family structure, and income. The spatial distribution of each variable at both the county and tract level is shown in Appendix A. The conceptual model for the study is given by the following equation:

$$\text{POV} = f(\text{DEM, EMPLOY, CTY/TR, FUND})$$

where POV is the poverty rate in 1999, DEM are the variables dealing with demographic factors, EMPLOY are the employment variables, CTY/TR corresponds to the variables concerning county/tract characteristics, and FUND represents the variables related to federal and state expenditures.

The education variable reflects the growing problem of high school dropouts across the United States, and is included here to ascertain whether higher levels of education result in better paying jobs and therefore lower poverty rates. With a total of 19.4 percent of the population not receiving a high school diploma, Oklahoma currently ranks 34th in the nation with respect to the percentage of people who do not have a high

[4] While the Census Bureau still maintains the category "race," the term "ethnicity" will be used here, as race is no longer believed to be a suitable classification (see Mitchell 2000).

school diploma or equivalent. Alaska is the state with the best high school completion rate with only 11.7 percent of its population not receiving a high school diploma. Mississippi is ranked 50th with just over 27 percent of its population not finishing high school.

With regard to ethnicity, Oklahoma is home to a diverse population including several large minority groups, such as Native Americans and Hispanics, for which poverty levels have typically been higher. Oklahoma has the fourth largest Native American population per capita in the nation, behind Alaska, New Mexico, and South Dakota. The state ranks 23rd in the nation with respect to the percentage of its population with Hispanic heritage. These groups also tend to inhabit specific parts of the state creating distinct spatial patterns in the distribution of these peoples.

The variables concerning age and family structure have been included since many government assistance programs specifically target families, children, and older adults. For example, the Oklahoma Department of Human Services (OKDHS) offers programs including child and adult protective services, transportation programs for older and/or disabled citizens, and the Temporary Assistance for Needy Families (TANF) program, among others.

Income is included as a measure of the overall wealth of each county/tract. Similarly, the employment variables are included as a measure of the general economic health and dependence of each area. As of the 2000 Census, the unemployment rate in Oklahoma was 3.3 percent, placing it 17th in the nation. While the current unemployment rate within the state has nearly doubled to 6.2 percent, its overall ranking within the U.S. has improved, now having the 9th lowest unemployment rate in the country (BLS 2009).

Within the nation, North Dakota currently has the lowest unemployment rate of 4.0 percent, while Michigan is ranked 50th with an unemployment rate of 12.9 percent. The variables concerning employment within the different industries throughout the state are included in order to assess how the economic dependence of each area affects the poverty rate across the state.

County/tract characteristics are included as a measure of the overall stability of each county, as well as evaluating rurality against poverty. Within the state, there are only two major metropolitan areas and a small number of moderately sized towns, leaving many of the state's residents living in areas considered to be rural. The percentage of the population within each county that has resided in the same county for at least five years is a reflection of the general stability of that county's population (Partridge and Rickman 2007).

Finally, data on federal spending for various programs is included to determine the overall effectiveness of such programs on poverty levels throughout the state. Duval-Diop (2006) utilizes similar federal spending variables in her research on poverty in the Mississippi Delta region. In order to make this data comparable between counties, it is calculated as per capita expenditures by county. Since these data are only available at the county level, these variables will only be used in county level modeling to determine the influence of these programs on poverty within the state and satisfy the third objective of this study.

For the variables concerning federal expenditures, the Census Bureau's Consolidated Federal Funds Report from 2000 supplies county level data on each program administered by the various federal agencies. Because of the immense number of programs offered, in order to facilitate data analysis, the USDA's Economic Research Service (ERS) has developed six general functional classes into which the various programs fall. These programs are aggregated into the following categories: 1) agricultural and natural resource spending, which includes money for research, land management, and recreational resources, 2) community resources spending for community and regional development, environmental protection, housing and transportation, and Native American programs, 3) defense and space spending that includes defense contracts as well as salaries and administration of defense programs, 4) human resources spending encompassing programs for elementary and secondary education, food and nutrition, health and social services, training, and employment, 5) income security spending for programs relating to medical and hospital benefits, public assistance, unemployment compensation, retirement, disability, and survivors social security payments, and 6) national function spending, including criminal justice, law enforcement and energy, as well as programs funding higher education (USDA 2005). Due to the paucity of federal funds for defense functions or national functions within the state of Oklahoma, these two categories are excluded from this research.[5]

In order to fully satisfy the third objective of this study, data on three specific programs available to Oklahoma residents are analyzed to assess the impact these programs have on poverty. Data for variables relating to these programs are gathered from OKDHS, which provides the data as part of their Monthly Statistical Bulletin available through their website (www.okdhs.org). In order to ensure that the data analyzed here are consistent with the remainder of the variables gathered from the 2000

[5] Only Oklahoma County, home to the state capital, received expenditures for defense funding in 2000. Five counties, including Cherokee, Cleveland, Oklahoma, Payne, and Tulsa counties received funds relating to national functions.

Census, the monthly figures from July of 2001, the earliest available month, are used. These variables measure the influence of the food stamps program, the Temporary Assistance for Needy Families (TANF) program, and also supplemental programs providing funds for the aged, blind, and disabled. The food stamps program, also known as the Supplemental Nutrition Assistance Program, provides funds for low-income households in order to increase overall nutrition and health levels among the population. The TANF program offers cash assistance to families on a temporary basis in order to ensure the basic needs of families are met. The program also provides employment services including training programs, as well as childcare assistance for those in need. In addition to these three specific programs, a variable covering the total per capital expenditures from OKDHS is also analyzed.

It should be noted that this research is conducted at both the county level as well as the census tract level, for several reasons. First, data for both units of analysis are readily available through the Census Bureau's internet data tables. County level statistics on the type and quantity of anti-poverty programs are accessible from the Census Bureau's Consolidated Federal Funds Report as well as through the OKDHS website (www.okdhs.org), and can therefore be easily compared to the results of the regression analysis at the county level. However, preliminary regression modeling at the county level failed to produce a statistically significant local model for poverty across the state. Further preliminary modeling shows that using a smaller unit of analysis, such as census tracts, does produce a significantly improved local model. Additionally, Peters (2009) demonstrates that the use of subcounty units of analysis can indeed highlight poverty-stricken areas that are concealed when county level analysis is employed. It has also been noted that the size and shape of spatial units of analysis can significantly affect the results of a regression analysis (Rogerson 2006). In addition to examining the social phenomenon of poverty, this study seeks to explore the sensitivity of the analysis by using both larger (county) and smaller (tract) areal units.

Methodology

Exploratory Spatial Data Analysis

The vital first step in this research is to perform exploratory spatial data analysis (ESDA) on each variable. This allows for a better understanding of how each variable will function in the regression models discussed later (Rogerson 2006). Choropleth mapping of each variable has been performed at the county and tract level (see Appendix A) in order to visually determine the spatial variation of each variable across the state. Unless otherwise noted, all choropleth maps displayed in this analysis use the quantile method of classification. This method breaks the classes so that an equal number of observations fall within each mapping category.

Another important measure that is utilized in this analysis is spatial autocorrelation (SAC). Griffith (1987) defines autocorrelation as, "...the relationship among values of some variable that is attributable to some underlying ordering of these values" (9). When applied to spatial data, this underlying ordering is the spatial distribution of the data itself. In other words, spatial autocorrelation quantifies the relationship between values depending on their proximity to each other. Positive SAC occurs when "like" values cluster together (either high-to-high values or low-to-low values); negative SAC occurs when the values that are near one another are different.

SAC can be measured at the global scale, where clusters of values in the overall region, such as across the entire state of Oklahoma, are highlighted, and at the local scale, which will highlight local clustering present among the individual counties and tracts in the state. It is important to assess the degree of SAC present because the presence of SAC violates the assumption of independence among observations in a dataset (Rogerson 2006).

One of the most common means of measuring SAC is the use of the Moran's *I* statistic, for which there is a global and a local variant (Anselin 1995). The global Moran's *I* value is given by the following formula:

$$I = \frac{n \sum_i \sum_j w_{ij} \left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\left(\sum_i \sum_j w_{ij}\right) \sum_i \left(x_i - \bar{x}\right)^2}$$

where *n* is the number of observations in the dataset, *i* represents each individual observation, *j* denotes the neighbor of each observation, x_i and x_j are the values of the observations at points *i* and *j*, and w_{ij} represents a weights value, which can be indicative of the distance between neighboring observations (Fotheringham, Brunsdon, and Charlton 2000). For the purposes of this study, rook contiguity was used as a means of determining the weight value between the observations. This means that for each county, all counties surrounding it that share a common edge are considered neighbors and are given a weighting of one in the contiguity matrix. All other counties in the state are assigned a weighting of zero with respect to that particular county.

The Moran's *I* statistic results in a value between -1 and +1, where values close to one display positive SAC meaning the distribution is more clustered. Values falling closer to zero represent a lack of SAC with the distribution being more random. Values approaching negative one signify negative SAC meaning the distribution of the values is more dispersed. However, as stated earlier, the global Moran's *I* value indicates the degree of SAC across the entire study area without considering where local variations within the data might exist. In order to determine this, Anselin (1995) created local indicators of spatial association (LISA), consisting of a variant of the Moran's *I* statistic that results in a unique measure of the degree of SAC for each observation in the dataset. The local Moran's *I* formula is denoted as:

$$I_i = \frac{(x_i - \bar{x})\sum_i w_{ij}(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2 / n}$$

where the notations are the same as in the global formula (Fotheringham, Brunsdon, and Charlton 2000). The local statistic is not scaled between -1 and +1; however, positive values still represent areas of positive SAC, negative values depict areas of negative SAC, and values close to zero denote where no SAC is present. The software program ArcMap 9.3 is used in this study to examine the various measures of SAC in order to gain a better understanding of how each variable may function with regards to poverty.

Regression analysis - Global regression

The next step in analyzing the relationship between the independent variables and poverty across the state will be by multivariate regression analysis at both the global and the local scale. The global regression analysis employs the ordinary least squares (OLS) method using the software package SPSS 16.0. In OLS regression, the independent variables are used to attempt to explain the variation present in the dependent variable by minimizing the sum of squared residuals from a best-fitting regression line. With this type of regression analysis, the variables are assumed to be independent of one another (Rogerson 2006). The global regression equation can be expressed as:

$$y = a + b_1 x_1 + b_2 x_2 + \cdots b_p x_p$$

where y is the dependent variable, a represents the value of the intercept of the regression line, x_1, x_2...x_p are the independent variables, and b_1, b_2...b_p are the parameter estimates for each of the independent variables. Examining the variables at this global scale will satisfy the first objective of this study by providing an indication of which variables exert the most influence on poverty across the entire state.

While this first step is vital to the overall understanding of poverty across the state, OLS regression analysis can be problematic, especially with respect to spatial data. This method results in one parameter estimate for each of the independent variables so that there is only one value assigned to measure the relationship between each independent variable and the dependent variable across the entire study area. More importantly, the relationship between the variables is assumed to be constant across the study area so that no variations in the relationships are detected (Fotheringham, Brunsdon, and Charlton 2000, 2002). As geographers have long recognized in the case of social phenomena such as poverty and the factors affecting poverty, rarely are the distributions, or the relationships between these distributions, stable across any geographic region, a concept known as spatial non-stationarity. As Fotheringham, Brunsdon, and Charlton (2002) note, “By their nature, local statistics emphasize differences across space whereas global statistics emphasize similarities across space”

(7). Therefore, another method utilizing local statistics is needed to explore the variations that might be present with respect to poverty in Oklahoma.

Regression analysis - Geographically weighted regression

The main focus of this analysis will be on developing a local regression model using the software package GWR 3.0 developed by Fotheringham, Brunsdon, and Charlton (2000, 2002). Unlike OLS regression, GWR, or geographically weighted regression, measures the influence of each variable at a point *i*, and weights the influence of the data around *i* according to distance decay. In other words, data closer to *i* will have a greater amount of influence than those data further away from point *i* (Fotheringham, Brunsdon, and Charlton 2000, 2002). For the Oklahoma data, this technique will show how each variable within a county/tract behaves in relation to the same variable in neighboring counties/tracts. For example, instead of one measure of how education influences poverty across the state, the GWR model will provide 77 measures, one for each county in the state. At the tract level, one measure for each tract will be produced, resulting in a total of 990 values. This will complete the second objective by allowing for an assessment of how the influence of education, and all other variables, affects poverty in each county/tract, highlighting the local variation across the state.

The GWR equation can be specified as:

$$y_i = a_0(u_i, v_i) + \sum_k a_k(u_i, v_i)x_{ik} + \varepsilon_i$$

where (u_i, v_i) represents the coordinates for the i^{th} point in space and $a_k(u, v)$ represents a continuous surface over which the parameter values are allowed to vary. To quantify this continuous surface, the GWR model uses a spatial kernel around each data point *i* to capture data within a certain distance of point *i*.

A GWR model can be calibrated with either a fixed or an adaptive spatial kernel. With a fixed kernel, the bandwidth remains constant for each data point *i* and captures data for only the neighbors within that bandwidth (Figure 8). Using a fixed kernel, radically different areal unit size and shape can affect the number of neighbors included for analysis at each data point. For example, an area with few data points surrounding it will have little neighboring data to rely on within the regression model. Using an adaptive kernel, however, the size of the bandwidth is allowed to vary across space so that the kernel always captures the same number of neighbors for each point *i* (Figure 9). In the case of both kernel types, the size and shape of the study area can greatly affect the outcome of the GWR model. In the specific case of Oklahoma, the shape of the state may create problems with the model calibration, especially for those counties/tracts in the panhandle region of the state. The three large counties that make up the panhandle have no other neighbors aside from themselves within the state and since GWR modeling relies on neighboring data points in order to assign parameter estimates, the data in this region may be too sparse to correctly estimate the coefficients. For this reason, a buffer zone has been created to include all counties and tracts within 100 miles of the Oklahoma border so that each areal unit within Oklahoma will have optimal neighboring data points for analysis.[6]

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[6] See Appendix B for a map of the region including the 100-mile buffer zone of counties and a list of all included counties.

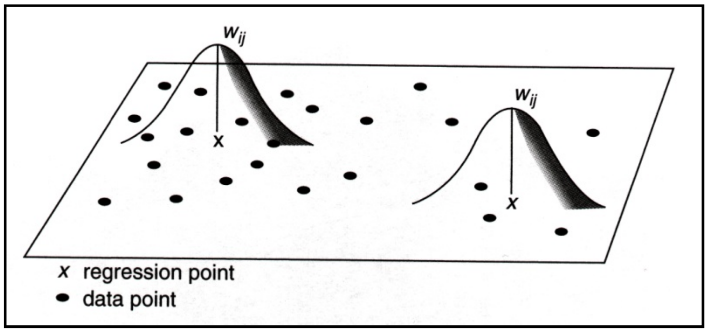

Figure 8. Fixed spatial kernels.
(from Fotheringham, Brunsdon, and Charlton 2002, 45)

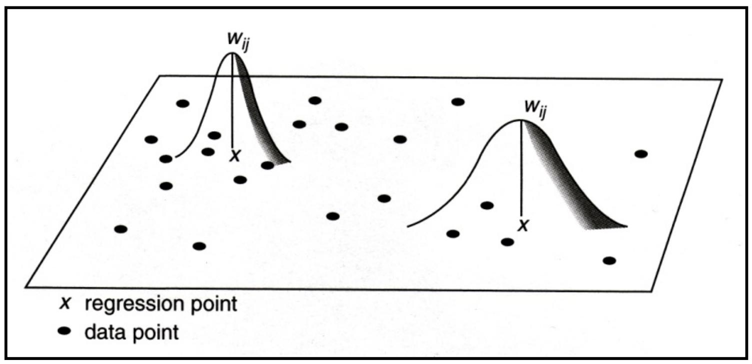

Figure 9. Adaptive spatial kernels.
(from Fotheringham, Brunsdon, and Charlton 2002, 47)

For either type of spatial kernel, optimal bandwidth selection is one of the most important aspects of the GWR model calibration since this will determine how many data points each observation relies on for its parameter estimate (Fotheringham, Brunsdon, and Charlton 2002; Guo, Ma, and Zhang 2008). There are several methods used for determining the optimal bandwidth. One method is for the user to define the size of the bandwidth manually. However, without *a priori* knowledge of which bandwidth distance is optimal for a particular study area, this method may not produce the most significant results. Another method for selecting the optimal bandwidth is by cross-validation (CV) which minimizes the squared error between the observed and predicted values of the model at point *i* while excluding *i* from the calculation.

Finally, the GWR software allows users to find the optimal bandwidth by minimizing the Akaike Information Criterion (AIC). The AIC is essentially a "goodness-of-fit" measure allowing an estimation of the amount of difference between the resulting GWR model and a "true" model (Fotheringham, Brunsdon, and Charlton 2002, 87). A smaller AIC signifies that the GWR model more closely approximates the true model; therefore minimizing the AIC will maximize the model's significance. When evaluating various GWR models, the model with the lowest AIC value will be considered the best fitting model. For the purposes of this study, an adaptive bandwidth calibrated with CV will be used on all GWR models. This is due to the fact that the GWR model will not calibrate properly when using a fixed kernel with a spherical coordinate system such as the one used in this dataset. Additionally, it has been noted in the literature that using the CV or the AIC method of calibration does not produce significantly different results as far as bandwidth selection is concerned (Fotheringham, Brunsdon, and Charlton 2002; Guo, Ma, and Zhang 2008). The GWR software provides an output of the coefficient for each variable within each county/tract. These outputs can be imported into a GIS software program, such as ArcMap 9.3, and the coefficient from each variable can be mapped separately for analysis.

The final objective for this study will be to compare the results of the local regression modeling with data on per capita federal expenditures for various programs across the state. This will be accomplished by developing two different county level GWR models that will analyze the spending in various parts of the state. The first model will be based on the entire study area, which includes the buffer zone of counties in neighboring states, and will incorporate all demographic, employment, and county characteristics variables as well as the variables pertaining to federally funded programs for agricultural, community and human resources, and income security. The second model will confine the study area to the 77 counties of Oklahoma and will include the variables related to spending on specific programs as reported by OKDHS. With these models complete, it will be possible to assess how federal expenditures in various parts of the state have influenced the poverty rate. It may also be possible to recommend ways in which different programs can be improved in specific areas of state in order to better serve the people of Oklahoma.

CHAPTER IV

FINDINGS

This chapter focuses on the results of the study beginning with the exploratory spatial data analysis (ESDA) and includes a discussion on the distribution of the raw variables as well as the results of the tests for spatial autocorrelation. I then concentrate on the regression analysis at both the global and local scale comparing county and tract level models for the variables concerning demographic factors, employment factors, and county/tract characteristics. Lastly, I discuss the GWR analysis of two county level models, one pertaining to federal expenditures and one focusing on several specific government-funded assistance programs within the state.

Exploratory Spatial Data Analysis

Thematic maps of each of the raw variables at both the county and tract level are found in Appendix A. Examining these is important in the overall understanding of how these variables might behave in the regression models discussed below. The first step in this process is determining the overall relationship each variable has with respect to poverty rates.

As is clear from a visual inspection of each of the mapped variables, a great deal of variation exists in the factors used in this study at both the county and tract levels.

Many of the variables, including those representing unemployment, educational attainment, and female-headed households appear to correlate closely with poverty rates. A Pearson's correlation coefficient, denoted *r*, can be used to determine how well these variables correlate with poverty by assessing the linear relationship between the variables (Rogerson 2006). A Pearson's coefficient of +1 would indicate a perfect positive relationship (i.e. an increase in the value of one variable would result in an increase in value of the other), while a coefficient of -1 signifies a perfect negative relationship (i.e. a decrease in the value of one variable would result in an increase in the value of the other). The closer the coefficient is to +1 or -1, the stronger the relationship is between the variables.

Table 4 provides the Pearson's *r* values for the variables with a strong correlation to poverty, that is, those with a coefficient greater than |0.5|. Note that all variables listed have a strong relationship with poverty rates at both the county and tract level with the exception of the variable representing minority populations, which only correlates strongly with poverty at the tract level. Percent Native American also correlates moderately strongly with poverty at the county level with a Pearson's *r* of 0.458, but only returns a coefficient of 0.229 at the tract level. As expected, per capita income has a strong negative relationship with poverty at both the county and tract level; as per capita income decreases, the poverty rate increases. As previously mentioned, data concerning federal and OKDHS expenditures are not available at the tract level, and therefore no correlations at the tract level are given in the table below for these variables.

*Table 4. Pearson's correlation coefficients between poverty and selected variables.**

Variable	County Level	Tract Level
UNEMPL	0.529	0.586
NO_HS	0.761	0.648
FEM_HH	0.511	0.634
MINOR	0.207	0.516
PCI	-0.828	-0.614
FED_HRS	0.760	---
FED_ISS	0.751	---
DHS_FS	0.672	---
DHS_SUP	0.801	---
DHS_TOTS	0.632	---

* All correlations are significant at the 0.01 level.

Looking at the maps depicting per capita federal expenditures, it would appear that the majority of federal monies are spent on agricultural and natural resource programs in the western part of the state. This area also corresponds to the region with the highest percentage of people employed in primary industries, which includes agricultural services (Figure 10). Many of the federal funds for community resource programs are spent in the counties surrounding the two major metropolitan areas of the state, Oklahoma City in the central region and Tulsa in the northeast. Human resource spending and funds for income security appear to visually correlate with areas of higher poverty rates in the southern parts of the state. This apparent correlation is verified with high Pearson's *r* values listed above in Table 4. These programs provide assistance for employment, education, and nutrition programs as well as public assistance, disability, and medical benefits. As the federal expenditures for these programs is higher in the most poverty-stricken areas of the state, a local regression model using GWR may shed light on whether this funding is indeed having the desired effect on the poverty rate.

Total per capita federal expenditures do not appear to correlate with poverty, however, as illustrated by a Pearson's coefficient of 0.039 (see also Figure 11).

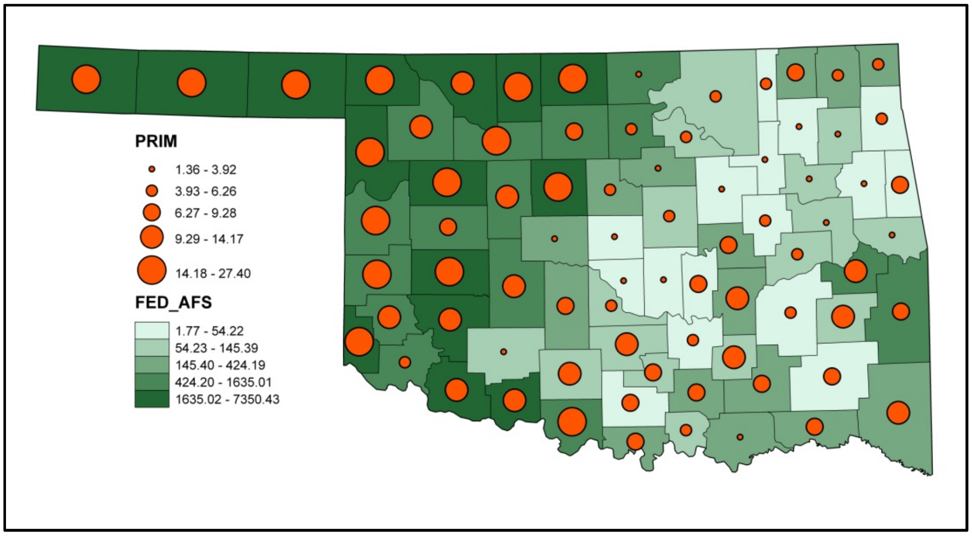

Figure 10. Spatial distribution of per capita federal expenditures for agricultural resources and percent employed in primary industries.

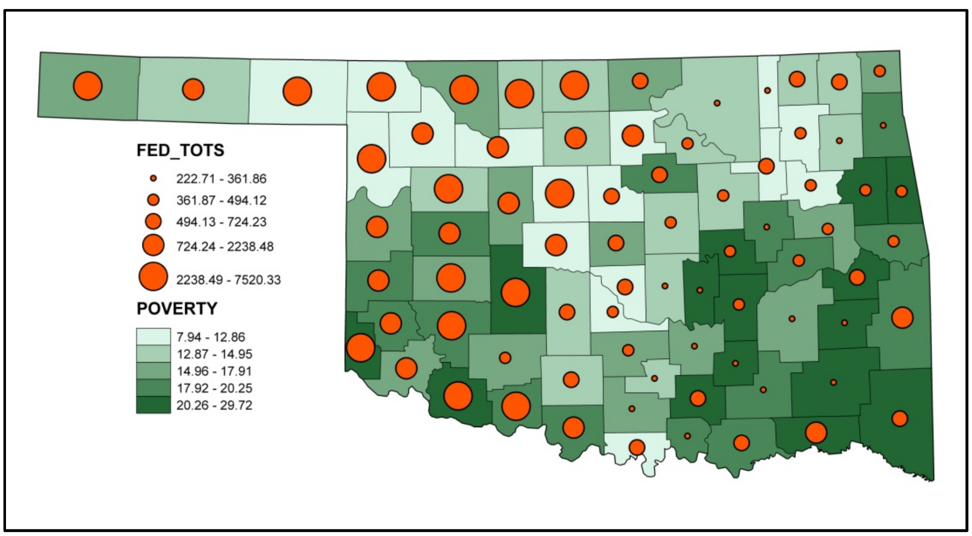

Figure 11. Spatial distribution of poverty and total per capita federal expenditures.

Examining the programs offered specifically by OKDHS, it would appear that the per capita spending on the food stamps program and supplemental programs, as well as overall per capita expenditures, is higher in areas where the poverty rates are also high (Figure 12). Pearson's correlation tests verify that the relationship between these programs and the poverty rate is strong. Again, regression modeling using GWR to test the influence of this spending on poverty in specific areas of the state is warranted in order to ascertain whether these programs are in fact beneficial to the people of these areas.

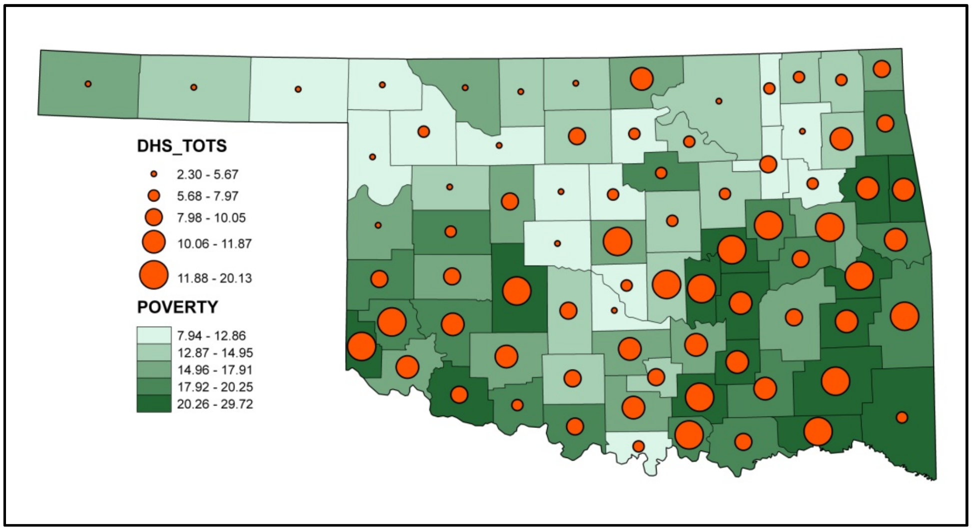

Figure 12. Spatial distribution of poverty and total per capita OKDHS expenditures.

Before continuing on to regression modeling, the next step in the process of ESDA is to test for the presence of spatial autocorrelation (SAC). As discussed in the methodology chapter, SAC is the degree of spatial dependence of the observations in a dataset. In order for proper interpretation of results from statistical testing, SAC should be assessed, especially when the data are spatially oriented (Rogerson 2006). SAC can be measured at the global scale across the entire study area with the Moran's *I* statistic, given by the equation on page 41. Because Moran's *I* measures spatial dependence based on the value of neighboring observations from each point, data for the entire study area including the 100-mile buffer zone of counties detailed in Appendix B, are used in the calculations regarding SAC. This is done so that counties on the periphery of the state, including those in the panhandle region, have the same chance of encountering full neighbor effects as counties located in the interior of the state. This is true for all variables except the ones pertaining to OKDHS spending, for which only data from Oklahoma's counties is used. Again, it should be noted that in order to determine the degree of neighbor effects, a spatial weights matrix using rooks contiguity, where only counties sharing a common edge are considered to be neighbors, is employed. However, for visualization purposes, the maps displayed here are clipped to only show the results within Oklahoma's counties and tracts.

The results of the global Moran's *I* calculations and corresponding z-scores for all variables at the county and tract level are given below in Table 5. At this global scale, all variables at both levels of analysis display some degree of positive SAC, as all values are positive. The degree of positive SAC is usually higher at the tract level. In addition, the data at the tract level appear to be much more significant with higher z-scores for all variables. This is expected, however, as sample size is a major influence in determining significance, and there are over ten times more tracts in the study area than counties. The variable exhibiting the highest degree of positive SAC at both the county and tract level is the percentage of Native Americans. Given the spatial distribution of the raw percentages of Native Americans in Oklahoma, this result is expected as higher percentages clearly cluster in the eastern part of the state. The largest difference between variables at the county and tract levels occurs with the variable pertaining to the percentage of people living in rural areas. At the county level, a global Moran's *I* of 0.08 implies that the distribution is nearly random, while a Moran's *I* of 0.80 at the tract level indicates a much more clustered distribution.

Table 5. Global Moran's I values for all variables.

Variable	County Level Data		Tract Level Data	
	Moran's *I*	**Z-Score***	**Moran's *I***	**Z-Score***
POV	0.48	13.85	0.55	54.10
UNEMPL	0.22	6.34	0.22	22.97
NO_HS	0.43	12.59	0.62	61.07
AM_IND	0.74	21.88	0.87	86.58
MINOR	0.53	15.50	0.74	72.99
HISP	0.55	16.14	0.70	69.59
MED_AGE	0.26	7.73	0.40	40.11
EDLER	0.36	10.49	0.47	46.80
FAM_SZ	0.37	10.89	0.52	51.49
FEM_HH	0.49	14.13	0.58	57.30
PCI	0.42	12.39	0.59	58.74
STABLE	0.20	5.99	0.41	40.41
PRIM	0.61	17.81	0.85	83.83
SEC	0.60	17.34	0.62	61.43
TER	0.19	5.53	0.43	42.73
QUAT	0.41	12.06	0.49	48.52
RURAL	0.08	2.34	0.80	78.73
FED_AFS	0.48	14.09	---	---
FED_CRS	0.17	5.37	---	---
FED_HRS	0.47	13.67	---	---
FED_ISS	0.49	14.32	---	---
FED_TOTS	0.47	14.07	---	---
DHS_FS*	0.40	5.92	---	---
DHS_SUP*	0.54	7.94	---	---
DHS_TANF*	0.26	3.99	---	---
DHS_TOTS*	0.37	5.58	---	---

* All variables are significant at the 0.01 level with the exception of RURAL, which is significant at the 0.05 level for county data.

When interpreting these results, however, it is important to remember that this global statistic could be masking locally occurring SAC *within* the dataset. For example, if there are areas of high positive SAC and areas of high negative SAC within a variable's distribution, the global statistic might indicate a more random distribution since the values of positive and negative SAC would cancel each other out. In order to test for the possibility of locally occurring pockets of SAC within the dataset, the local Moran's *I* statistic, denoted I_i and given by the equation on page 42, is used. Figures 13 through 19 illustrate the results of this testing for the variables pertaining to poverty, educational attainment, percent Native American, and percent rural. The maps showing the z-scores of the I_i statistics indicate where pockets of significant positive (red) and negative (blue) SAC are occurring. The z-scores, however, do not reveal whether the SAC is the result of high values clustering with other high values, or low values being surrounded by other low values; to determine this, the cluster maps must also be examined. On the cluster maps, the red areas indicate where high values cluster together, and blue areas indicate a cluster of low values. Similarly, areas of high-low and low-high negative SAC are displayed on the cluster maps as pink and light blue shaded areas, respectively.

The global Moran's *I* values for the poverty variable at the county (0.48) and tract (0.55) levels indicate positive SAC across the state. As expected based on the distribution of the raw poverty rates, local Moran's *I* values reveal that high poverty rates are clustered in counties in the southwest and southeast corners of the state (Figure 13). The cluster map also reveals an area of positive SAC near Tulsa where lower poverty rates cluster. At the tract level, high-high and low-low clusters are even more evident within the two metropolitan areas (Figure 14). With respect to educational attainment, the local Moran's *I* maps also depict the presence of positive SAC at both county and tract levels (Figures 15 and 16). At the county level, high-high values are significantly clustered in the southeastern and southwestern counties, while clusters of low values are evident near the two metropolitan areas, as well as in counties along the northern edge of the state. The similarity of the high-high clustering of values between educational attainment and poverty indicates that the lack of a high school diploma might indeed have a significant influence on poverty in a GWR model. Again, tract level local Moran's *I* maps indicate more significant positive SAC in tracts within the Oklahoma City and Tulsa areas with low-low values clustering at the periphery of both cities.

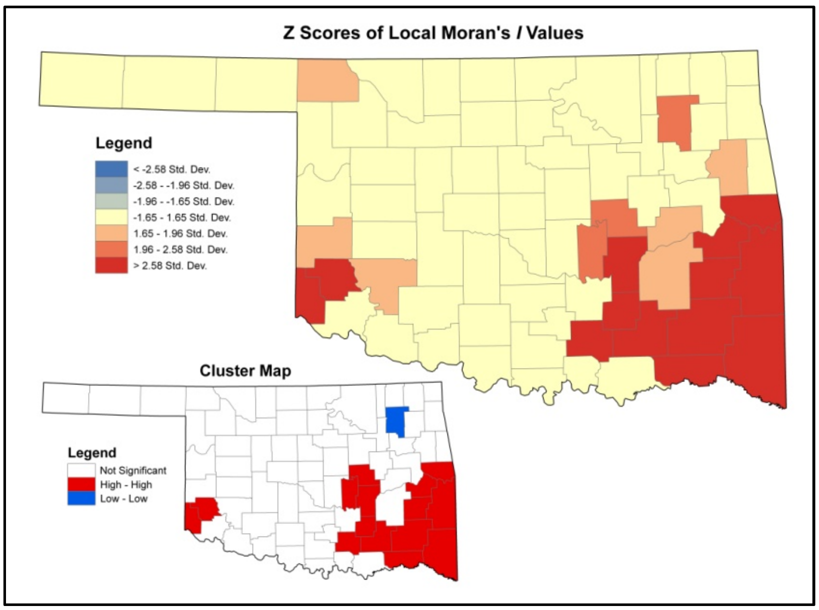

Figure 13. Local Moran's I *maps for poverty at the county level.*

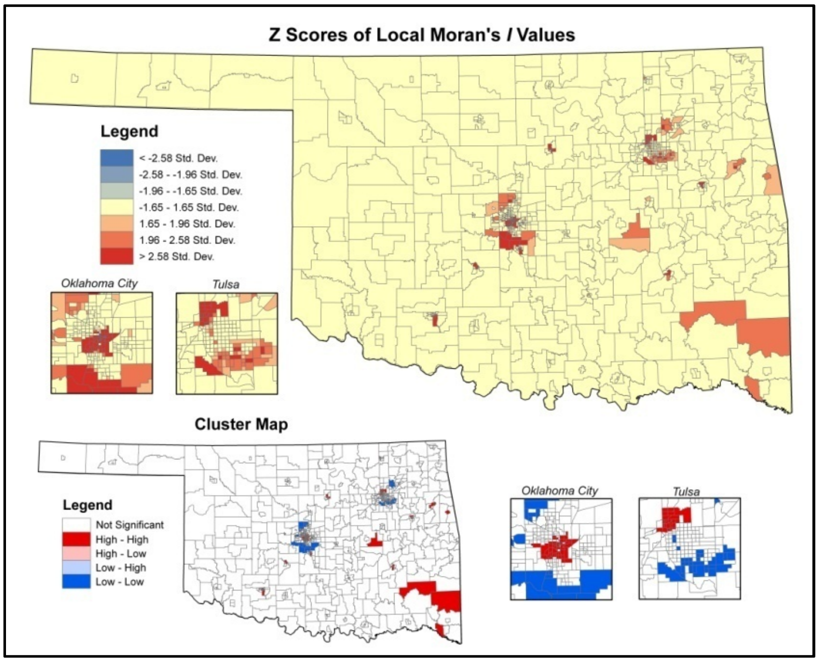

Figure 14. Local Moran's I *maps for poverty at the tract level.*

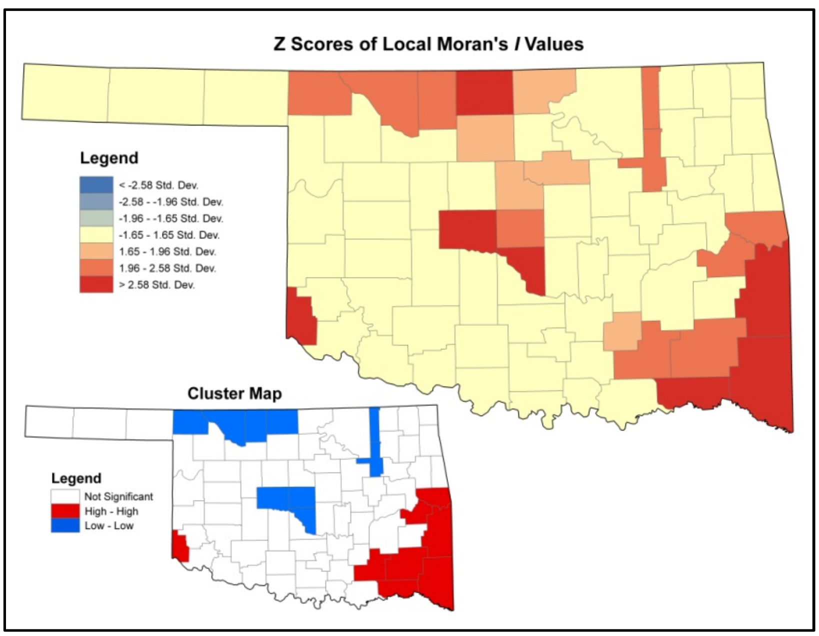

Figure 15. Local Moran's I *maps for educational attainment at the county level.*

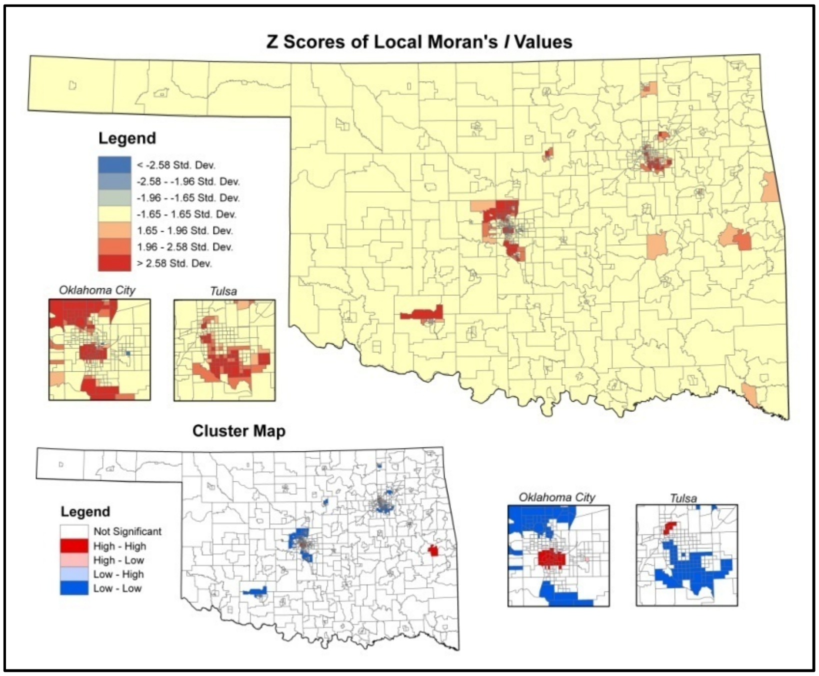

Figure 16. Local Moran's I *maps for educational attainment at the tract level.*

The opposite can be said about the tract level maps depicting localized SAC for the percentage of Native Americans, where the most significant clustering of values occurs outside the two metro areas. However, at both levels of analysis, high-high values clearly dominate the eastern portion of the state (Figures 17 and 18). Finally, Figure 19 illustrates that while the global Moran's *I* for the variable RURAL was 0.08, which indicates a more random distribution, there are clearly pockets of locally occurring positive and negative SAC within the state, with positive SAC occurring in counties surrounding the two metropolitan areas as well as near the panhandle, and significant negative SAC present in two northern counties. The presence of positive SAC among all variables indicates that, as expected, the variables do exhibit spatial dependence, which must be considered during regression analysis.

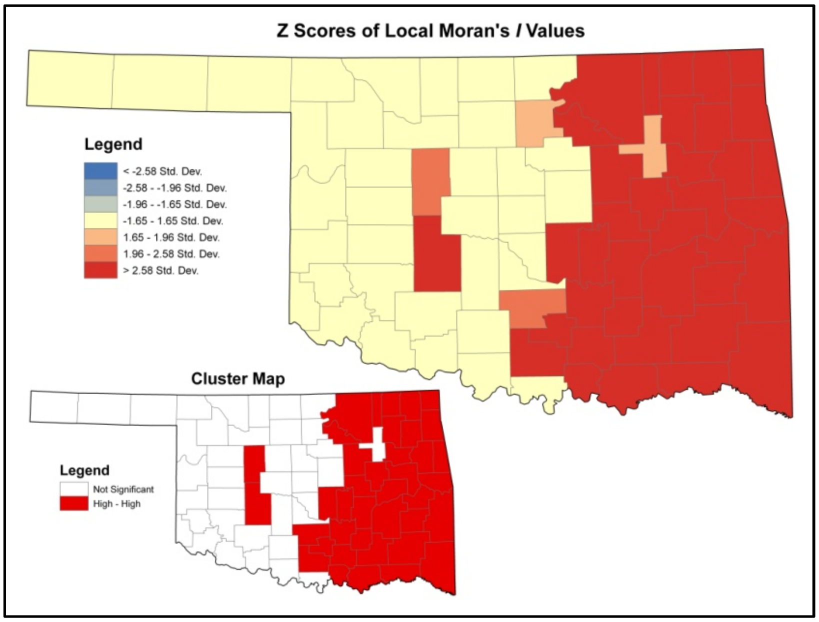

Figure 17. Local Moran's I *maps for percent Native American at the county level.*

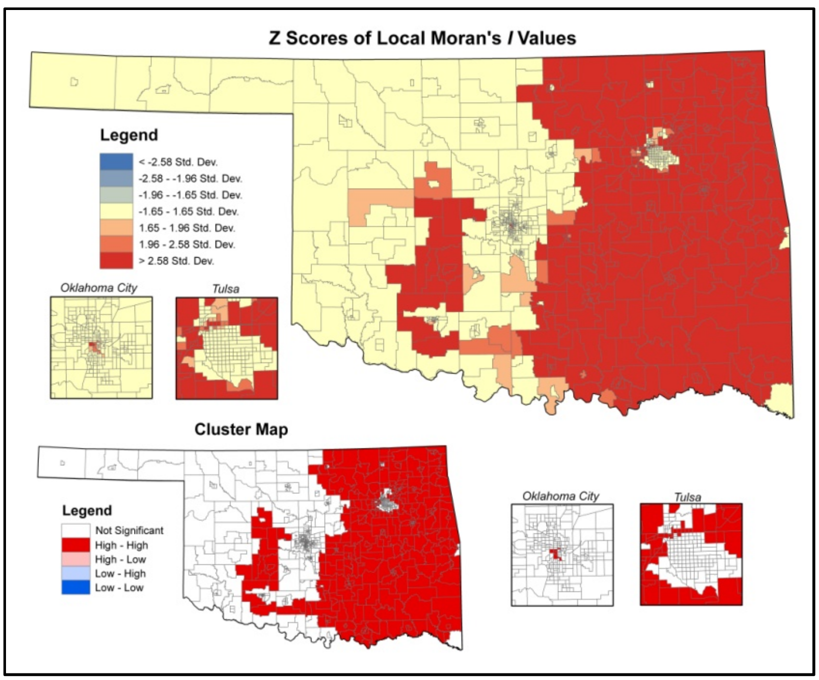

Figure 18. Local Moran's I *maps for percent Native American at the tract level.*

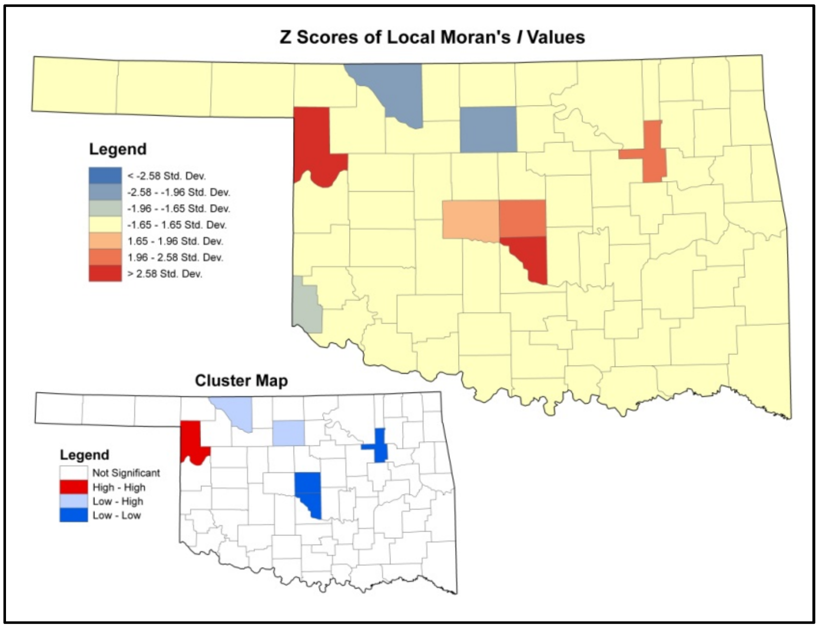

Figure 19. Local Moran's I *maps for percent rural at the county level.*

Regression Analysis

Global regression of county level data

In order to determine which variables most influence poverty across the entire state of Oklahoma, a global regression model is developed using the software program SPSS 16.0.[7] To be most comparable to the GWR models run later, the first set of global models employs only the variables relating to demographic factors, employment factors, and county/tract characteristics. Further global modeling at the county level including the variables pertaining to per capita federal expenditures will be discussed below.

As indicated above, one way to examine how different variables will behave in a regression model is to analyze the amount of correlation that exists between them. This will indicate the potential for multicollinearity, which occurs when independent variables

[7] Because global regression modeling does not rely on neighboring observations to calculate relationships between variables, only data for counties and tracts within Oklahoma is used in this portion of the analysis.

correlate highly with one another (Rogerson 2006). As the presence of multicollinearity violates one of the basic regression assumptions, it is important to determine the strength of the relationships between the independent variables. A Pearson's correlation test revealed that several of the independent variables are highly correlated. The highest correlation exists between the two variables representing age (median age and percent elderly), with a Pearson's *r* of 0.867. The next highest correlation is between the educational attainment variable and per capita income, with a strong negative relationship (r = -0.791). Lastly, the percentage of female-headed households and the unemployment rate are highly correlated with a Pearson's coefficient of 0.731.

Several model calibrations were examined in order to arrive at the most parsimonious model to describe the influence of the independent variables on poverty (see Table 6). The first model employs the enter method, which assesses the relationship of all variables by adding them all to the model. The resulting adjusted R^2 value, which signifies the explanatory power of the model, is 0.871, indicating that just over 87 percent of the variation within the poverty rate across the state can be explained by this model. However, the only significant variable in this model, as indicated by the *t* test for significance, was the lack of a high school diploma. Also problematic in this model is the presence of several high variance inflation factors (VIF), which is indicative of a high degree of multicollinearity. As a general rule, a VIF greater than 5 usually signifies the presence of multicollinearity (Rogerson 2006). As expected, the variables for median age and percent aged 65+ have VIFs between 13 and 16. Other moderately high VIF values are found for the variables representing educational attainment, female-headed households, and per capita income.

*Table 6. Global regression models for county and tract level analyses.**

Model	Level**	Method	Variables Used***	Adjusted R^2	F (p-value)	Significant Variables
1	County	Enter	DEM, EMPLOY, CTY	0.871	35.22 (0.0000)	NO_HS
2	County	Enter	DEM, EMPLOY, CTY (excluding MED_AGE)	0.864	35.475 (0.0000)	NO_HS, PCI
3	County	Stepwise	DEM, EMPLOY, CTY (excluding MED_AGE)	0.859	78.036 (0.0000)	PCI, FEM_HH, PRIM, NO_HS, QUAT, ELDER
4	County	Enter	DEM, EMPLOY, CTY, FED_FUND (excluding MED_AGE)	0.894	36.542 (0.0000)	NO_HS, FAM_SZ, PCI, FED_TOTS
5	County	Stepwise	DEM, EMPLOY, CTY, FED_FUND (excluding MED_AGE)	0.869	102.188 (0.0000)	PCI, FED_ISS, QUAT, NO_HS, FED_TOTS
6	County	Enter	DEM, EMPLOY, CTY, DHS_FUND (excluding MED_AGE)	0.877	31.174 (0.0000)	PCI, DHS_SUP
7	County	Stepwise	DEM, EMPLOY, CTY, DHS_FUND (excluding MED_AGE)	0.880	62.759 (0.0000)	PCI, DHS_SUP, QUAT, ELDER, UNEMPL, TER, DHS_FS, FEM_FF, HISP
8	Tract	Enter	DEM, EMPLOY, TR	0.702	155.837 (0.0000)	All variables except HISP, FAM_SZ, RURAL
9	Tract	Enter	DEM, EMPLOY, TR (excluding MED_AGE)	0.698	164.114 (0.0000)	All variables except HISP, ELDER, FAM_SZ, RURAL
10	Tract	Stepwise	DEM, EMPLOY, TR (excluding MED_AGE)	0.698	254.404 (0.0000)	NO_HS, SEC, AM_IND, STABLE, MINOR, UNEMPL, FEM_HH, PCI, PRIM

*Shaded cells represent models for which the formal regression equation is given below.
**For county level models, n = 77; for tract level models, n = 990.
***DEM = demographic variables, EMPLOY = employment variables, CTY or TR = county and tract characteristics, FED_FUND = variables pertaining to federal expenditures, DHS_FUND = variables pertaining to specific OKDHS expenditures.

As Rogerson (2006) notes, there are several potential ways to solve the problem of multicollinearity, one being to drop one of the variables responsible for the high values, or possibly combining problematic variables into a single value. For further global modeling at the county level, the variable representing median age was excluded from the regression model in order to account for the high degree of correlation between it and percent elderly. As the other variables with higher VIFs most likely significantly contribute to the poverty rates across the state, none of these are excluded. In the case of the moderately high correlation between female-headed households and unemployment rate, perhaps the best solution would ultimately be to combine the two into one variable representing the unemployment rate *among* female-headed households. However, since the Census Bureau does not measure unemployment rates by the type of household, this may be more difficult to quantify.

The second model also utilizes the enter method, but excludes the median age variable as discussed above. The resulting explanatory power is slightly lower with an adjusted R^2 of 0.864, but only one additional variable appears to be significant within this model. In addition to the percent with no high school diploma, per capita income significantly predicts poverty using this model calibration.

The third and final model executed at the county level includes all variables from Model 2, but uses the stepwise method of regression, which only brings significant variables into the model and excludes those that are not significant (Rogerson 2006). Variables are added to the model, but only if they significantly improve the model in relation to the other variables selected. While the final model resulted in a lower adjusted R^2 of 0.859, the F statistic, which tests the overall significance of the model was much higher than the same statistic for either previous model, indicating that this model is more statistically significant. The formal regression equation representing this final model, with the independent variables listed in order of significance, can be written as:

$$POV = 1.59 + 0.32(QUAT) + 0.35(NO\_HS) + 0.50(FEM\_HH) - 0.0007(PCI) + 0.12(PRIM) + 0.20(ELDER)$$

This is interpreted in the following manner: a one percent increase in the percent employed in quaternary industries results in a 0.32 percent increase in the poverty rate; a one percent increase in the percent with no high school diploma results in a 0.35 percent increase in the poverty rate, and so on.

Global regression modeling at the county level that included variables relating to per capita federal expenditures was also performed. However, this modeling is difficult to assess because of the high correlation rates between the funding variables and many of the other independent variables. All Pearson's *r* coefficients higher than |0.5| for the federal expenditures variables are listed in Table 7, including assessments of how certain funding programs correlate strongly with other funding programs.

*Table 7. Pearson's correlation coefficients for variables related to federal expenditures.**

Variables	UNEMPL	NO_HS	AM_IND	FEM_HH	PCI	PRIM
FED_AFS	-0.535	---	---	-0.536	---	0.747
FED_HRS	---	0.712	---	---	-0.664	---
FED_ISS	0.632	0.584	---	0.751	-0.550	---
FED_TOTS	---	---	---	---	---	0.718
DHS_FS	0.671	0.594	0.516	0.688	-0.603	---
DHS_SUP	---	0.828	0.532	0.515	-0.757	---
DHS_TANF	---	---	---	0.593	---	---
DHS_TOTS	0.643	---	---	0.734	-0.528	---
Variables	**FED_AFS**	**FED_HRS**	**FED_ISS**	**DHS_FS**	**DHS_SUP**	**DHS_TANF**
FED_ISS	---	0.716	---	---	---	---
FED_TOTS	0.981	---	---	---	---	---
DHS_FS	---	0.592	0.790	---	---	---
DHS_SUP	---	0.697	0.703	0.821	---	---
DHS_TANF	---	---	0.716	0.754	---	---
DHS_TOTS	---	0.564	0.800	0.975	0.793	0.837

* Only correlations higher than |0.5| are shown; duplicate coefficients are not included.

As expected, per capita income correlates with almost all funding variables with a negative coefficient, indicating that spending is lower in areas where per capita incomes are high. The variables pertaining to unemployment and female-headed households also correlate negatively with the funding variable representing expenditures for agricultural and natural resources suggesting that in areas where this type of funding is prevalent, the percentage of female-headed households and unemployment rates are lower. All other correlations noted are positive. It is interesting to note that all four variables relating to expenditures by OKDHS correlate strongly with the percentage of female-headed households across the state.

Because of the relatively high number of strong correlations between the funding variables and other independent variables, global regression modeling is problematic. Models were run using both the enter and stepwise methods, but variables describing federal expenditures were analyzed in separate models from those pertaining to specific OKDHS spending in order to avoid the influence of these highly correlated funding variables (see Tables 6 and 7). Both models using the enter method resulted in high VIF values for the majority of the variables indicating a significant degree of multicollinearity is present. Using the stepwise method with variables for federal funding, significant funding variables include the per capita total expenditures and the per capita expenditures for programs related to income security. However, both of these coefficients are positive (FED_ISS = 0.053, FED_TOTS = 0.0005), indicating that an increase in per capita expenditures will lead to an increase in the poverty level as well. Examining the stepwise model when OKDHS funding variables are present also results in two significant funding variables. The variable pertaining to expenditures for the food stamps program carries a coefficient of -0.424 signifying a one dollar increase in this type of funding will result in a 0.42 percent decrease in poverty. However, the variable relating to funding for supplemental programs, such as those for the aged, blind, and disabled, has a positive coefficient of 3.54, suggesting a one dollar increase in the funding for these programs results in a 3.5 percent increase in the poverty rate. Local modeling using GWR may help to shed light on these differences and explain some of the inconsistencies that appear to be present under a global regression model.

Global regression of tract level data

Analysis at the tract level also began with an examination of the correlation coefficients between the independent variables. Two pairs of variables had moderately high correlations; median age and percent over 65 years of age again correlated strongly with a Pearson's *r* of 0.709, as well as female-headed households and percent minority with a coefficient of 0.769. Again, a preliminary model run using all variables resulted in a VIF over 6 for the median age variable; this variable was therefore excluded in all subsequent models.

Overall, the tract level models were more significant than the county level models illustrated by higher F statistics (Table 6). Using the enter method (Model 9), the model predicts nearly 70 percent of the variation in poverty, and the only variables that were not significant at the tract level were percent Hispanic, average family size, and percent rural. To arrive at a final model for the tract level data, stepwise regression was again used, resulting in a model with an R^2 of 0.698 and a significant F of 254.40. The final formal regression equation arrived at using tract level data can be expressed as:

$$POV = 17.55 + 0.44(NO\_HS) - 0.32(SEC) + 0.25(AM\_IND) - 0.13(STABLE) + 0.11(MINOR) + 0.71(UNEMPL) + 0.21(FEM\_HH) - 0.0002(PCI) + 0.08(PRIM)$$

These are again presented in order of significance with the percentage of people not completing high school being the most significant indicator of poverty at the tract level.

These global regression results at both the county and tract levels help to establish the factors affecting the overall poverty rate across the state of Oklahoma. The four significant variables common at both levels of analysis are per capita income, having a negative effect on poverty rates, percent of female-headed households, percent with no high school diploma, and percent employed in primary industries, all contributing positively to poverty rates. However, it must be remembered that the global regression models assume that these results are constant across the entire study area with no variation in the effects of the variables in different parts of the state. In order to ascertain whether this variation does exist, and where the effects of different factors might be varying, it is necessary to turn to local regression modeling using GWR. The fact that the tract level models are much more significant than the county level models is most likely an indication of how these two different levels of analysis will perform using GWR modeling, with smaller units of analysis being more likely to produce significantly better models at the local level.

Geographically weighted regression (GWR)

While this study has largely followed the work of Dominique Duval-Diop's (2006) analysis of poverty in the Mississippi Delta region, the GWR models discussed below are intended to go beyond Duval-Diop's study in several ways. First, I have included several additional variables that may relate to the poverty rate specific to Oklahoma, such as the presence of large Native American and Hispanic populations. Additionally, the models presented here attempt to account for the broader neighbor effects than the ones presented in Duval-Diop's work. Her study area consisted of counties from several states covering the entire Mississippi Delta region, but did not encompass any counties outside this region as a potential buffer zone. For the models described below, I have included counties and tracts within 100 miles of Oklahoma's borders in order to properly assess neighbor effects for all counties in the study area.[8] Lastly, Duval-Diop's work concentrated on county level models only, while I test the significance of the GWR technique at two different levels of analysis, the county and Census tract level.

The first two GWR models presented here are designed to satisfy the second objective of this study, which is to determine how the influence of the different factors varies across the state at both the county and tract level. In order to ensure comparability between the county and tract level models, the variables pertaining to per capita federal expenditures are excluded from these opening models, as these figures are not available at the tract level. It should also be noted that despite several highly correlated variables, all variables referring to demographic, employment, and county/tract characteristics are included in the GWR models in order to analyze the amount of local variation present for each variable.

The relevant results of the county and tract level GWR models are detailed in Table 8. Two important figures to consider when evaluating the GWR models are the

[8] GWR models at both county and tract level were run for only the data within the 77 counties of Oklahoma. Details on these models are available in Appendix C.

bandwidth and the AIC. As discussed in the methodology chapter, a smaller AIC would indicate a model that more closely approximates a true model; therefore lower AIC values are desired. Examining the AIC values between the two models, it would appear that the county level model is by far a better fitting model than the tract level model. However, due to vast difference in the number of observations within each dataset (county: n=306, tract: n=3622), which affects the degrees of freedom present in each model, the AIC values between the two models are not comparable and therefore the significance of the models cannot be evaluated based on AIC alone. It should be noted, however, that for both the county and tract level analyses, the GWR model does result in a lower AIC than the global model, indicating that the GWR models are indeed more significant.

Another important calculation that must be evaluated is the size of the optimal bandwidth selected during model calibration. As Fotheringham, Brunsdon, and Charlton (2000) note, selection of bandwidth size can greatly affect the outcome of the GWR results. For example, if the bandwidth chosen is too small, the resulting calculations may not measure the influence of neighboring observations, but might reflect only the data at point *i* itself. On the other hand, if the bandwidth is large enough to encompass the majority of the study area, the results will approximate a global model and locally occurring variations in the data will be masked. In the case of the two models presented here, at the county level, bandwidth selection converges at 285 nearest neighbors. In a study area with only 306 total counties, including 285 nearest neighbors in the calculations for each data point covers over 93 percent of the study area. While localized variation in the variables might be occurring at the county level, the GWR model may not be detecting it with such a large bandwidth. At the tract level, however, the bandwidth consists of a sample size of 838 neighbors, or just over 23 percent of the 3622 total tracts. With this bandwidth size, it is much more likely that using tract level data will capture true spatial variation in the influence of various factors on poverty.

Table 8. Results of county and tract level GWR models.

	County Model Parameter Coefficients		Tract Model Parameter Coefficients	
Variable	Global	GWR (range)	Global	GWR (range)
Intercept (POV)	457.211	-1849.427 to 2306.194	10.946	-7205.959 to 4177.604
UNEMPL	0.492	0.278 to 0.633	0.657	0.171 to 1.110
NO_HS	0.244	0.151 to 0.324***	0.422	0.143 to 0.656**
AM_IND	0.087	0.029 to 0.194**	0.209	-2.133 to 0.980***
MINOR	0.015	-0.017 to 0.099*	0.029	-0.081 to 0.217*
HISP	0.017	-0.055 to 0.017***	-0.076	-0.230 to 0.099***
MED_AGE	-0.230	-0.433 to -0.092	-0.091	-0.593 to 0.405
EDLER	0.155	0.099 to 0.364	0.112	-0.395 to 0.357*
FAM_SZ	-6.476	-8.776 to -3.977	-1.534	-10.480 to 8.013
FEM_HH	0.475	0.244 to 0.535	0.325	0.042 to 0.661
PCI	-0.001	-0.001 to -0.0003	0.000	-0.0005 to 0.0001***
STABLE	-0.057	-0.116 to -0.023	-0.094	-0.201 to -0.002
PRIM	-4.117	-22.628 to 18.932	0.165	-41.297 to 72.490
SEC	-4.215	-22.752 to 18.795	-0.106	-41.583 to 72.154
TER	-4.217	-22.772 to 18.794	0.037	-41.570 to 72.116
QUAT	-4.126	-22.648 to 18.916	0.007	-41.511 to 72.077
RURAL	0.022	-0.002 to 0.026	0.006	-0.037 to 0.068*
Bandwidth	---	285	---	838
AIC	1289.81	1276.83	22290.10	21140.79
Adjusted R^2	0.812	0.833	0.739	0.819
F statistic	3.079	---	10.451	---

*Variable displays significant spatial non-stationarity at the 5% significance level.
**Variable displays significant spatial non-stationarity at the 1% significance level.
***Variable displays significant spatial non-stationarity at the 0.1% significance level.

Further validation that tract level modeling may produce a better fitting model than county level modeling can be found in the F statistic, which is higher for the tract level model, indicating a greater degree of significance. Examining the adjusted R^2 values for the models, the tract level model also presents a greater degree of enhancement in the predictive power of the variables with the R^2 increasing from 0.739 to 0.819. At the county level, the increase in the explanatory power of the model is not as pronounced with an increase from 0.812 in the global model to 0.833 in the GWR model.

Figures 20 and 21 depict the range of localized R^2 values across the state for the county and tract level models, respectively. For the county map, the local R^2 values range from 0.823 in the western part of the state to 0.874 in the northeast. With a global R^2 of 0.812, it is evident that the county level model performs on scale with the global model in the western part of the state, while the predictive power of the GWR model is greater than that of the global model in the northeast. At the tract level, the local R^2 values fall slightly below the global R^2 of 0.739 in the west central portion of the state with values as low as 0.708. In the far western panhandle and in the eastern and southern parts of the state, the GWR model results in a better fitting model with R^2 values reaching 0.873. It is interesting to note that this model better predicts poverty in the tracts surrounding Tulsa than in the tracts around the Oklahoma City area.

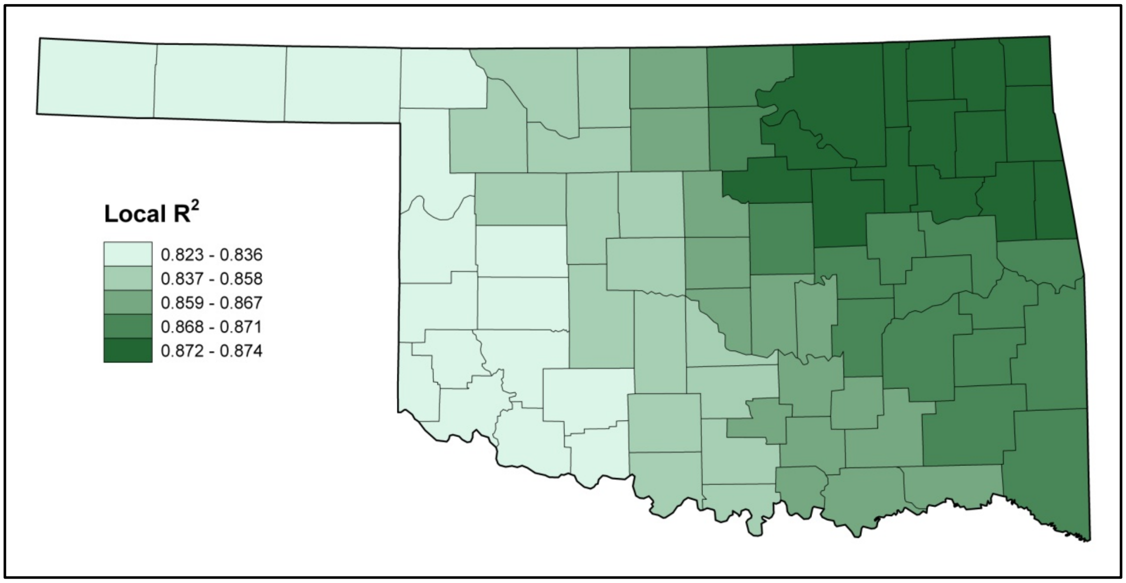

Figure 20. Localized R^2 *values for the county level GWR model.*

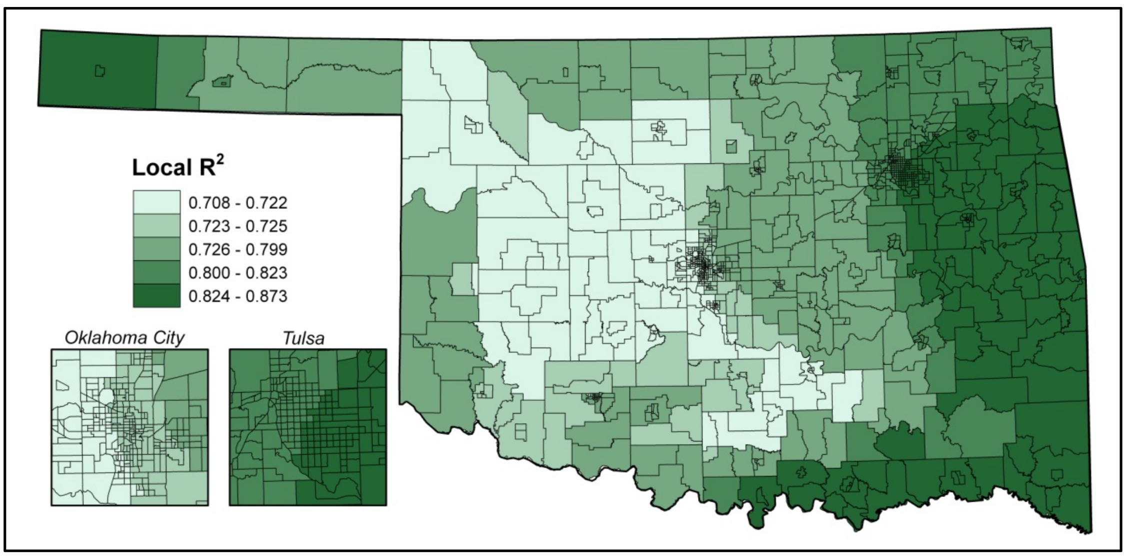

Figure 21. Localized R^2 *values for the tract level GWR model.*

The next step in assessing the models is to examine the resulting parameters themselves. Because spatial non-stationarity can be the result of random sampling variation, the GWR software uses a Monte Carlo simulation to test whether or not the various parameter coefficients exhibit a statistically significant degree of spatial variability (Fotheringham, Brunsdon, and Charlton 2000). At the county level, the variables pertaining to educational attainment, as well as all three variables relating to ethnicity, are found to exhibit significant spatial variation in their prediction of poverty across the state. The parameter coefficients for three of these variables are mapped in Figures 22 through 24, where the patterns of variation can be more easily evaluated.[9]

The coefficients for the variables representing the percentage with high school diploma and the percentage of Native Americans are positive throughout the state, indicating that as the value of these percentages increase poverty will also increase. However, the influence of these two variables on poverty is felt differently throughout the state. The influence of educational attainment is higher in the northeastern part of the state, while the percent Native American is more influential with respect to poverty in the southwest. This may seem curious given the high percentages of Native American populations that cluster in the eastern part of the state (see Figures 17 and 18). However, Native Americans within the state are afforded many government aid programs, such as free health care, education, and housing assistance, which may account for why this variable has less influence on poverty in areas where Native American populations are highest.

[9] Mapped parameter coefficients for all variables in this, and all subsequent GWR models, are presented in Appendix D.

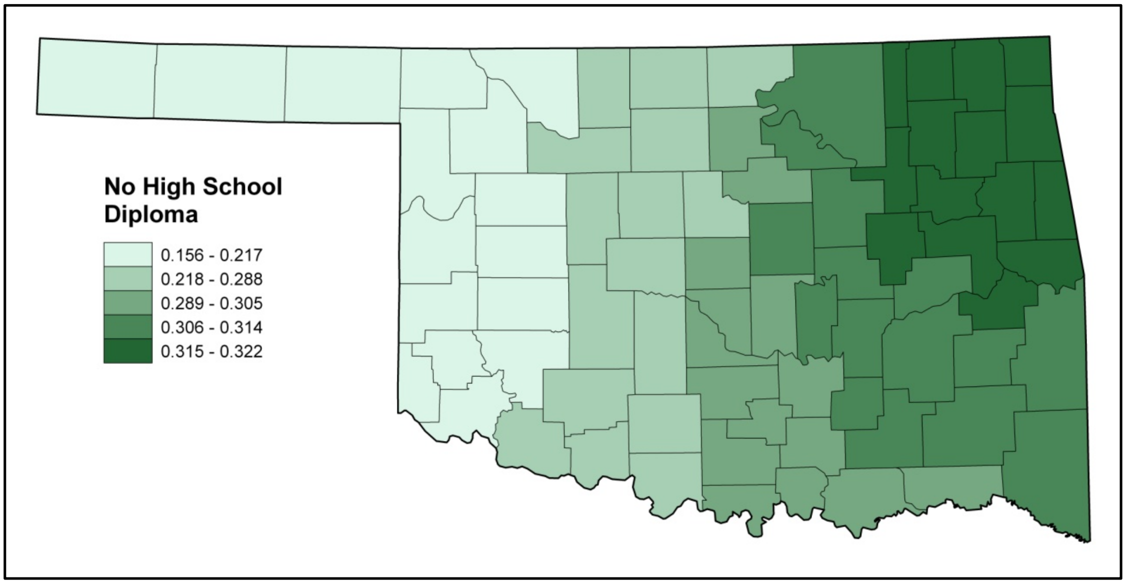

Figure 22. Parameter coefficients for percent with no high school diploma.

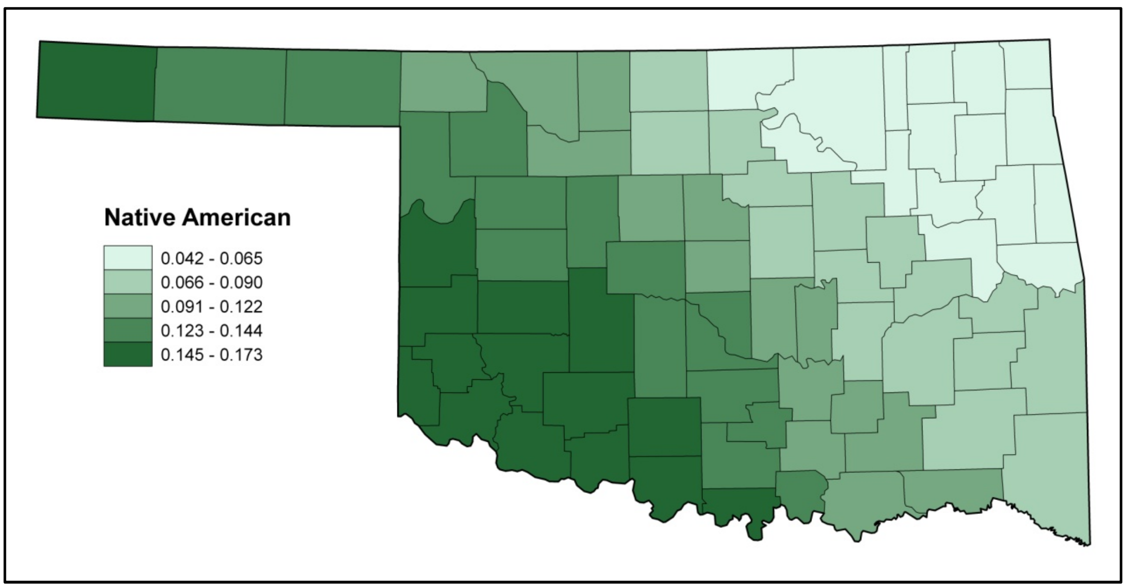

Figure 23. Parameter coefficients for percent Native American.

Figure 24 depicts the influence of percent Hispanic on poverty at the county level. Unlike the previous two variables, the coefficients for this parameter are almost all negative, indicating that as the percentage of Hispanics increases, poverty will decrease. This is especially true in the central and southern parts of the state where the degree of the negative influence of this variable is strongest. This could be the result of capturing neighbor effects from large metropolitan areas such as Oklahoma City and Dallas, Texas. The counties where the coefficients for this parameter are positive are located in the far western part of the state, including all three counties in the panhandle.

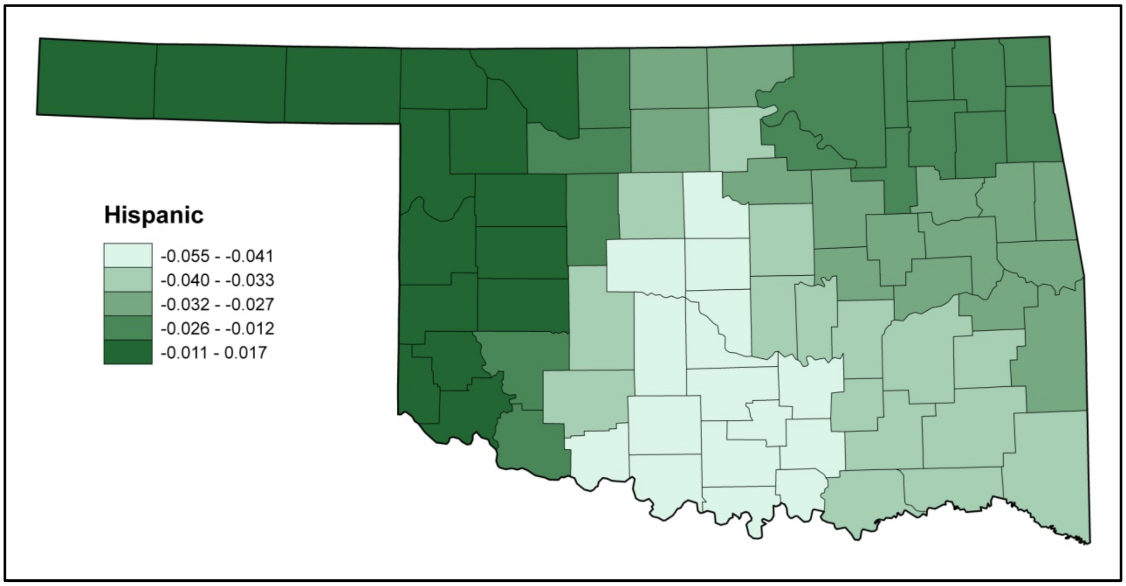

Figure 24. Parameter coefficients for percent Hispanic.

At the tract level, there are a total of seven variables displaying a significant amount of spatial variation, including percent Hispanic, percent Native American, percent other minority, percent aged 65+, percent rural, per capita income, and educational attainment. In order to best compare these results to the ones presented from the county level model, parameter coefficients for educational attainment, percent Native American and percent Hispanic are presented below in Figures 25 through 27. While the influence of educational attainment is strongest in the northeast area of the state at the county level, it is the southern and central portions of the state where this variable is most influential at the tract level (Figure 25). This includes the Oklahoma City metropolitan area, while the influence of this variable in the Tulsa area is much lower.

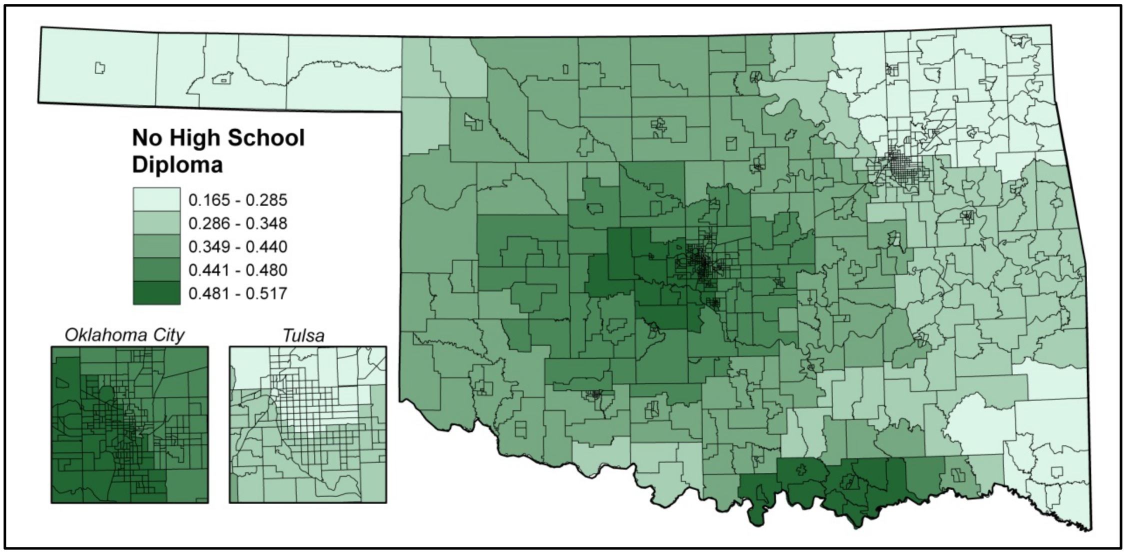

Figure 25. Parameter coefficients for percent with no high school diploma.

The patterns exhibited by the parameter coefficients for percent Native American at the tract level are more closely related to the mapped coefficients for this same variable using county level data (Figure 26). At both levels of analysis, the influence of this variable over poverty is lowest in the northeast region of the state where Native American populations are the highest. Again, the strongest influence of this variable over poverty exists in the far western panhandle region of the state, although this could be a reflection of the influence of high Native American populations in the neighboring counties of New Mexico.

Perhaps the most notable difference between the county and tract level models appears with the influence of the variable pertaining to the percent of Hispanic people in the state. Recall that at the county level, the majority of the coefficients were negative, with positive coefficients present in the western part of the state. However, at the tract level, the data reveal almost the opposite with the majority of tracts in the state having negative coefficients in the west and positive coefficients in tracts in the east. It should be noted, however, that the influence of the negative coefficients is stronger with values reaching -0.204 whereas positive coefficients only reach 0.099.

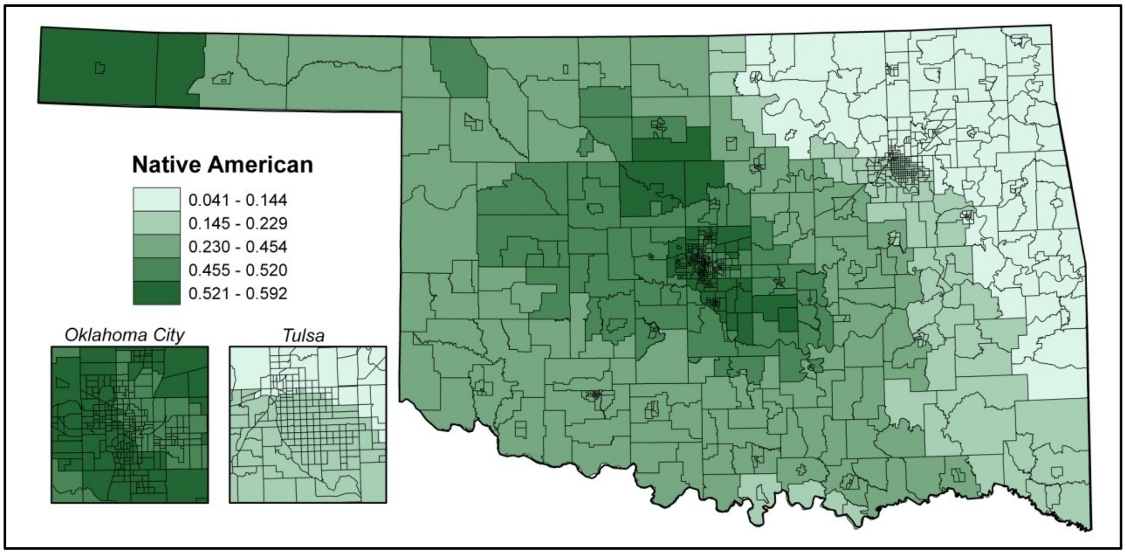

Figure 26. Parameter coefficients for percent Native American.

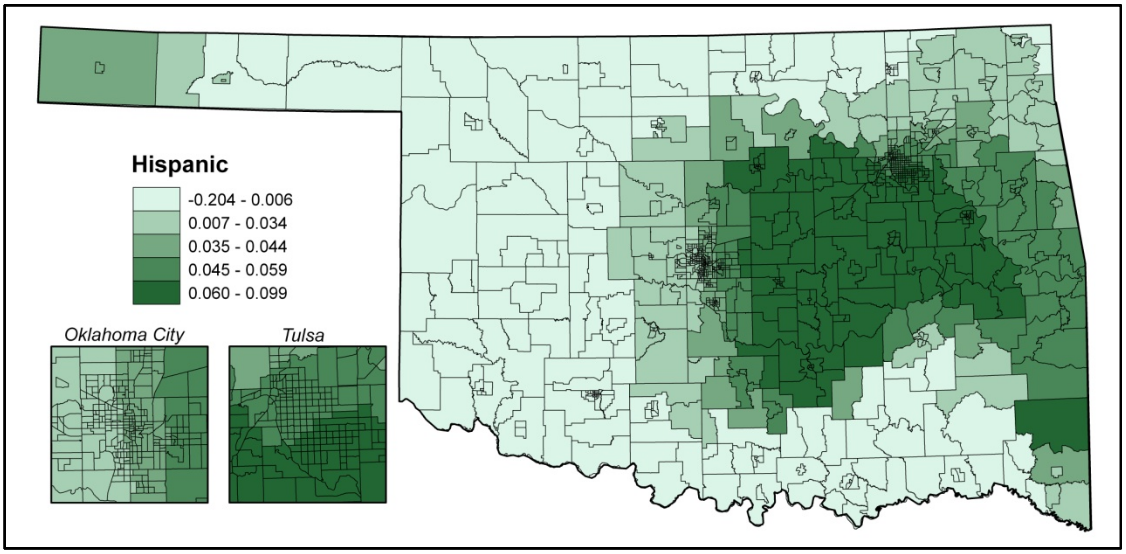

Figure 27. Parameter coefficients for percent Hispanic.

The final two GWR models presented here are designed to examine whether per capita expenditures for various types of government aid are influential over the poverty rate within the state. They are also intended to investigate the local variations in the influence of these programs that could lead to recommendations of how these monies could be better implemented to serve the people of Oklahoma. Details on both of these models can be found in Table 9. Unfortunately, as indicated by the models described above, county level GWR models at this scale are not as useful in determining where spatial variations might be present, as optimal bandwidths tend to include the vast majority of the study area, therefore approximating a global regression model. However, some interesting patterns can still be observed in the following models making it possible to suggest some solutions for the problem of persistent poverty in Oklahoma.

The first of these two models concentrates on the per capita federal expenditures gathered from the Census Bureau's Consolidated Federal Funds Report. As these data are available and consistent for all counties in the United States, this model utilizes the data included in the 100-mile buffer zone of counties surrounding Oklahoma. The lower AIC value for the GWR model indicates that this is indeed a better fitting model than the global one, despite the bandwidth size of 293 neighbors. Again however, with 306 total observations, an optimal bandwidth of 293 encompasses almost 96 percent of the entire study area, making the GWR model very similar to the global one. Regardless, a map of the localized R^2 values for this model indicates that the model performs better than the global model in all areas of the state with values ranging from 0.862 in the west to 0.894 in the northeast (Figure 28).

Table 9. Results of GWR models pertaining to federal expenditures.

Variable	FED_FUND Model Parameter Coefficients		DHS_FUND Model Parameter Coefficients	
	Global	GWR (range)	Global	GWR (range)
Intercept (POV)	-174.856	-2112.887 to 1164.289	3507.020	-1931.349 to 2377.744
UNEMPL	0.387	0.212 to 0.526	0.577	0.148 to 0.974
NO_HS	0.197	0.105 to 0.269***	0.174	-0.016 to 0.248
AM_IND	0.078	0.044 to 0.123	0.065	0.038 to 0.128
MINOR	0.017	-0.022 to 0.089*	0.084	-0.037 to 0.141
HISP	0.014	-0.050 to 0.015*	0.023	0.014 to 0.163
MED_AGE	-0.298	-0.382 to -0.222	-0.432	-0.597 to -0.300
EDLER	0.214	0.180 to 0.329	0.475	0.186 to 0.567
FAM_SZ	-5.465	-7.348 to -3.284	-4.971	-12.241 to -2.753
FEM_HH	0.243	0.036 to 0.258	0.275	-0.249 to 0.609***
PCI	-0.0004	-0.001 to -0.0003	-0.0004	-0.001 to -0.0004
STABLE	-0.088	-0.116 to -0.056	-0.008	-0.121 to 0.157
PRIM	2.212	-11.109 to 21.535	-34.638	-23.231 to 19.670
SEC	2.125	-11.201 to 21.424	-34.748	-23.304 to 19.613
TER	2.112	-11.271 to 21.416	-34.824	-23.409 to 19.582
QUAT	2.211	-11.160 to 21.540	-34.555	-23.159 to 19.874
RURAL	0.016	-0.002 to 0.019	-0.001	-0.008 to 0.002
FED_AFS	0.020	-0.045 to 0.028	---	---
FED_CRS	0.020	-0.045 to 0.028	---	---
FED_HRS	0.026	-0.035 to 0.035	---	---
FED_ISS	0.067	0.013 to 0.069	---	---
FED_TOTS	-0.020	-0.028 to 0.045	---	---
DHS_FS	---	---	0.060	-0.723 to 0.158
DHS_SUP	---	---	3.080	1.524 to 5.811**
DHS_TANF	---	---	0.245	-0.937 to 0.591
DHS_TOTS	---	---	-0.220	-0.227 to 0.404
Bandwidth	---	293	---	75
AIC	1248.655	1238.238	316.600	338.446
Adjusted R^2	0.839	0.857	0.882	0.911
F statistic	2.925	---	2.566	---

*Variable displays significant spatial non-stationarity at the 5% significance level.
**Variable displays significant spatial non-stationarity at the 1% significance level.
***Variable displays significant spatial non-stationarity at the 0.1% significance level.

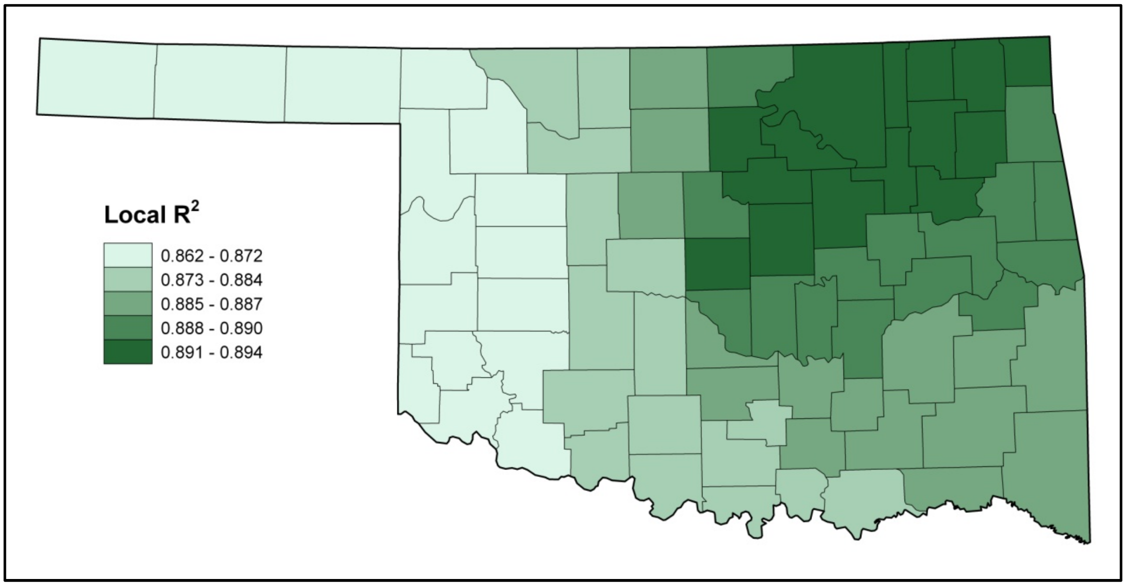

Figure 28. Localized R^2 *values for the FED_FUND GWR model.*

Only three variables in the dataset, educational attainment, percent minority and percent Hispanic, exhibit significant spatial variation and the localized influences of these variables behave much the same as they did in the first GWR model described above. Disappointingly, none of the funding variables display significant spatial non-stationarity with respect to their influence on poverty. The parameter coefficients for the two funding categories that should potentially have the most influence on poverty, the ones pertaining to human resources and income security spending, are mapped below in Figures 29 and 30. The amount of per capita spending on human resource programs does have the desired effect on poverty, but only in the western part of the state where parameter coefficients are negative (Figure 29). Unfortunately, in areas of the state where higher poverty rates are persistent, such as the southeast corner, increases in human resources spending correlates with increases in poverty rates as well. Much the same can be said for the variable relating to income security spending, whose parameter coefficients are positive throughout the state (Figure 30). Notably, again the highest level of influence in this variable is consistent with areas where high poverty rates are clustered (see Figure 13).

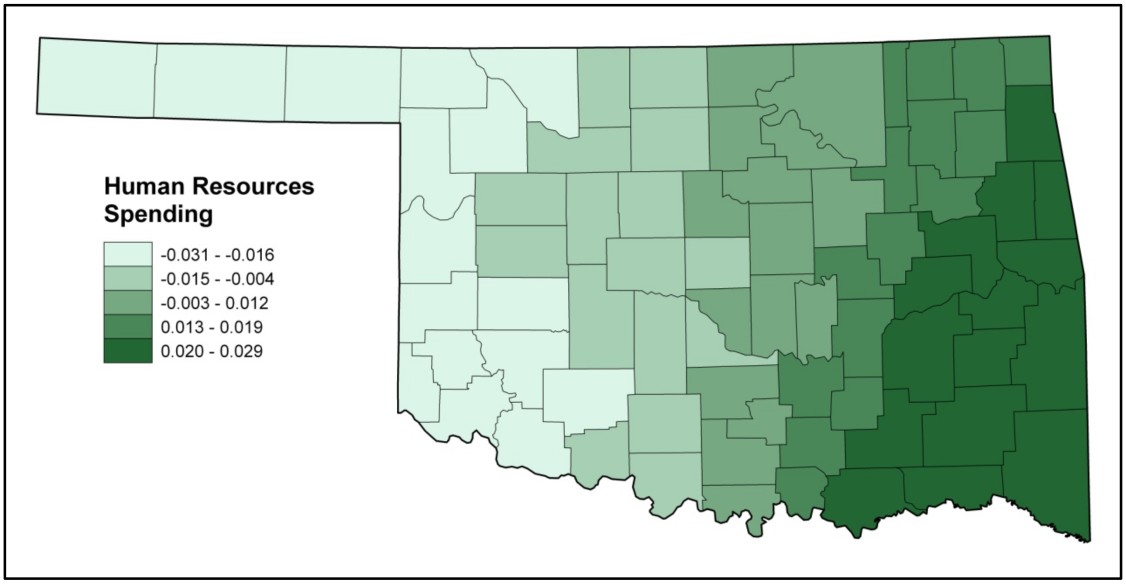

Figure 29. Parameter coefficients for per capita human resources spending.

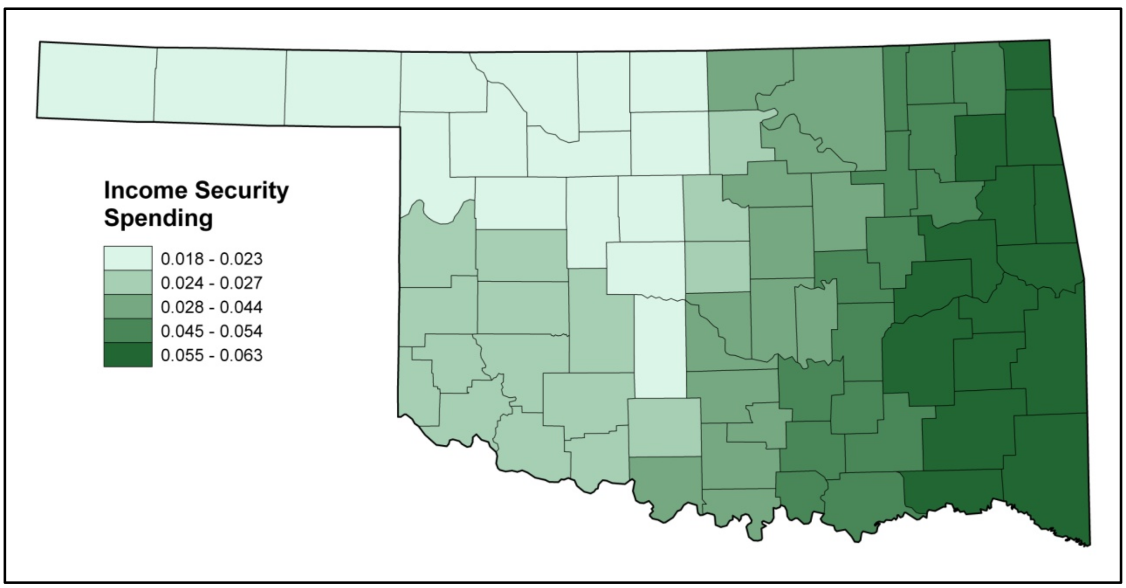

Figure 30. Parameter coefficients for per capita income security spending.

There are many reasons why these anomalies might exist including the specifications of the model at this level of analysis. Also, these variables are made up of aggregated data representing dozens of different federally funded programs dealing with various aspects of human resources and income security. It is possible that what may be represented in the GWR model is the effect of specific programs within the data that are not necessarily aimed at targeting poverty overshadowing the effects of programs that do target poverty.

The final GWR model employs the data on several specific programs offered to Oklahoma residents by OKDHS. Like the previous model, the size of the optimal bandwidth selected causes a close approximation to the global regression model with data from 75 of 77 counties being used for each observation. However, the mapped localized R^2 values again suggest that the GWR model performs better than the global one with localized R^2 values falling in a range well above the global R^2 of 0.882 (Figure 31). It should be noted, however, that the AIC value for the GWR model in this case is higher than the AIC value for the global model, indicating that this GWR model is not significantly improved over the global model. Regardless, the one non-funding related variable that exhibits a significant degree of spatial non-stationarity is the percentage of female-headed households (Figure 32). In the majority of the central and eastern part of the state, the coefficients for this parameter are positive, indicating an increase in the percentage of female-headed households also signals an increase in poverty. There are some counties in the far western portion of Oklahoma where the coefficients are negative, however.

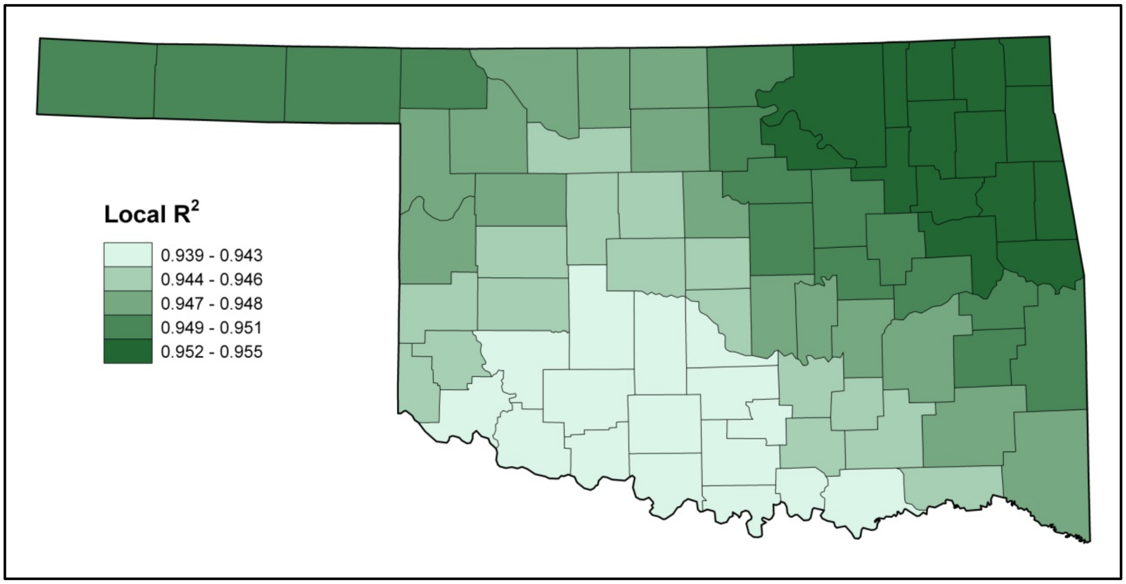

Figure 31. Localized R^2 *values for the DHS_FUND GWR model.*

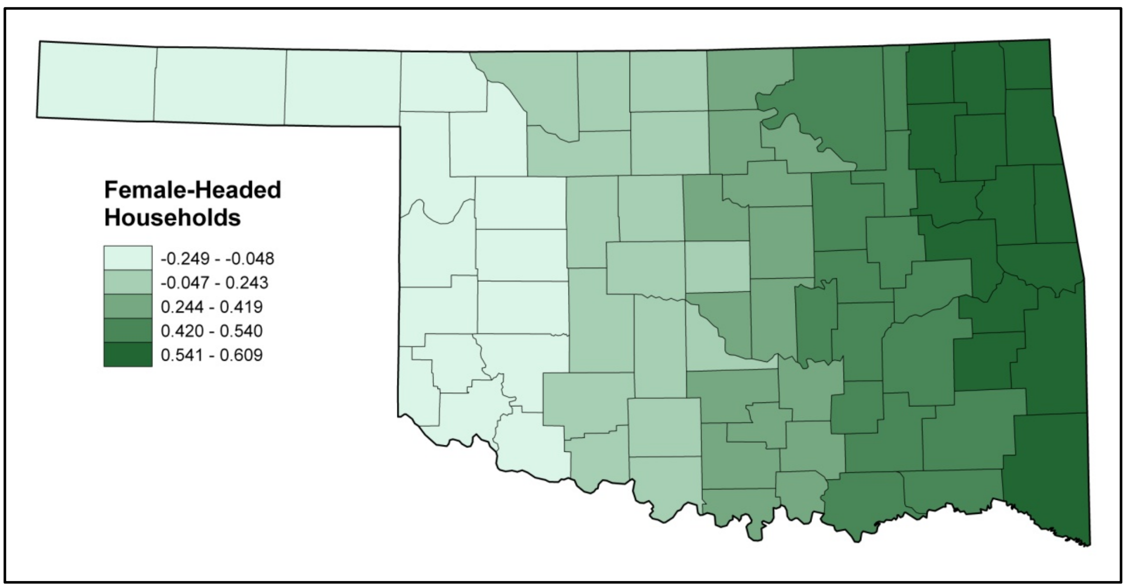

Figure 32. Parameter coefficients for percent female-headed households.

Only one of the funding related variables, relating to expenditures for supplemental programs, exhibits significant spatial variation, but coefficients for all four have been mapped below in Figures 33 through 36 for comparative purposes.

Unfortunately, parameter coefficients for the variable pertaining to spending for supplemental programs are positive throughout the state, indicating that increased spending for these programs also correlates with an increase in the poverty rate (Figure 33). The variables related to spending for the food stamps and TANF programs have both positive and negative coefficients varying across the state (Figures 34 and 35). For both of these programs, the greatest amount of influence is felt in a wide swath of counties trending northeast to southwest. In these areas, negative coefficients indicate that these programs may be having the desired effect of lessening poverty. In the areas with the highest poverty rates, however, increased expenditures for the food stamps program actually relates to an increase in the poverty rate as well.

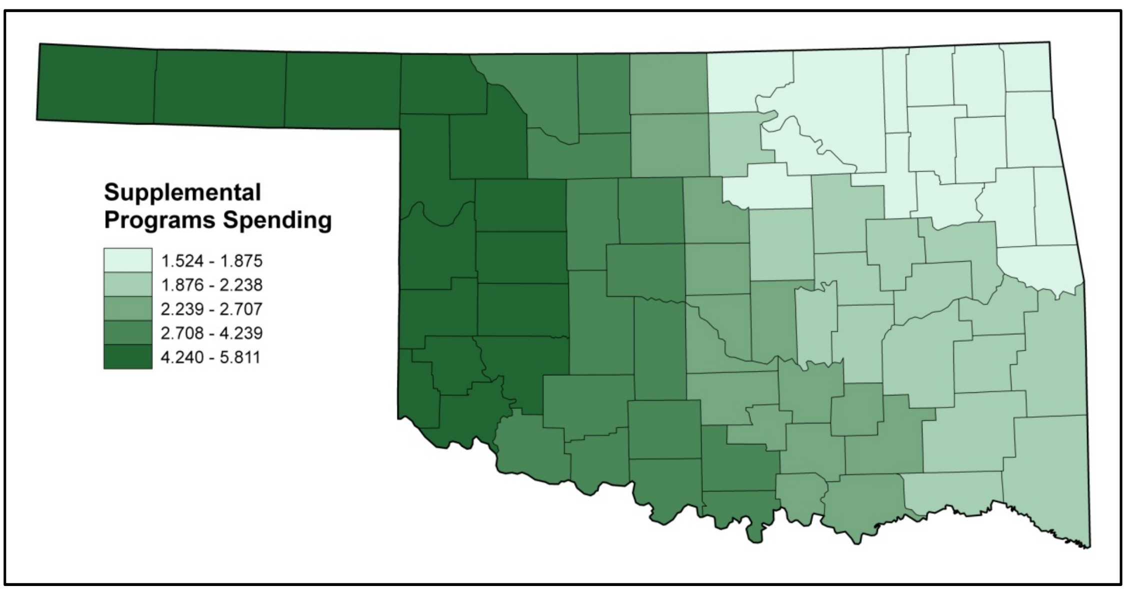

Figure 33. Parameter coefficients for per capita funding of supplemental programs.

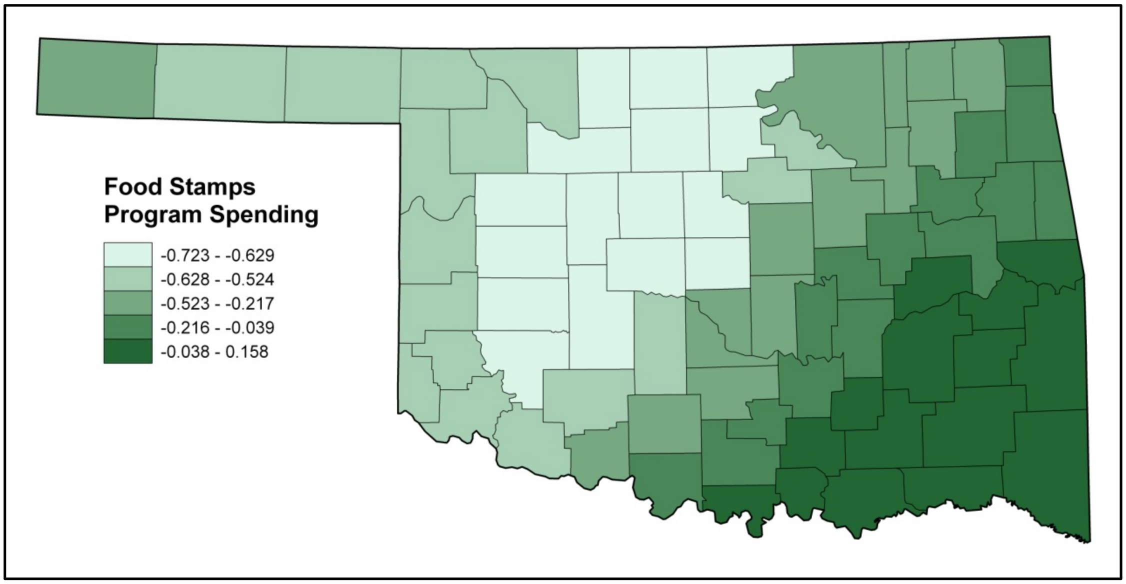

Figure 34. Parameter coefficients for per capita funding of food stamps program.

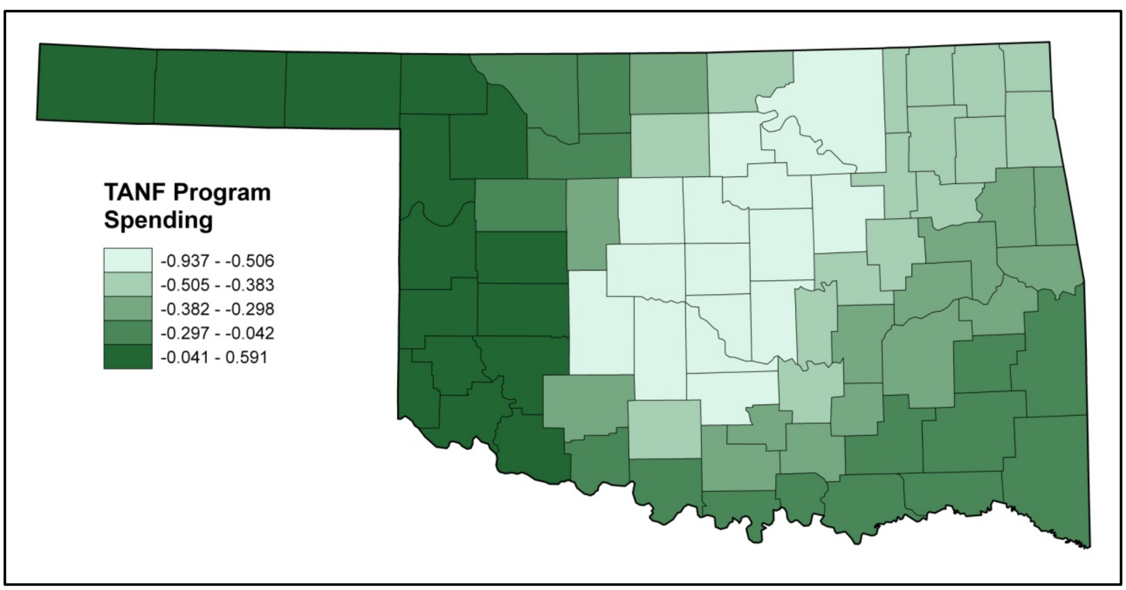

Figure 35. Parameter coefficients for per capita funding of TANF program.

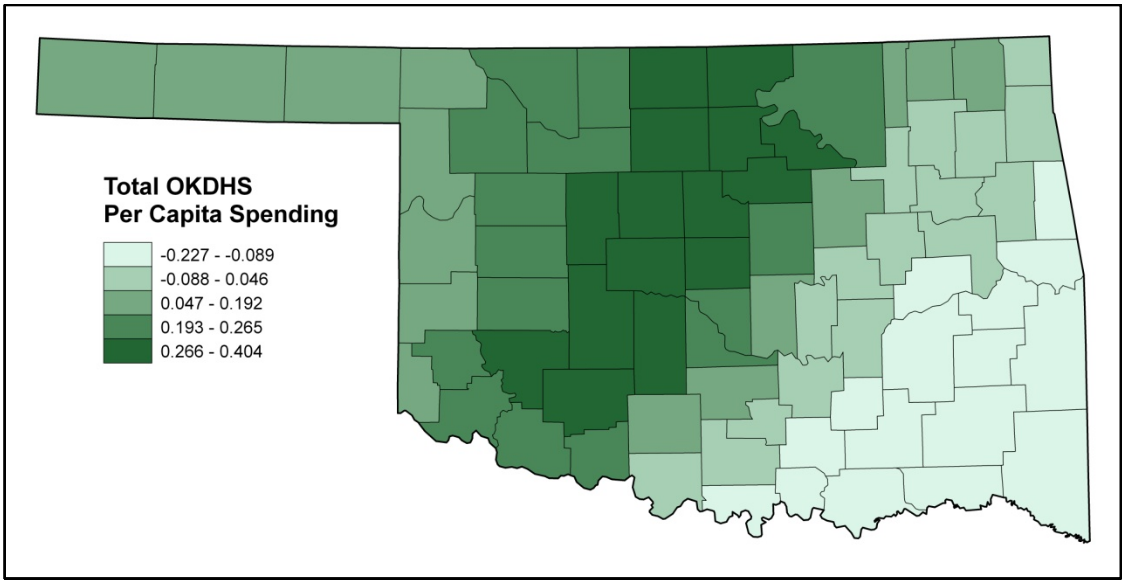

Figure 36. Parameter coefficients for total per capita OKDHS expenditures.

The parameter coefficients for the total per capita expenditures by OKDHS indicate that overall funding may actually be helping in areas that are most poverty stricken. The majority of counties within the two lightest categories in Figure 36 have negative coefficients, signifying that OKDHS expenditures may be improving the poverty rates among the people living here. There are possibly other programs aside from the food stamps, supplemental, and TANF programs quantified within this category that are unaccounted for in this model and that are having the desired effect on poverty in the highest poverty areas. It is also possible that it is the combination of these various programs calculated together into a total spending category that allows for poverty to be helped by these programs in the highest poverty areas. Regardless, the results of all regression models present some options for policy recommendations, discussed in the following chapter, which could be valuable in the fight against poverty in Oklahoma.

CHAPTER V

CONCLUSION

This study has presented an analysis of poverty and the factors that influence poverty throughout the state of Oklahoma at several different spatial levels. Both county and Census tract data were used in order to gain a better understanding of how various factors influence poverty at these different scales. Also, global and local regression modeling was employed to highlight how the factors influence poverty in specific locations throughout the state. This final chapter features a discussion of the results of these analyses along with recommendations for potential programs that might help to improve the poverty rate across the state. It also includes a discussion of the limitations of the study and suggestions for future research emphasizing the potential application of studies like this for real world solutions to the problem of poverty.

Discussion of Results

The overall goal of this research is to use the results of local regression modeling to make explicit policy recommendations for specific areas within the state based on local variations in the influence of various factors, as well as federal funding for assistance programs, in order to better target poverty relief in areas where poverty is persistent. However, based on the available data, this is not easily done. As discussed above, because optimal bandwidth selection for county level GWR models closely approximates a global regression model, what is represented by the results of these models may not actually denote the local variations hoped for by using GWR. Therefore, the results of these models must be interpreted with caution, as they may not correspond to the true nature of these phenomena. Unfortunately, the data representing the amount of per capita expenditures for various programs are only available at the county level at this time. What these local models do depict is that increased funding for several government assistance programs seems to increase the poverty rate in areas of the state where poverty is already rampant. The main question then becomes: are specific government assistance programs actually encouraging people to remain in poverty as public perception has entertained, or is this a problem with the model calibrations used to analyze the variables relating to funding for these programs against poverty? Unfortunately, because this relates to a social phenomenon, this question is nearly impossible to answer. That being said, it is possible to combine the results of all regression analyses in order to make some general recommendations on ways to better target poverty across the state.

Using global regression modeling, four factors appear to be significant indicators of poverty at both the county and tract level: per capita income, the percentage of people with no high school diploma, the percentage of female-headed households, and the percentage of people employed in primary industries. When the factors are studied at a local scale using GWR, county level models indicate that the percentage of those without a high school diploma, the percentage of Native Americans, the percentage of other minorities, the percentage of Hispanics, and the percentage of female-headed households all display significant variation in their influence over poverty across the state. In addition to these variables, the variables concerning per capita income, the percentage of people aged 65+, and the percentage of people living in rural areas exhibit significant spatial variation when examined at the tract level.

No matter the regression technique or level of analysis used, it is clear that the lack of a high school education dominates as a leading factor influencing poverty among Oklahomans. Examining a county map of poverty rates and educational attainment together, it is clear that poverty rates are higher where the percentage of people with no high school diploma is also high (Figure 37). Results from the regression modeling verify this correlation in both global and local models, even though direction of causality within this relationship might be difficult to assign. Does a higher number of non high school graduates contribute more to higher poverty levels, or do higher poverty rates force teens to quit school in search of employment before graduating? In either case, more government funded programs providing incentives for people to finish high school may help to lower poverty rates throughout the state. From the county level GWR model, it would appear that these programs are most needed in the northeast part of the state where the influence of this variable over poverty is the strongest. However, the tract level model indicates that areas in the southern, as well as central region, including within the Oklahoma City metro area, would most benefit from these types of programs. While encouraging young people to complete high school may be one of the best ways to combat poverty, increased funding for job training and employment programs for non high school graduates would also certainly contribute to better paying jobs for those people without a high school diploma.

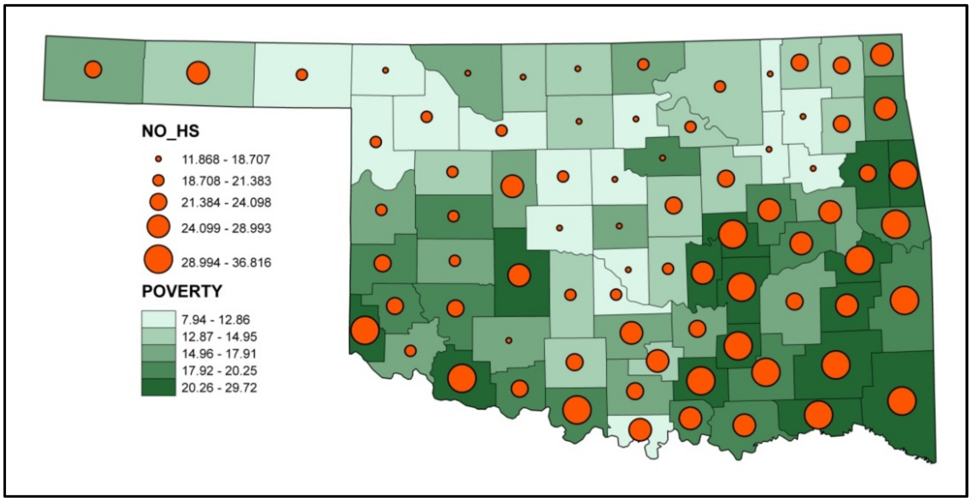

Figure 37. Spatial distribution of poverty and educational attainment.

Another variable that appears to influence poverty at both the county and tract level is the percentage of female-headed households. While this variable did not register as significant in the basic county and tract level GWR models, it did exhibit significant spatial variation in the county level model depicting per capita expenditures by OKDHS, as well as being as significant indicator of poverty in both global regression models. As mentioned in the discussion of the global models, this variable correlates highly with the unemployment rate at both the county and tract level. Better-funded programs, including assistance for childcare and insurance, which would enable more single mothers to join the workforce, would certainly be warranted. According to the tract level GWR model, these programs would be most beneficial to implement in the northeastern region of the state where the influence of this variable on poverty is strongest. While programs such as these might be helpful in relieving poverty in some areas, the scale at which they are applied would certainly affect their influence.

If this analysis is to be truly successful at recommending explicit policy changes, it needs to be repeated to examine the influence of current spending patterns on poverty using an analysis unit smaller than the county level. What is clear from the results of this study is that the factors influencing poverty do not behave the same throughout the state, nor does the implementation of specific programs meant to alleviate poverty. The amount of local variations in these factors must be taken into account by policymakers when designing programs centered on poverty reduction. Thus, targeting poverty at local scales by implementing place-based policies as Partridge and Rickman (2006, 2007) have suggested, would perhaps be the most successful strategy to employ to best serve the people of Oklahoma.

Limitations of Study

There are several basic limitations in terms of the data used that should be addressed. First, as discussed in the introductory chapter, the Census Bureau's measurement of the poverty rate is fundamentally flawed and most likely underestimates the actual poverty rate among U.S. citizens (Rodgers 2006). It is, however, still a useful measure since it provides a relative assessment of poverty among people in various geographic regions. Second, with the exception of the data on OKDHS expenditures, all data were gathered from the Census Bureau, whose enumeration process takes place every ten years. With this current study being done at the very end of one of these ten-year cycles, the data available for these analyses are nearly a decade old. Updated data reflecting details of the current population might very well alter the findings of this study significantly. Lastly, other categories measured by the Census Bureau reflect only certain subsets of the population. For example, educational attainment is calculated only for those people over 25 years of age. Given the results of this analysis and the importance of educational attainment as it correlates to the poverty rate, it might also be helpful to have a calculation of the percentage of 18-24 year olds who have not completed high school.

As discussed previously, being able to acquire the variables pertaining to government expenditures at the county level only is perhaps the greatest limitation of this particular analysis. With the overall goal being to model the local variations present among the factors influencing poverty, the county level GWR models were not able to capture these potential local variations due to the size of the optimal bandwidth selected for analysis. This is most likely due to the relatively small sample size of only 77 counties within the state. It was hoped that expanding the study area to include counties in neighboring states would strengthen the county model's significance. However, this too resulted in a model approximating a global regression model, potentially masking any local variations present among the variables.

Another potential limitation encountered when using GWR modeling is that the technique is especially sensitive to the size and shape of the analysis units that make up the study area (Fotheringham, Brunsdon, and Charlton 2000, 2002). While counties certainly differ immensely in terms of their size and shape, this could be more problematic at the tract level as tracts are much less uniform in size and shape. For example, Oklahoma County, which includes the Oklahoma City metropolitan area, contains 227 Census tracts of varying shapes and sizes. This is contrasted to Cimarron County at the far western end of the panhandle, which contains only two Census tracts, one bounding the town of Boise City, and the other encompassing the remainder of the county. One of the values of using tract level data, however, is that the populations within tracts are much more homogenous than the populations of entire counties. All of these limitations must be taken into account when interpreting the results of studies such as this, and should be considered when formulating future research projects within this arena as well.

Suggestions for Future Research

There are numerous avenues of potential future research into poverty and the factors that influence it. Specific to this particular study, updating the regression models using data from the 2010 Census when it becomes available would certainly be pertinent. This would not only allow for modeling of characteristics of the current population, but would also provide an opportunity to examine the changes between the data presented here and more current data.

This study utilized data relating to several key demographic factors, as well as employment variables and county/tract characteristics. However, there are certainly countless other variables that might be added to future research to reveal a more complete picture of poverty in Oklahoma. For example, factors relating to economic change over time and other historical factors reflecting changes in the overall character of the population, as well as socioeconomic facets of specific subsets of the population might add to a better understanding of poverty. Also, following the work of Minot, Baulch, and Epprecht (2006) on poverty in Vietnam, it would be useful to include several geographic determinants of poverty in Oklahoma as well. For example, climatic variations across the state, land use and land cover attributes, and distance from major urban centers might well play a part in determining where poverty has persisted within the state.

Within Oklahoma, a comparison of poverty inside the two metropolitan areas would make another valuable avenue of research for future studies. As shown by this current study, there is indeed a lot of variation in the influence of various factors between, as well as within, the two cities. Using tract level data, or perhaps even smaller units of analysis, such as Census block groups or blocks, might reveal how and why poverty varies so much within these large metropolitan areas. Conversely to these micro scale studies, research focusing on more of a macro scale is warranted as well. Expanding the study area to include a more regional view of poverty might well enhance the understanding of this phenomenon within Oklahoma. For example, Duval-Diop's (2006) work focused not on one state in particular, but on a geographic region crossing many state boundaries. The same could be accomplished for Oklahoma by incorporating it into a larger region within the United States. Because of Oklahoma's geographic position within the U.S., it could easily be included in any number of larger regions consisting of the greater southwest, the southeast, or the central Plains regions.

Another avenue for potentially useful research would be to examine the influence of specific government funded programs on poverty within the state. For ease of analysis, this study utilized the funding variables available from the Census Bureau's Consolidated Federal Funds Report as aggregated by the USDA. However, these broad categories encompass a vast array of different programs aimed at targeting specific subsets of the population. Looking at these individual programs in order to better ascertain how they might be helping or hindering poverty relief in particular areas, could allow for more explicit policy recommendations to be made concerning how to best alleviate poverty throughout Oklahoma.

In conclusion, there is no shortage of ideas for potential future research into the problem of poverty. Specifically in the United States, because the Census Bureau's measurement of the poverty rate is so skewed, it is especially important to analyze it from various perspectives and at different levels in order to better understand it. This study aimed to prove that local variation in poverty, and the factors influencing it, exists within Oklahoma. Using geographically weighted regression to analyze this phenomenon, these local variations were indeed highlighted throughout the state. Applying GWR to further studies on poverty can only help to define more of the reasons behind the persistence of poverty at various geographic levels and ultimately enhance the potential for more targeted policies to reduce poverty in Oklahoma, and throughout the world.

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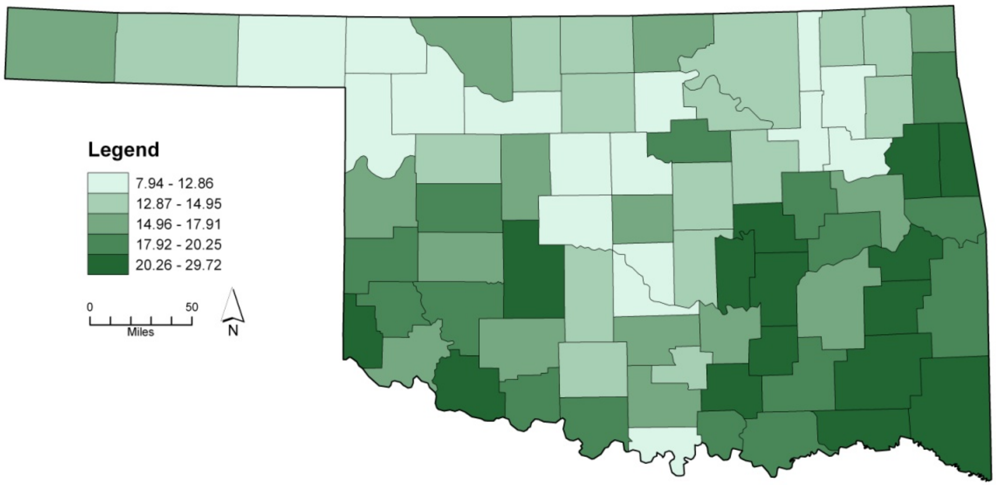
APPENDICES

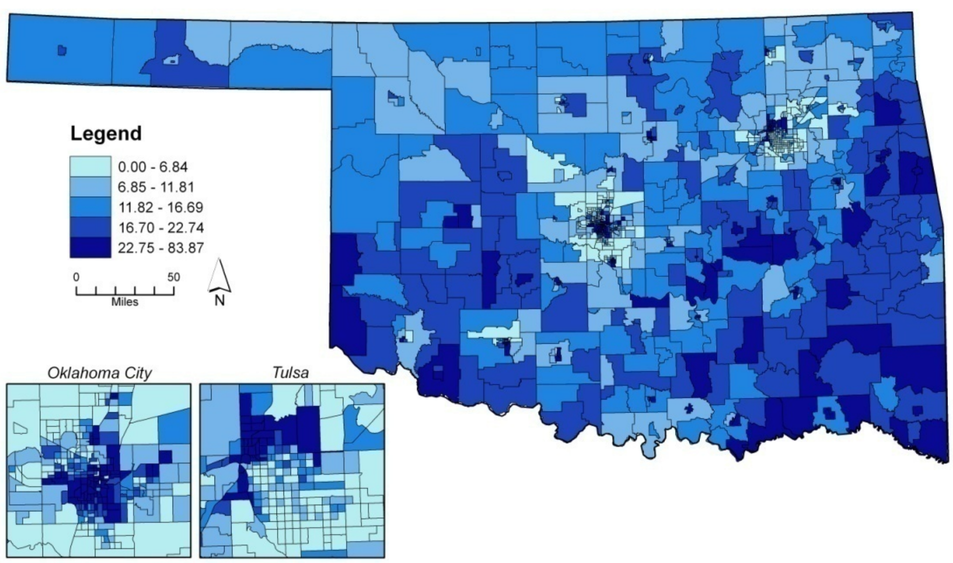
APPENDIX A

Spatial distribution of raw variables at county and tract levels

Percentage of the total population living below the poverty line

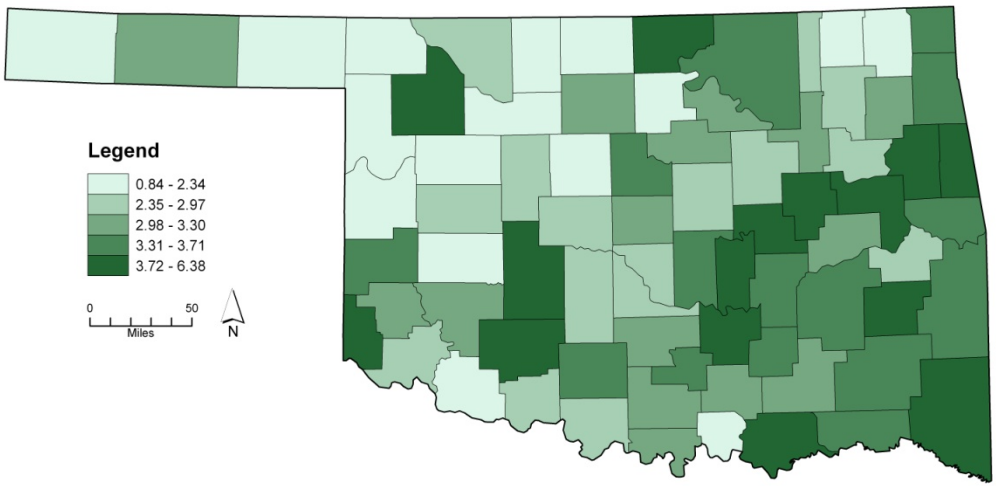


Percentage of the total population living below the poverty line

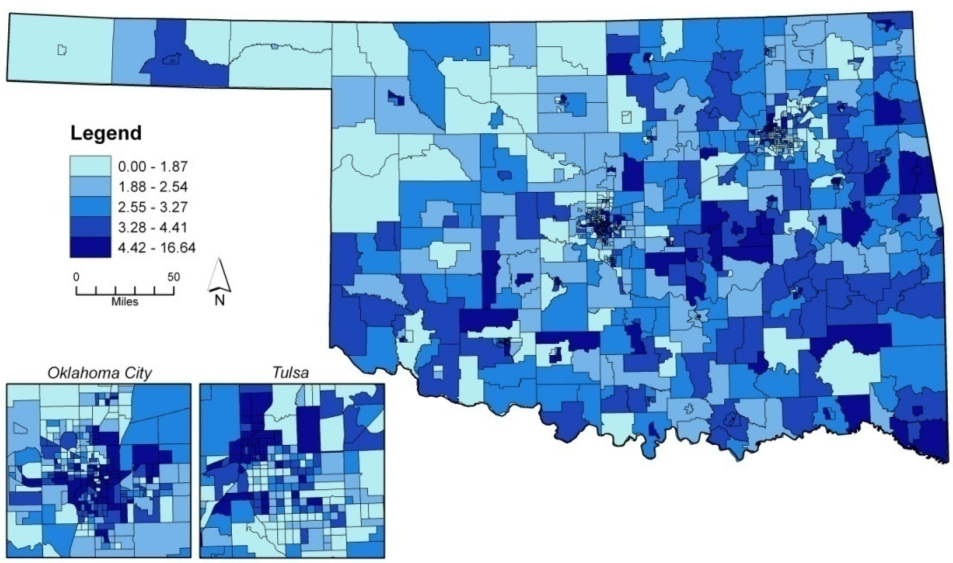


Note: all maps presented here use the quantile method of classification.

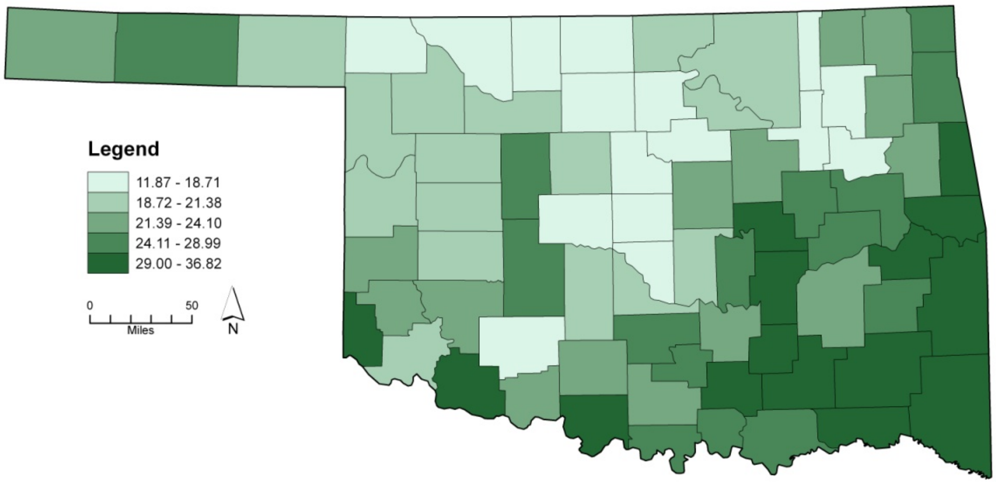
Percentage of the population 16+ years of age in the labor force who are unemployed



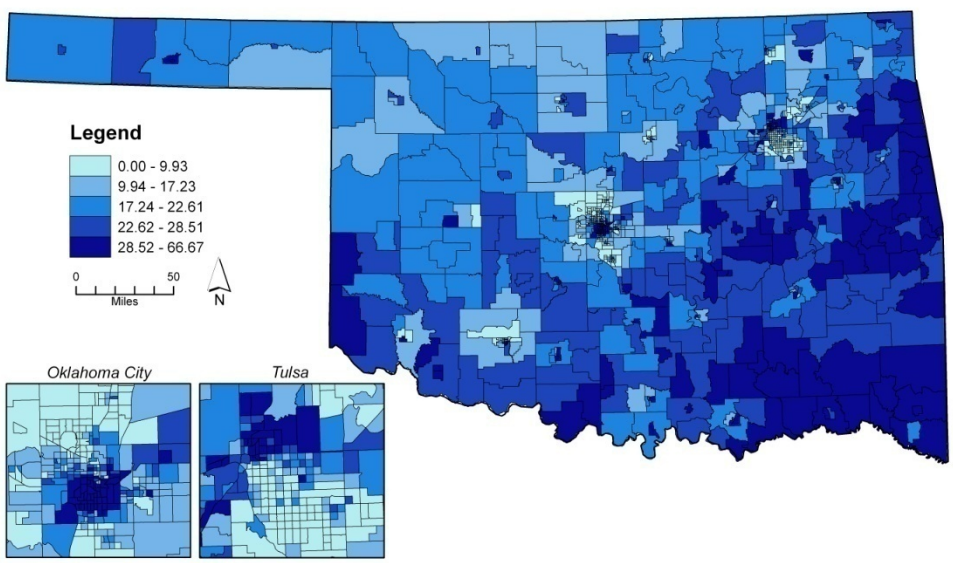
Percentage of the population 16+ years of age in the labor force who are unemployed



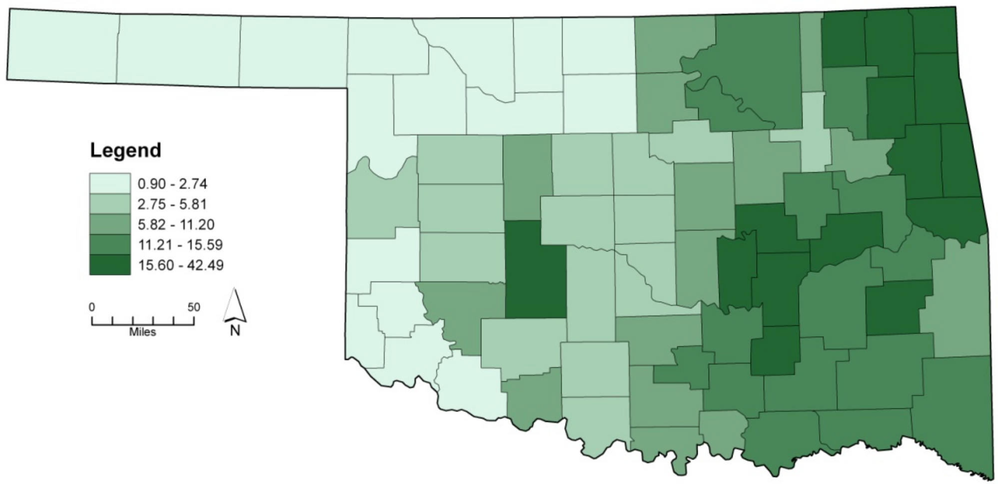
Percentage of the population 25+ years of age
with no high school diploma



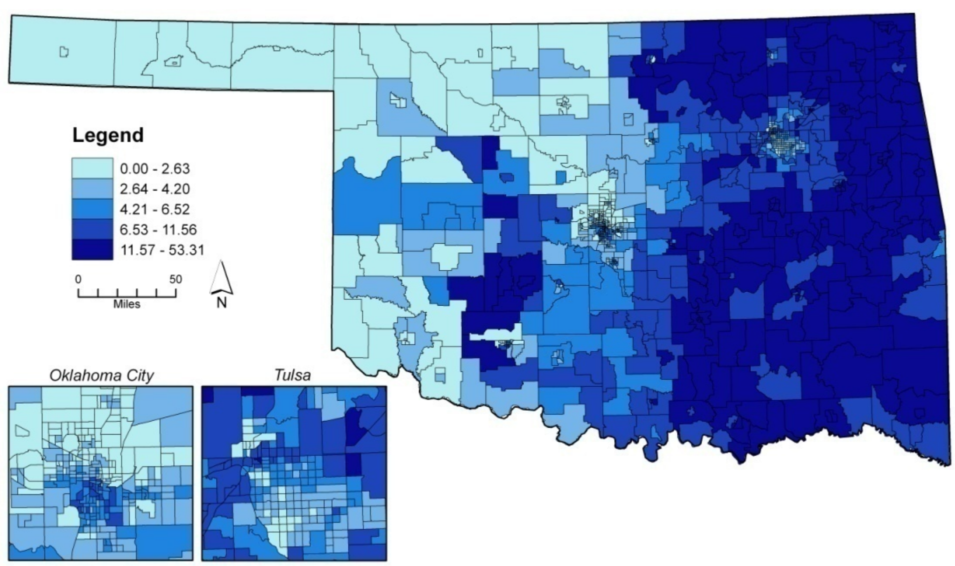
Percentage of the population 25+ years of age
with no high school diploma



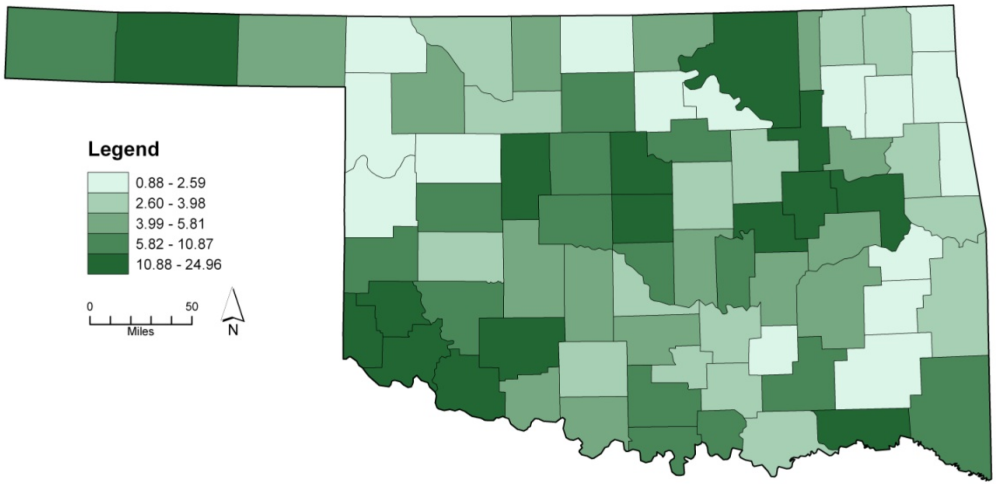
Percentage of the total population who are American Indian



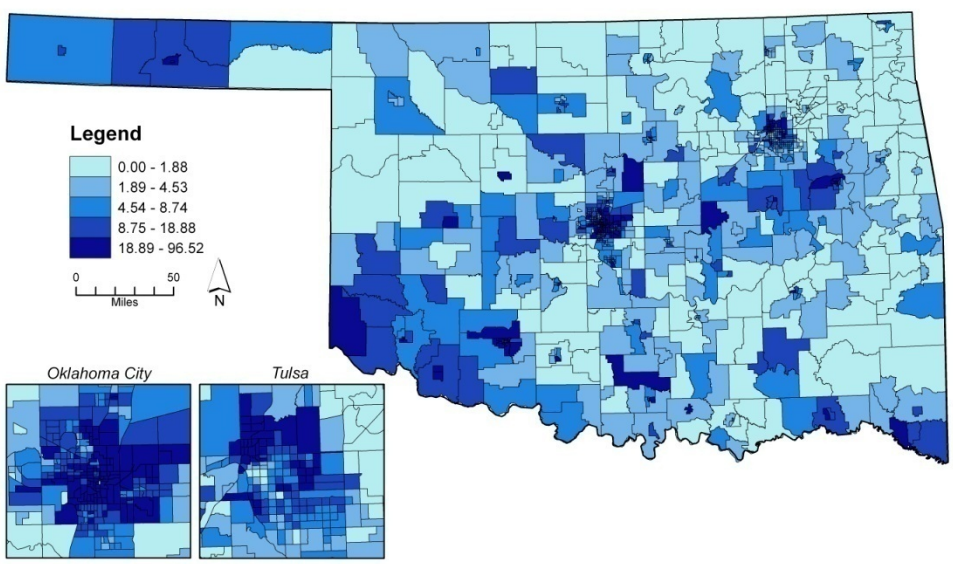
Percentage of the total population who are American Indian



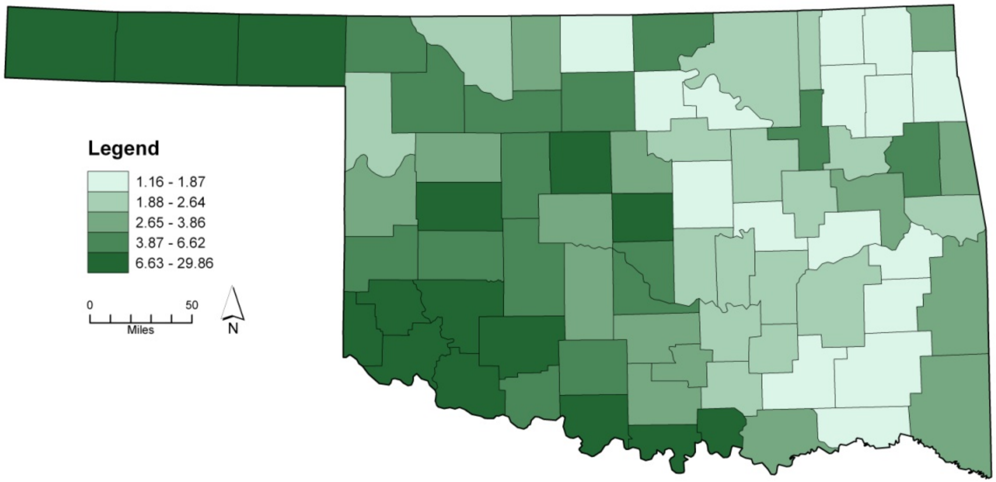
Percentage of the total population who are of other minority groups



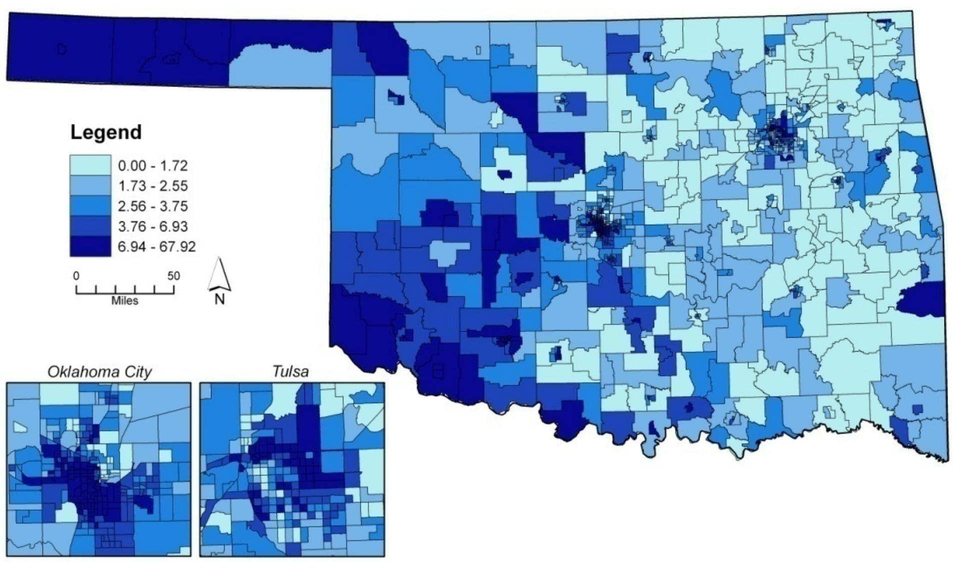
Percentage of the total population who are of other minority groups



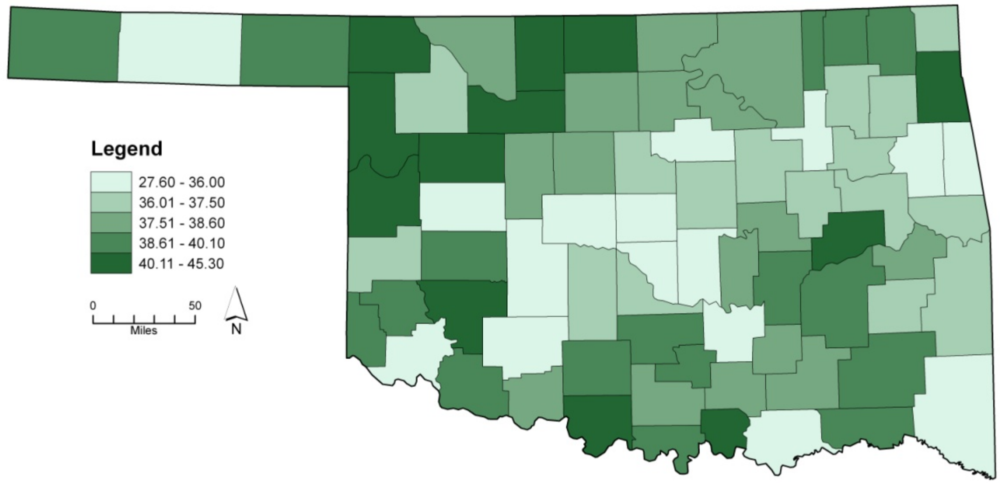
Percentage of the total population who are Hispanic



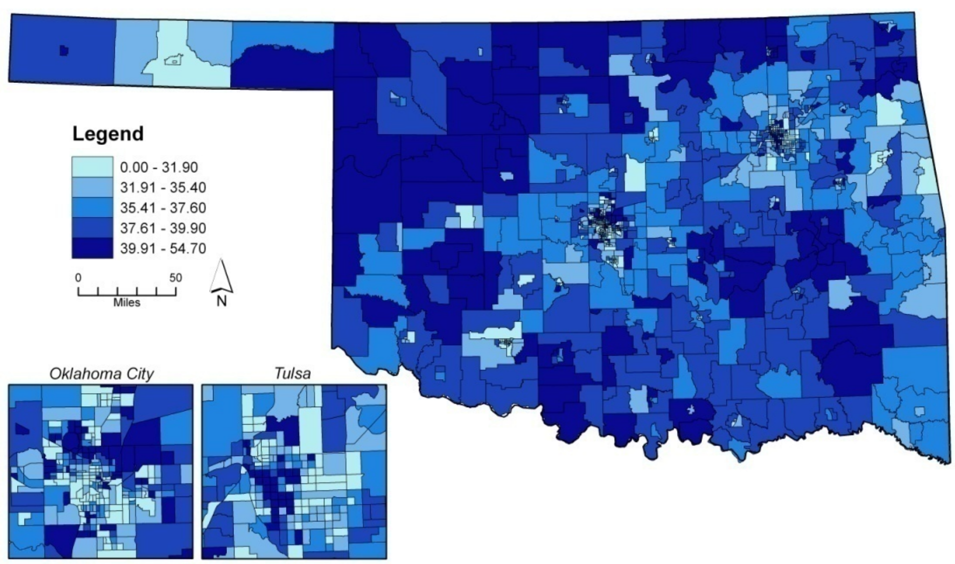
Percentage of the total population who are Hispanic

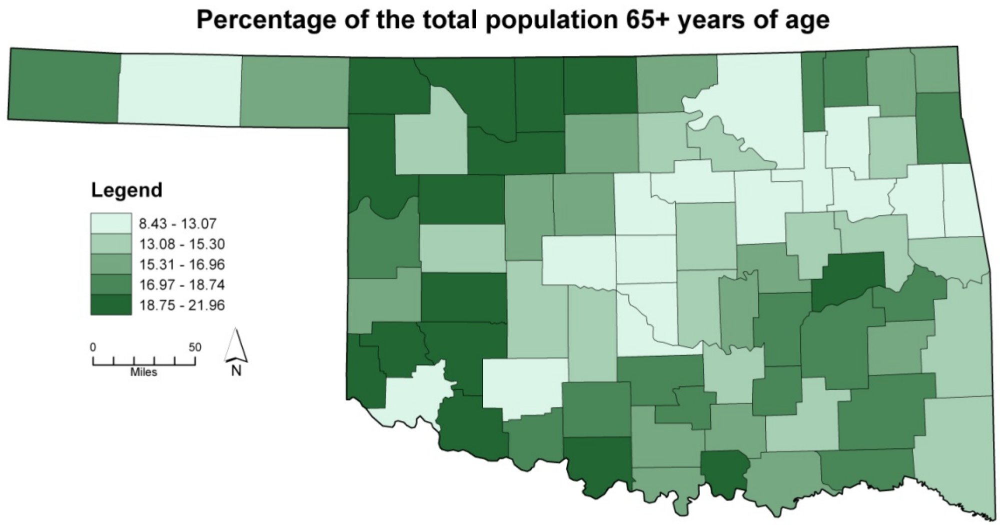


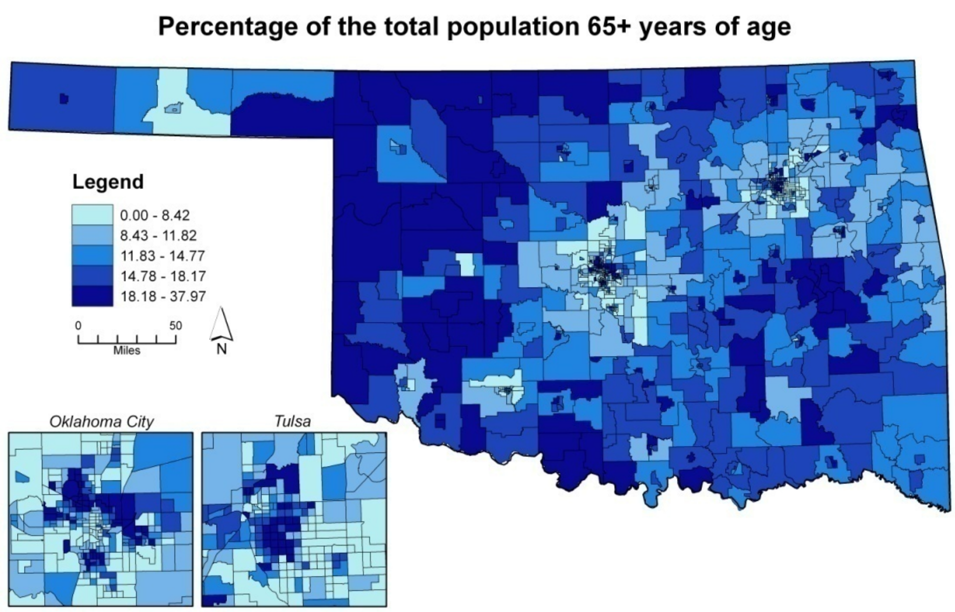
Median age

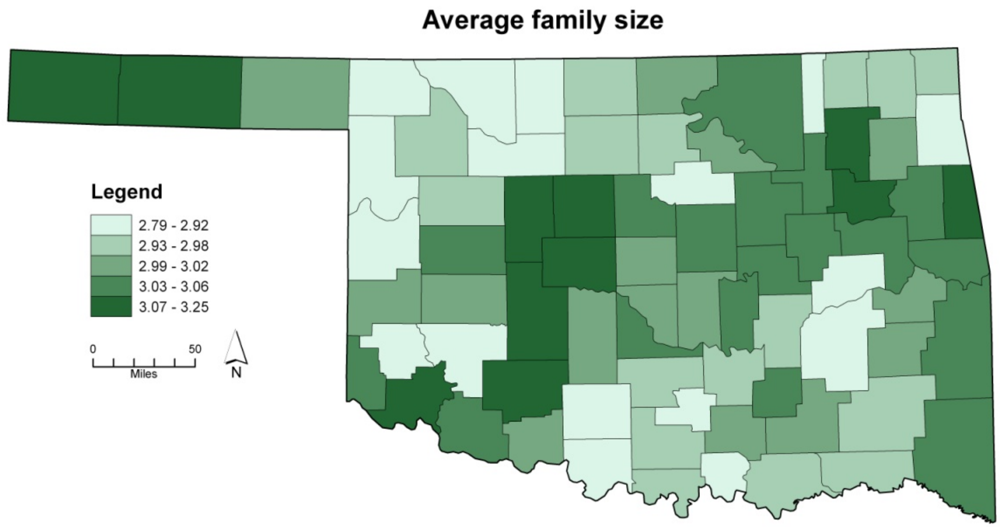


Median age

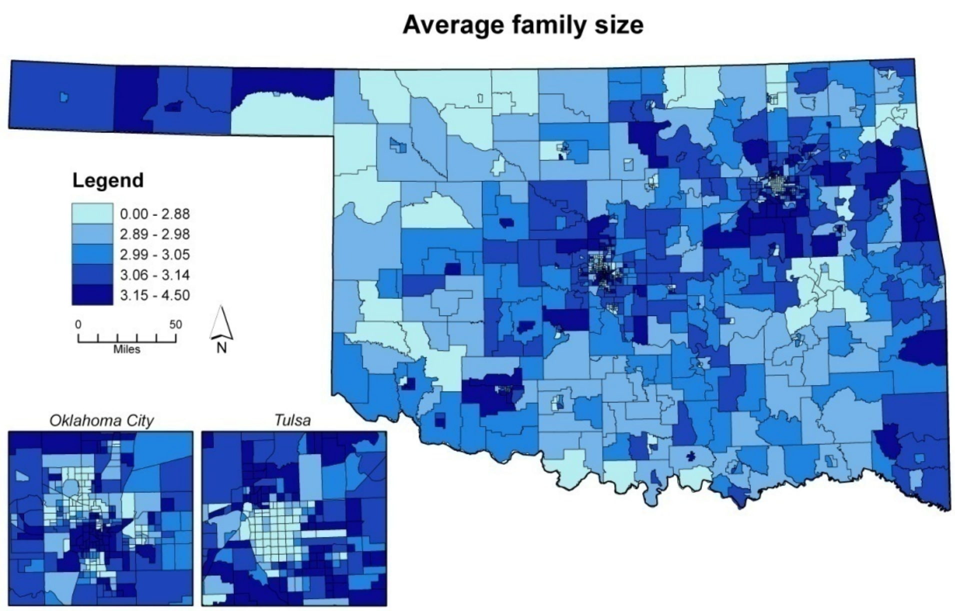



Percentage of the total population 65+ years of age
Legend
8.43 - 13.07
13.08 - 15.30
15.31 - 16.96
16.97 - 18.74
18.75 - 21.96
0
50
Miles
N


Percentage of the total population 65+ years of age
Legend
0.00 - 8.42
8.43 - 11.82
11.83 - 14.77
14.78 - 18.17
18.18 - 37.97
0
50
Miles
N
Oklahoma City
Tulsa

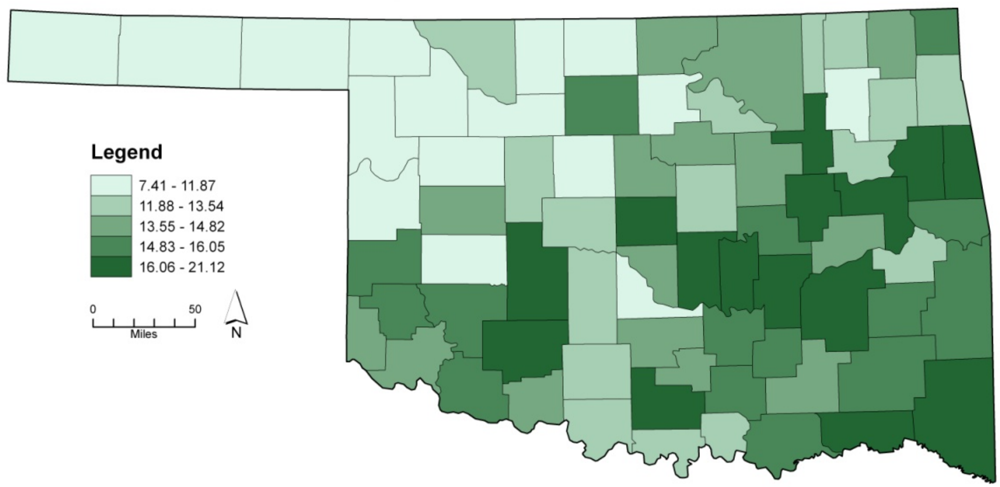


Average family size
Legend
2.79 - 2.92
2.93 - 2.98
2.99 - 3.02
3.03 - 3.06
3.07 - 3.25
0
50
Miles
N

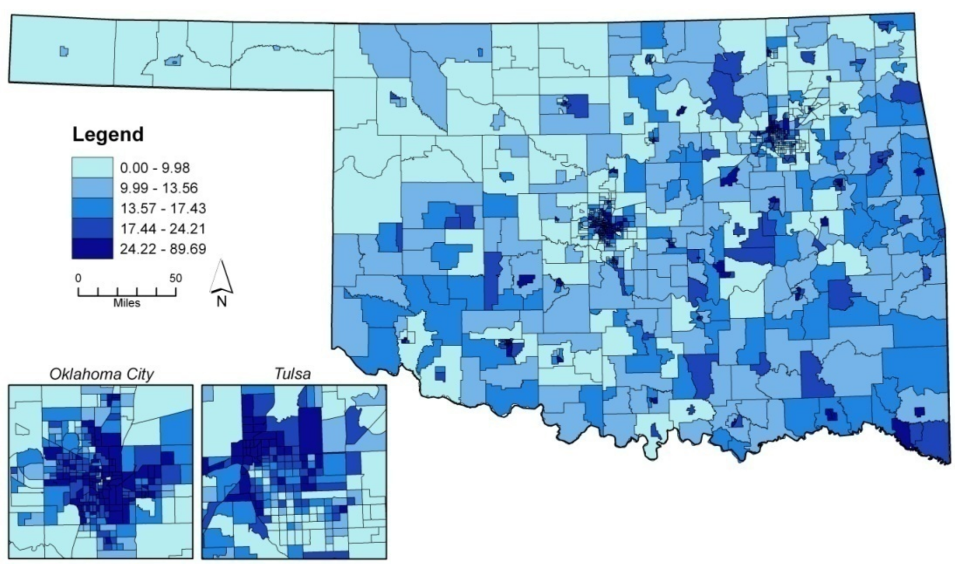


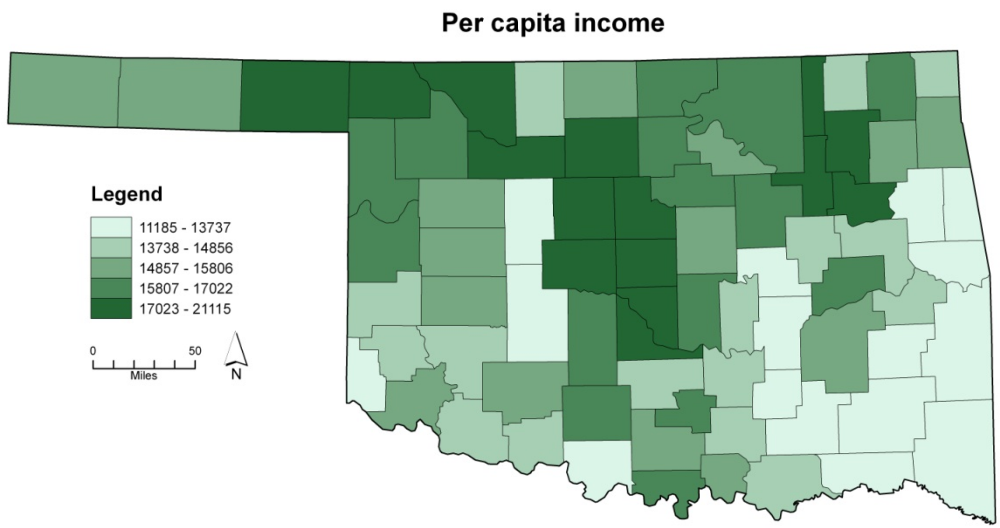
Average family size
Legend
0.00 - 2.88
2.89 - 2.98
2.99 - 3.05
3.06 - 3.14
3.15 - 4.50
0
50
Miles
N
Oklahoma City
Tulsa

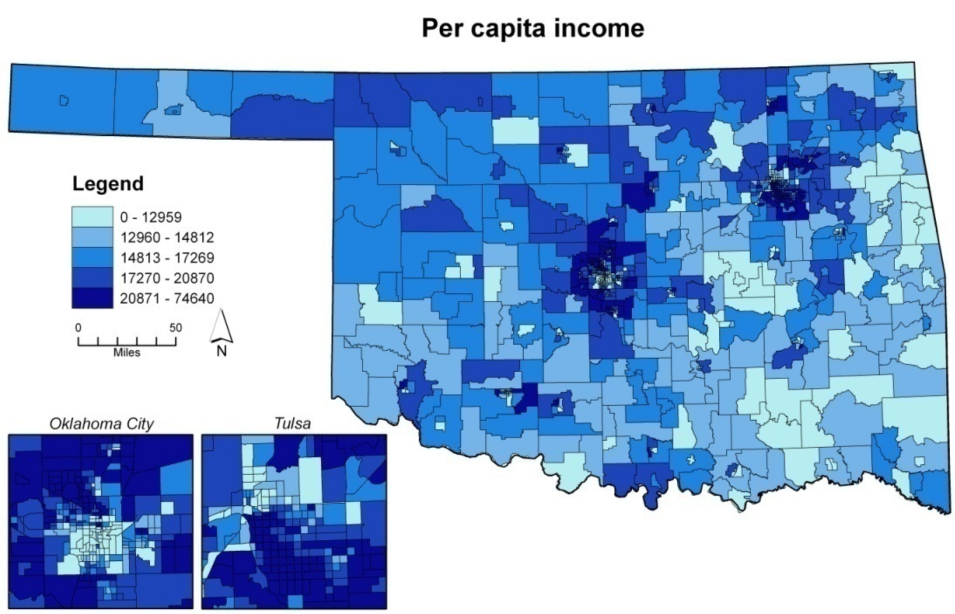
Percentage of female-headed households



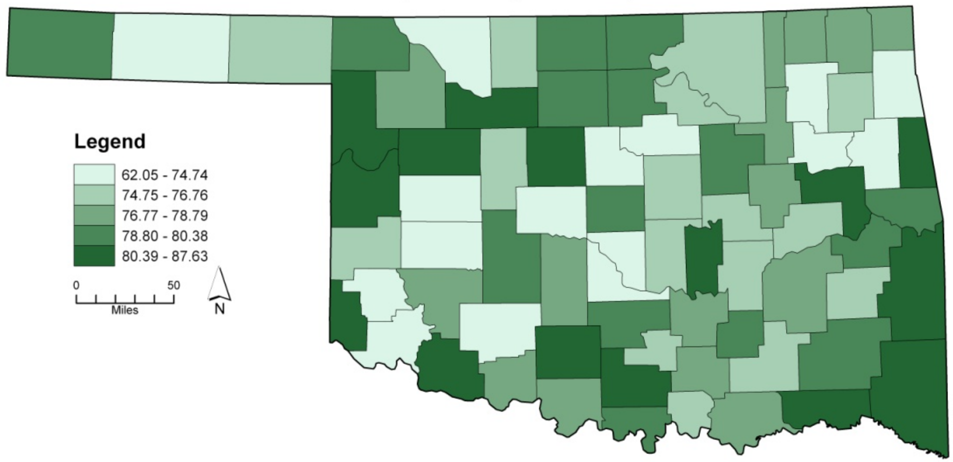
Percentage of female-headed households



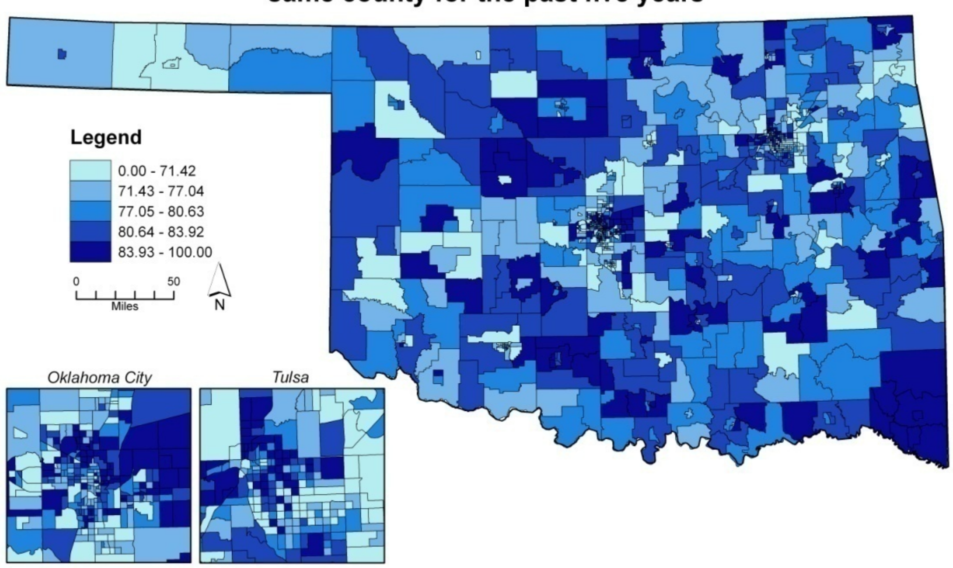

Per capita income
Legend
11185 - 13737
13738 - 14856
14857 - 15806
15807 - 17022
17023 - 21115
0
50
Miles
N

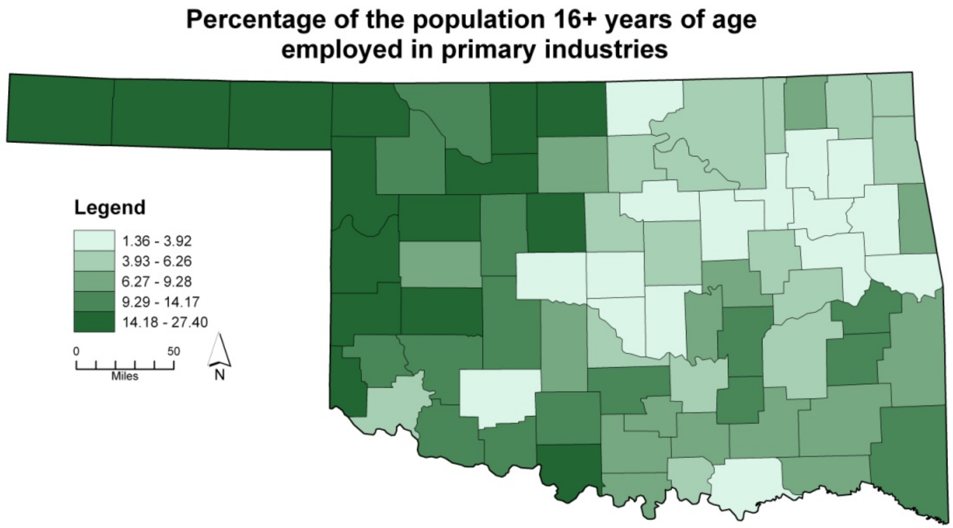

Per capita income
Legend
0 - 12959
12960 - 14812
14813 - 17269
17270 - 20870
20871 - 74640
0
50
Miles
N
Oklahoma City
Tulsa

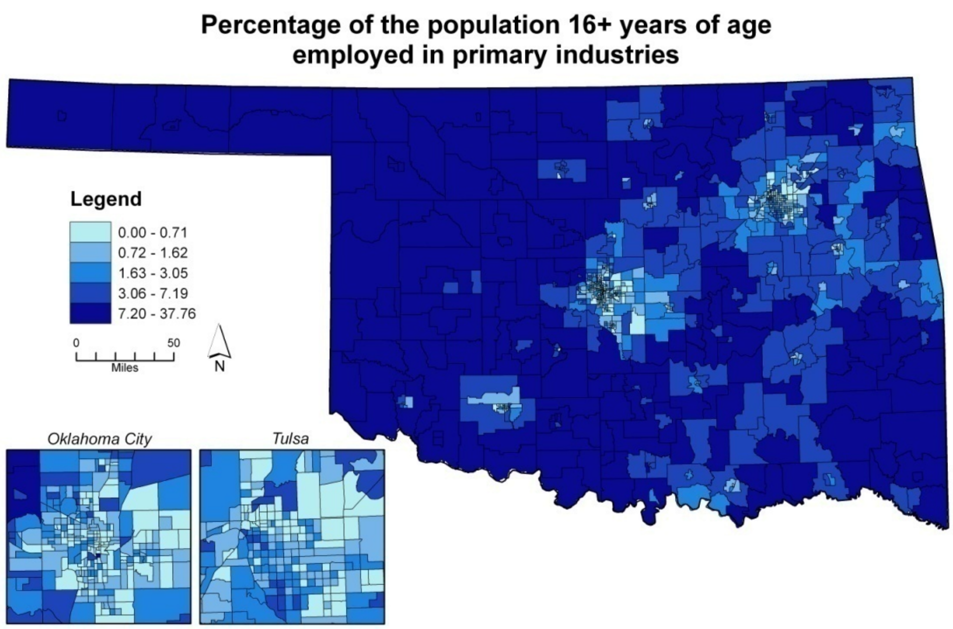
Percentage of the population 5+ years of age living in the same county for the past five years



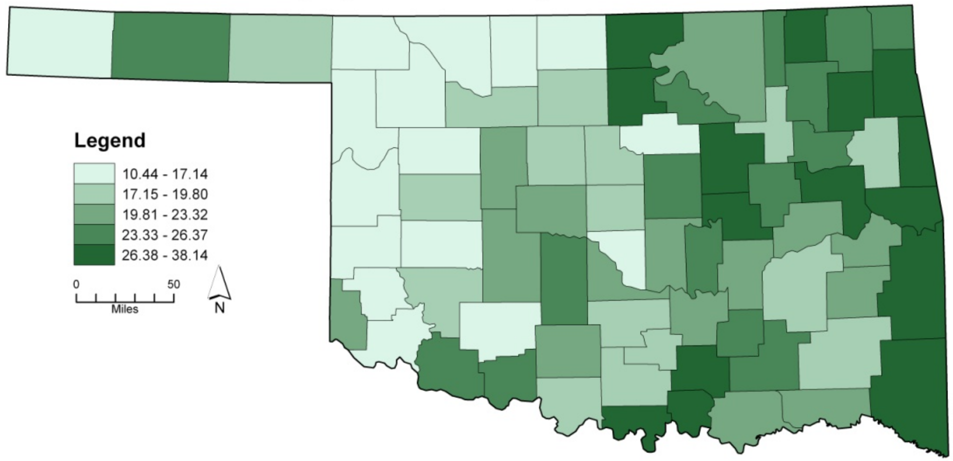
Percentage of the population 5+ years of age living in the same county for the past five years



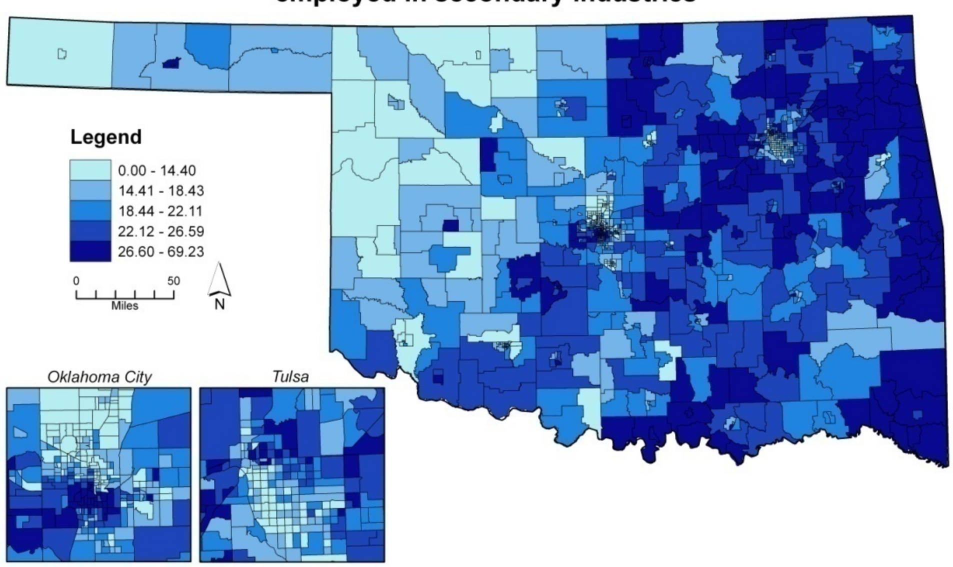

Percentage of the population 16+ years of age
employed in primary industries
Legend
1.36 - 3.92
3.93 - 6.26
6.27 - 9.28
9.29 - 14.17
14.18 - 27.40
0
50
Miles
N


Percentage of the population 16+ years of age
employed in primary industries
Legend
0.00 - 0.71
0.72 - 1.62
1.63 - 3.05
3.06 - 7.19
7.20 - 37.76
0
50
Miles
N
Oklahoma City
Tulsa

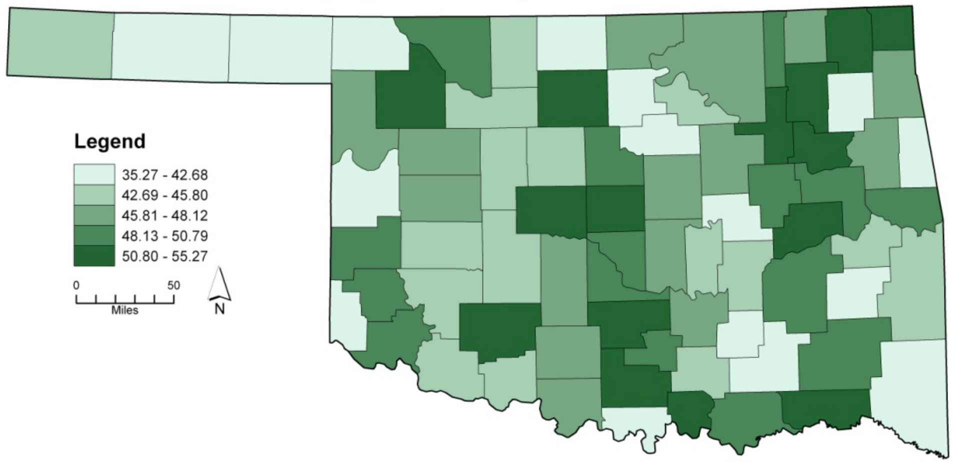
Percentage of the population 16+ years of age employed in secondary industries



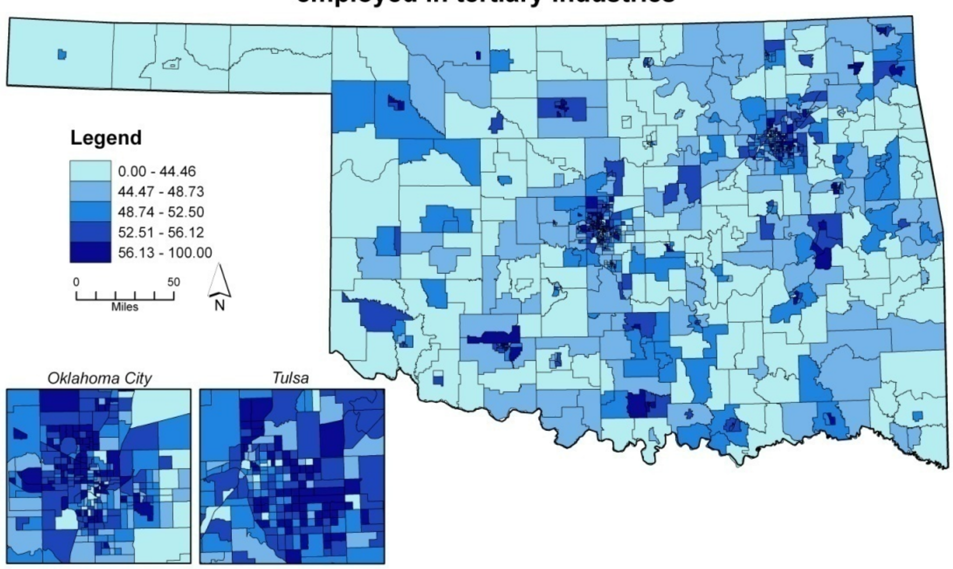
Percentage of the population 16+ years of age employed in secondary industries



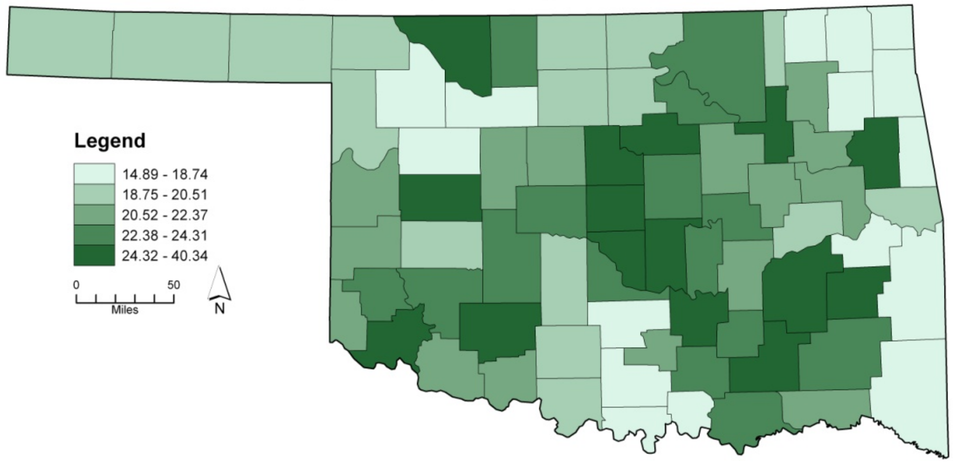
Percentage of the population 16+ years of age employed in tertiary industries



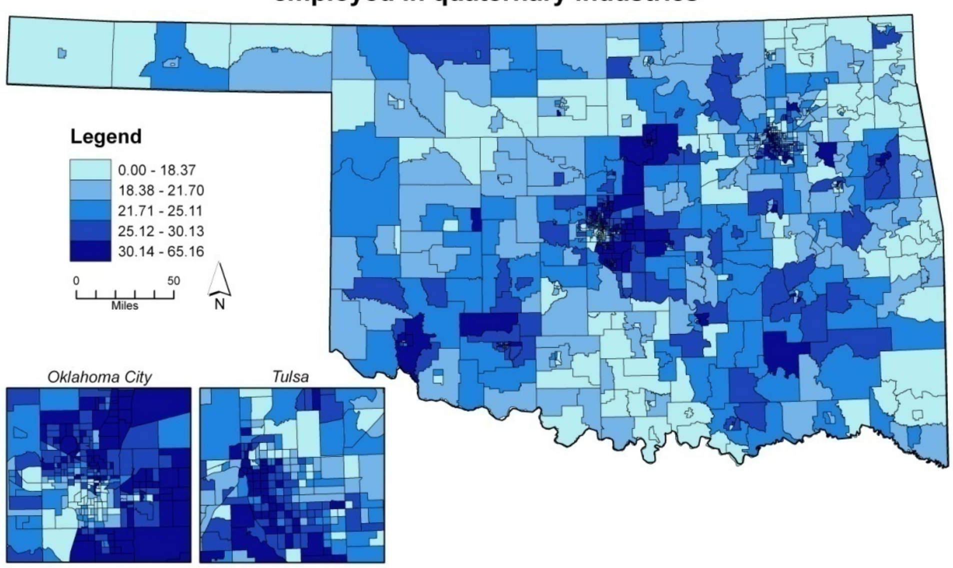
Percentage of the population 16+ years of age employed in tertiary industries



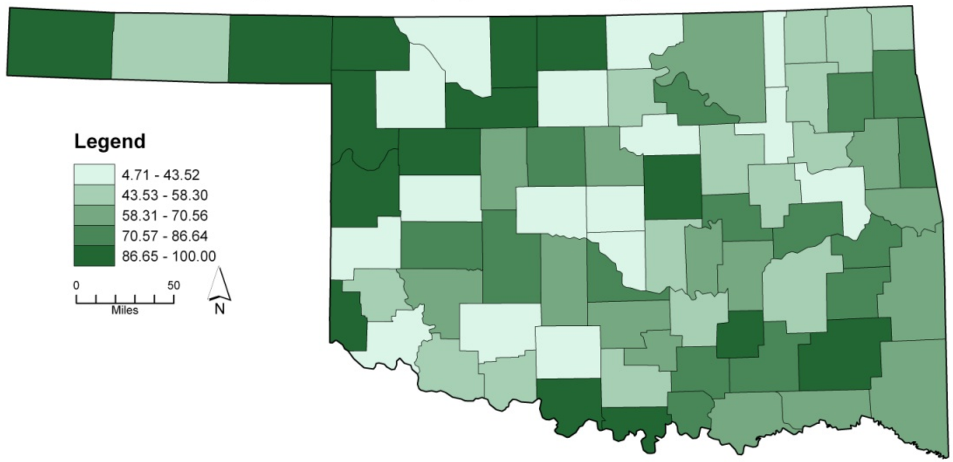
Percentage of the population 16+ years of age employed in quaternary industries



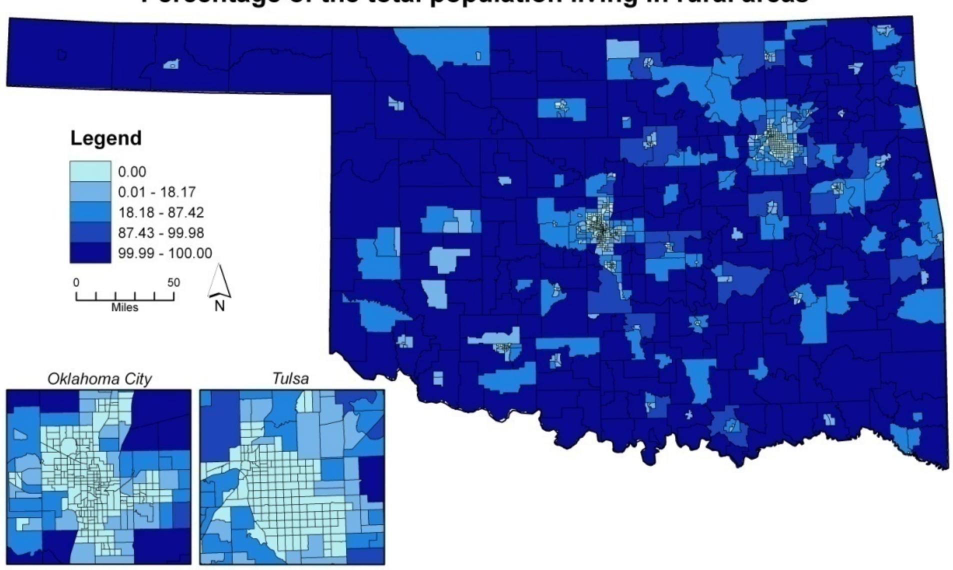
Percentage of the population 16+ years of age employed in quaternary industries



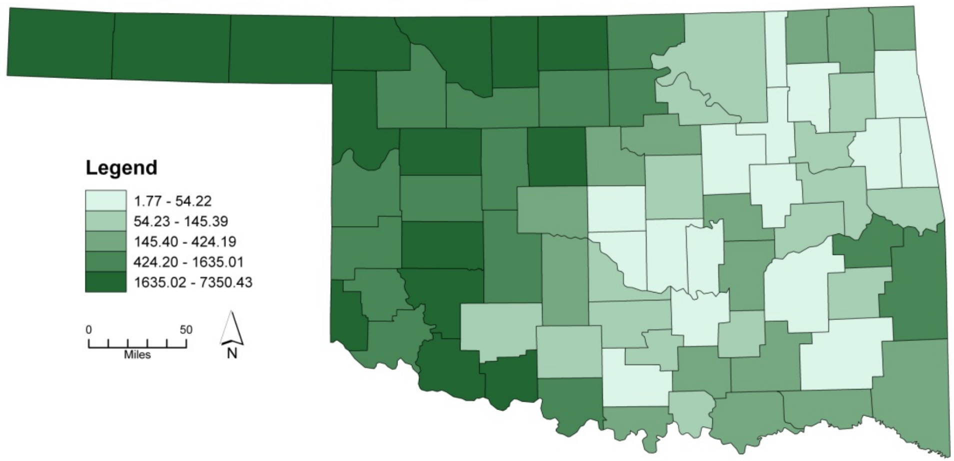
Percentage of the total population living in rural areas



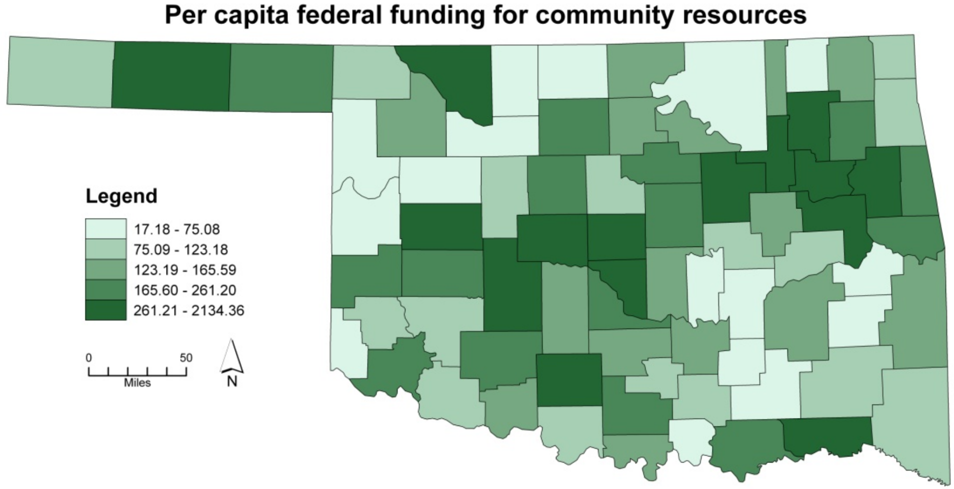
Percentage of the total population living in rural areas



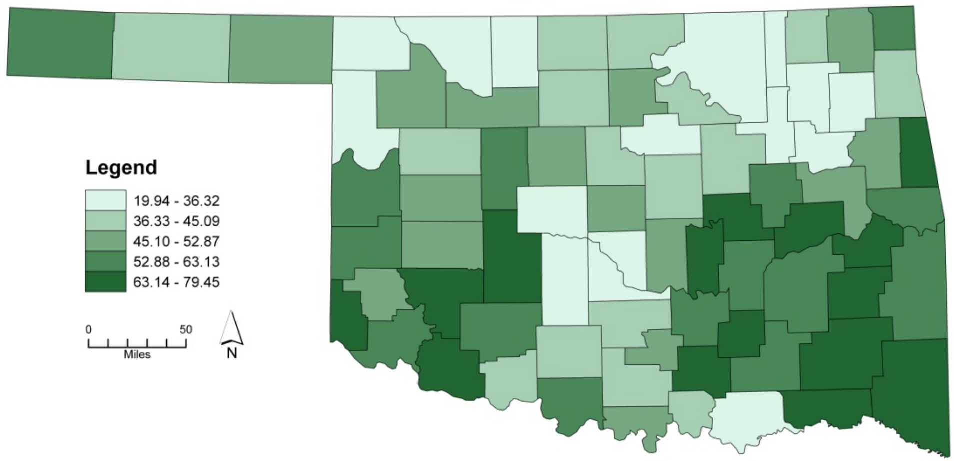
Per capita federal funding for agricultural and natural resources



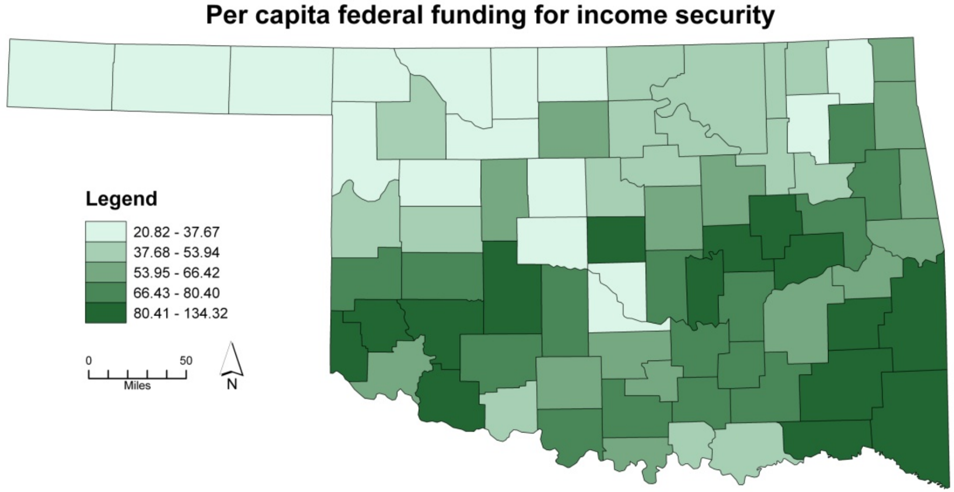
Per capita federal funding for community resources



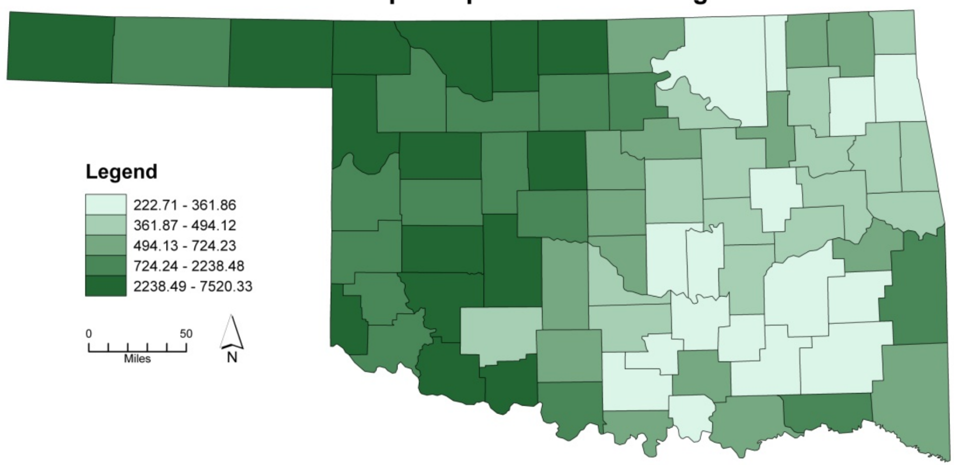
Per capita federal funding for human resources



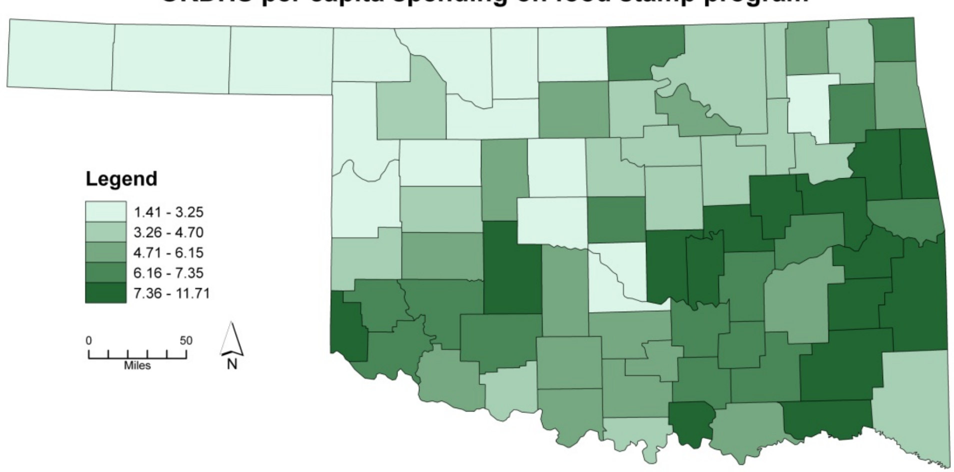
Per capita federal funding for income security

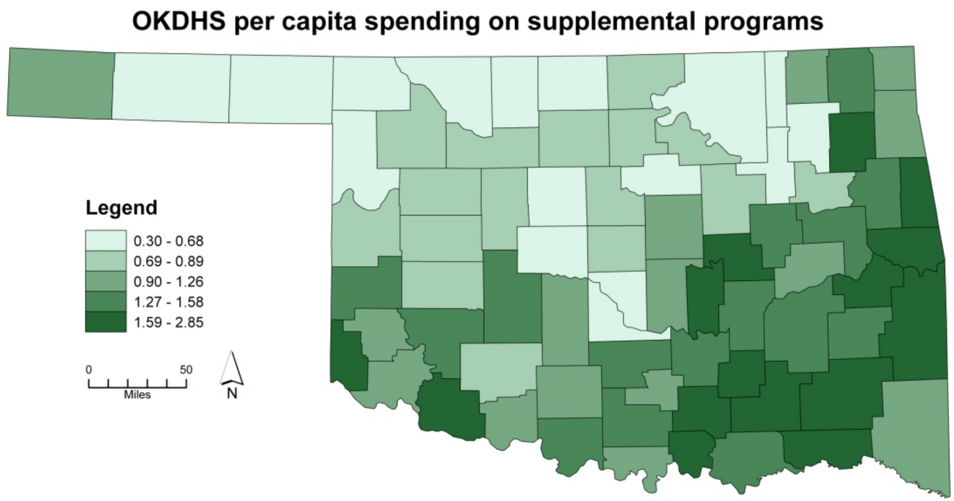


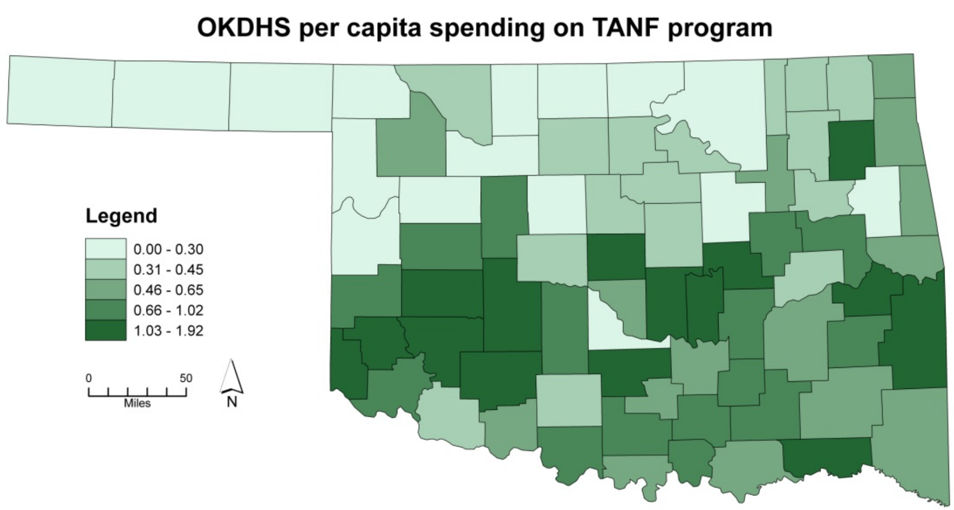
Total per capita federal funding

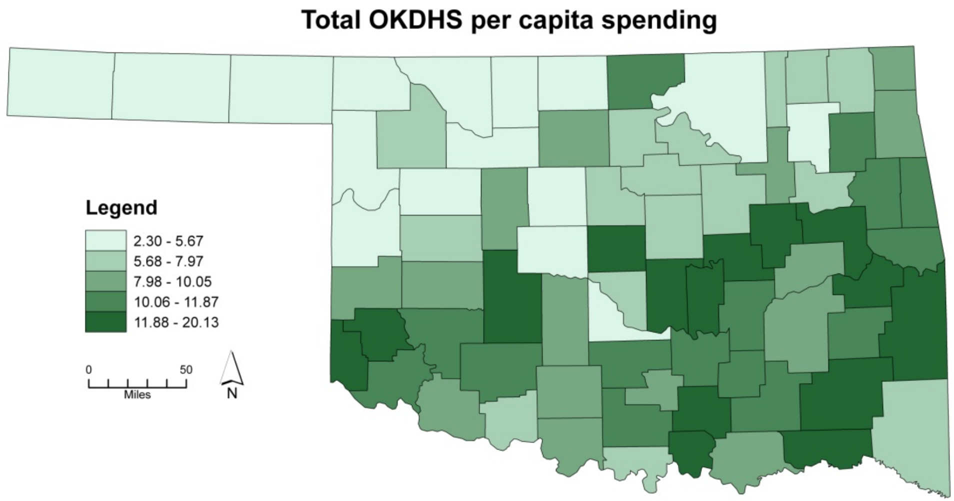


OKDHS per capita spending on food stamp program



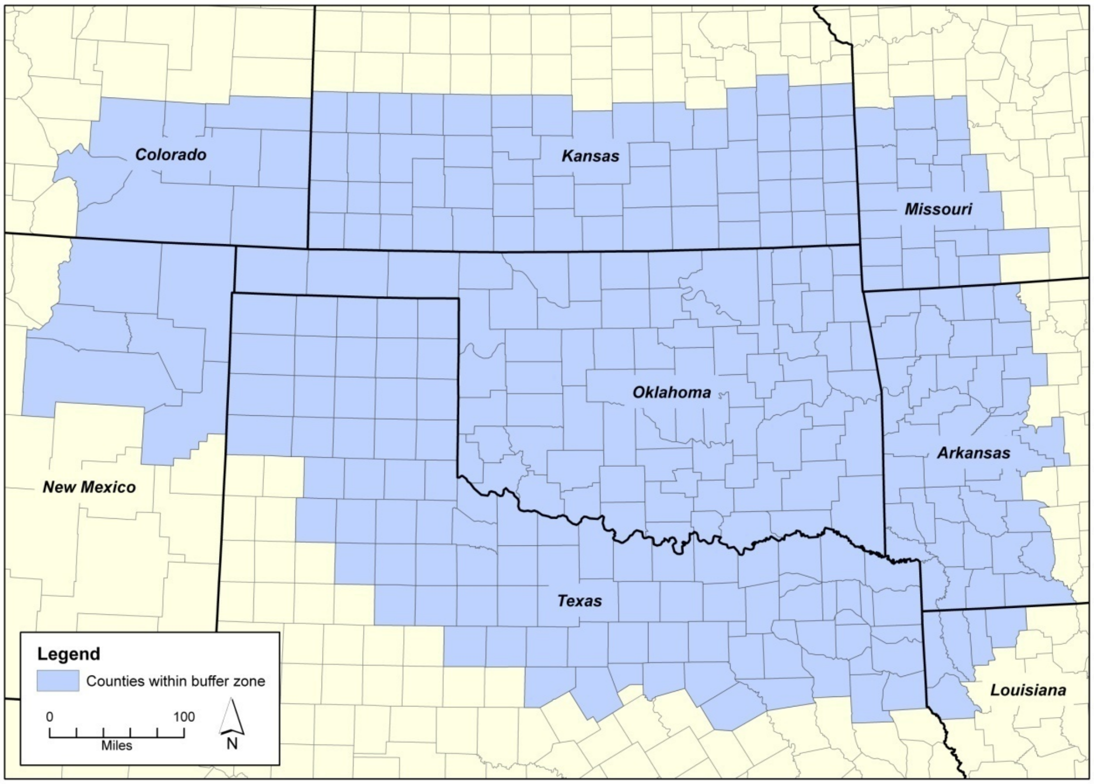

OKDHS per capita spending on supplemental programs
Legend
0.30 - 0.68
0.69 - 0.89
0.90 - 1.26
1.27 - 1.58
1.59 - 2.85
0
50
Miles
N


OKDHS per capita spending on TANF program
Legend
0.00 - 0.30
0.31 - 0.45
0.46 - 0.65
0.66 - 1.02
1.03 - 1.92
0
50
Miles
N


Total OKDHS per capita spending
Legend
2.30 - 5.67
5.68 - 7.97
7.98 - 10.05
10.06 - 11.87
11.88 - 20.13
0
50
Miles
N

APPENDIX B

Study area including 100-mile buffer zone



The study area was achieved by allowing ArcMap to select all counties in neighboring states that were within 100 miles from any section of the Oklahoma state border. A list of all counties (or equivalents) included in the study from neighboring states is given below. At the tract level, all Census tracts located within the given counties were included in the study.

Arkansas

- Benton
- Boone
- Calhoun
- Carrol
- Clark
- Columbia
- Conway
- Crawford
- Dallas
- Franklin
- Garland
- Hempstead
- Hot Spring
- Howard
- Johnson
- Lafayette
- Little River
- Logan
- Madison
- Marion
- Miller
- Montgomery
- Nevada
- Newton
- Ouachita
- Perry
- Pike
- Polk
- Pope
- Pulaski
- Saline
- Scott
- Searcy
- Sebastian
- Sevier
- Union
- Van Buren
- Washington
- Yell

Colorado

- Baca
- Bent
- Crowley
- Huerfano
- Kiowa
- Las Animas
- Otero
- Prowers
- Pueblo

Kansas

- Allen
- Anderson
- Barber
- Barton
- Bourbon
- Butler
- Chase
- Chautauqua
- Cherokee
- Clark
- Coffey
- Comanche
- Cowley
- Crawford
- Edwards
- Elk
- Finney
- Ford
- Franklin
- Grant
- Gray
- Greeley
- Greenwood
- Hamilton
- Harper
- Harvey
- Haskell
- Hodgeman
- Kearny
- Kingman
- Kiowa

Kansas (cont.)

- Labette
- Lane
- Linn
- Lyon
- Marion
- Mcpherson
- Meade
- Miami
- Montgomery
- Morton
- Neosho

Louisiana

- Bossier
- Caddo
- Clairborne
- De Soto
- Webster

Missouri

- Barry
- Barton
- Bates
- Benton
- Cedar
- Christian
- Dade
- Dallas
- Douglas
- Greene
- Henry
- Hickory
- Jasper
- Lawrence
- McDonald
- Newton
- Polk
- St. Clair
- Stone
- Taney
- Vernon
- Webster

New Mexico

- Colfax
- Harding
- Mora
- Quay
- San Miguel
- Union

Texas

- Archer
- Armstrong
- Baylor
- Bowie
- Briscoe
- Camp
- Carson
- Cass
- Childress
- Clay
- Collin
- Collingsworth
- Cooke
- Cottle
- Crosby
- Dallam
- Dallas
- Deaf Smith
- Delta
- Denton
- Dickens
- Donley
- Eastland
- Ellis
- Erath
- Fannin
- Floyd
- Foard
- Franklin
- Gray
- Grayson
- Gregg
- Hale
- Hall

Texas (cont.)

- Hansford
- Hardeman
- Harrison
- Hartley
- Haskell
- Hemphill
- Henderson
- Hood
- Hopkins
- Hunt
- Hutchinson
- Jack
- Johnson
- Jones
- Kaufman
- Kent
- King
- Knox
- Lamar
- Lipscomb
- Marion
- Montague
- Moore
- Morris
- Motley
- Navarro
- Ochiltree
- Oldham
- Palo Pinto
- Panola
- Parker
- Potter
- Rains
- Randall
- Red River
- Roberts
- Rockwall
- Rusk
- Shackelford
- Sherman
- Smith
- Stephens

Texas (cont.)

- Stonewall
- Swisher
- Tarrant
- Throckmorton
- Titus
- Upshur
- Van Zandt
- Wheeler
- Wichita
- Wilbarger
- Wise
- Wood
- Young

APPENDIX C

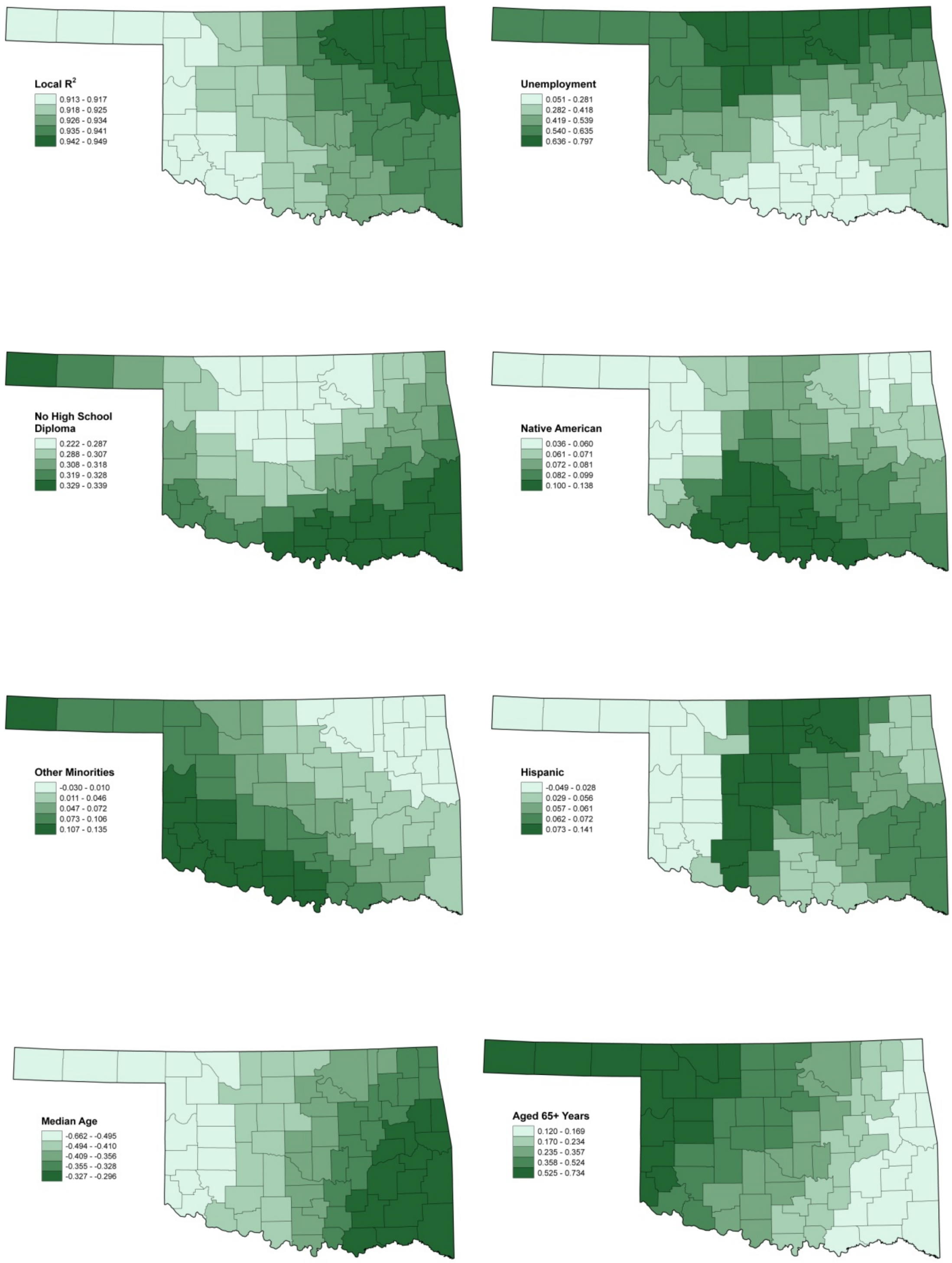
Details of additional GWR models using data from Oklahoma counties/tracts only

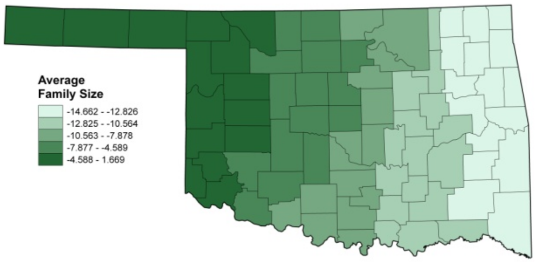
Table C-1. Results of county and tract level GWR models.

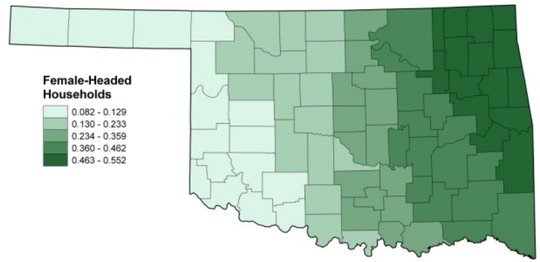
	County Model Parameter Coefficients		Tract Model Parameter Coefficients	
Variable	Global	GWR (range)	Global	GWR (range)
Intercept (POV)	2270.325	-1542.504 to 3237.270	4.901	-16206.333 to 11790.488
UNEMPL	0.361	0.051 to 0.787	0.706	-0.448 to 1.678
NO_HS	0.341	0.222 to 0.339	0.429	-0.042 to 0.607
AM_IND	0.086	0.036 to 0.138	0.270	-0.236 to 3.403***
MINOR	0.103	-0.030 to 0.135	0.089	-0.158 to 0.660**
HISP	-0.006	-0.049 to 0.141	0.045	-0.872 to 0.776
MED_AGE	-0.454	-0.662 to -0.296	0.322	-1.048 to 0.886
EDLER	0.477	0.120 to 0.734	-0.258	-0.771 to 0.440
FAM_SZ	-6.172	-14.662 to 1.669	-1.045	-27.589 to 10.977
FEM_HH	0.252	0.082 to 0.552	0.290	-0.394 to 1.008*
PCI	-0.001	-0.001 to -0.0004	0.000	-0.001 to 0.0001
STABLE	0.041	-0.068 to 0.221	-0.140	-0.326 to 0.068
PRIM	-22.295	-32.900 to 16.267	0.217	-117.052 to 161.658
SEC	-22.391	-32.952 to 16.077	-0.239	-117.202 to 161.940
TER	-22.433	-32.980 to 15.960	0.082	-117.221 to 161.867
QUAT	-22.151	-32.677 to 16.204	0.079	-117.294 to 161.934
RURAL	0.002	-0.013 to 0.011	-0.009	-0.145 to 0.048***
Bandwidth	---	75	---	209
AIC	315.687	328.916	6301.505	5905.236
Adjusted R^2	0.868	0.984	0.702	0.851
F statistic	2.410	---	5.938	---

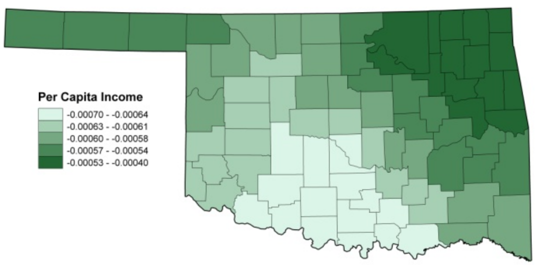
*Variable displays significant spatial non-stationarity at the 5% significance level.
**Variable displays significant spatial non-stationarity at the 1% significance level.
***Variable displays significant spatial non-stationarity at the 0.1% significance level.

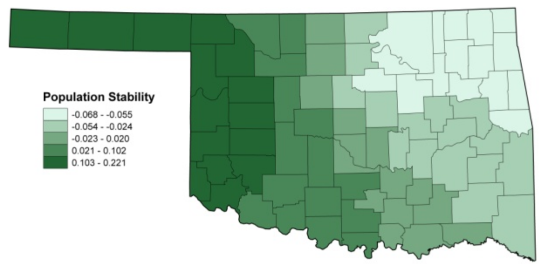
Localized R^2 values and parameter coefficients for county level model

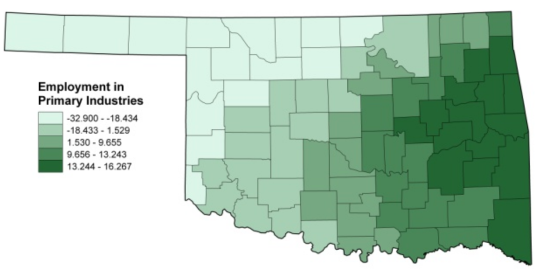


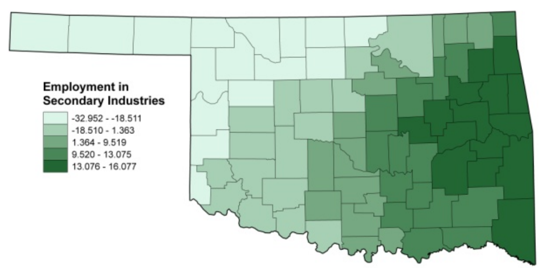

Average
Family Size
-14.662 - -12.826
-12.825 - -10.564
-10.563 - -7.878
-7.877 - -4.589
-4.588 - 1.669

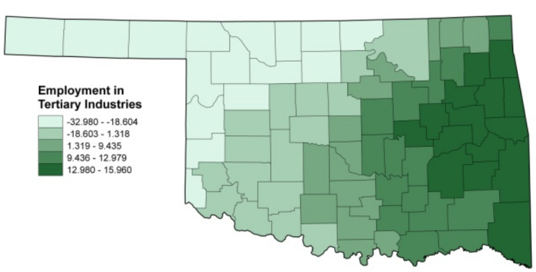

Female-Headed
Households
0.082 - 0.129
0.130 - 0.233
0.234 - 0.359
0.360 - 0.462
0.463 - 0.552

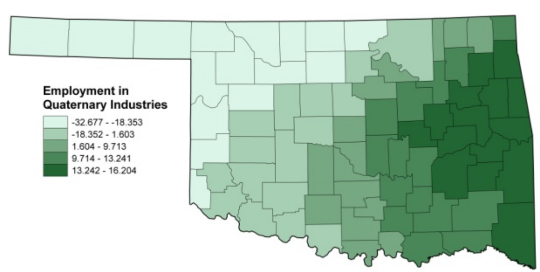

Per Capita Income
-0.00070 - -0.00064
-0.00063 - -0.00061
-0.00060 - -0.00058
-0.00057 - -0.00054
-0.00053 - -0.00040

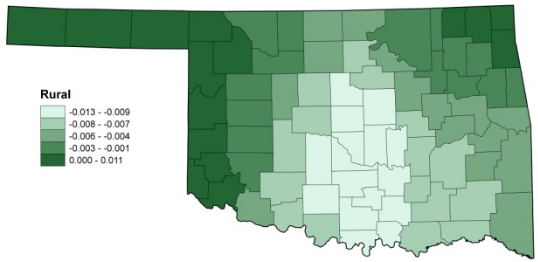

Population Stability
-0.068 - -0.055
-0.054 - -0.024
-0.023 - 0.020
0.021 - 0.102
0.103 - 0.221


Employment in
Primary Industries
-32.900 - -18.434
-18.433 - 1.529
1.530 - 9.655
9.656 - 13.243
13.244 - 16.267

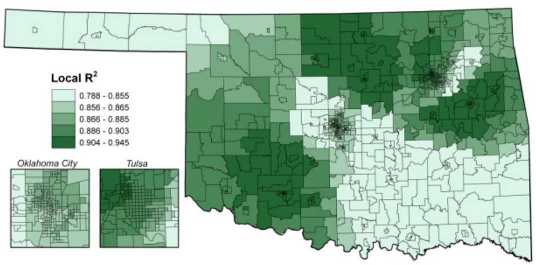

Employment in
Secondary Industries
-32.952 - -18.511
-18.510 - 1.363
1.364 - 9.519
9.520 - 13.075
13.076 - 16.077

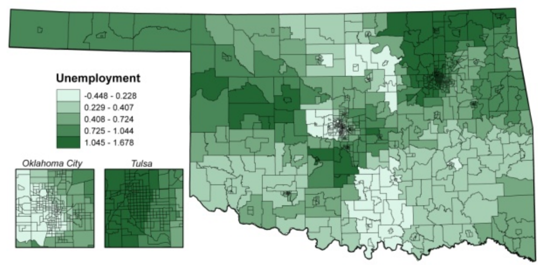

Employment in
Tertiary Industries
-32.980 - -18.604
-18.603 - 1.318
1.319 - 9.435
9.436 - 12.979
12.980 - 15.960

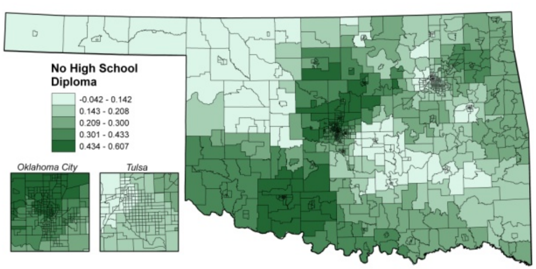

Employment in
Quaternary Industries
-32.677 - -18.353
-18.352 - 1.603
1.604 - 9.713
9.714 - 13.241
13.242 - 16.204

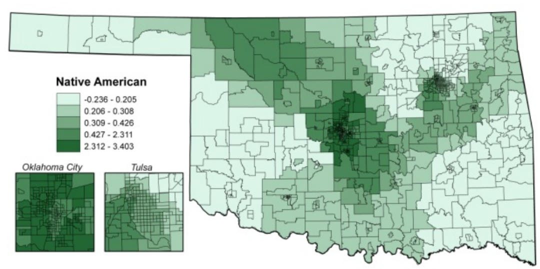


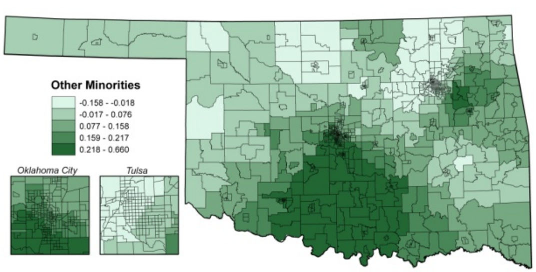
Localized R^2 values and parameter coefficients for tract level model

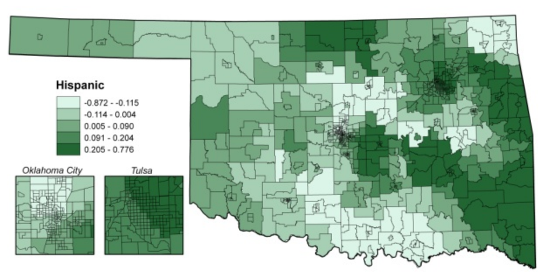


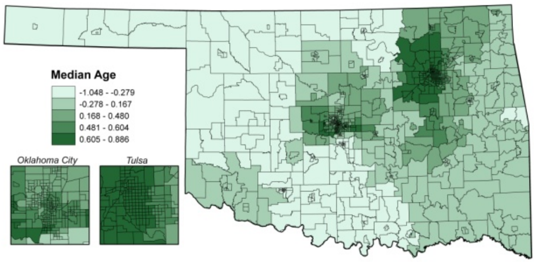


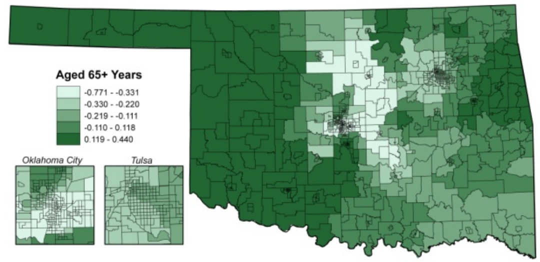


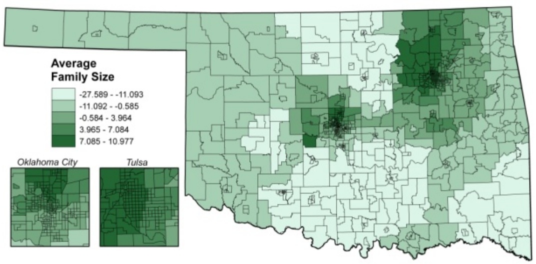


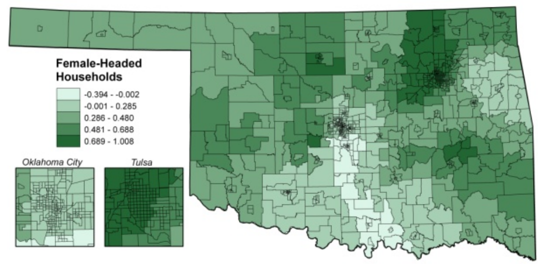


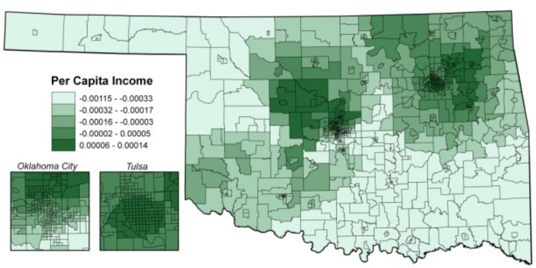


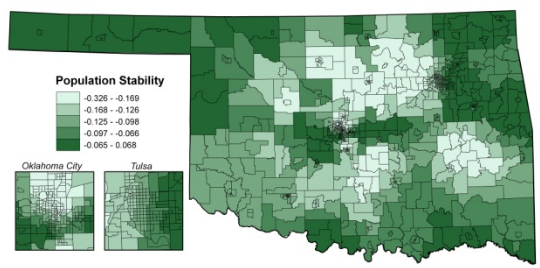

Median Age
-1.048 - -0.279
-0.278 - 0.167
0.168 - 0.480
0.481 - 0.604
0.605 - 0.886
Oklahoma City
Tulsa

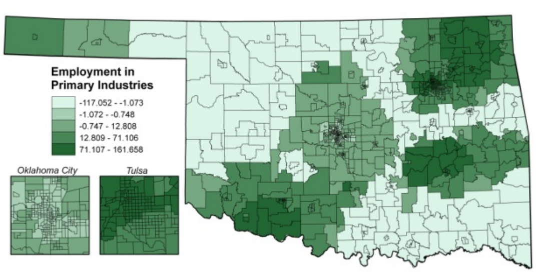

Aged 65+ Years
-0.771 - -0.331
-0.330 - -0.220
-0.219 - -0.111
-0.110 - 0.118
0.119 - 0.440
Oklahoma City
Tulsa

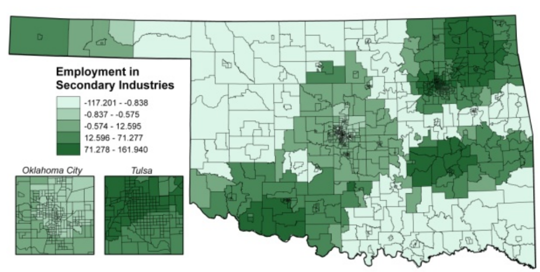

Average
Family Size
-27.589 - -11.093
-11.092 - -0.585
-0.584 - 3.964
3.965 - 7.084
7.085 - 10.977
Oklahoma City
Tulsa

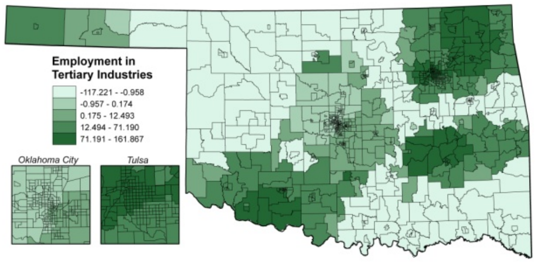

Female-Headed
Households
-0.394 - -0.002
-0.001 - 0.285
0.286 - 0.480
0.481 - 0.688
0.689 - 1.008
Oklahoma City
Tulsa

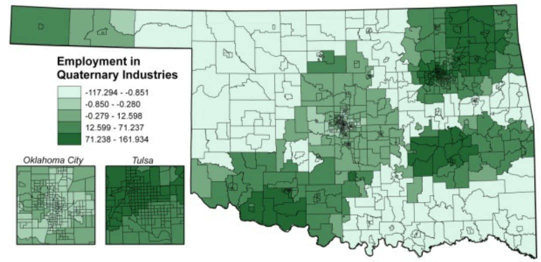

Per Capita Income
-0.00115 - -0.00033
-0.00032 - -0.00017
-0.00016 - -0.00003
-0.00002 - 0.00005
0.00006 - 0.00014
Oklahoma City
Tulsa

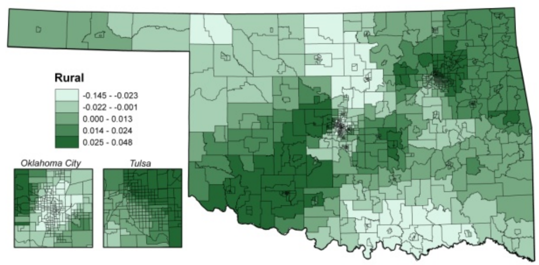

Population Stability
-0.326 - -0.169
-0.168 - -0.126
-0.125 - -0.098
-0.097 - -0.066
-0.065 - 0.068
Oklahoma City
Tulsa


Employment in
Primary Industries
-117.052 - -1.073
-1.072 - -0.748
-0.747 - 12.808
12.809 - 71.106
71.107 - 161.658
Oklahoma City
Tulsa


Employment in
Secondary Industries
-117.201 - -0.838
-0.837 - -0.575
-0.574 - 12.595
12.596 - 71.277
71.278 - 161.940
Oklahoma City
Tulsa


Employment in
Tertiary Industries
-117.221 - -0.958
-0.957 - 0.174
0.175 - 12.493
12.494 - 71.190
71.191 - 161.867
Oklahoma City
Tulsa

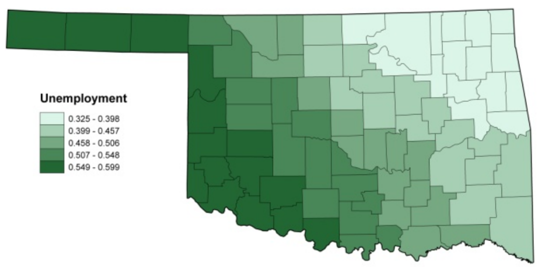

Employment in
Quaternary Industries
-117.294 - -0.851
-0.850 - -0.280
-0.279 - 12.598
12.599 - 71.237
71.238 - 161.934
Oklahoma City
Tulsa

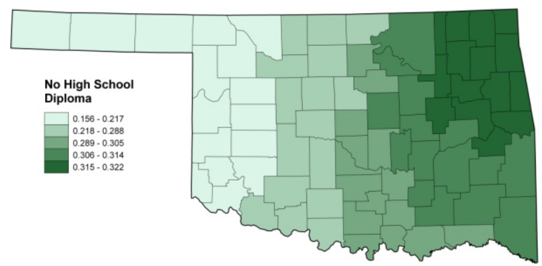

Rural
-0.145 - -0.023
-0.022 - -0.001
0.000 - 0.013
0.014 - 0.024
0.025 - 0.048
Oklahoma City
Tulsa

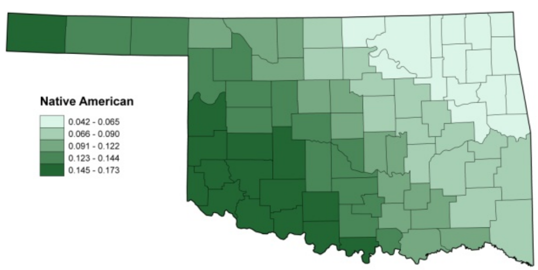
APPENDIX D

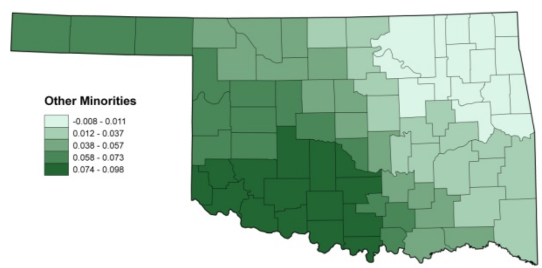
Mapped parameter coefficients for all independent variables in all GWR models

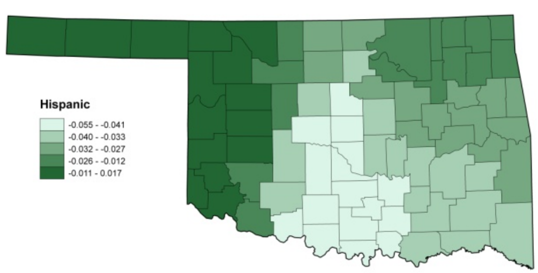
Parameter coefficients for basic county level model

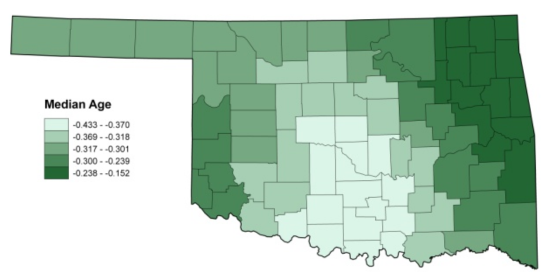


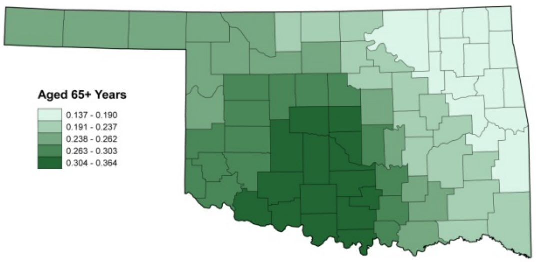


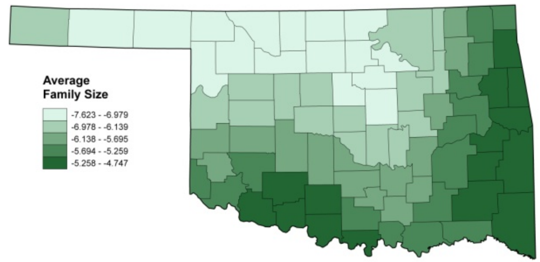


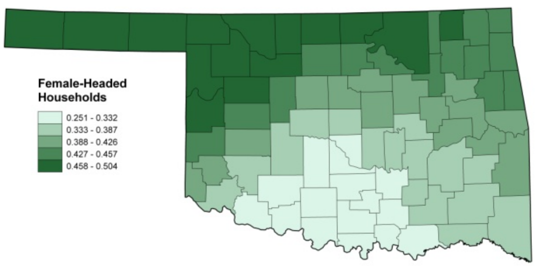


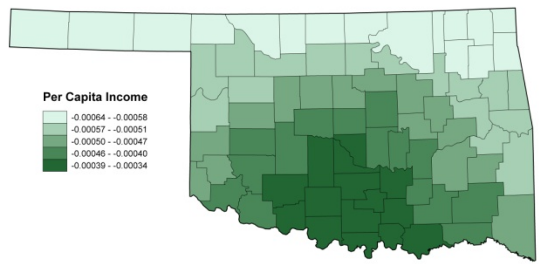


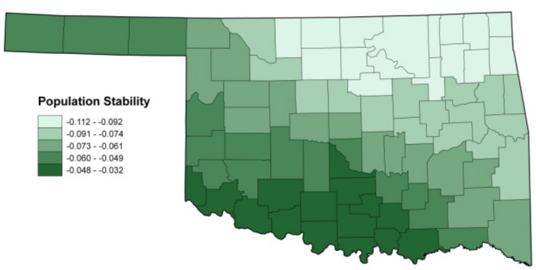


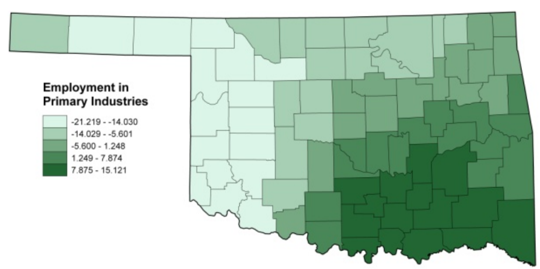

Aged 65+ Years
0.137 - 0.190
0.191 - 0.237
0.238 - 0.262
0.263 - 0.303
0.304 - 0.364

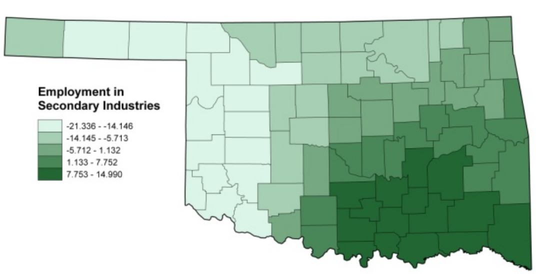

Average
Family Size
-7.623 - -6.979
-6.978 - -6.139
-6.138 - -5.695
-5.694 - -5.259
-5.258 - -4.747

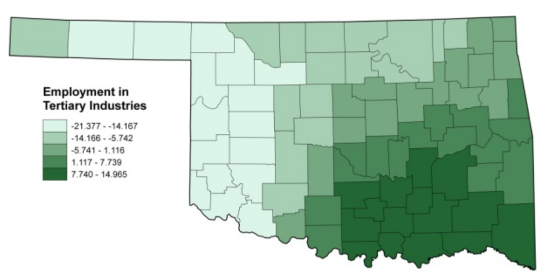

Female-Headed
Households
0.251 - 0.332
0.333 - 0.387
0.388 - 0.426
0.427 - 0.457
0.458 - 0.504

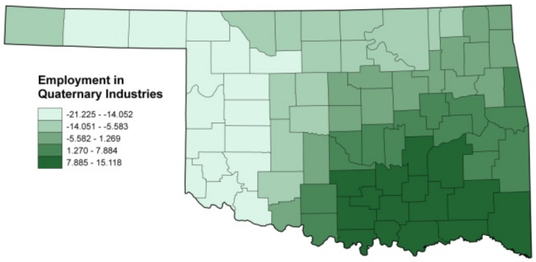

Per Capita Income
-0.00064 - -0.00058
-0.00057 - -0.00051
-0.00050 - -0.00047
-0.00046 - -0.00040
-0.00039 - -0.00034

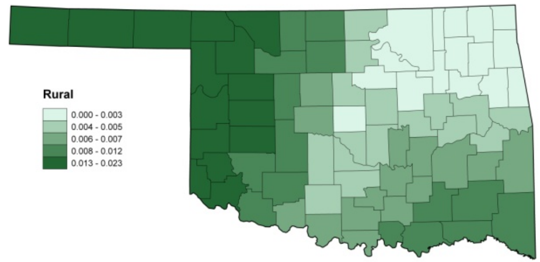

Population Stability
-0.112 - -0.092
-0.091 - -0.074
-0.073 - -0.061
-0.060 - -0.049
-0.048 - -0.032


Employment in
Primary Industries
-21.219 - -14.030
-14.029 - -5.601
-5.600 - 1.248
1.249 - 7.874
7.875 - 15.121

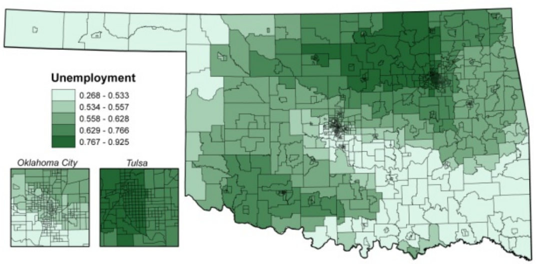

Employment in
Secondary Industries
-21.336 - -14.146
-14.145 - -5.713
-5.712 - 1.132
1.133 - 7.752
7.753 - 14.990

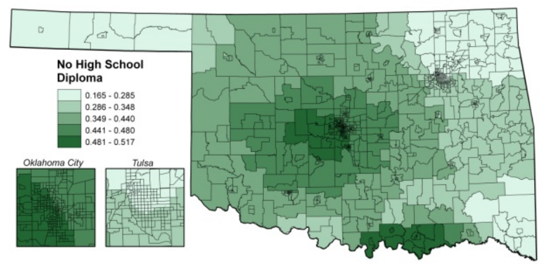

Employment in
Tertiary Industries
-21.377 - -14.167
-14.166 - -5.742
-5.741 - 1.116
1.117 - 7.739
7.740 - 14.965

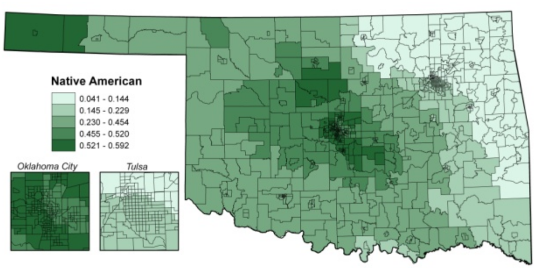


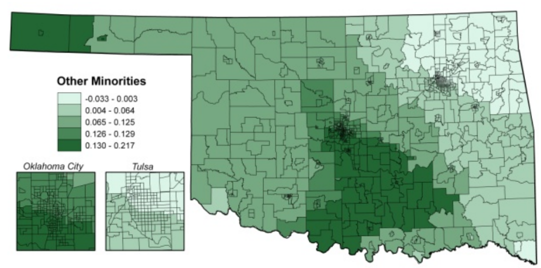


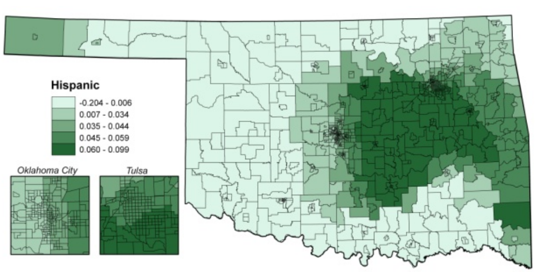
Parameter coefficients for basic tract level model

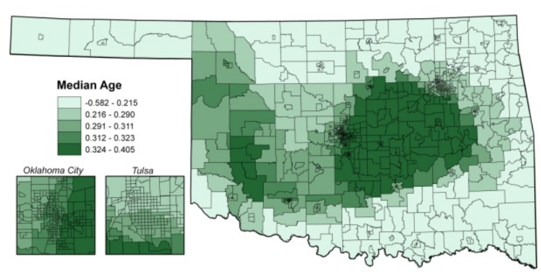


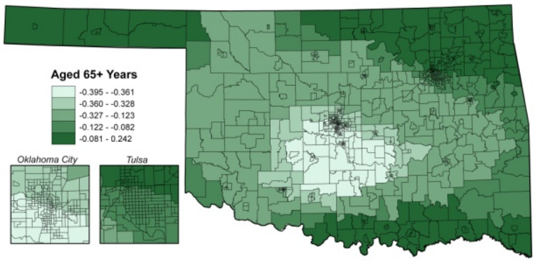


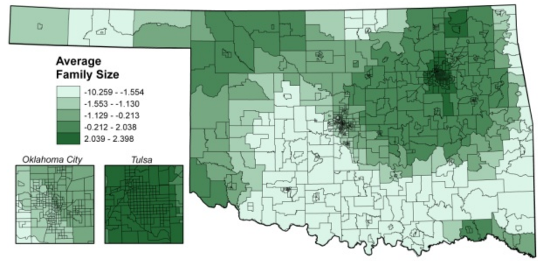


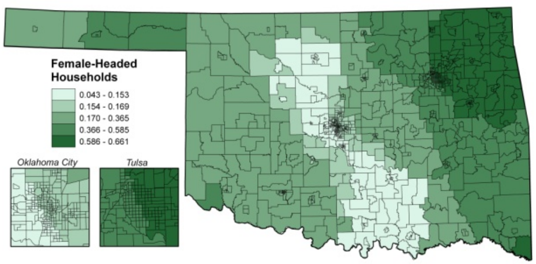


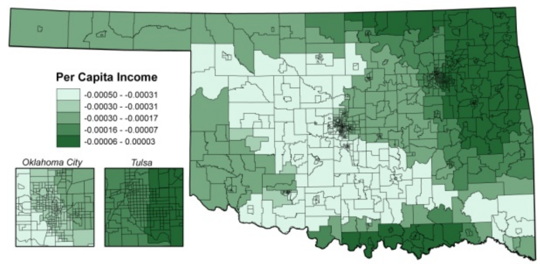


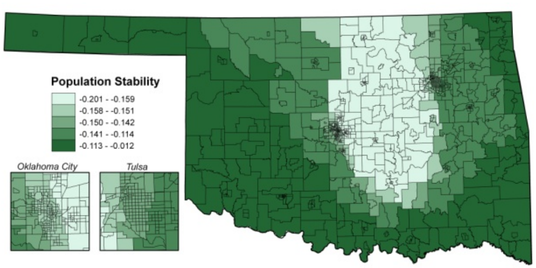


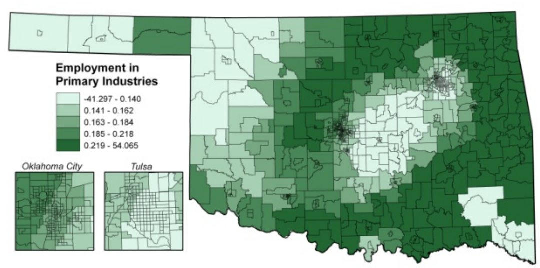

Aged 65+ Years
-0.395 - -0.361
-0.360 - -0.328
-0.327 - -0.123
-0.122 - -0.082
-0.081 - 0.242
Oklahoma City
Tulsa

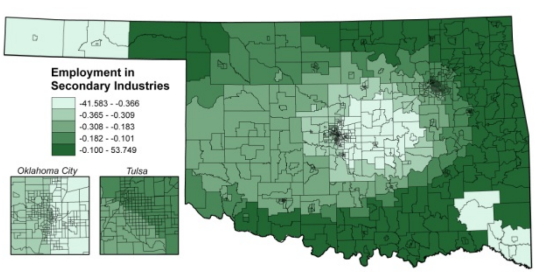

Average Family Size
-10.259 - -1.554
-1.553 - -1.130
-1.129 - -0.213
-0.212 - 2.038
2.039 - 2.398
Oklahoma City
Tulsa

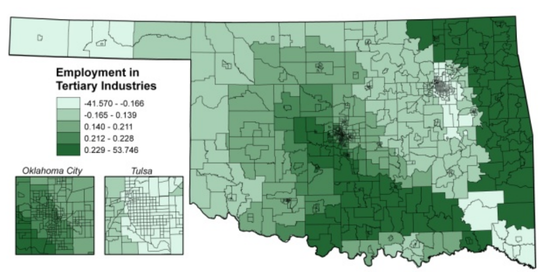

Female-Headed Households
0.043 - 0.153
0.154 - 0.169
0.170 - 0.365
0.366 - 0.585
0.586 - 0.661
Oklahoma City
Tulsa

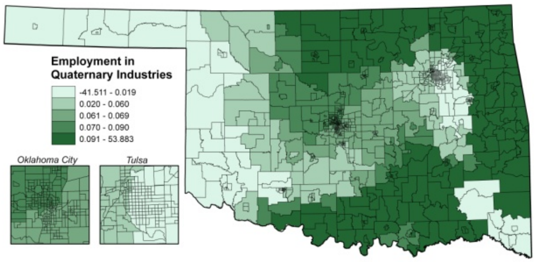

Per Capita Income
-0.00050 - -0.00031
-0.00030 - -0.00031
-0.00030 - -0.00017
-0.00016 - -0.00007
-0.00006 - 0.00003
Oklahoma City
Tulsa

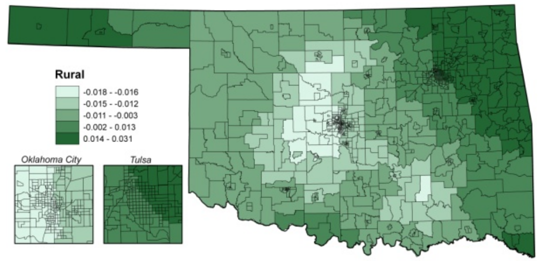

Population Stability
-0.201 - -0.159
-0.158 - -0.151
-0.150 - -0.142
-0.141 - -0.114
-0.113 - -0.012
Oklahoma City
Tulsa


Employment in Primary Industries
-41.297 - 0.140
0.141 - 0.162
0.163 - 0.184
0.185 - 0.218
0.219 - 54.065
Oklahoma City
Tulsa

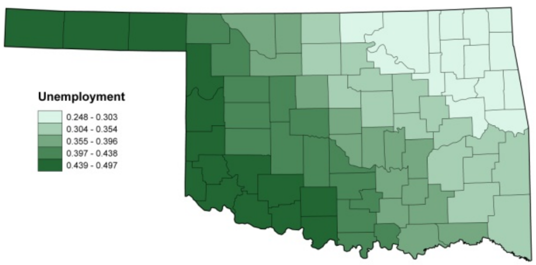

Employment in Secondary Industries
-41.583 - -0.366
-0.365 - -0.309
-0.308 - -0.183
-0.182 - -0.101
-0.100 - 53.749
Oklahoma City
Tulsa

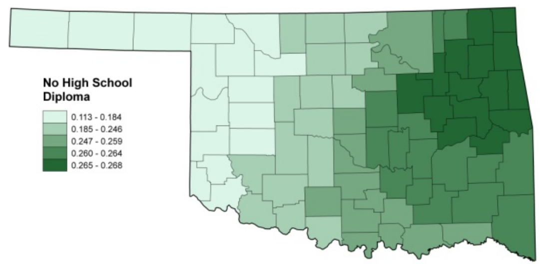

Employment in Tertiary Industries
-41.570 - -0.166
-0.165 - 0.139
0.140 - 0.211
0.212 - 0.228
0.229 - 53.746
Oklahoma City
Tulsa

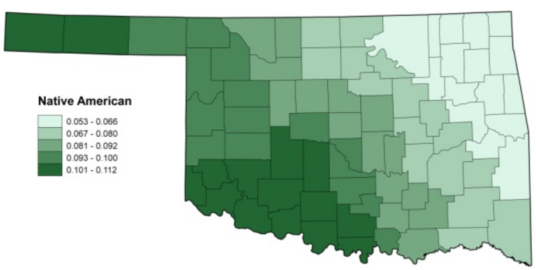


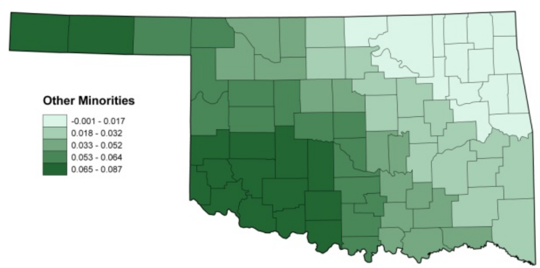


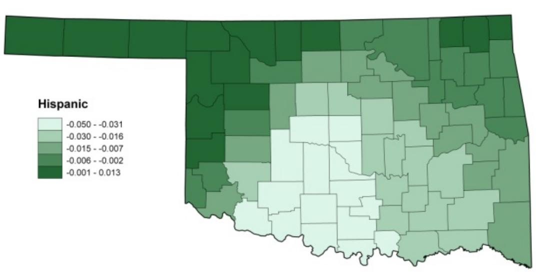
Parameter coefficients for FED_FUND model

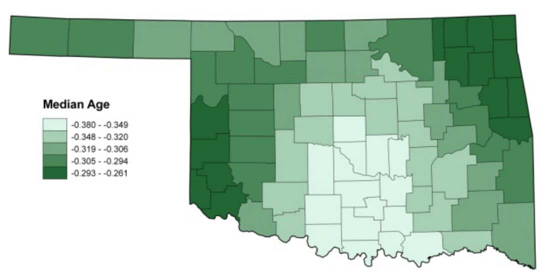


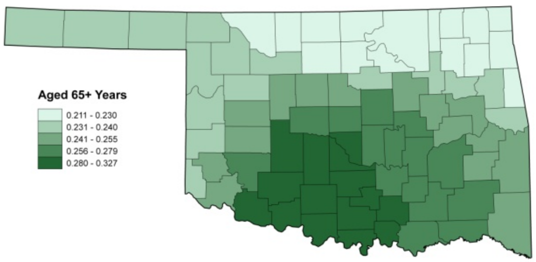


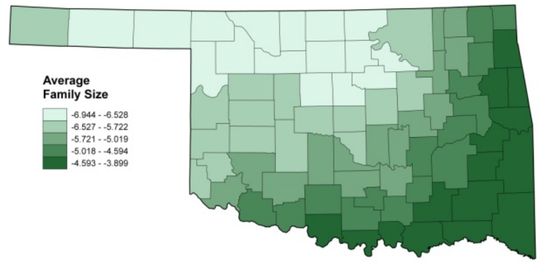


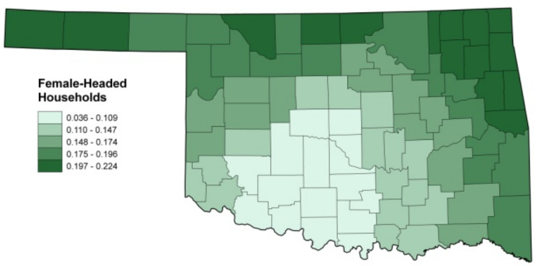


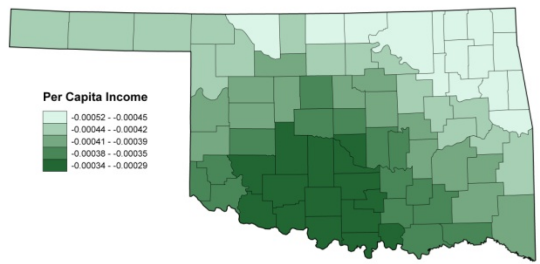


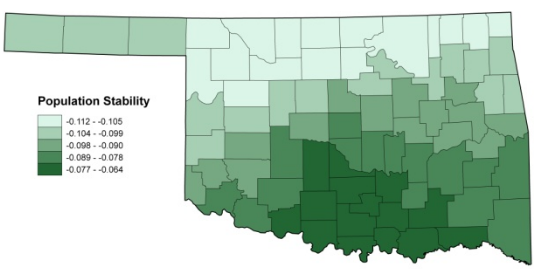


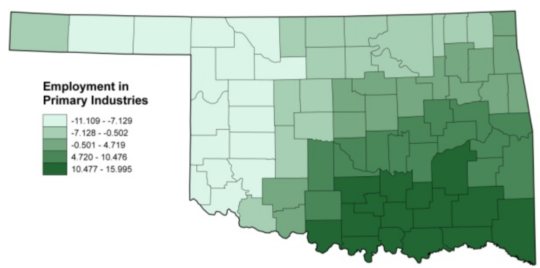

Aged 65+ Years
0.211 - 0.230
0.231 - 0.240
0.241 - 0.255
0.256 - 0.279
0.280 - 0.327

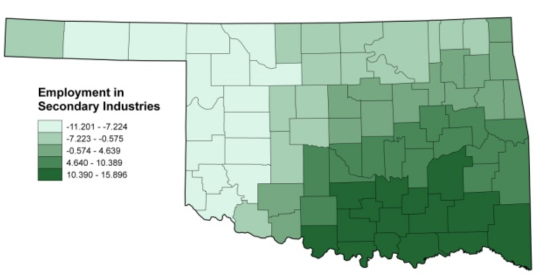

Average
Family Size
-6.944 - -6.528
-6.527 - -5.722
-5.721 - -5.019
-5.018 - -4.594
-4.593 - -3.899

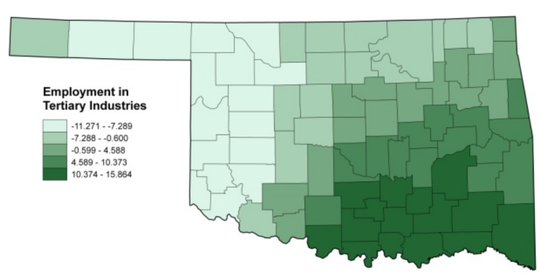

Female-Headed
Households
0.036 - 0.109
0.110 - 0.147
0.148 - 0.174
0.175 - 0.196
0.197 - 0.224

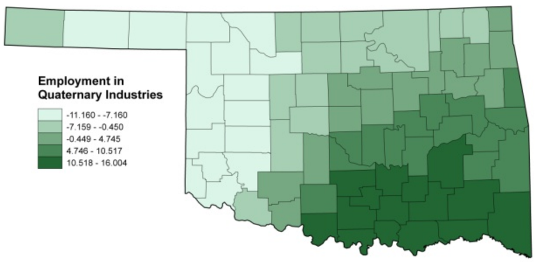

Per Capita Income
-0.00052 - -0.00045
-0.00044 - -0.00042
-0.00041 - -0.00039
-0.00038 - -0.00035
-0.00034 - -0.00029

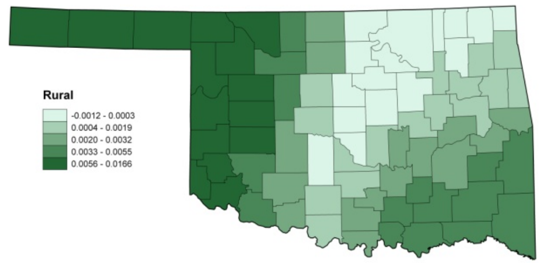

Population Stability
-0.112 - -0.105
-0.104 - -0.099
-0.098 - -0.090
-0.089 - -0.078
-0.077 - -0.064

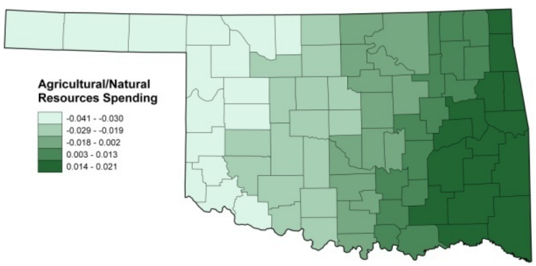

Employment in
Primary Industries
-11.109 - -7.129
-7.128 - -0.502
-0.501 - 4.719
4.720 - 10.476
10.477 - 15.995

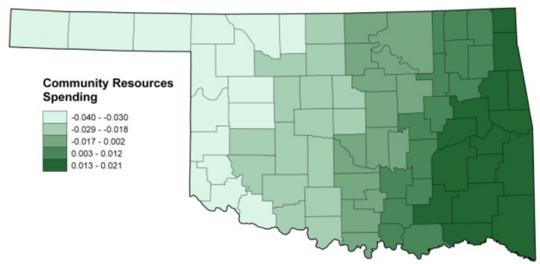

Employment in
Secondary Industries
-11.201 - -7.224
-7.223 - -0.575
-0.574 - 4.639
4.640 - 10.389
10.390 - 15.896

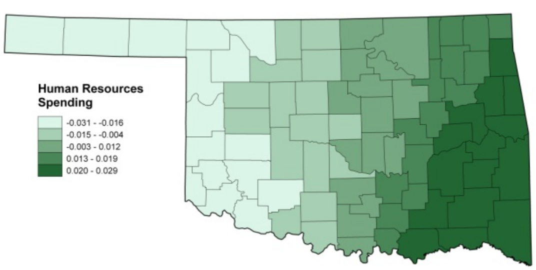

Employment in
Tertiary Industries
-11.271 - -7.289
-7.288 - -0.600
-0.599 - 4.588
4.589 - 10.373
10.374 - 15.864

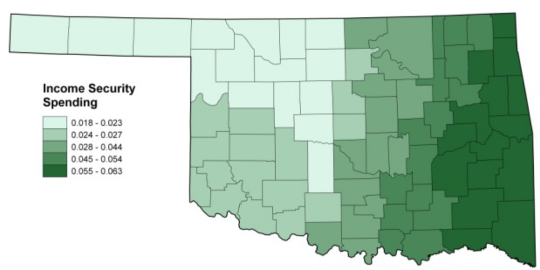

Employment in
Quaternary Industries
-11.160 - -7.160
-7.159 - -0.450
-0.449 - 4.745
4.746 - 10.517
10.518 - 16.004

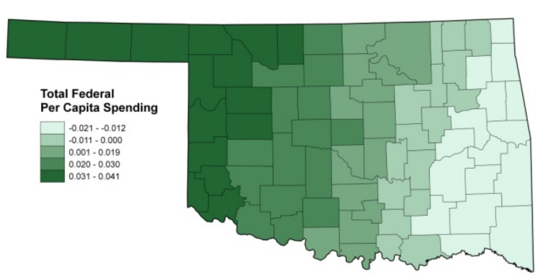

Rural
-0.0012 - 0.0003
0.0004 - 0.0019
0.0020 - 0.0032
0.0033 - 0.0055
0.0056 - 0.0166


Agricultural/Natural
Resources Spending
-0.041 - -0.030
-0.029 - -0.019
-0.018 - 0.002
0.003 - 0.013
0.014 - 0.021

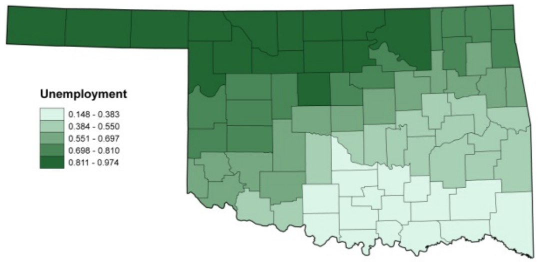

Community Resources
Spending
-0.040 - -0.030
-0.029 - -0.018
-0.017 - 0.002
0.003 - 0.012
0.013 - 0.021

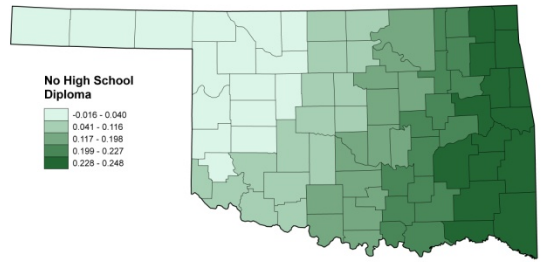

Human Resources
Spending
-0.031 - -0.016
-0.015 - -0.004
-0.003 - 0.012
0.013 - 0.019
0.020 - 0.029

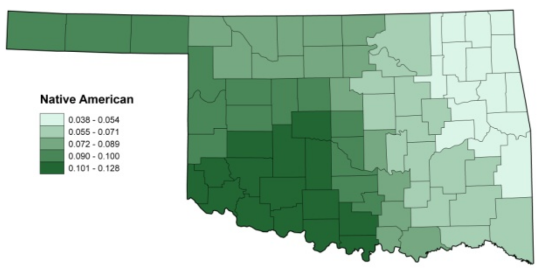

Income Security
Spending
0.018 - 0.023
0.024 - 0.027
0.028 - 0.044
0.045 - 0.054
0.055 - 0.063

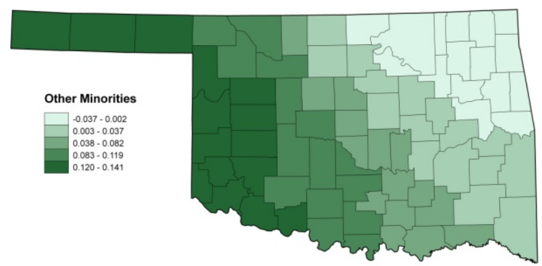

Total Federal
Per Capita Spending
-0.021 - -0.012
-0.011 - 0.000
0.001 - 0.019
0.020 - 0.030
0.031 - 0.041

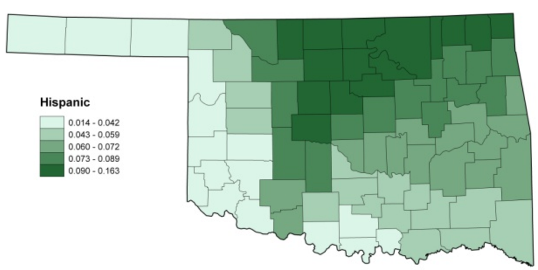
Parameter coefficients for DHS_FUND model

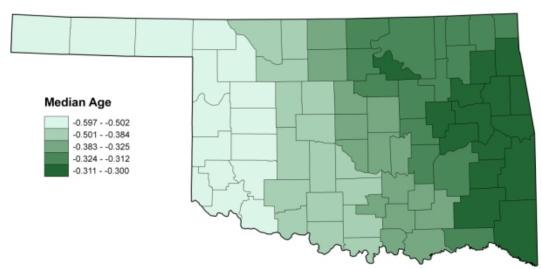


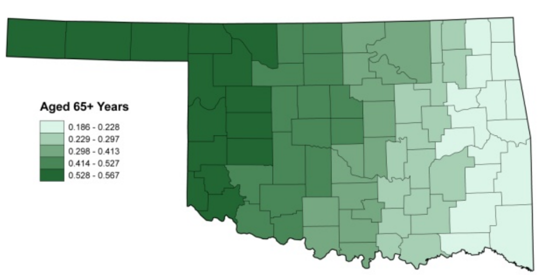


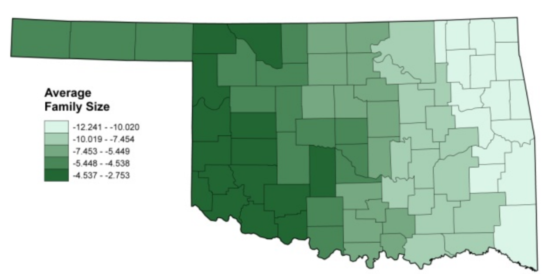


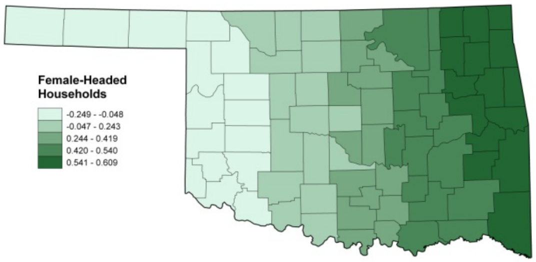


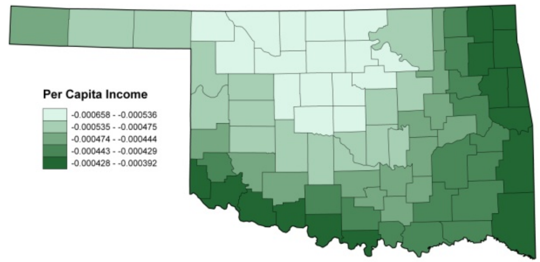


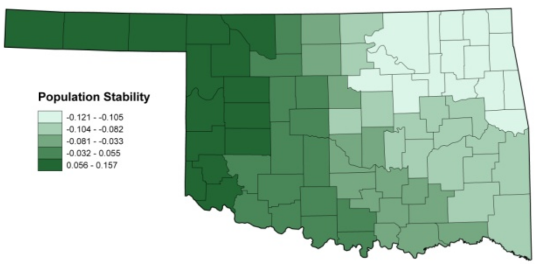


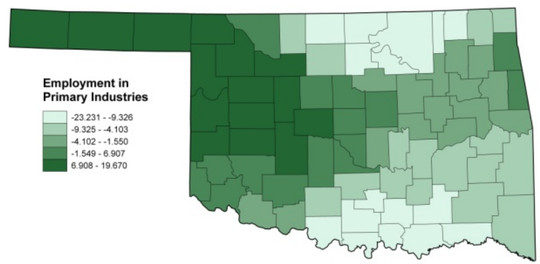


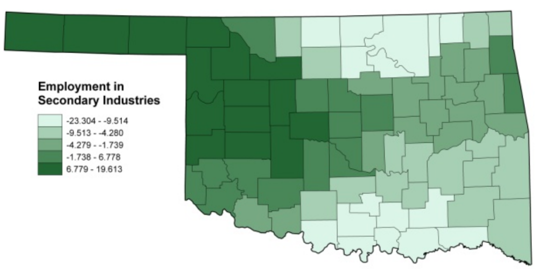


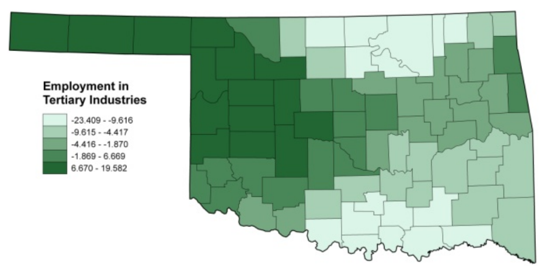

Female-Headed
Households
-0.249 - -0.048
-0.047 - 0.243
0.244 - 0.419
0.420 - 0.540
0.541 - 0.609

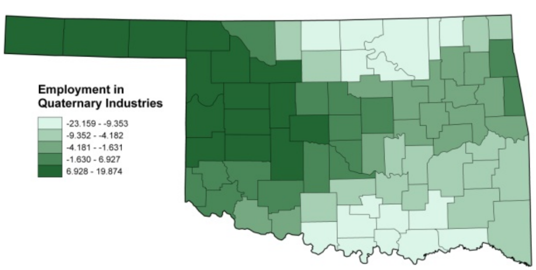

Per Capita Income
-0.000658 - -0.000536
-0.000535 - -0.000475
-0.000474 - -0.000444
-0.000443 - -0.000429
-0.000428 - -0.000392

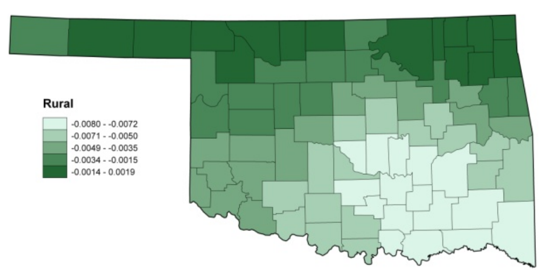

Population Stability
-0.121 - -0.105
-0.104 - -0.082
-0.081 - -0.033
-0.032 - 0.055
0.056 - 0.157

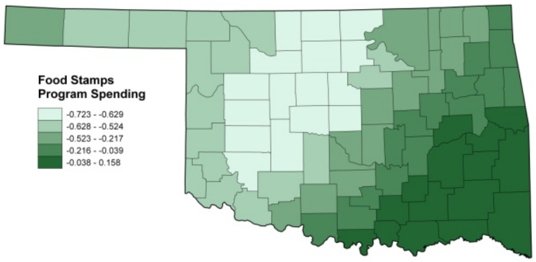

Employment in
Primary Industries
-23.231 - -9.326
-9.325 - -4.103
-4.102 - -1.550
-1.549 - 6.907
6.908 - 19.670

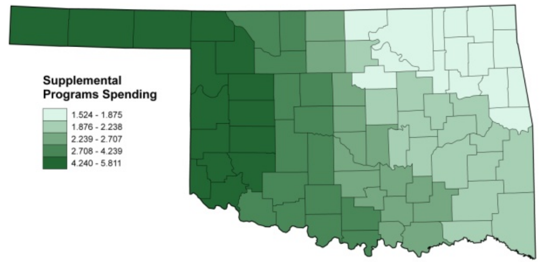

Employment in
Secondary Industries
-23.304 - -9.514
-9.513 - -4.280
-4.279 - -1.739
-1.738 - 6.778
6.779 - 19.613

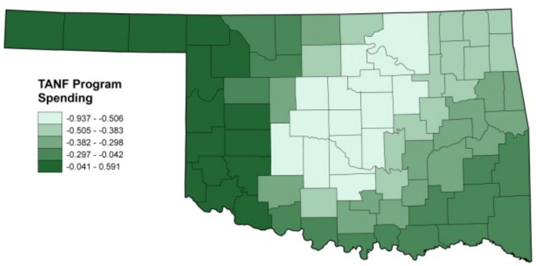

Employment in
Tertiary Industries
-23.409 - -9.616
-9.615 - -4.417
-4.416 - -1.870
-1.869 - 6.669
6.670 - 19.582

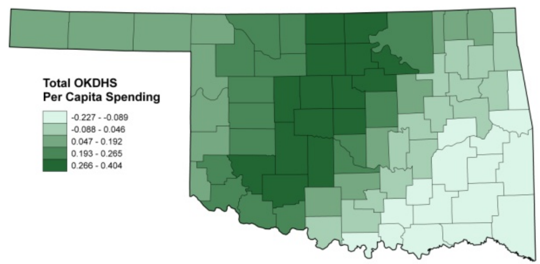

Employment in
Quaternary Industries
-23.159 - -9.353
-9.352 - -4.182
-4.181 - -1.631
-1.630 - 6.927
6.928 - 19.874


Rural
-0.0080 - -0.0072
-0.0071 - -0.0050
-0.0049 - -0.0035
-0.0034 - -0.0015
-0.0014 - 0.0019


Food Stamps
Program Spending
-0.723 - -0.629
-0.628 - -0.524
-0.523 - -0.217
-0.216 - -0.039
-0.038 - 0.158


Supplemental
Programs Spending
1.524 - 1.875
1.876 - 2.238
2.239 - 2.707
2.708 - 4.239
4.240 - 5.811


TANF Program
Spending
-0.937 - -0.506
-0.505 - -0.383
-0.382 - -0.298
-0.297 - -0.042
-0.041 - 0.591


Total OKDHS
Per Capita Spending
-0.227 - -0.089
-0.088 - 0.046
0.047 - 0.192
0.193 - 0.265
0.266 - 0.404

VITA

Amy Kristine Graham

Candidate for the Degree of

Master of Science

Thesis: MEASURING THE SPATIAL DIMENSIONS OF POVERTY IN OKLAHOMA

Major Field: Geography

Biographical:

Personal Data: Born in Ponca City, Oklahoma on January 4, 1974, the daughter of Voyle Douglas and Judy Kay Graham.

Education: Graduated from Ponca City High School in Ponca City, Oklahoma in May 1992. Received Bachelor of Arts degree in Anthropology from the University of Oklahoma, Norman, Oklahoma in December 1996. Completed the requirements for the Master of Science in Geography at Oklahoma State University, Stillwater, Oklahoma in July 2009.

Experience: Employed by the Department of Geography at Oklahoma State University as a graduate teaching assistant and graduate research assistant from 2007 to 2009. Employed by the Illinois Transportation Archaeological Research Program, University of Illinois, Champaign-Urbana, Illinois as field crewmember and laboratory supervisor from 1998 to 2007.

Professional Memberships: Association of American Geographers

Name: Amy Kristine Graham Date of Degree: July, 2009

Institution: Oklahoma State University Location: Stillwater, Oklahoma

Title of Study: MEASURING THE SPATIAL DIMENSIONS OF POVERTY IN OKLAHOMA

Pages in Study: 143 Candidate for the Degree of Master of Science

Major Field: Geography

Scope and Method of Study:

This study utilizes exploratory spatial data analysis (ESDA), global, and local regression modeling in order to better understand the spatial distribution of poverty across Oklahoma, as well as the underlying factors that influence it in various parts of the state. Geographically weighted regression (GWR) is used to highlight local variations in the poverty rate at both the county and Census tract levels. Variables pertaining to demographics, employment, county/tract characteristics, and federal program spending are examined to assess how the influence of these factors over poverty varies throughout the state.

Findings and Conclusions:

Using a global regression technique, county and tract level models reveal that among the variables that most influence poverty in Oklahoma are the percentage of people who lack a high school diploma, the percentage of female-headed households, per capita income, and the percentage of people employed in primary industries. However, global regression modeling assumes that the influence of these variables is constant across space. Contrary to this assumption, GWR modeling demonstrates that significant local variation in the influence of these factors does indeed exist at both the county and tract level. For example, the lack of a high school diploma is most influential among the northeastern most counties of the state, and in the southern and central regions at the tract level. County level models that included variables pertaining to federal program spending revealed that there are some areas of the state where increases in funding also signal an increase in the poverty rate, especially in the southeast corner of the state where poverty rates are higher overall. However, these county level models must be interpreted with caution as the relatively small sample size of 77 counties hinders GWR's ability to produce a statistically significant model. What is clear is that antipoverty programs should be designed with these local variations in mind in order to better target poverty in specific areas of the state.

ADVISER'S APPROVAL: Dr. Jonathan Comer