SPATIAL PATTERNS OF MENTAL HEALTH TREATMENT IN OKLAHOMA

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SPATIAL PATTERNS OF MENTAL HEALTH

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Abstract: Mental Illness has significant economic and social ramifications for communities and encompasses a wide range of disorders demanding different levels of treatment. Oklahoma consistently ranks among the states with the most prevailing mental health issues in America. Understanding the place characteristics associated with the spatial patterns of higher mental health service utilization is crucially needed to highlight areas where mental health treatment may need to be strengthened in the future. These studies analyze demographic, social, and economic patterns in local populations seeking treatment in Oklahoma through services provided by the Oklahoma Department of Mental Health and Substance Abuse from 2011-2014. Spatial statistical techniques are employed to investigate the spatial relationships between mental health treatment for Oklahoma patients and the characteristics of the zip codes they reside.

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CHAPTER I

SPATIAL CONSIDERATIONS IN MENTAL HEALTH

Introduction

Mental illnesses affect a large proportion of the population and include a wide variety of conditions such as depression, bipolar disorder, anxiety disorders, addictive behaviors, and psychotic disorders like schizophrenia (Mayo Clinic 2016). Importantly, mental disorders are among the leading causes of poor health and disability worldwide (World Health Organization 2011; World Health Organization 2013). As of 2015, over 43.8 million Americans were living with a mental or neurological disorder, and approximately one fifth of the population experiences at least one mental health concern within a given year (National Alliance on Mental Illness 2015). Mental disorders have significant social ramifications and extensive direct and indirect economic costs to both the individuals suffering from these illnesses and their communities (Insel 2008). Spatially, the disease burden is not evenly dispersed (Oklahoma State Department of Health 2014; Mental Health America 2015). According to Place Vulnerability Theory, adverse life circumstances do not affect all places uniformly, and certain factors make some places more vulnerable to diseases and death than others (Oppong and Harold 2009). Ultimately, there is spatial variation in mental illness rates within the United States. For example, Oklahoma consistently ranks among the states with the poorest mental health outcomes in the U.S. (Mental Health America 2015).

As of 2015, Oklahoma ranked 49th nationally for adult mental health, and it surpassed the nationwide average for mental illness, with about 20 percent of adult Oklahomans reporting a mental health issue and many more cases likely remaining unreported (Oklahoma Health Improvement Plan 2015; Mental Health America 2015; Substance Abuse and Mental Health Services Administration 2015). Not only does the state have high overall mental illness prevalence and incidence rates, it also is consistently among the highest in the region for suicide (Oklahoma Health Improvement Plan 2015). Therefore, it is critical to find what factors drive elevated mental illness patterns in Oklahoma and uncover any spatial variation of poor mental health within the state. In other words, are some Oklahoma areas or populations disproportionately impacted by adverse mental health conditions and, if so, what are the characteristics of those locations?

Scholars suggest that the social and physical environment of the neighborhood where individuals reside can influence individual health in a multitude of ways (LaVeist 2012; Halpern 2014; Barr 2014). Therefore, the broader community-level sociodemographic characteristics of locations and the reported mental disorder rates of those areas will be analyzed. Moreover, the social ecological model (SEM) explains that individuals are embedded deeply in larger social systems and their physical surroundings (Golden and Earp 2012). Within this framework, geographic and ecological studies have the potential to contribute to mental health research in many ways (Holley 1998). Medical geography, a sub-discipline of human geography dealing with the geographic aspects of health and healthcare, focuses on the links between health and place (Kearns 1993; Curtis 2010; Meade 2010). A medical geographic approach can provide a spatial perspective on mental health services and disease burdens on the landscape, by focusing on location and how it may impact health issues. The application of a spatial perspective and the utilization of quantitative methods may prove essential in understanding disparities in mental health and service use in Oklahoma. Additionally, these techniques shed light on factors that may contribute to Oklahoma's increased mental illness rates and identify regional differences in socioeconomic, demographic, and environmental characteristics of areas or populations vulnerable to higher rates of mental illness.

Purpose of Articles

This dissertation is divided into three separate articles. All three articles analyze patient data for individuals who accessed care from services connected to the Oklahoma Department of Mental Health and Substance Abuse Services (ODMHSAS) from 2011-2014. The relationships between geographic patterns in reported disorders and demographic, socioeconomic, and environmental characteristics of local populations seeking treatment is the primary focus of this research. Each article addresses one of the following questions.

1) **How can the social ecological model be used to study patterns of mental health treatment rates in Oklahoma?**
2) **What are the spatial patterns of mental health issues in Oklahoma, and what place characteristics are associated with these patterns?**
3) **How does the way rurality is measured affect our understanding of mental health patient rates in rural Oklahoma?**

The purpose of the first article, *Understanding Oklahoma's Spatial Patterns in Mental Health through the Social Ecological Model*, is to investigate how a social ecological framework, commonly employed in public health research and interventions, may be applied to geographical studies on mental health. The social ecological modeling framework supports the notion that individuals are embedded deeply in broader social systems and their environment (Golden and Earp 2012). This model has evolved to include six different levels: 1) the intrapersonal level to understand how individual characteristics are associated with certain behaviors, 2) the interpersonal level, or social relationships, 3) the organizational level, 4) the broader community level, 5) public policy considerations, and 6) the physical environment (McLeroy et al. 1988; Stokols 1996; Stokols, Allen, and Bellingham 1996; Golden and Earp 2012). McLeroy et al. (1988) and Stokols (1996) emphasized the best way to address public health concerns is to consider the multiple scales in which people operate, interact, and are influenced. For this reason, I utilize the social ecological model to guide methods and study design. Specifically, I analyze individuals' mental health treatment data aggregated to zip code of residence, as well as neighborhood and broader community levels. K-means cluster analysis is used to group zip codes with similar socio-demographic traits recorded by the United States Census Bureau. Furthermore, within those similar community environments, I explore if mental illness treatment, mental health service availability, and reported poor mental health days appear more frequently in some socioeconomic grouped community environment areas than others. Also, I examine whether certain racial groups experience higher than expected mental illness issues within these areas. The exploration into racial differences in mental health is based on previous literature suggesting that minority populations may potentially be at higher risk for poorer health due to differential socioeconomic and structural barriers (LaVeist 2012; Barr 2014). The individual patients are situated within broader environments so investigating spatial patterns of socio-demographic characteristics and mental illness treatment records can help us make inferences about possible influences at different scales. Findings may also indicate certain groups or environments that need to be further targeted for public mental health interventions.

The second article, *Spatial Variations in Oklahoma Mental Illness*, focuses on locating areas with high reported rates of mental illness and determining what population characteristics may drive mental health treatment patterns in Oklahoma. By investigating spatial patterns in treatment rate data, I discover if there are variations in accessed mental health treatment between areas within Oklahoma. Specifically, reported poor mental health measures are mapped and areas that are vulnerable to selected mental health concerns are identified. Next, global regression models and geographically weighted regression (GWR) techniques are utilized to explore the spatial relationships between zip code level mental health treatment rate patterns, and socioeconomic, demographic, and environmental characteristics of the locations associated with reported mental health measures. These procedures are conducted at several levels including the whole state, rural zip codes alone, and separately for the urban areas of Tulsa and Oklahoma City.

Delving into what neighborhood social, economic, or demographic attributes may be contributing to higher rates of reported mental health issues in Oklahoma and how much certain characteristics influence poor mental health patterns in different portions of the state can offer crucial insight into a severe public health problem. Additionally, separating rural from urban areas allows for gaining insight into the differences in place characteristics associated with mental health treatment rates in these two distinct types of landscapes. Understanding the spatial aspects of mental health issues in Oklahoma may also be economically beneficial for state mental health resource allocation and to indicate differentiated mental health needs in different locations for improved public health. More importantly, these methods and considerations can be applied in different regions to inform locations of their spatial patterns in mental health and the characteristics associated with populations' poor mental health. Ultimately, this research and methods provide support for the utility of geographic investigations into mental health.

Finally, the third article, *Improving our Understanding of Rurality and Mental Health Using Remote Sensing*, addresses how the method of defining rurality may affect how mental illness rates are analyzed and understood. Studies concentrating on the connection between a neighborhood's built environment and population health (Evans 2003; Galea et al. 2005; Cooper et al. 2009; Halpern 2014), as well as studies focusing on the social and environmental determinants of health are popular in medical geography and mental health research (Fisher and Baum 2010; Lorenc et al. 2012; Barahmand, Shahbazi, and Shahbazi 2013). However, previous works have primarily focused on the inner-city or broader urban areas (Leventhal and Brooks-Gunn 2003; Macintyre and Ellaway 2003; Kubzansky et al. 2005; Diez Roux and Mair 2010; Zhang et al. 2011). There is growing interest in mental health patterns in rural areas and rural populations (Windley and Scheidt, 1983; Roberts, Battaglia, and Epstein 1999; Arcury et al. 2005; Levin and Leyland 2005; Mohatt et al. 2006; Smalley et al. 2010; Smalley and Warren 2012; Jensen and Mendenhall 2018). Our work expands on the knowledge of predictors of rural areas' mental health issues. This article specifically concentrates on what is driving spatial patterns of ODMHSAS mental health patient rates in Oklahoma. More importantly, it addresses how different classifications of rural and urban can impact research results and proposes a more geographically explicit way to define rurality using an index including remotely sensed National Land Cover Database (NLCD) land use/land cover data.

The remainder of the dissertation is comprised of three articles, each containing a literature review, methods section, results section, discussion, and conclusion. Although each of these articles focuses on a different aspect of mental health, they have a shared objective of considering the fundamental ways in which places may affect the mental health of their residents. Indicating possible areas, population characteristics, and groups prone to adverse mental health is of the utmost importance and the goal of these three pieces. These works coincide with a push to explore spatial components of health. Meade (2010) emphasized medical geography's role in analyzing the relationships between health patterns and both the social and physical environments. Additionally, Rosenberg (2016) explained that mental health and health inequality studies are two vital expanding dimensions for medical geographic research. Therefore, the growing demand for insight into this topic as well as the local need to explore this urgent health concern in Oklahoma from different perspectives motivates this research.

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CHAPTER II

UNDERSTANDING OKLAHOMA'S SPATIAL PATTERNS IN MENTAL HEALTH THROUGH THE SOCIAL ECOLOGICAL MODEL

This chapter presents the first article, *Understanding Oklahoma's Spatial Patterns in Mental Health through the Social Ecological Model*, which was written by Stephanie Heald from the Geography Department of Oklahoma State University with contributions from Dr. Chandra Story, Associate Professor in the Department of Health and Human Performance at Middle Tennessee State University. Formerly, Dr. Chandra Story worked as an Assistant Professor of Health Education and Promotion at Oklahoma State University. The intended journal for publication of this article is Health and Place. Health and Place publishes a substantial amount of medical geography research and emphasizes the importance of analyzing differences in health and health care patterns between places. Therefore, article one, with its concentration on place characteristics associated with poorer mental health in communities, meets the criteria and aligns with the interests of this journal.

Understanding Oklahoma's Spatial Patterns in Mental Health through the Social Ecological Model

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Highlights

- We mapped the spatial patterns for patients who received treatment from Oklahoma Department of Mental Health and Substance Abuse Service (ODMHSAS) at the zip code level
- Zip codes with similar socioeconomic and demographics were linked together through K-Means clustering to group areas with similar community environments
- Average reported poor mental health days and ODMHSAS patient percentages were highest in community environments characterized by lower SES
- Race/ethnicity disparities in ODMHSAS treatment were also identified within the different community environments
- Using the social-ecological framework in tandem with spatial analysis techniques allows for unique ways to consider the importance of place and environment in health and could prove beneficial for public health endeavors

Abstract

Mental illness is a leading cause of poor health and a growing public health concern in America. Locating and analyzing areas where significant portions of the populations are experiencing poor mental health is crucial. This study focuses on how the characteristics of place may help explain mental health patterns in both rural and urban areas. The social ecological framework is used to justify the need to distinguish community patterns and identify mental health patterns at broader environmental levels. Most public health research concentrates on the individual, however, this research specifically, examines the spatial patterns in mental illness in Oklahoma, using GIS to locate types of community environments that may be more vulnerable to poor mental health. Additionally, within the different community environments identified through K-means clustering, this article uncovered that underlying racial/ethnic disparities exist, especially in the proportions of Hispanic and Native American populations seeking mental health treatment. Looking at broader community patterns of poor mental health may help target areas and groups that could benefit from new public health strategies.

Keywords

Social-Ecological Model, Mental Health, Neighborhood Environment, Spatial Patterns, Medical Geography

1. Introduction

Mental disorders comprise a substantial portion of the disease burden in the U.S. and are responsible for approximately one-fourth of disability cases throughout the nation (Centers for Disease Control and Prevention (CDC), 2005). This is a serious issue as positive mental health is a fundamental part of overall health and well-being (CDC, 2005; Barry, 2009). When individuals are free from anxiety, depression, addictions, excessive stress, and other psychological problems, they are able to experience a higher quality of life (Rhode Island Psychological Association, 2016). The U.S. spends an estimated $150 billion annually on mental illness, not including community and individual social costs (CDC, 2005; NASMHPD, 2006; DeVol et al., 2007; Insel, 2008). Therefore, treating mental health concerns should be met with urgency and be considered a top public health priority (CDC, 2005; U.S. Department of Health and Human Services, 2014(b)). Describing mental health treatment by geographical area can aid in developing targeted and effective interventions. The purpose of this paper is to investigate mental health treatment patterns within the context of different environments to highlight possible disparities between populations and places.

1.1 Literature Review

Public health refers to all systematic measures to prevent disease, promote health, and extend life expectancy among populations as a whole (World Health Organization, 2015). Successful public health endeavors sustain positive mental health through the equitable and effective allocation of mental health resources, the prevention and treatment of avoidable disorders, and the maximization of healthy environments (Tulchinsky and Varavikova, 2014). The mission to maximize healthy environments comes from public health practitioners' realization that individual illness and overall population health may be impacted by the areas in which people reside, work, and interact with each other (Simons-Morton et al., 2011; Golden and Earp, 2012). This concept is at the core of the social ecological model (SEM), in that the entire ecological system in which an individual is situated must be analyzed to fully understand health outcomes (Bronfenbrenner, 1975(a), Bronfenbrenner, 1975(b), Bronfenbrenner, 1979; Bronfenbrenner, 1994; Simons-Morton et al., 2011; Golden and Earp, 2012).

The SEM includes six different levels: the intrapersonal level (how individual characteristics are associated with certain behaviors), interpersonal level (social relationships), the organizational level (the organizations one takes part in such as school, work, religious, or recreational), the broader community level (characteristics of the community in which one lives), public policy considerations (policies in place to support healthy or unhealthy behaviors), and the environment (physical surroundings) (McLeroy et al., 1988; Stokols, 1996; Stokols et al., 1996; Sallis et al., 2008; Simons-Morton et al., 2011; Golden and Earp, 2012). The adoption and implementation of the SEM in public health is highly recommended and enables researchers to focus on a broader context beyond the scope of patients and their immediate network (Sallis et al., 2008; Marmot et al., 2008; Espelage and Swearer, 2009; Simons-Morton et al., 2011; Golden and Earp, 2012; Latkin et al., 2013; Baral et al., 2013; Baron et al., 2014; Ross et al., 2014; U.S. Department of Health and Human Services, 2014(a); Golden et al., 2015; CDC, 2015; World Health Organization, 2016). Applying ecological models to mental illness has been less widely employed compared to physical health studies, but allows for a more inclusive outlook on mental health problems and provides a comprehensive framework for understanding the multiple and interacting determinants related to mental illness (Naar-King et al., 2006; Visser, 2007; Sallis et al., 2008; Baral et al., 2013; Barahmand et al., 2013).

The SEM may contribute greatly to the study of population mental illness. However, most mental health research in medical geography does not explicitly utilize the social ecological framework. Medical geography, a sub-discipline of human geography, focuses on the links between health and place, and deals with the geographic aspects of health and healthcare by providing spatial perspectives on health services and disease burdens over the landscape (Mayer, 1984; Brown et al., 2009; Meade, 2010). Therefore, geographic mental health research emphasizes place effects on spatial health patterns and attempts to identify how the contextual characteristics of an area relate to health issues in the location (Cummins et al., 2007; Curtis, 2010). This inherently corresponds with the broader community and environmental levels of the social ecological model.

One predominant way in which spatial studies have examined community level or environmental effects and health outcomes is by statistically analyzing an area's socioeconomic and demographic characteristics and their relationships to disease or service use patterns at the individual level, and broader neighborhood or community level (Yen and Kaplan, 1999; Yen and Syme, 1999; Diez Roux, 2001; Weich et al., 2002; Galea et al., 2005; Rehkopf and Buka, 2006; Cummins et al., 2007; Kelly et al., 2010; Zhang et al., 2011; Hudson and Soskolne, 2012; Brown, 2013; Barahmand et al., 2013). Research has revealed that in both urban and rural settings, adverse conditions in the social and built environment are equated with poor mental health (Krieger et al., 1997; Wainer and Chesters, 2000; Evans, 2003; Leventhal and Brooks-Gunn, 2003; Stafford and Marmot, 2003; Philo et al., 2003; Diez Roux and Mair, 2010; Zhang et al., 2011; Bond et al., 2012; Halpern, 2014). The environment can either exert or alleviate stress on individuals' daily lives depending on its conditions (Macintyre and Ellaway, 2003). Therefore, the social and built environment can have detrimental impacts on mental well-being, if it is violent, unsafe, or filled with harmful characteristics. A lack of necessary resources like healthcare, transportation, sufficient housing, and secure nonhazardous employment can be detrimental to health outcomes as well (Stokols, 1996; Macintyre and Ellaway, 2003).

Most researchers agree that degradation of the built environment (i.e. lack of amenities, housing insecurity) can cause elevated levels of stress, increasing urban residents' vulnerability towards experiencing a mental disorder (Weich et al., 2002; Kawachi and Berkman, 2003; Evans, 2003; Cooper et al., 2009; Curtis, 2010; Halpern, 2014). Correspondingly, Galea et al. (2005) found that poor quality of the built environment had a significantly greater likelihood for reported individual depression. However, in rural areas, economic stress due to less predictable natural environments, physical isolation, increased travel times, and sparse infrastructure (including low accessibility and availability of mental healthcare services) can contribute to poor mental health outcomes. (Humphreys, 1998; Philo et al., 2003; Arcury et al., 2005; Mohatt et al., 2006; Fortney et al., 2007; Kelly et al., 2010; Smalley et al., 2012; Edwards et al., 2015). Additionally, in rural areas, the elderly commonly comprise a larger proportion of the population and are at increased risk for mental illness (Human and Wasem, 1991; Bolin et al., 2015). Increased risk may also be due to decreased accessibility to services as a result of less individual mobility (Windley and Scheidt, 1983; Gamm et al., 2010; Nelson and Gingerich, 2010; Bolin et al., 2015).

Social aspects of environments may also cause prolonged chronic stress and aggravate both physical and mental health issues for urban and rural residents (Latkin and Curry, 2003; Lorant et al., 2003; Kubzansky et al., 2005; Marmot and Wilkinson, 2005; Curtis, 2010; CDC, 2013; Barr, 2014). Areas with populations experiencing increased adverse social conditions such as low socioeconomic status (SES), unemployment, weak social networks, low levels of integration, and poverty experience higher rates of physiological disorders (Kohn et al., 1998; Wilkinson and Marmot, 2003; Artazcoz et al., 2004; Muntaner et al., 2004; Saraceno et al., 2005; Fisher and Baum, 2010; CDC, 2013). In both rural and inner-city areas, research suggests limited resources, reduced job opportunities, lack of insurance, and poverty may contribute to poorer mental health (Saraceno and Barbui, 1997; Humphreys, 1998; Wainer and Chesters, 2000; Wilkinson and Marmot, 2003; Eberhardt and Pumak, 2004; Marmot et al., 2008; Fisher and Baum, 2010). Lastly, racial minority groups may be more vulnerable to disease and have poorer overall health, in part, due to underlying differences in access to care (House and Williams, 2000; Chow et al., 2003; LaVeist, 2012; Barr, 2014). For this reason, investigating disparities between racial or socioeconomic groups in a neighborhood and between neighborhoods is meaningful in understanding mental health disparities (Diala et al., 2000; Baicker et al., 2004; and Zhang et al., 2011; Weaver et al., 2015).

Overall, the apparent association between mental illness and neighborhood or place characteristics suggests that improvements to adverse social or environmental influences can advance mental health and well-being in populations (Dalgard and Tambs, 1997; Macintyre and Ellaway, 2000; Diez Roux and Mair, 2010; Bond et al., 2012; U.S. Department of Health and Human Services, 2014(a);

U.S. Department of Health and Human Services, 2014(b)). Understanding determinants of mental illness from a SEM framework has powerful implications for public health practice. Thus, more studies adopting a social ecological approach by considering individuals' surrounding structural factors and investigating environmental impacts on mental health are needed (Simons-Morton et al., 2011; Golden and Earp, 2012).

1.2 Research Questions

The aim of this study is to use an SEM framework to identify the characteristics of environments that are more prone to poor mental health issues. In Oklahoma, identifying areas and populations disproportionately experiencing mental health issues is a pressing topic that has seen little to no attention in medical geography or public health research. To achieve the aim of this study, I employ medical geography tools and a spatial perspective used in combination with SEM to examine contemporary population mental health disorders. Specifically, I use the SEM to conceptualize the possible neighborhood or zip code level and broader community environment level influences on populations' mental health in Oklahoma. Using geographic methods, this study attempts to uncover whether poorer individual mental health is spatially associated with areas of social disadvantage and if certain groups within those areas experience mental health disparities. By examining the types of environments that seem to foster poorer mental health and the populations within those areas that appear to be the most vulnerable, we can target and design mere effective and efficient public mental health strategies order to achieve healthier communities. Therefore, the research questions are:

1) **How do mental illness treatment patterns, average reported poor mental health days (PMHD), and mental health service coverage compare among neighborhoods characterized by similar SES, age structure, and race/ethnicity?**

2) **Are certain race/ethnicity groups possibly underrepresented in the population of patients seeking mental health treatment from the Oklahoma Department of Mental Health and Substance Abuse Services (ODMHSAS)?**

1.3 Study Area

Oklahoma (**Figure 1**), a less researched region, provides a unique study area for this spatial investigation because 66% of the population resides in urban locations and approximately 34% are located in rural areas (United States Census Bureau, 2010). More vitally, Oklahoma is ranked 49th in the nation for mental health, has a suicide rate that is 36 percent higher than the national rate, and is regularly among the states with the poorest health outcomes and the highest prevalence of behavioral health concerns (CDC, 2005; Substance Abuse and Mental Health Services Administration 2015; Oklahoma State Department of Health, 2014; Oklahoma Health Improvement Plan, 2015; Mental Health America, 2015). Additionally, Oklahoma faces multiple social and economic challenges associated with poor mental health, such as high unemployment rates, low educational attainment, elevated substance abuse rates, poverty, and significant healthcare shortages (Oklahoma Health Improvement Plan, 2015; Oklahoma Employment and Security Commission, 2016; HRSA, 2016). Therefore, it may prove important to identify characteristics and locations of areas associated with higher recorded mental illness in Oklahoma.

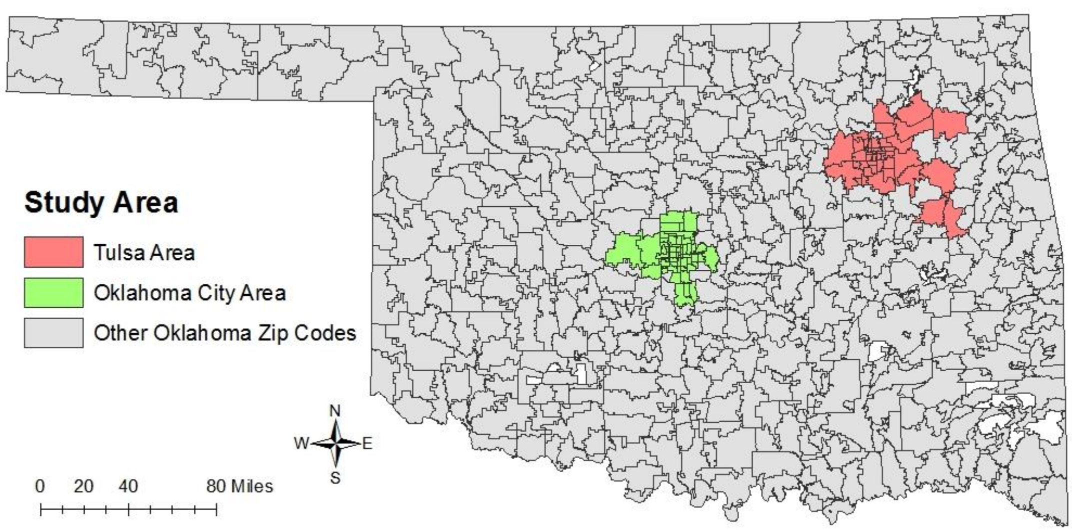

Fig. 1. Oklahoma Zip Codes with Major Population Centers Labeled

2. Material and Methods

2.1 Mental Health Data

In order to ascertain the characteristics and locations of Oklahoma areas prone to poor mental health, this study utilizes individual mental health data obtained from the ODMHSAS. After eliminating unreliable or incomplete records, 289,767 cases of fully admitted individuals who accessed care from services connected to the ODMHSAS from 2011-2014 were analyzed. Patients' reported poor mental health days (PMHD), primary presenting problems, individual demographic information, and zip code of residence were included in the records. However, to protect confidentiality, all individuals were given unique and random identifiers by the ODMHSAS and patients were aggregated to their zip code of residence for this study. Therefore, this project was ruled exempt from the Institutional Review Board (IRB), a board that reviews all research involving human subjects to ensure that studies conducted abide by federal and ethical guidelines. The overall, recorded ODMHSAS patient rates and reported PMHD for individual zip codes were then mapped to reveal the overall geographic distribution of mental illness issues throughout the state. Furthermore, the rate of an area's available ODMHSAS mental health affiliated facilities per person was derived by combining state funded facilities affiliated with ODMHSAS divided by the population per zip code and multiplied by 1000. These rates were also mapped to illustrate the geographic distribution of ODMHSAS mental health service coverage throughout the state.

By looking at spatial patterns in mental health treatment, PMHD, and available services in zip codes throughout the state, small pockets of poor reported mental health and reduced coverage were pinpointed and their populations and neighborhood characteristics explored. However, with 648 zip codes these neighborhood characteristics may not help us understand broad patterns of the environments that are associated with increased mental illness. Therefore, grouping these smaller zip code units together through shared socioeconomic and demographic traits aided in defining broader community environments whose mental illness burden can then be explored, compared, and analyzed.

2.2 Neighborhood-Level Data

To examine if certain environments were more vulnerable to increased mental health issues, the spatial patterns of the zip code aggregated individual patient data were compared with the patterns in socioeconomic and demographic characteristics of the 648 zip codes in which the patients reside. The community or neighborhood level information was derived from the 2010 U.S. Census and the Census Bureau's 2014 American Community Survey (ACS) at the zip code level for uniformity. Although a smaller spatial unit would be preferable, due to confidentiality zip codes are often used as proxies for neighborhoods in spatial studies on health (Krieger et al., 1997). Multiple zip codes, however, were left out of this study due to inaccurate or missing data. Based on the review of literature, community-level socioeconomic and demographic variables measuring poverty, race/ethnicity, family structure, residential stability, educational attainment, employment, and sparse infrastructure were obtained from the 2014 ACS 5-year estimates and analyzed (Krieger et al., 1997; Holley, 1998; Macintyre and Ellaway, 2003; Diez Roux and Mair, 2010; Bond et al., 2012. Based on the exploratory analysis of ACS variables, the following SES characteristics were selected for this study:

- Percent of the population that has obtained higher education by receiving at least some schooling after high school
- Percent below the poverty line,
- Percent of the population that rents their home,
- Percent of the population with incomes over $100,000,
- Percent of female-headed households,
- Percent uninsured,
- Percent unemployed

Percent of the population living in rural areas per zip code is another selected variable accessed from the 2010 U.S. Census Bureau and is used to broadly classify sparse infrastructure in this study. Additionally, the percentage of the population over 65 years of age, and the percentages of the population that are Hispanic, African American, White, and Native American are demographic characteristics chosen to help classify zip codes with similar community environments.

2.3 Clustering and Comparison Methods

A K-Means cluster analysis of the selected community level educational attainment, income, employment, and demographic data for Oklahoma zip codes was conducted in order to group zip codes with similar SES and demographic traits. These K-Means grouped zip codes represent the broadest environment level in the SEM at which the population mental health patterns was compared to answer the first research question. K-Means clustering is a method commonly used for grouping data that utilizes an algorithm to partition observations in a preselected number of groups. Initial clusters alter as each observation is assigned to the closest cluster center which then changes the overall cluster means. After iterations, once there are no changes in group assignments of observations, the clustering is complete and units with similar characteristics are grouped (MacQueen, 1967). After assessing the means and distributions of the clusters, six clusters were selected for this study due to best fit. Labels were assigned to each cluster based on their final mean cluster centers for each characteristic. If mean centers were high for adverse socioeconomic characteristics these areas were classified as low SES. Correspondingly, low mean centers for adverse socioeconomic traits and high mean centers for higher income and education helped designate environments as high SES. The spatial distribution of these SES and demographically grouped zip codes were then mapped. The overall recorded ODMHSAS patient rates, reported PMHD, and ODMHSAS facilities per person rates for the zip codes grouped by similar community environments were compared to highlight possible mental health disparities between these areas.

Prior studies have determined that striking health differences may exist between differing demographic groups (Fisher and Baum, 2010). Therefore, to address the second research question, individual mental healthcare patients' race/ethnicity were analyzed to find if there are racial disparities in mental health treatment rates in and between different community environments. The census-reported demographic distribution of each area was compared to the demographic patterns of those who sought treatment from ODMHSAS services in order to determine if racial disparities exist in community locations throughout Oklahoma. Results for these procedures are provided in the following section.

3. Results

3.1 Neighborhood-Level/Zip Code Patterns in Mental Health Measure

The spatial distribution of patients seeking treatment from ODMHSAS services is not uniform throughout the state (**Figure 2**). Several zip codes within the urban areas of Tulsa and Oklahoma City have higher proportions of their total populations that have sought treatment from ODMHSAS. Additionally, there is a higher concentration of mental health patients residing in the more rural southeastern portion of the state. When looking at patterns in average reported PMHD, patients in the southeast corner experienced a higher number of days than many other areas in the state (**Figure 3**). Also, several urban zip codes in Oklahoma City have residents with a higher number of average PMHD and many of these zip codes also have higher patient rates revealing more reported mental health issues in these areas. However, several rural zip codes in the southern portion of the state exhibit higher numbers of average reported PMHD but lower rates of patients (**Figures 2-3**). For example, the rural zip code 73562 in the central portion of southwestern Oklahoma has the highest number of average PMHD per ODMHSAS patients, but has a comparatively lower patient rate than many other zip codes in the state.

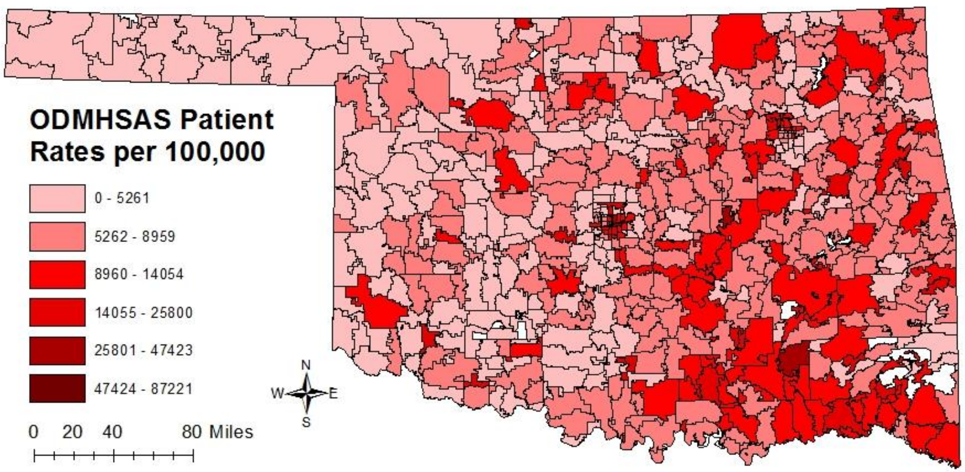

Fig. 2. Rate of ODMHSAS Patients per 100,000 by Zip Code

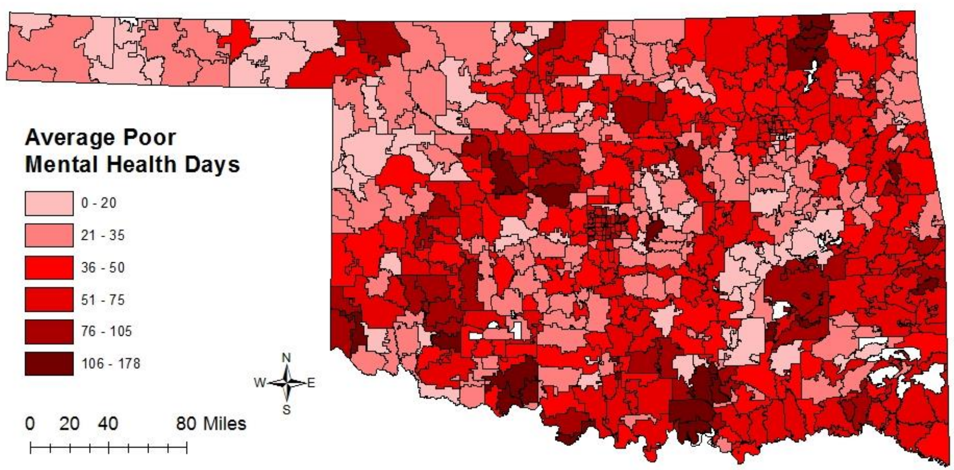

Fig. 3. Reported Poor Mental Health Days (PMHD) by Zip Code

Furthermore, although urban areas boast the highest number of ODMHSAS mental health services, many of the highest rates of mental health services (per 1,000 people) appear in the southeastern corner of the state. Oklahoma City zip codes and several urban Tulsa zip codes also have higher rates of service coverage as well. Therefore, many of the areas with a high percentage of patients and an increased number of PMHD have higher numbers of available services. The exception appears to be in several south-central and southeastern zip codes that have comparatively high numbers of average PMHD but less available services for their populations (**Figure 4**).

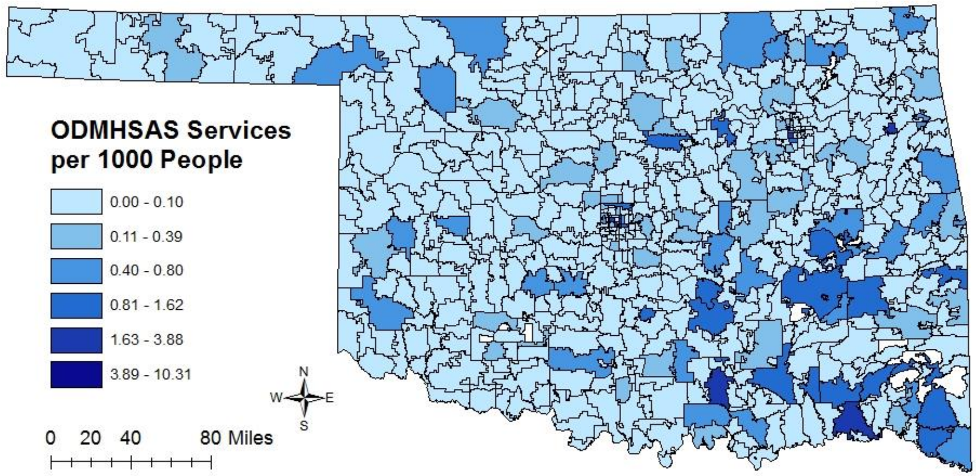

Fig. 4. ODMHSAS Services/Facilities per 1,000 People by Zip Code

3.2 Community Environment Mental Health Comparisons

Next, the smaller zip code units representing the community level of SEM were grouped together through a K-Means clustering of socioeconomic and demographic traits in order to define broader community environments whose mental illness burden was then be explored, compared, and analyzed. In total, 644 zip codes were grouped into six clusters. Four zip codes were left out of the clustering due to missing data in one or more of their variables. These community environment clusters are identified based on their similar SES and population characteristics (**Table 1**). Contingent upon the averages of each variable in a cluster, the six similar environments are named and identified: Urban Low SES Racial Minority Majority, Peri-Urban Higher SES, Highly Urban Low to Moderate SES Increased Hispanic Presence, Rural Higher SES Predominantly White, Rural Moderate SES Increased Elderly and White Presence, and Rural Low SES Increased Native American Presence (**Table 1**).

Table 1
Community Environment Clusters

Cluster #s	Final Clusters Centers					
	1	2	3	4	5	6
Cluster Names	Urban Low SES Racial Minority Majority	Peri-Urban Higher SES	Urban *Low to Moderate* SES Increased Hispanic Presence	Rural Higher SES Predominantly White	Rural Moderate SES Increased Elderly and White Presence	Rural Low SES Increased Native American Presence
Number of zip codes in each Cluster	11	115	68	125	186	139
% 65 and Over	14.832	14.845	11.129	17.835	19.603	16.627
% Hispanic	3.843	6.047	17.614	5.115	4.224	7.171
% Native American	1.119	8.261	4.376	2.908	7.245	16.684
% African American	72	4	12	1	1	3
% Uninsured	21.453	16.241	23.183	11.435	20.392	24.539
% Higher Education	22.875	31.601	27.976	29.983	18.487	19.358
% Poverty	32.7	14.8	23.4	9.4	18.1	22.4
% Rent	45.711	27.741	50.033	17.704	22.406	23.267
% Income over $100,000	6.3	18.7	10.7	20.7	10.1	9.4
% Rural	35	31	4	99	99	99
% White	14.784	73.310	56.224	86.457	79.987	60.882
% Female-headed Household	21.519	11.552	15.111	6.493	9.406	12.418
% Unemployed	8.014	3.865	5.058	2.630	3.630	4.357

*** The highest cluster means are shown in red and the lowest means are in blue.**

The map of zip codes with similar community environments indicates that areas linked through SES and demographic characteristics do not necessarily border each other, although some spatial patterns do exist (**Figure 5**). Areas classified as *Urban Low SES Racial Minority Majority* are predominantly in the two largest metropolitan areas, Oklahoma City and Tulsa. Similarly, *Urban Low to Moderate SES Increased Hispanic Presence* are most common in urban Oklahoma City, Tulsa, and Lawton. *Peri-Urban Higher SES* classified areas are often zip codes that encompass smaller county seats throughout the state. Contrastingly, *Rural Higher SES Predominantly White* classified zip codes are mainly located in Northwestern Oklahoma, while *Rural Low SES Increased Native American Presence* are concentrated more in the Eastern portion of the state. Finally, *Rural Moderate SES Increased Elderly and White Presence* characterize the largest number of zip codes and they are spatially dispersed throughout Oklahoma (**Figure 5**).

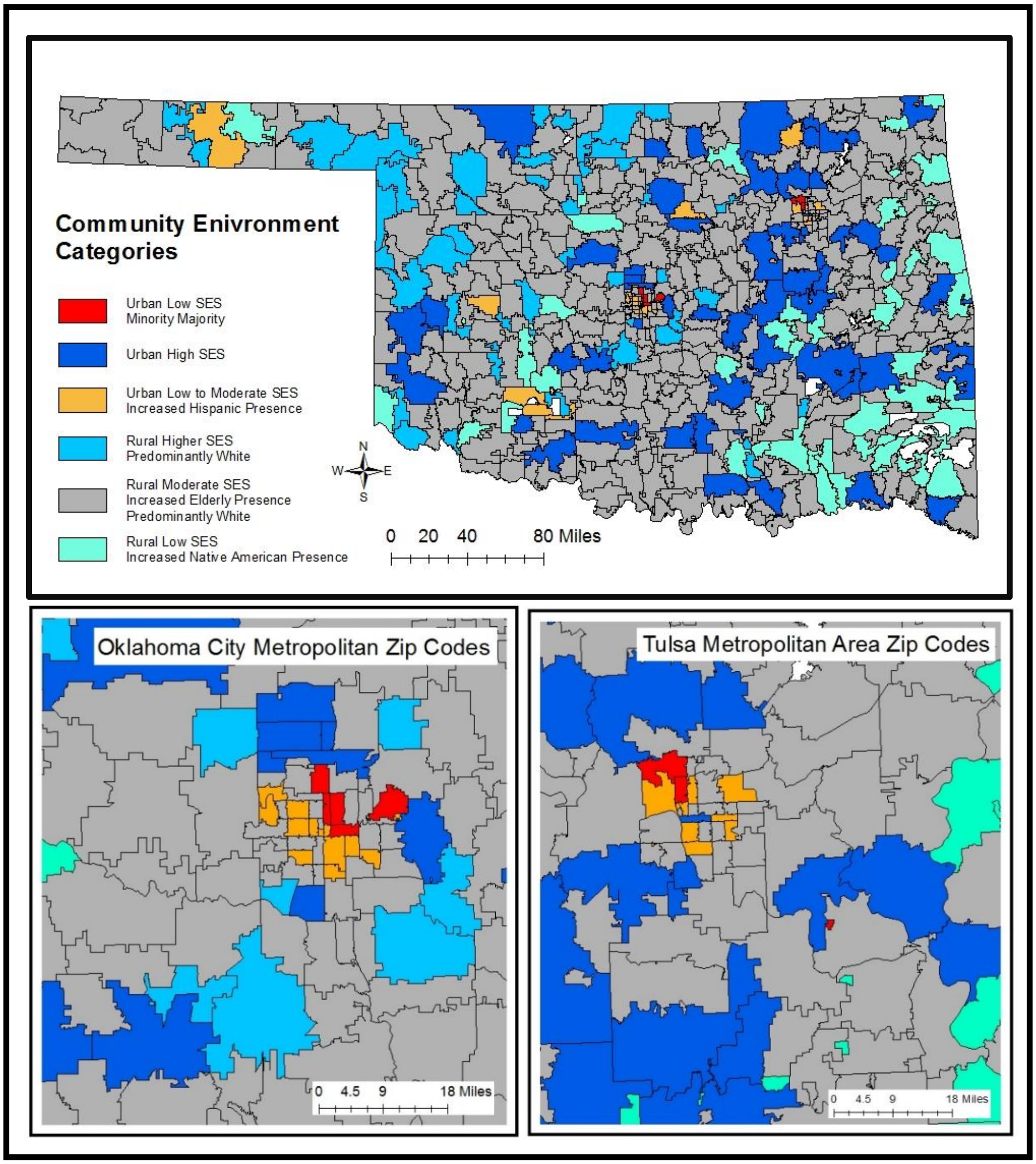

Fig. 5. Map of Similar Community Environment Categories: (a) Statewide Map, (b) Oklahoma City Area, (c) Tulsa Area.

Notable differences in mental health treatment patterns and average reported PMHD within these broader community environments exist. These areas, additionally, had different levels of access to mental health services measured by the rate of mental health services per 1,000 population rate (**Table 2**). The three areas classified by the lowest SES in the state had the poorest reported mental health according to the two variables measured. *Urban Low SES Racial Minority Majority* environments had the highest percentage of the population seeking mental health treatment from

ODMHSAS affiliated facilities and the highest number of average PMHD. *Urban Low to Moderate SES Increased Hispanic Presence* is the environment that had the second highest number of average PMHD and proportion of patients to the population. Rural Low SES areas had the next highest figures, while rural and peri-urban environments characterized by higher SES had lower PMHD and percent of the population that were ODMHSAS patients comparatively. Finally, urban environments had the highest service to population rates, while rural environments that tend to be comprised of larger area zip codes had less services per 1,000 people. This suggests possible availability and accessibility issues within rural environments in Oklahoma, which corresponds with previous literature (**Table 2**).

Table 2
Oklahoma Zip Code Community Environments' Mental Health Measures.

Cluster Groups	Total Population	Total Patients	ODMHSAS Patients % of Population	Average MHD 2011-2014 per Patient	Mental Health Services/Facilities	Mental Health Services per 1,000 People
Urban Low SES Racial Minority Majority	80200	15560	19.40	78.38	47	.5860
Peri-Urban Higher SES	1811367	125847	6.95	43.30	765	.4223
Urban Low to Moderate SES Increased Hispanic Presence	1109854	103863	9.36	52.62	709	.6388
Rural Higher SES Predominantly White	209390	10101	4.82	38.41	21	.1003
Rural Moderate SES Increased Elderly and White Presence	340679	25263	7.42	48.27	64	.1879
Rural Low SES Increased Native American Presence	263801	20222	7.67	49.79	84	.3184

***The highest measures are shown in red and the lowest are in blue.**

3.3 Demographic Comparisons in Mental Health Measures

Additionally, in these community environments some racial/ethnic groups are represented disproportionally in the population of patients seeking OSDMHSAS treatment (**Table 3**). In all six similar community environments, Native Americans comprised more of the patient population than was expected based the percent of the overall population they made up in each area. Similarly, African

American residents were overrepresented in the ODMHSAS patient population. African Americans made up a higher proportion of the patient population than anticipated based on the percent of the overall populations they comprise in each area, with the exception of the *Urban Low SES Racial Minority Majority Environment* in which African Americans make up the majority of the population. In the *Urban Low to Moderate SES Increased Hispanic Presence Environment*, African American residents represented almost ten percent more of the ODMHSAS treated population than they did the overall population. Contrastingly, in all six similar community environments, Hispanics/Latinos were underrepresented in the patient population, although the differences were very small in the *Rural Higher SES Predominantly White* and R*ural Moderate SES Increased Elderly Presence Predominantly White* environments. In the environment where Hispanics/Latinos were the largest percentage of the population, they comprised more than seven percent less than proportionately expected of the ODMHSAS patient population. Finally, in the three areas with higher levels of SES, white residents proportionately comprised significantly lower percentages of the population admitted to ODMHSAS treatment than expected based on the large proportions of the population they make up in these environments. However, in the lower SES areas the proportion of the population seeking mental health treatment that was white was slightly higher or almost the same as the percent of the overall population that was white (**Table 3**).

Table 3
Community Environments' Race/Ethnicity Percentages vs. Areas' Race/Ethnicity Patient Percentages

Cluster Groups	% Hispanic Of Total Population	% Hispanic Of Patient Population	% White Of Total Population	% White Of Patient Population	% African American Of Total Population	% African American Of Patient Population	% Native American Of Total Population	% Native American Of Patient Population
Urban Low SES Racial Minority Majority	6.17	3.47	18.50	18.46	66.43	62.58	1.65	2.74
Peri -Urban Higher SES	5.90	4.38	74.11	60.86	3.78	6.61	7.22	9.65
Urban Low to Moderate SES Increased Hispanic Presence	18.42	10.99	56.59	58.04	12.13	21.94	3.91	6.01
Rural Higher SES Predominantly White	4.97	4.49	83.33	74.19	1.27	3.86	4.81	6.50
Rural Moderate SES Increased Elderly and White Presence	3.79	3.45	78.03	72.95	1.84	4.07	8.42	10.01
Rural Low SES Increased Native American Presence	6.93	4.20	60.65	62.14	2.70	4.71	18.38	19.66

Moreover, at the individual zip code level, in almost a sixth of Oklahoma zip codes, the African American population receiving treatment was at least 5% higher than the proportion of the population African Americans make up in each of the zip codes. In only 29 zip codes African Americans consisted of at least 5% less of the ODMHSAS patient population than they comprised in the overall population. The difference was also noted for the Native American population in zip codes. In 113 individual zip codes the Native American ODMHSAS patient population was at least 5% greater than proportionally expected based on their percentage of the overall population, and only 62 zip codes had lower than expected rates. Contrastingly, 108 zip codes were identified in which the Hispanic/Latino population receiving treatment was lower by at least 5% than proportionally expected based on the demographic composition of the zip codes. In just 57 zip codes did the Hispanic/Latino population have at least a 5% higher difference between patient proportions and the overall percentage of the Hispanic/Latino population in each zip code. Finally, 254 zip codes were found to have lower percentages of the white population being admitted for ODMHSAS treatment compared to the proportion of the population they comprise. However, in 163 zip codes white patients made up proportionately more than expected of the overall patient population. Therefore, when considering the smaller neighborhood zip code level or the broader community environments of grouped zip codes, striking differences in recorded mental health measures exist between SES and demographic characterized areas and between race/ethnicity groups. Ways to interpret these findings are presented below.

4. Discussion

4.1 SES Environments and Mental Health Discussion

The community or neighborhood level of SEM was represented by the zip code level, and mental health characteristics for zip codes were mapped and analyzed in this research to reveal disparities in mental health between different locations throughout the state. More broadly, however, according to SEM, the environment level consists of a place's social culture and physical surroundings. Understanding the dynamics of the environment may help public health practitioners to prevent and treat mental health concerns (Simons-Morton et al., 2011). By using K-Means clustering to group zip codes with similar SES and demographic characteristics, I compared mental illness treatment patterns, average reported PMHD, and mental health service coverage among neighborhoods characterized by similar SES, age structure, and race/ethnicity.

The measures calculated for each of the six classified community environments supports previous literature that socioeconomic characteristics of place may correspond to differences in population mental health (Evans, 2003; Curtis, 2010; Barr, 2014; Halpern, 2014). Community environments classified as urban with low SES and low to moderate SES tended to have higher percentages of their population who have received ODMHSAS treatment between 2011-2014. This pattern reveals that environments with higher percentages of adverse social and economic conditions had increased mental health issues. This suggests that aspects of both the urban environment and social characteristics of lower SES environments may contribute to increased levels of stress on significant portions of these community populations and present challenges to residents' mental well-being. Rural low SES environments followed by rural moderate SES communities had the next highest percentages of ODMHSAS patients and PMHD, therefore potential economic strains in these areas combined with reduced opportunities to access health resources may have exacerbated mental health issues One important consideration, however, is that low income individuals can receive reduced fee treatment from ODMHSAS. Therefore, poorer individuals may obtain services more easily if they are accessible. This could be one reason why poorer environments housing more low income residents appear to have higher rates of treatment usage. Notably, poor urban places have higher reported mental issues than poor rural places. Even though financial resources might be available for low income individuals in both areas, urbanites may have more available means of transportation to obtain treatment. Furthermore, there is a greater mental health service density in urban Oklahoma so residents will likely have shorter distances to travel.

Contrastingly, higher SES rural and urban areas appear to have less PMHD, as well as smaller percentages of their population obtaining treatment. Specifically, rural areas with higher SES seem to experience the least mental health issues in their population. However, reduced ODMHSAS rates in rural high SES environments may be an artifact of less available mental health services for residents in those areas. Many of these residents may be deterred from treatment not because they experience positive mental health, but instead because services are not as readily available in rural areas. Differences found in rural and urban reported mental health patterns may also be partially explained by stigma which operates at the intrapersonal and interpersonal levels of SEM. Roberts et al. (1999) explains that stigma on mental illness and a fear of lack of anonymity is heightened in rural environments due to the small populations and overlapping social networks. Additionally, the self-reliant culture of many in these communities can greatly impact the acquisition of services for these residents (Roberts et al., 1999; Fuller et al., 2000). Although my methods primarily focus on the community or broader environment levels of SEM, future research can be conducted at the intrapersonal and interpersonal levels to explore the effects of stigma in these communities.

4.2 Demographic Comparisons Discussion

When analyzing patterns in patient demographics compared to neighborhood and community demographic patterns, several key findings with respect to race and ethnic differences in area mental health patterns were revealed. We confirmed that certain race/ethnicity groups seem overrepresented, while others appear underrepresented in the population of patients seeking mental health treatment from ODMHSAS. For example, in all but one community environment, African Americans acquire more services than would be anticipated based on population statistics. Particularly, the only community environment where African Americans received treatment less than proportionally expected was in the area in which they were the majority. Some studies have reported that having racial minority status in an area alone causes increased levels of stress which could result in poor health and increased psychological issues for individuals in those groups (Williams et al. 1997; Barr 2014). However, the relationship between minority status and health is not always clear once confounding variables like SES are controlled for. Previous research clearly indicates that racial differences in psychological distress are complexly interconnected with SES (Aneshensel and Sucoff, 1996; Bratter and Eschbach, 2005). Thus, racial or ethnic health outcomes must be understood as being situated and entangled within socioeconomic conditions because of structural, cultural, and historical factors that have disenfranchised minority groups throughout time (Cooper and David, 1986; Krieger et al., 1997; Williams et al., 1997; Macintyre and Ellaway, 2003).

The most notable finding for race/ethnic groups are that Hispanic/Latino populations accessed comparably fewer mental health services in every community setting, while Native Americans utilized equivalently more services throughout all communities. The Hispanic/Latino population comprises less of the ODMHSAS treated population than proportionally expected, indicating a possible underserved population in many neighborhoods and communities. Treatment findings could reflect the prospect that Hispanics/Latinos suffer less mental illness in part due to strong social ties in Hispanic/Latino families and neighborhoods (Rios et al., 2012; Ruiz et al., 2016). The results may also support the commonly discussed Hispanic paradox that although Hispanic/Latino populations may have lower SES, which is usually equated to poorer health, Hispanic/Latino populations may defy the expected statistics and experience lower rates of morbidity and mortality (Barr, 2014; Ruiz et al., 2016). Another possibility is that Hispanics/Latinos experience or perceive higher levels of stigma associated with seeking mental health treatment. Alvidrez and Azocar (1999) found that in distressed women's clinic patients, Hispanic/Latino women were more likely to report anticipated stigma-related barriers to treatment. Moreover, Interian et al. (2007) and Cooper et al. (2003) both found that for Latinos, stigma towards taking antidepressant medications was a significant concern and often impacted their treatment adherence.

Another contributing factor to reduced mental health treatment rates in Oklahoma Hispanic/Latino populations may be a potential a language barrier or concerns of a language barrier (Barr, 2014). Finally, it may also be that some individuals in this population may not have legal citizenship. Therefore, the fear of deportation or steep penalties due to their status as undocumented immigrants could discourage them from pursuing mental health services and be a continual source of stress in illegal residents' daily lives. Similar patterns in Hispanic/Latino mental health and treatment seeking disparities have been reported in other regions. Moreover, mental health is a crucial aspect of overall well-being, thus more research into what is possibly deterring Hispanics/Latinos from seeking care must be explored in Oklahoma to maximize healthy communities.

Contrastingly, Native Americans appear to be overrepresented in the populations seeking services for mental disorders at the neighborhood level and in all six classified community environments. This was an unexpected finding because in Oklahoma, documented Native Americans can receive treatment through Indian Health Services (IHS) or programs within their tribes. Although wealthy Native Americans with mental health concerns and with insurance tied to their employers may acquire treatment from private mental health providers, many Native Americans in Oklahoma fall below the poverty line. Therefore, because there are other financially accessible outlets in which Native Americans can seek mental healthcare, a higher proportional number in ODMHSAS patient rates for Native American may signify that these groups of people have increased mental health issues compared to other race-ethnicities in the state, regardless of community environment. Many other studies support the findings that Native Americans often suffer poorer mental health and higher rates of substance abuse (Beals et al., 2005; Bratter and Eschbach, 2005; Harris et al., 2005; Gone and Trimble, 2012). Historical trauma, the psychological wounding of generations due to significant mistreatment and disenfranchisement, is a possible explanation for this (del Vecchio, 2015). However, these higher patient rates may also reflect that Native Americans may attach less stigma to mental health and substance abuse or find it more culturally acceptable to seek services from the state compared to other groups (Grandbois, 2005).

With these findings in mind, the importance of this geographical investigation into mental health is the realization that if we know specifically what groups seem to be overrepresented or underrepresented in the ODMHSAS patient data, then we can address mental health issues more directly within communities. Public mental health practitioners may begin to investigate ways to best help these communities and populations within these areas to reduce some of their mental health concerns. By linking zip codes or communities by SES and demographic similarities, public health practitioners could institute a mental health initiative in a community that is classified with the same environmental characteristics as a community that found success with that certain program. This is a logical way to use spatial thinking to more effectively implement public health strategies. Thus, connecting communities and classifying them with similar environments can aid in a more efficient strategy to address populations' mental health issues.

4.3 Limitations

This study has a number of considerations and limitations that are important to identify. Notably, this analysis was conducted at the zip code level, and the modifiable areal unit problem (MAUP) recognizes that the results may differ if the spatial analysis was performed at a different scale of the aggregation unit (Holley, 1998; Wong, 2009). Furthermore, these results are based on ODMHSAS patient data and other funded mental health services or private mental health entities are not included. Therefore, patients with adequate insurance coverage may seek services from private mental health practitioners. Also, Native Americans may utilize services through their tribal affiliations that would be available to them at reduced fees. Therefore, although Native Americans are proportionally overrepresented in the ODMHSAS records, their disease burden and treatment rates are likely even higher. Finally, stigma and fear of lack of anonymity may deter many individuals from seeking help for mental illness, particularly in rural settings, thus these data cannot fully depict the mental illness burden in Oklahoma (Corrigan, 2004; Thornicroft, 2008; Hatzenbuehler et al., 2013; Roberts et al., 1999). Treatment data is desirable due to data availability, a large number of records, and broad geographic coverage throughout the state. However, it can only inform researchers based on the population that has accessed mental health services and not unmet needs or those deterred from seeking treatment (Holley, 1998). Despite the limitations, this paper contributes to the literature by investigating patterns of mental health issues in communities and devising a way to link areas with similar social environments to enable public health practitioners to look at these mental health issues from a broader spatial perspective.

5. Conclusions

The idea that the attributes of the area in which people reside may exacerbate mental illness and increase the likelihood for detrimental mental health is supported by this research and reinforces the geographic notion that space and place impact physiological well-being. The SEM emphasizes that neighborhood communities and the broader environmental level are both stages in which people interact with their surroundings and health is impacted. This research proposed a social ecological framework coordinated with geographic techniques to conceptualize mental health patterns by grouping areas by their SES and demographic community characteristics into similar environments. The overall findings suggest that areas with greater rates of poverty coupled with low SES indicators may be environments prone to more population mental health concerns in the form of average PMHD and overall patient percentages. Additionally, Hispanic populations were most likely to appear underserved while Native Americans consistently sought more treatment for mental health issues in Oklahoma. Furthermore, rural areas and areas with a higher proportion of the elderly should be targeted for an in-depth investigation into service use, accessibility, and physiological well-being. Exploring the spatial patterns associated with mental health disparities between population groups living within similar or differing community environments is vital. These endeavors may potentially shed light on places and populations to target with public health prevention strategies to alleviate differences in poor mental health outcomes in Oklahoma.

We recommend these considerations be replicated when trying to understand mental health issues in any region. By highlighting inequalities in ODMHSAS treatment data between groups at both the basic zip code level and at the K-Means grouped zip code level, a better understanding of environmental conditions and populations vulnerable to poorer recorded mental health is gained.

Analyzing potential mental health disparities at the broader community environment level, eradicates issues of small numbers. Furthermore, the comparison at different spatial units of neighborhoods and communities can confirm that mental health disparities identified are not just artifacts of the unit at which the data were recorded.

Most mental health findings are commonly produced at the county level for state reports; however, this study provides a finer zip code or neighborhood level analysis which offers a more detailed investigation on the spatial patterns of mental health. Still, the major contribution of this work is the method to group communities with similar environments (for the purpose of health investigation) that may not intuitively be connected because they are not geographic neighbors. It serves as a starting point to identifying locations and postulating reasons why areas and groups experience mental health treatment disparities. Spatial investigations of mental health patterns at the neighborhood level can pinpoint more specific areas that are experiencing increased mental illness or service concerns. Likewise, classifying areas with similar SES and demographics can aid public health officials in strategizing where to allocate resources and devise which mental health programs may be successful in specific locations. For example, Oklahoma's rural areas are underserved due to budget cuts to ODMHSAS. Financial restraints coupled with Oklahoma's growing mental health concerns make it necessary to highlight areas for service to maximize community health. More effectively addressing these concerns will be even more important in the future (Putnam 2016; Shanahan 2016; Storm 2016). Furthermore, strains on mental health resources are not just intrinsic to Oklahoma. Consequently, these spatial considerations can prove useful in other geographic locations and ultimately help improve public mental health research and psychological well-being in communities.

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CHAPTER III

SPATIAL VARIATIONS IN OKLAHOMA MENTAL ILLNESS

This article, *Spatial Variations in Oklahoma Mental Illness*, was written by Stephanie Heald and Dr. Jonathan Comer of the Oklahoma State University Geography Department, is anticipated for submission to the journal of Applied Geography. Applied Geography publishes studies that utilize geographic approaches to address societal issues. Often, Applied Geography articles analyze the spatial components related to resource allocation or social, economic, and environmental problems. Therefore, article two, with its concentration on the use of spatial statistics to identify place characteristics driving poor mental health patterns in Oklahoma, meets the criteria and aligns with the interests of this journal.

Spatial Variations in Oklahoma Mental Illness

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Highlights

- Patterns for six poor mental health measures in Oklahoma were mapped
- Global regressions of the mental health measures and census data are performed
- Geographically Weighted Regressions increase explanation of mental health patterns in statewide, urban, and rural analyses
- Findings expand knowledge of the place characteristics associated with rural mental health issues

Abstract

Locating areas and identifying the characteristics of places vulnerable to poor mental health is necessary for public health interventions and the adequate allocation of health resources. The purpose of this study is to identify Oklahoma areas experiencing higher reported poor mental health and explore possible contributing socioeconomic, demographic, and environmental factors of the places that patients reside. Geographically weighted regressions (GWR) are performed on Oklahoma Department of Mental Health and Substance Abuse Services (ODMHSAS) patient rates, patients' average reported poor mental health days, and selected primary presenting problem rates in Oklahoma zip codes to identify place characteristics contributing to community patterns of poor mental health. Next, GWR results were compared at three levels: statewide, individually for the two largest urban centers, and for rural Oklahoma. Overall, findings suggest that each of the mental health measures has different possible place characteristics driving their patterns in different settings. Urban residents' mental health patterns were most successfully explained by place characteristics, while the rural analysis yielded less explanation. However, this research added to our understanding of spatial patterns in rural mental health and highlights the need to deepen our understanding of the complex influences of social networks, multi-racial identity, and Hispanic identity on mental health issues.

Keywords

Mental Health, Medical Geography, Local Spatial Autocorrelation, Geographically Weighted Regression, Rural-Urban Health Differences

Introduction

Mental wellbeing is a critical aspect of individual and population health (Barry, 2009). Mental disorders are possibly disabling, costly to treat, and a principal cause of poor health and debilitation globally (Insel, 2008; Fortney et al., 2007; World Health Organization, 2011). Approximately twenty percent of Americans struggle with mental health concerns (Mental Health America, 2015; Mayo Clinic, 2016). Mental health issues are diagnosed as mental illnesses when ongoing symptoms cause individuals frequent stress and inhibit daily functioning (Mayo Clinic 2016). Preventing and properly treating mental illnesses can improve personal and community well-being, life expectancy, worker productivity, and finances (Kessler et al., 2005; NASMHPD, 2006; Hansson, 2006; Colton and Manderscheid, 2006; Newcomer and Hennekens, 2007; DeVol et al. 2007; Insel, 2008; Nordentoft et al., 2013; Alegría et al., 2015).

Distinguishing where mental illnesses occur most frequently and understanding the place characteristics associated with higher disorder rates are crucial considerations for public health prevention strategies. However, research indicates that a substantial number of mental illnesses go unreported and untreated, so the disease burden is likely much higher than realized (Wittchen et al., 2003; Eaton, 2012; Takayanagi et al., 2014). Mental illness patterns in communities are also difficult to fully identify due to the varied symptoms, the broad range of disorders that fall under the umbrella of mental illness, and differences in frequency or duration of conditions. Moreover, the causes and contributors to poor mental health are not completely understood (Mayo Clinic, 2016). Most research has found that both genetic and environmental factors are linked to poor mental health (Evans, 2003; Barr, 2014; Halpern, 2014; Mayo Clinic, 2016). Environmental exposures before birth, differences in brain chemistry, and genetically inherited traits are possible causes for mental disorders. However, it may be trying life circumstances or stressful environments that trigger the onset of symptoms (Barr, 2014; Mayo Clinic, 2016). Therefore, mental well-being, like physical health, may be greatly affected by social and physical conditions of the built and natural environment (Curtis, 2010: Halpern, 2014).

The fact that the mental illness burden is not evenly dispersed throughout space provides further support for this claim. Residents in some areas experience poorer mental health than in other communities (Mental Health America, 2015). According to Place Vulnerability Theory, trying life circumstances do not affect all places uniformly and specific characteristics make some places more vulnerable to diseases and death than others (Oppong and Harold, 2009). For example, Oklahoma has some of the highest mental illness rates in the U.S. and some counties are more severely afflicted than others (Oklahoma State Department of Health, 2014; Mental Health America, 2015). Therefore, one area in which mental health topics are gaining scholarly attention is geography.

Geographers have a unique spatial perspective combined with the ability to employ geographic information systems (GIS) and spatial statistics to uncover and explain disease patterns in ways that other fields or methodologies may overlook (Brown, 2013). In particular, medical geography, a sub-discipline of human geography, concentrates on the intricate relationships existing between health and place. Medical geographers examining mental health commonly focus on the spatial patterns in mental disorders or healthcare services. Identifying disease pattern connections with environmental characteristics of vulnerable landscapes is an additional topic of interest for geographers (Kearns, 1993; Holley, 1998; Rehkopf and Buka, 2006; Curtis, 2010; Hudson, 2012; Brown, 2013). The objectives of this article are to employ spatial techniques to identify patterns in Oklahoma's reported mental health issues, and explore what socioeconomic, demographic, and environmental characteristics influence these patterns through geographically weighted regression (GWR). This leads to three basic research questions:

Research Questions:

1) Where are the spatial patterns of mental health patient rates, primary presenting problem rates, and average poor mental health days located in Oklahoma?

2) What place characteristics are associated with an area's patient rates, primary presenting problem rates, and average poor mental health days in Oklahoma?

3) Are variations in rural and urban areas' mental health patterns explained by different variables?

Study Area

Oklahoma provides a study area suitable for investigation into spatial patterns in mental health, as it is consistently ranked as one of the most mentally unhealthy states (Vieth, 2013; Kemp, 2014; Muchmore, 2014; Mental Health America, 2015). Thus, there is a critical need to examine this population and the place characteristics exacerbating mental disorders. On average, Oklahomans have comparatively lower socioeconomic status (SES), high proportions of uninsured adults, statewide shortages of psychiatrists and mental health workers, and limited rural clinic availability (United States Census Bureau, 2010(a); Oklahoma Health Improvement Plan, 2015 HRSA, 2016). Furthermore, Oklahoma's population varies spatially across the state with 34% dwelling in rural locations and 66% living in urban areas, the majority of whom reside in the metropolitan areas of Oklahoma City and Tulsa (United States Census Bureau, 2010(b)).

A significant contribution of this research is identifying local mental illness patterns in Oklahoma and the characteristics associated with areas of higher reported poor mental health. The following literature review provides an overview of quantitative methods used to analyze population mental health over time. Then, a methods section outlines the specific procedures that are employed in this study. Finally, the subsequent sections include the spatial analysis results, a discussion of findings, and conclusions.

Literature Review

The notion of "unhealthy spots" or place characteristics that foster disease is not new. Lind (1771, p. 162) was one of the first to suggest that some populations were more vulnerable to diseases than others due to the environmental characteristics of their habitats. However, the majority of geographic health-related studies has focused on physical illness, while mental health has received less scholarly attention (Kearns, 1993; Holley, 1998; Barrett, 2000; Valenčius, 2000; Brown et al., 2009; Curtis, 2010). Early works on geographic characteristics of mental health used simplistic comparative statistics to examine patterns in consistently reported measurements like service utilization or suicide mortality records (Tuke, 1858; Jarvis, 1866; Tuke, 1878; Durkheim, 1951; Gesler, 1986; Holley, 1998; Schwab, 2013). Later, studies evolved to include correlation methods that allowed researchers to identify relationships between SES variables and health measures (Pearson, 1907; Faris and Dunham, 1939; Hudson, 2012).

Subsequently, the first small 'wave' of mental health geography emerged, and clustering, correlation, and regression methods were commonly used (Giggs and Copper, 1987; Gould et al., 1989; Holley, 1998; Wolch and Philo, 2000; Elliott and Wartenberg, 2004; Brown et al., 2009; Meade, 2010; Lawson, 2013). Statistically identifying concentrations or "clusters" of mental disorders, mental health services, or suicide rates is a common theme among mental health studies (Qi et al., 2010; Moscone and Knapp, 2005; Moreno et al., 2008; Middleton et al., 2008; Pankratz, 2011; Gruebner et al., 2011(a); Gruebner et al., 2011(b); Ngui, and Vanasse, 2012; Salinas-Pérez et al., 2012; Jones et al., 2013; Ngui et al., 2013; Yang and Mu, 2015).

Although cluster analysis is useful in identifying *locations* with higher rates of mental health issues, it cannot shed light on *characteristics* associated with those higher rates. Consequently, multivariate regression methods prove valuable in exposing causal or predictive relationships between independent variables and an outcome variable (Getis, 2008). Therefore, geographic studies utilizing various forms of regression attempt to explain contributing factors to residents' mental health outcomes with socioeconomic, demographic, and environmental attributes (Congdon, 1996; Agbayewa et al., 1998; Andrews et al., 2001; Chow et al., 2003; Arcury et al., 2005; Rehkopf and Buka, 2006; Perälä et al., 2008; Hudson, 2012; Suzuki et al., 2013; Lawson, 2013). These models assess plausible predictive attributes of locations that are potentially susceptible to similar mental health concerns. For example, Hempstead (2006) and Chang et al. (2011) explored suicide patterns through regression to reveal that less populated locations were associated with higher suicide rates. Linking rates of depression to social, demographic, environmental, and economic characteristics of places is another current use of regression techniques (Weich et al., 2002; Henderson et al., 2005; Galea et al., 2005; Kubzansky et al., 2005; Fortney et al., 2007; Nutsford et al., 2013). Galea et al. (2005) used regression analysis to determine that poor quality of the urban built environment was associated with increased depression rates. Additionally, multiple studies highlight poverty, low SES, economic deprivation, and income inequality as driving factors for population mental illness rates (Latkin and Curry, 2003; Lorant et al., 2003; Boydell et al., 2004; Mair et al., 2008; Santiago et al., 2011; Cromley et al., 2012).

In the previous examples, global univariate regression offers explanations about environmental variables that may help in predicting population mental health patterns, but the use of local techniques in regression has become the preferred practice. Geographically weighted regression (GWR) is a relatively new method that attempts to tease out local variations that global regressions may ignore (Fotheringham et al., 1997; Brunsdon et al., 1998). Local regression methods model spatially-varying relationships between dependent and independent variables (Fotheringham, 1992; Openshaw, 1993; Bailey, 1994; Fotheringham, 1997; Fotheringham et al., 1997). GWR is designed to highlight geographic differences by creating many regression equations, one for each location in the study area (Fotheringham et al., 1997). The local variations that GWR may reveal has great potential to better inform medical geographers. For instance, findings may show that the link between certain place characteristics and higher disease rates in some areas are not the same factors that appear to be contributing to increased illness rates in other locations. For this reason, GWR analysis can better model the dimensions and complex relationships integral to a population's mental health.

While GWR has been used in numerous medical geography studies (Nakaya et al., 2005; Comber et al., 2011; Shah and Bell, 2013), few have dealt explicitly with mental health (Ngui and Caron, 2012; Cromley et al., 2012; Salinas-Pérez et al., 2015; Trgovac et al., 2015; Gruebner et al., 2016). Recent works that have utilized GWR examined local variations in suicide patterns (Helbich et al., 2012; Trgovac et al., 2015), or analyzed factors contributing to mental disorder prevalence (Ngui and Caron, 2012; Salinas-Pérez et al., 2015; Gruebner et al., 2016). Notably, highly urbanized areas are the focus of the majority of these works (Ngui and Caron, 2012; Cromley et al., 2012; Salinas-Pérez et al., 2015). For example, Salinas-Pérez et al. (2015) explored the relationship between psychiatric treatment patterns and socioeconomic characteristics in macro-urban communities through GWR. One major contribution of our study is that it provides more insight to spatial patterns of rural mental health and the place characteristics driving the patterns, a topic which previous health geography research has largely overlooked. Local regression techniques should be employed to explore aspects of mental health in a broader environment. Therefore, the GWR analyses are conducted separately for urban areas, for rural Oklahoma, and for the entire state. In particular, rural populations are analyzed because they are reported to be at higher risk for poor mental health (Mohatt et al., 2006). Rural dwellers may also experience mental illness burdens differently than urban residents and could face dissimilar challenges based on their built and social environments (Human and Wasem, 1991; Mohatt et al., 2006; Fortney et al., 2007; Perälä et al., 2008; Kelly et al., 2010). Thus, it is important to ascertain if rural settings have different place characteristics associated with poor mental health outcomes.

Material and Methods

To investigate the spatial patterns of mental health in Oklahoma, treatment records from the Oklahoma Department of Mental Health and Substance Abuse Services (ODMHSAS) are utilized. This dataset consists of all admitted individuals to an ODMHSAS-affiliated clinic from 2011-2014. For confidentiality reasons, patients' names and home addresses are excluded. Instead, records are assigned a unique numerical identifier and only the zip code of residence is provided. Patients who listed a PO Box only zip code are assigned to the nearest polygon zip code for analysis. Additionally, there are multiple zip codes left out of this study due to inaccurate or missing data. Therefore, the study concentrates on over 298,000 individuals aggregated to 644 zip codes based on recorded residence. A finer geographical unit is desirable but to preserve patient anonymity, the zip code level is the smallest obtainable geographical unit. Moreover, zip codes are commonly utilized as a proxy for communities and are often the unit that geographers work with to study local patterns of health (Krieger, 1997; MacIntyre et al., 2002; Kawachi and Berkman, 2003; Almog et al., 2004).

Overall patient rates, average reported poor mental health days (PMHD), and selected primary presenting problems including depression rates, other behavioral disorders, emotional disorders, and developmental disorders per zip code are the six mental health variables investigated. The primary presenting problems are issues that patients seeking treatment reported. These issues are grouped and then categorized based on the ODMHSAS Behavioral Health Customer Data sheet. Each mental health variable is mapped to illustrate its spatial patterns. To uncover which area characteristics are spatially associated with mental health issues in Oklahoma, stepwise global regression techniques are used on each mental health variable at the statewide level, for the two largest urban areas, and on rural Oklahoma. Regression analysis models the association between the independent predictor variables and the outcome or dependent variable (Gordon, 2015). These models illustrate how much power the selected independent variables have in explaining mental health patterns, and are an established method of highlighting the potential individual, community, and environmental risk factors for poor mental health or inadequate mental health coverage (Latkin and Curry, 2003; Lorant et al., 2003; Galea et al., 2005; Fortney et al., 2007; Nutsford et al., 2013). Specifically, stepwise regression techniques generate multiple predictive models for each dependent variable and systematically exclude independent variables that do not effectively add explanatory power to the dependent variable's patterns.

For the stepwise regression analysis, forty independent demographic and socioeconomic variables are derived from the 2010 U.S. Census and the U.S. Census Bureau's 2014 American Community Survey (ACS) at the corresponding zip code level. ACS 5-year estimates for zip codes are selected because they are the most recent data, yield a larger sample size, and correspond with the ODMHSAS data time frame. Furthermore, the social, economic, and demographic selected census variables are chosen based on previous studies identifying poverty, social class, and SES as consistent drivers of individual mental illness (Krieger, 1997; Saraceno and Barbui, 1997; Evans et al., 2003; Murali and Oyebode, 2004; Muntaner et al., 2004; Curtis, 2007; Curtis, 2010; Halpern, 2014). Specifically, measures of race/ethnicity, age cohorts, educational attainment, income characteristics, marital status, household size, employment characteristics, percent vacancy, percent living below poverty, the percent on public assistance, and health insurance coverage characteristics are selected as independent variables.

The census measure of percent rural per zip code is also included as an independent variable to represent the effects of reduced infrastructure. Additionally, a variable that addresses the social environment is generated using a yellow page scraper. All schools, religious organizations, and civic organizations' names and addresses are obtained by software utilizing an algorithm designed to extract business information from the Yellow Pages directory. Through a lengthy process, the data is manually cleaned and all locations verified through Google Maps. Next, the number of these organizations in each zip code is converted into a rate per 1,000 people and is labeled the "community opportunities rate" variable. The Community opportunities rate, a broad proxy for potential social networks or connectedness, is also included as an independent variable.

The most parsimonious stepwise regression model with the highest explanation using the fewest amount of variables for each mental health measure is selected. Spatial autocorrelation of residuals and Koenker (BP) Statistic Analyses on the models revealed significant non-stationarity in many of the models and confirmed that they would be appropriate candidates for GWR. Thus, the independent variables explaining the global patterns of each of the stepwise regressions for the six mental health measures are used in a GWR model using an adaptive bi-square kernel (Figure 1).

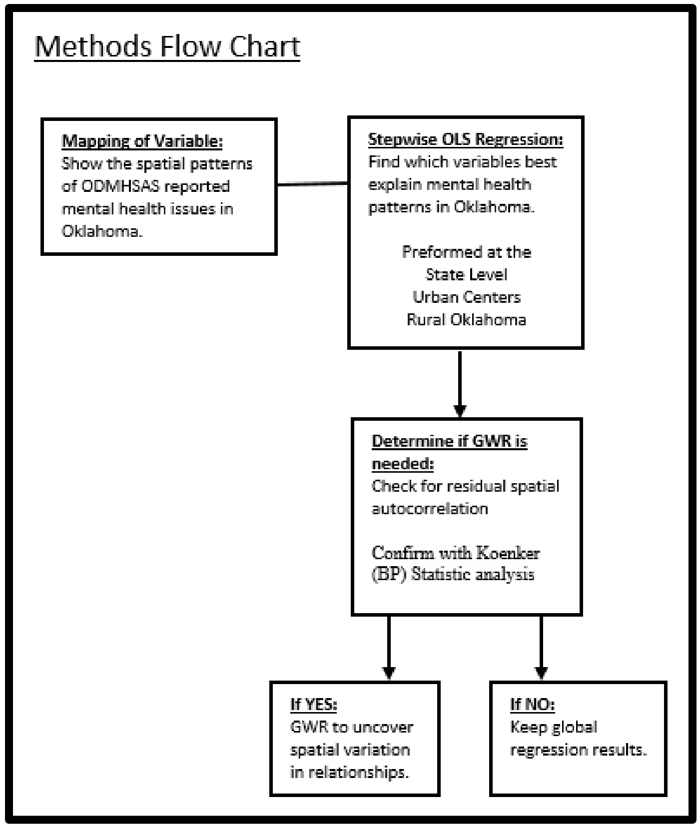

Figure 1: Methods utilized in this study

The adaptive bandwidth specification in GWR is recommended when the data is non-uniformly distributed across space. The adaptive bandwidth maintains consistent sample sizes by increasing or decreasing the geographic extent of each kernel (Charlton et al., 2009). This is an appropriate selection in Oklahoma because the zip codes are not uniformly distributed across space. The GWR software uses an iterative process to select the optimal bandwidth size that results in the best model based on the AICc criterion. In the adaptive bi-square GWR the regression is performed with local windows centered on each zip code centroid and each observation is then weighted according to its proximity to the center of the window to curtail sudden changes in the local statistics computed in adjacent windows (Goovaerts, 2009).

Implementing GWR provides a means to show the locational variance in explanatory power of the independent socioeconomic and demographic variables and lends finer discernment into the place characteristics influencing mental illness in Oklahoma zip codes. The GWR on variables that had the most explanatory power for patterns of each mental health measure is performed at the state level, and then separately for the Oklahoma City urban area, the Tulsa urban area, and rural Oklahoma. This enabled further comparisons across the state so a more explicit knowledge of the place characteristics associated with mental health issues in differing settings is obtained. The results of these procedures are presented in the following section.

Results

In response to the first research question, the spatial distributions of ODMHSAS patient rates, average PMHD, and primary presenting problem rates were mapped (Figure 2). Higher ODMHSAS patient rates are concentrated in the southeast and several Tulsa and Oklahoma City area zip codes (Figure 2(a)). The spatial patterns of other behavioral disorder rates is similar to that of total ODMHSAS patient rates (Figure 2(d)). Zip codes with higher emotional disorder rates are concentrated in rural Eastern Oklahoma and urban Tulsa and Oklahoma City (Figure 2(f)). Areas with higher depression rates follow a similar spatial pattern, however, there are several more zip codes in the Northwest with higher depression rates (Figure 2(c)). In comparison, patterns in higher average PMHD and developmental disorder rates are more dispersed throughout Oklahoma (Figure 2(b) and 2(e)). In all maps, zip codes within the panhandle have the least reported ODMHSAS mental health issues. This pattern may reflect that many panhandle residents do not acquire treatment because they have greater travel distances to ODMHSAS facilities. These findings may also indicate that residents of panhandle communities seek care in other nearby states, or potentially just have better mental health.

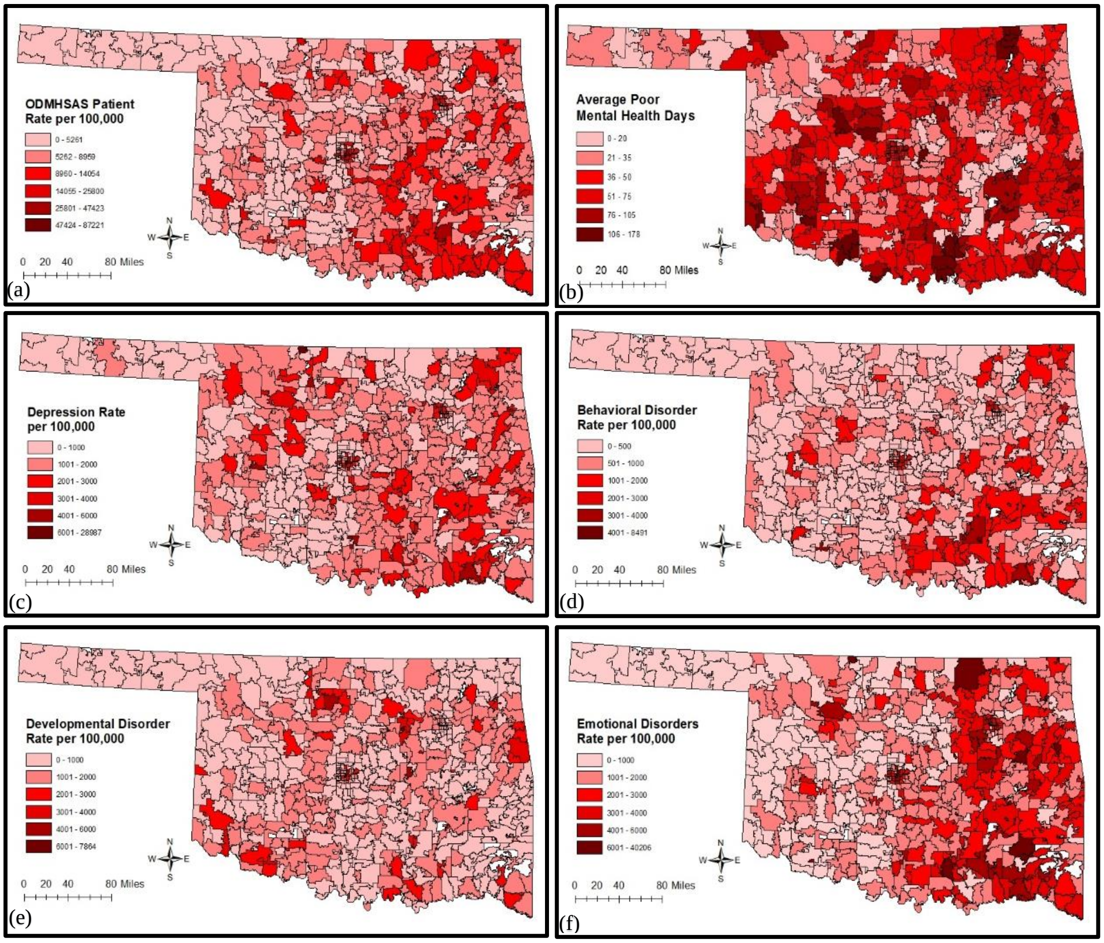

Figure 2: Maps revealing the spatial distributions of mental health issues: (a) ODMHSAS Patient Rates, (b) PMHD Rates, (c) Depression Rates, (d) Other Behavioral Disorder Rates, (e) Developmental Disorder Rates, (f) Emotional Disorder Rates

Next, to address the second research question, the place characteristics associated with Oklahoma zip codes' patient rates, average PMHD, and primary presenting problem rates were identified through global and local regressions. The global stepwise regressions for each mental health issue revealed that the spatial patterns of these measures are not explained by the same variables. At the state level nearly 41% of the pattern in ODMHSAS patient rates can be explained by seven independent variables (Table 1). Similarly, 41% of the variation of depression rates can be explained using only six variables. In both models the increased community opportunities in areas, lower levels of rurality, and higher percentages of population living alone, uninsured, and not in the labor force add explanatory power. However, reduced housing vacancy helps explain depression patterns, while the percent of the population that is African American and the percent unemployed enter into the ODMHSAS patient rates model (Table 1). The spatial patterns of average PMHD, other behavioral disorder rates, developmental disorder rates, and emotional disorder rates are each explained by different place characteristics. However, in contrast with the ODMHSAS patient rate and depression rate models, stepwise regressions fail to explain a large portion of variation within these variables (Table 1).

Table 1: Stepwise global regression results for Oklahoma zip codes' mental health issues at the statewide level.

Dependent Variables	Global R^2	Global AICc	Independent variables significant in Global Regression	GWR R^2	GWR AICc
ODMHSAS Patients Rate	.408	12738.5	% Live Alone % African American % Not in Labor Force % Uninsured Community Opportunities Rate % Rural (-) % Unemployed	.735	12474.0
Average PMHD	.054	6110.2	% African American % with Income over $100,000 (-) % Poverty	*No Local Variation*	
Depression Rate	.410	11130.0	Community Opportunities Rate % Live Alone % Uninsured % Rural (-) % Not in Labor Force %Vacant (-)	.787	10685.4
Other Behavioral Disorders Rate	.150	10249.3	% with Income over $100,000 (-) % White (-) % Hispanic (-) % Rural (-)	.409	10152.7
Developmental Disorders Rate	.129	10454.3	% with Income over $100,000 (-) % African American % Native American (-) % On Public Assistance	.478	10310.3
Emotional Disorders Rate	.244	11731.2	% Uninsured % African American % Live Alone % Unemployed Community Opportunities Rate % Hispanic (-)	.813	11264.4

*The most parsimonious models for each dependent variable was chosen. In the fourth column, local variables run in GWR are shown in red. Variables that appeared negative in the model are shown with the symbol (-). Additionally, all variables are significant at the p=.000 to p=.005 range.

Although these relatively low R^2 values show little explanation at the global level, the power of explanation at the local level can be explored through GWR. The GWR revealed that multiple variables within these six regression equations had significant local variation. The localized regression equations improved the ability of the same independent variables to explain spatial patterns in mental health issues. Through GWR, patterns in depression rates were explained up to almost 79% by the six variables, and the original seven independent variables explained about 74% of ODMHSAS patient rates. These were huge improvements from the global results of 41% for these variables. The GWR of emotional disorder rates improved the most with about 81% of variation explained by the model (Table 1). The lower AICc numbers for the GWR models also confirm that the local models provide a better fit. Additionally, the GWR maps illustrate that in some Oklahoma zip codes, these independent variables may have an even greater influence on mental health patterns (Figure 3). The GWR results of PMHD was not mapped because no significant local variation was found. Furthermore, the Koenker (BP) Statistic test confirmed that the relationships between variables in the PMHD regression were stationary thus confirming local models were not needed. Therefore both global and local regression techniques failed to adequately explain the variation in PMHD patterns.

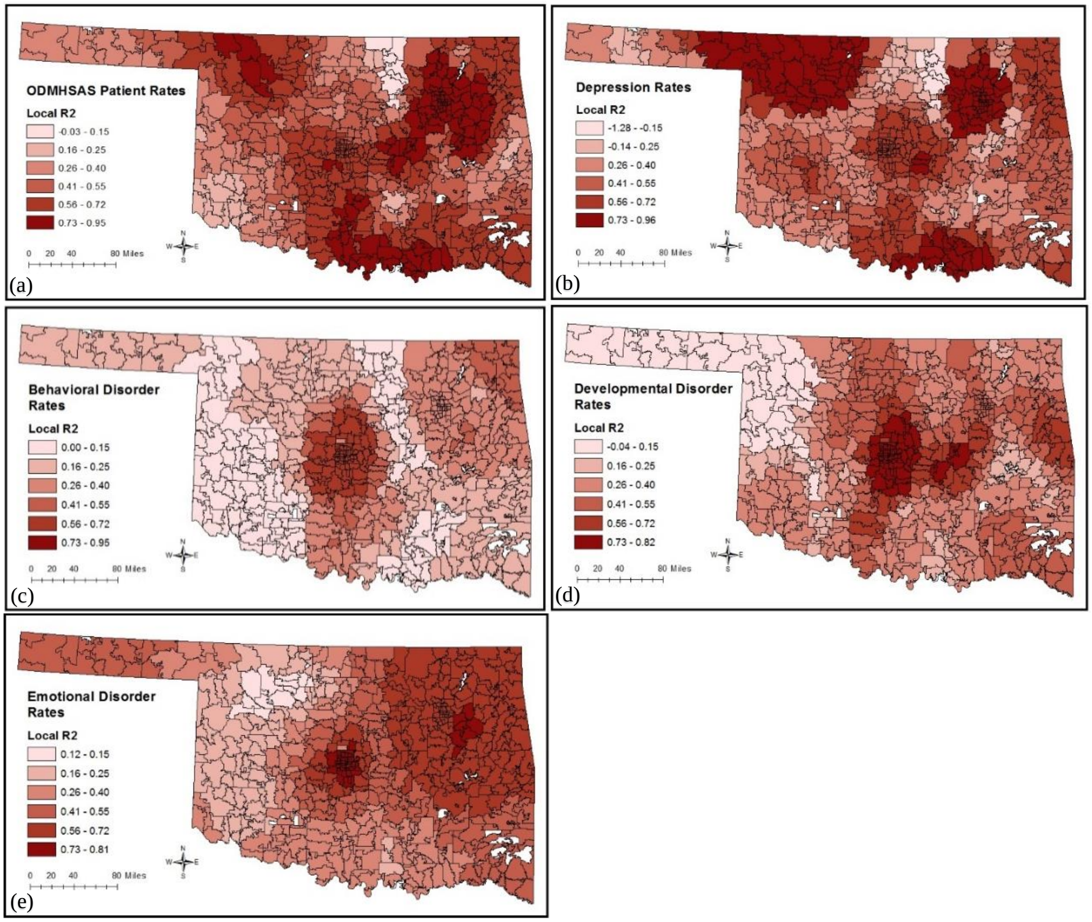

Figure 3: GWR **local R^2** maps of Oklahoma mental health issues including: (a) ODMHSAS Patient Rates GWR, (b) Depression Rates GWR, (c) Other Behavioral Disorder Rates GWR, (d) Developmental Disorder Rates GWR, (e) Emotional Disorder Rates GWR

Figure 3(a) reveals that in Tulsa and multiple south-central zip codes, up to 95% of the variation in ODMHSAS total patient rates can be explained. By comparing the GWR maps to the maps showing the spatial distribution of ODMHSAS patient rates, it is apparent that the GWR model has high explanatory power in many of the areas that contain high patient rates. The GWR map of depression rates illustrates that within the Tulsa area, south-central Oklahoma, and many northwestern zip codes, patterns can be explained by the six community-level variables up to 96% (Figure 3(b)). However, some of the southeastern zip codes with higher rates of depression are not well explained by this model. Similarly, the GWR of behavioral disorder rates does not adequately explain spatial variations in southeast Oklahoma, but greatly improved explanation to over 55% in

Oklahoma City zip codes (Figure 3(c)). Developmental disorder rates were also best explained in the Oklahoma City corridor with the original four community measures explaining over 80% in some zip codes. However, the model only slightly improved explanation of developmental disorders in many northern and southern zip codes (Figure 3(d)). Finally, in Oklahoma City and many eastern zip codes where there are higher rates of emotional disorders, the GWR model significantly improved explanation of the spatial patterns of emotional disorder rates from between about 50% to 80% (Figure 3(e)).

Upon analysis of the regression results and GWR maps, it is apparent that in many cases, the regression models at the state level lend more explanation to the variation in mental health patterns within urban areas but provide much less insight into the local characteristics influencing rural mental health patterns. Therefore, the urban and rural areas in the state were analyzed separately to see if a finer knowledge about the place characteristics driving Oklahoma mental health patterns could be gained. The state was divided into three study areas: urban Oklahoma City area, urban Tulsa area, and rural Oklahoma. Overall, there were 55 Oklahoma City area zip codes, 46 Tulsa area zip codes, and 469 rural Oklahoma zip codes explored. Throughout the state, 74 urban zip codes that were not located within the two major metropolitan areas were omitted from the GWR analysis (Figure 4).

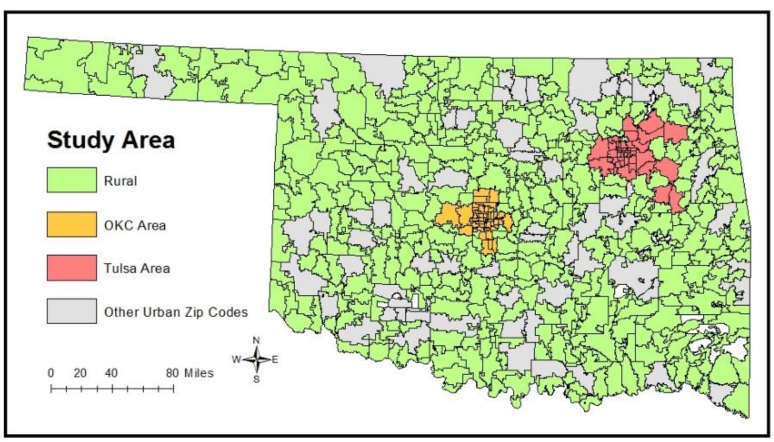

Figure 4: The three groups of zip codes compared in this study.

The same procedures run at the statewide level were carried out for the three different study areas. Regressions with the SES, environmental, and demographic variables entered in at the state level were run on the two urban areas separately. When the original significant variables in the statewide regression were forced into a regression, the results indicated even higher R^2 in these urban areas (Table 2). Next, a stepwise global regression of the original 40 SES, demographic, and environmental variables revealed that different variables best explained mental health patterns for each of the urban areas (Table 2). Additionally, fewer independent variables were needed to explain variations in these urban centers. Among all variables except average PMHD in both urban centers and ODMHSAS patient rates in Tulsa, the regressions could explain over 75% of the variation in poor mental health measures. Moreover, area characteristics of zip codes in Tulsa had slightly more power of explanation than in Oklahoma City (Table 2). Overall, when GWR is run on significant place characteristics explaining urban mental health variations, fewer variables exhibit local variation compared to the state level. This may be because the urban areas measured were geographically smaller and contain more similar types of environments than the diverse array of environmental characteristics across the entire state. Moreover, when GWR indicated variables were local, the R^2 values were even higher in some urban zip codes than the already high global measures (Table 2). This reveals that place characteristics associated with poor mental health can lend significant explanation to patterns in ODMHSAS mental health issues in Tulsa and Oklahoma City areas.

Table 2: Stepwise global regression results for Tulsa area and Oklahoma City area zip codes' mental health issues.

Dependent Variables	Urban Area	Global R^2 of variables entered in the state level	Global R^2 results of Independent variables significant in Regressions of individual urban centers: R^2	Global R^2 results of Independent variables significant in Regressions of individual urban centers: AICc	Independent variables significant in Global Regression of individual urban centers	GWR R2 results of Independent variables significant in Regressions of individual urban centers: R^2	GWR R2 results of Independent variables significant in Regressions of individual urban centers: AICc
ODMHSAS Patients Rate	OKC	.627	.675		% On Public Assistance % African American	*No Significant Local Variation*	
	Tulsa	.920	.965		% Not in Labor Force % 65 Years or Older (-) % Live Alone % Vacant (-)	*No Significant Local Variation*	
Average PMHD	OKC	.420	.425	470.8	% White (-) % Live Alone	.501	469.14
	Tulsa	.125	.362		Community Opportunities Rate % Not in Labor Force (-)	*No Significant Local Variation*	
Depression Rate	OKC	.694	.766		% On Public Assistance % Live Alone	*No Significant Local Variation*	
	Tulsa	.904	.960	762.2	% Not in Labor Force % 65 Years or Older (-) % Renting % On Public Assistance (-)	.962	762.2
Other Behavioral Disorders Rate	OKC	.758	.842	775.0	% White (-) % On Public Assistance % Multiple Race	.843	776.3
	Tulsa	.462	.929		% Not in Labor Force % 65 Years or Older (-) % Live Alone % African American	*No Significant Local Variation*	
Developmental Disorders Rate	OKC	.814	.838	817.6	% On Public Assistance % African American % Unemployed	.841	817.5
	Tulsa	.337	.843	664.2	% Not in Labor Force % Renting % Vacant (-) % Rural	.861	663.5
Emotional Disorders Rate	OKC	.842	.897	837.9	% On Public Assistance % African American % Rural (-)	.899	837.1
	Tulsa	.804	.965	765.4	% Not in Labor Force % 65 Years or Older (-) % Renting % On Public Assistance (-) % Higher Education (-)	.972	754.8

*The most parsimonious models for each dependent variable was chosen. In the sixth column, local variables run in GWR are shown in red. Additionally, all variables are significant at the p=.000 to p=.005 range.

Similar to the procedures used to examine urban mental health patterns, the original variables significant in the statewide regression were entered into a regression for rural Oklahoma zip codes. When analyzing rural areas alone, regressions did not adequately describe the variations in most mental health patterns, with only explanations of depression rate patterns improving. However, a stepwise global regression preformed on the original 40 SES, demographic, and environmental variables revealed that different variables explained mental health patterns slightly better than the variables that were significant statewide (Table 3). Specifically, in rural Oklahoma, increased community opportunities, higher percentages of the population claiming two or more races, increased elderly populations, higher proportions not in the work force, less vacant housing, and lower numbers of residents achieving higher education explained almost 55% of the variation in rural depression rates. This was about 15% more explanation than stepwise regressions revealed at the state level. Furthermore, when several of these variables were run as local in GWR, 73% to 85% of depression rate patterns could be explained in the northwest and western zip codes (Figure 4(b)).

Table 3: Stepwise global regression results for rural Oklahoma zip codes' mental health issues.

Dependent Variables	R^2 of global variables entered in the state level	Global R^2 results of Independent variables significant in Global Regression of rural Oklahoma		Independent variables significant in Global Regression of rural Oklahoma	GWR R^2 results of Independent variables significant in Regressions of rural Oklahoma	
		R^2	AICc		R^2	AICc
ODMHSAS Patients Rate	.346	.367	9150.8	% Not in Labor Force Community Opportunities Rate % African American % Hispanic (-) % On Public Assistance % Live Alone	.668	9001.6
Average PMHD	.035	.032	4506.2	% African American % On Public Assistance	.373	4463.5
Depression Rate	.521	.546	7830	Community Opportunities Rate % Not in Labor Force % Vacant (-) % Multiple Race % 65 Years or Older % Higher Education (-)	.690	7752
Other Behavioral Disorders Rate	.103	.138	7404.1	% Multiple Race % with Income over $100,000 (-) % Vacant (-) % Hispanic (-) Community Opportunities Rate (-)	.392	7336.7
Developmental Disorders Rate	.082	.102	7682.1	% On Public Assistance % Multiple Race % Native American (-) % with Income over $100,000 (-) % Higher Education	.272	7653.8
Emotional Disorders Rate	.229	.242	8547.6	% Unemployed % African American % Female-headed Household Community Opportunities Rate % Uninsured % Hispanic (-)	.739	8229.8

*The most parsimonious models for each variable was chosen. In the fourth column, local variables run in GWR are shown in red. Additionally, all variables are significant at the p=.000 to p=.005 range.

The GWR of rural Oklahoma areas yielded much higher explanation than the results of the global regressions in the rural regions. For example, in the south-central and northeastern regions up to 87% of ODMHSAS patient rates were explained by the six variables that were significant in the most parsimonious rural stepwise regression model (Figure 5(a)). Also, in some northeastern zip codes as much as 98% of the variation in emotional disorder rates could be explained through GWR of selected SES, demographic, and environmental characteristics (Figure 5(e)). However, the zip codes yielding the highest R^2 for other behavioral disorder rates and developmental disorder rate patterns could only explain up to 45% of the variation (Figures 5(c-d)).

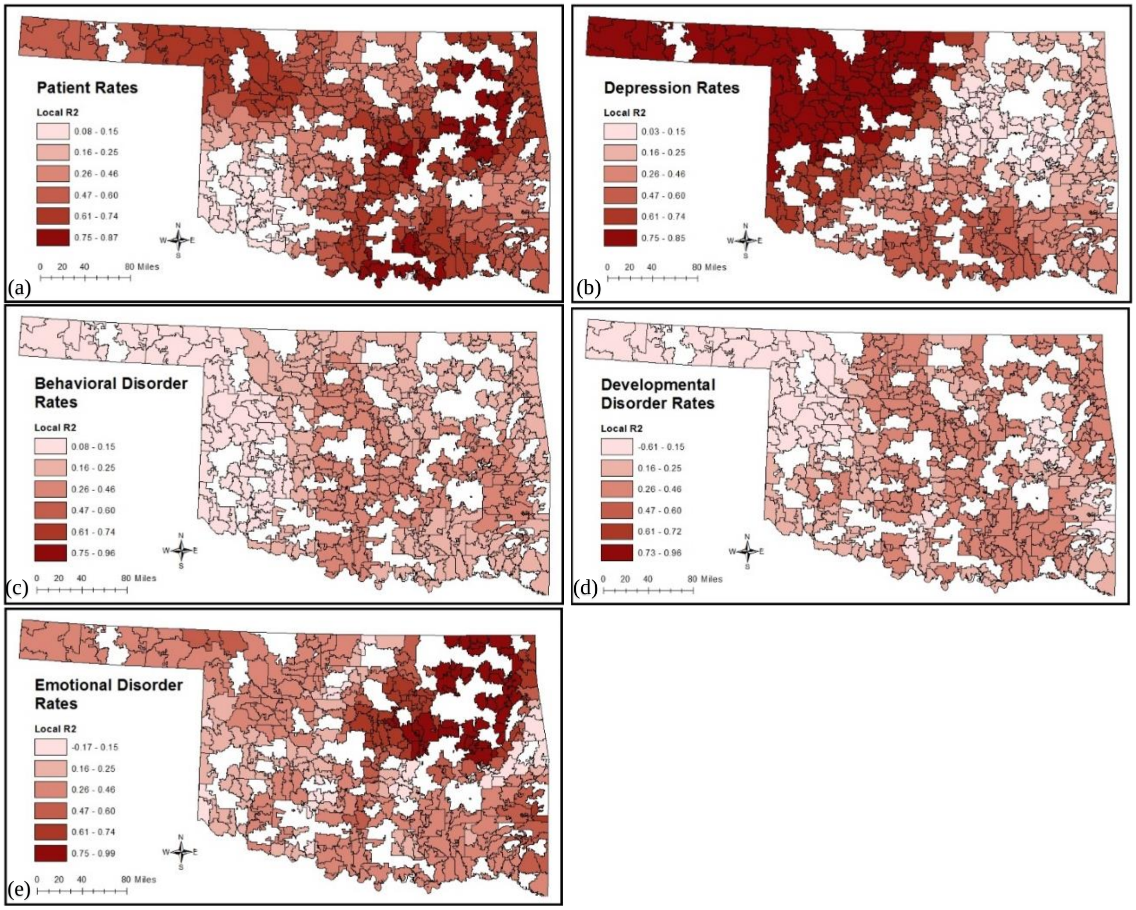

Figure 5: GWR maps of rural Oklahoma mental health issues including: (a) ODMHSAS Patient Rates GWR for rural Oklahoma, (b) Depression Rates GWR for rural Oklahoma, (c) Other Behavioral Disorder Rates GWR for rural Oklahoma, (d) Developmental Disorder Rates GWR for rural Oklahoma, (e) Emotional Disorder Rates GWR for rural Oklahoma

Findings also verified that variations in rural and urban areas' mental health patterns are explained by different variables, which answers the third research question. For example, increased community opportunities was a prominent factor in explaining poor mental health patterns in rural areas, but only contributed explanation to the average PMHD model in urban Tulsa zip codes. Additionally, in this study higher proportions of the population age 65 or older significantly helped explain depression rate patterns in rural Oklahoma zip codes. However, this was not the case in urban settings, where the percent of the population age 65 or older was negatively related to patterns of behavior disorders, developmental disorders, depression rates, and ODMHSAS patient rates.

Variables indicating race or ethnicity also had differing impacts on rural and urban models. For example, in urban zip codes and at the state level, an increased African American presence or a smaller proportion of white residents helped explain the spatial patterns of the selected mental health variables. In rural Oklahoma, areas with higher proportions of those identifying with multiple races or as African American contributed explanatory power to the models. Additionally, an increased Hispanic or Native American presence had a negative relationship with multiple mental illness patterns in rural areas. Furthermore, the percent of the population that is Hispanic offered no power to the models in urban areas, but helped explain patterns in ODMHSAS patient rates, behavior disorder rates, and emotional disorders in rural settings and emotional and behavior disorder rates at the state level. These models reveal that areas with higher Hispanic populations were associated with reduced mental illness rates in areas.

Notably, a social environment variable that contributes a differing amount of explanation to mental health patterns in different types of areas is the percent living alone. The percent living alone had much more significance in explaining urban and statewide mental health patterns than those in rural regions. In fact, the percent living alone only contributed to the explanation of ODMHSAS patient rates in rural areas. This may be because in small communities, social networks are tight knit and residents may look out for each other more even if they don't dwell in the same household.

Compared to the urban locations it also took many more variables to explain much lower portions of mental health patterns, indicating that other characteristics may be driving poor mental health in Oklahoma's rural regions. Furthermore, rural areas had a higher number of variables that showed local variation than urban areas did in the GWR models. This is likely due to the expansive area that the rural region encompasses and the variation of place characteristics across the region compared to the smaller, more compact, and more homogeneous urban centers. However, the state level model had the most variables that exhibited local variation. Urban and rural place conditions vary so much that the state level variation is likely a reflection of the significant difference in environments throughout Oklahoma. In the following section the significance and limitations of these results are discussed.

Discussion

Findings indicate that at the broader state level, in urban zip codes, and within rural settings different place characteristics may drive different mental health patterns. However, in both rural and urban Oklahoma, the percent of the population on public assistance explains more patterns of mental health than all other SES measures. In Oklahoma City the percent on public assistance lends explanation to every mental health pattern except PMHD, and it helped describe variations in PMHD, ODMHSAS patient rates, and developmental disorder rates in rural Oklahoma. This variable may best explain variations in ODMHSAS patient records because poorer residents can qualify to receive free or reduced fee treatment from ODMHSAS. Therefore, in areas where many individuals qualify and are aware of how to receive financial benefits, many may also be aware of how to actively seek the mental health services available to them. Interestingly, this variable appears to lend important explanation to urban Oklahoma City patterns but less so in urban Tulsa zip codes.

When looking at the GWR results for ODMHSAS patient rates, the percent not in the labor force contributed explanation to every model except that of Oklahoma City. Additionally, the percent not in the labor force lent explanatory power to all Tulsa mental health models. This variable includes all individuals 16 years of age and older who are not in the labor force due to their status as students, housewives, seasonal workers, institutionalized, or retired (United States Census Bureau, 2017) . In places where there are many people with significant mental health issues, they may make up part of the population that is too impaired to work consistently. If areas have high rates of those with physical disabilities, comorbidity with mental health issues has also been found (National

Institute of Mental Health, 2016). Additionally, if there are high rates of people unable to consistently work for various reasons, this may be a stressor that could contribute to poor mental health (Strandh et al., 2014). Finally, if an area consists of many retired individuals, research indicates that elderly persons are at risk for poor mental health (Kubzansky et al., 2005).

The elderly are at an increased risk for depression, in part because they tend to have reduced mobility and are more dependent on locally provided services and sources of social support (Kubzansky et al., 2005). Clinical depression is a mood disorder that causes distress, sadness, anxiousness, or hopelessness and impairs daily activities (National Institute of Mental Health, 2016). Research suggests that social isolation, living alone, and reduced social networks are environmental factors that contribute to depression (Santini et al., 2015). Rural communities are often disproportionately comprised of the elderly, and in Oklahoma the percent of the population age 65 and older contributes explanation to depression rate patterns. Therefore, rural areas potentially have populations vulnerable to depression and are likely more isolated due to issues of distance. Furthermore, these areas may actually suffer an even more elevated depression burden than is known because some may not acquire treatment due to financial, transportation, or mobility obstacles.

Areas where many individuals live alone and do not have a support network within the home, or are not in the labor force thus lack a social network at work also correspond to areas with higher depression in many Oklahoma models. This is consistent with previous findings indicating the importance of social support to mental well-being (Santini et al., 2015). A larger number of clubs, community organizations, schools, and churches that a resident can chose to join is thought to be a protective factor for mental health because of the potential for social support and stronger social networks (Macintyre et al., 2002; Kawachi and Berkman, 2003; Barr, 2014). However, the community opportunities rate which was entered as a proxy for organized social networks did not show a negative relationship with poor mental health in Oklahoma. In fact, in rural zip codes where there were higher rates for community opportunities there was increased depression. Moreover, increased community opportunities was a crucial component for explaining poor mental health patterns in rural areas and patient rates, depression rates, and emotional disorder rate patterns at the state level. It is likely that this variable may be a geographic artifact of where there is increased infrastructure and community organizations there is also potentially more physical access to mental healthcare facilities. In these locations more individuals may acquire treatment because they are in closer proximity to clinics. Therefore, more mental illness problems are reported in these areas compared to more remote regions. Future research should focus on alternative methods for measuring the impact of social networks and social environment on communities' patterns of mental illness.

More research also needs to be conducted on racial minority health outcomes, especially in rural areas. Racial or ethnic minorities' health outcomes are complexly intertwined with socioeconomic conditions because of historical structural factors that have disenfranchised racial minorities throughout time (Krieger et al., 1997; Williams et al., 1997; Macintyre and Ellaway, 2003). This research indicates that patterns in populations' race and ethnicity help explain the variations in mental health patterns in Oklahoma. In rural areas, higher proportions of those identifying with multiple races contributed explanatory power to the models. There is small but growing attention towards the topic of health and multiracial identity. As the demographics of America change over time more individuals can classify themselves as multiracial. However, the way health and demographic data are collected and categorized may often hinder our interpretation of findings on the mental health of multiracial individuals (Tabb, 2016). The fact that increases in the proportion of the multi-race population are associated with increased mental health issues in rural areas is a concern that must be explored further.

Higher proportions of the population that are Hispanic was linked to lower patient rates, behavioral disorder rates, and emotional disorder rates in rural Oklahoma. This may mean that Hispanics may dwell in places where there are fewer environmental stressors and where residents happen to possess better mental health. However, some research suggests that Hispanics have better health, in part, due to strong social ties in Hispanic families and neighborhoods; therefore, the mental health of residents in these areas may be a reflection of that trend (Rios et al., 2012; Barr, 2014; Ruiz et al., 2016). This finding could also point to Hispanics being potentially underserved and thus underrepresented in ODMHSAS treatment records. Lastly, there is the option that many of these demographic and SES measures are more connected to mental health at the individual level, but not at the population level. Therefore, community poverty, low SES, and race/ethnic makeup of a community may not add an increased strain on residents' mental health and these patterns are reflective of an independent variable not captured in the study.

Limitations

Several other considerations and limitations of this research must be acknowledged. This study recognizes the potential for ecological fallacy, or the logical misconception in which inferences about the nature of individual cases are presumed based on the interpretation of broader population-based statistical data (Krieger, 1997; Holley, 1998; Macintyre and Ellaway, 2000; Curtis, 2010). Therefore, the SES, demographic, and environmental community-level characteristics analyzed cannot be directly attributed to individuals. Instead, this study suggests that in areas where higher proportions of residents have low SES many individuals in the population may experience prolonged stress due to the continued struggle for resources. Therefore, these conditions may be associated with increased rates of mental concerns in areas.

A second limitation of this study is that the data was collected by health inventories patients fill out at ODMHSAS mental health facilities when they seek treatment. The highest percentage of ODMHSAS services are clustered in urban realms, therefore urban patients may more easily acquire healthcare. Rural residents may have to travel farther and have less proximity to mental health clinics due to issues of distance, physical access, and resource coverage, which may result in rural patients not seeking treatment as often as their urban counterparts. Consequently, rural Oklahoman's mental illness may be underreported. Additionally, because only ODMHSAS clinic data are used, patients who sought treatment from Native American tribal clinics, Indian Health Services, other commercial mental health services, or at private mental health facilities are not represented in this dataset. Therefore, results may not depict the full mental health burden in Oklahoma.

Lastly, the modifiable areal unit problem (MAUP) may impact findings. This analysis was conducted at the zip code level due to data availability; however, at a different scale of analysis, or if the same data was aggregated in a different way, the results may be altered (Holley, 1998; Wong, 2009). However, by exploring models at three different levels of analysis, insight to how patterns would change if the data was divided and analyzed differently is provided. Even with these considerations, examining spatial techniques' ability to uncover community factors associated with mental health issues makes strides towards a better understanding of spatial variations in mental health.

Conclusions

In contemporary medical geography there is a push to explore measurements of well-being beyond physical health (Brown et al., 2009; Curtis, 2010; Rosenberg, 2016). This analysis explores the geography of mental health issues. Investigations into mental illness are an urgent demand for Oklahoma and a crucial concern for the well-being of populations worldwide. Findings maintain that the social and built environment of a place can impact mental health. In Oklahoma at all levels of analyses, GWR proved beneficial in exploring variations in the characteristics associated with mental health issues. It provided the opportunity to investigate locational nuances in the relationships between socioeconomic, demographic, and environmental features of communities and their mental illness patterns that global regression methods are incapable of capturing.

In urban Oklahoma zip codes, especially, variations in ODMHSAS patient rates, depression rates, other behavioral disorder rates, emotional disorder rates, and developmental disorder rates patterns can be significantly explained by place characteristics. Additionally, whereas Salinas-Pérez et al. (2015) and others focused on urban settings for GWR analyses of psychiatric issues, this article carried out GWR on poor mental health measures in rural areas, thus contributing a more detailed understanding of the local community influences on rural mental health. Although the models' explanation of the spatial patterns of mental health issues in rural Oklahoma were improved after rural areas were isolated and analyzed separately from urban zip codes, a significant amount of variation cannot be explained. Much is still unknown about rural mental illness burdens and environmental contributing factors, indicating further research should focus on these topics.

Overall, the localized geographic considerations in this study allow for a finer understanding of some of the characteristics in areas that may cause stress and exacerbate mental illness in Oklahoma. This provides clues to the types of communities that may need to be targeted for health interventions and increased services. In this vein, another significant contribution of this research is the findings on the influences of multi-racial and Hispanic populations to the explanation of spatial patterns in mental health issues in Oklahoma communities. The complexities and dynamic nature of categorizing race impacts our understanding of populations' mental health. Therefore, further research on the mental health patterns of individuals in these groups and communities with higher proportions of these populations must be pursued in both Oklahoma and throughout the United States.

The methods in this study and the explicit concentration on the spatial aspects of reported mental health issues can offer potential insight to preventative community-level measures for increased public mental health. Plausibly, this research reveals that a one-size-fits all approach to population mental health may not be beneficial in certain areas and could inform public health officials about which underlying factors contributing to poor mental health should be addressed in different locations.

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CHAPTER IV

IMPROVING OUR UNDERSTANDING OF RURALITY AND MENTAL HEALTH USING REMOTE SENSING

The third article *Improving our Understanding of Rurality and Mental Health Using Remote Sensing* is intended for *The Professional Geographer*. This article, written by Stephanie Heald with contributions from Dr. Amy Frazier, Assistant Professor of Geography at Oklahoma State University, is a geographic exploration of the importance of considering how rurality is defined in health research. It contributes methodologically by developing an approach to integrate land cover data in an index to define rurality. This index including spatial considerations is applied to Oklahoma mental health research for a case study investigation. The Professional Geographer has published several articles on defining rurality, often publishes applied geography research, and favors innovative ideas. The inclusion of land cover to define rural areas and exploring the impact of rurality on health issues is an important new consideration and should be applicable to this journal.

Improving our Understanding of Rurality and Mental Health Using Remote Sensing

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Abstract

The methods by which rural and urban places are demarcated influence healthcare planning and health research outcomes. However, the definition of rurality is not regularly analyzed. Instead, studies often haphazardly select commonly accepted rural definitions lacking spatially explicit considerations for their research. This study recommends the use of a rural index (RI) comprised of variables derived from remotely sensed data measuring land cover, along with population density, and a proxy for community resource availability. Geographically weighted regression is performed on Oklahoma Department of Mental Health and Substance Abuse Services (ODMHSAS) mental health patient rates to reveal how rurality may contribute to patient rate patterns in the state and what areas RI may offer the most explanation towards these patterns. Results reveal that RI improved explanation of the variation in ODMHSAS mental health patient rates up to 68%. This is a considerable contribution compared to the census derived percent rural variable that contributed significantly less than RI to the regression models. *Key Words: Mental Health, Remote Sensing, Rural Index, Geographically Weighted Regression*

Introduction

Combatting mental illness is a critical population health concern in America. Mental disorders can reduce an individual's life expectancy, hinder social relationships, increase risk for financial hardships, and negatively impact physical health, quality of life, and well-being (Kessler et al. 2005; NASMHPD 2006; Newcomer and Hennekens 2007; Colton and Manderscheid 2006; Sano and Richards 2011; Nordentoft et al. 2013; Alegría et al. 2015). Beyond individual ramifications, poor mental health costs the U.S. billions of dollars in treatment expenditures and loss of worker productivity (DeVol et al. 2007; Insel 2008). Therefore, understanding the characteristics associated with poor mental health and the locations vulnerable to those conditions is crucial.

Research has shown that some areas are more vulnerable to mental illness than others (Burton et al. 2013; Singh and Siahpush 2014; Mental Health America 2015). Rural Americans are at risk for poor mental health and have high rates of depression, substance abuse, and suicide (Human and Wasam 1991; Eberhardt and Pamuk 2004; Mohatt et al. 2006; Hirsch 2006: Fontanella et al. 2015). About one fifth of the nearly 60 million rural residents in the U. S. battle mental illness (Gamm, Stone, and Pittman 2010). Compared to their urban counterparts, rural residents also have greater risk factors for poor mental health including: lower socioeconomic status (SES), lower educational attainment, reduced employment opportunities, larger aging populations, restricted physical activity, increased poverty, and increased pressure to suppress non-mainstream cultural beliefs (Human and Wasam 1991; Ricketts 1999; Burton et al. 2013; Bolin et al. 2015; Council of Economic Advisors 2010; Office of Rural Health Policy 2014; Rural Health Information Hub 2016).

Individuals living in remote regions also face challenges in acquiring necessary treatment. Rural residents are more likely to be uninsured, encounter financial obstacles to accessing adequate psychiatric services, have increased physical distance to health resources, lack public transportation, and experience shortages of mental healthcare professionals (Bird, Dempsey, and Hartley 2001; Cook and Hoas 2007; Smalley and Warren 2012; Office of Rural Health Policy 2014; U.S. Department of

Health and Human Services 2015; Jensen and Mendenhall 2018). For example, Mohatt et al. (2006) observed that rural mental healthcare consumers may travel hundreds of miles weekly to access care only available in more densely populated areas. Furthermore, in rural settings, a culture of self-reliance, economic hardships relating to diminishing resources, amplified stigma associated with seeking treatment, and overlapping social networks contributing to confidentiality issues may limit service acquisition and exacerbate mental illness (Roberts, Battaglia, and Epstein 1999; Fuller et al. 2000). These social, environmental, and demographic elements of rural communities can translate into poor health outcomes for more remote populations and contribute to geographically differing disease burdens (Ricketts 1999; Wainer and Chesters 2000; Office of Rural Health Policy 2014).

Over the past several decades, rural health disparities have been a growing concern (Human and Wasem 1991; Paykel et al. 2000; Gamm, Stone, and Pittman 2010; Buzza et al. 2011; Fontanella, et al. 2015; Davis et al. 2016; Harris et al. 2016). Healthy People 2020 recognizes rurality as one of the 14 disparities contributing to poor health in America (Bolin et al. 2015). The question remains, however, what areas and populations should be considered rural (Berry et al. 2000; Rural Health Information Hub 2018)? Distinguishing rural from urban places is not a simple task as there is no universally accepted definition for rurality (Wakerman 2004; Hart, Larson, and Lishner 2005; Coburn et al. 2007; Cromartie and Bucholtz, 2008; Paniagua 2016; USDA 2016; Rural Health Information Hub 2018). Philo, Parr, and Burns (2003) explain that most studies do not attempt to undertake the challenge of defining rurality and instead utilize conventional categories based on statistical indicators.

Typically, rural areas are defined based on demographic variables (e.g., population size or density), selected socioeconomic variables (e.g., employment characteristics), access to health care, economic concepts (e.g., the lack of economic ties to the core counties measured by labor-force commuting), or even administrative boundary decisions (Cromartie and Bucholtz 2008; U.S. Census Bureau 2010; Office of Management and Budget (OMB) 2015). More nuanced definitions of rurality involving land cover and the physical environment are less common (Nielsen and Johansen 2009). Ultimately, the variation in rural classification schemes makes it challenging to compare and interpret findings (Johnson-Webb et al. 1997; Philo, Parr, and Burns 2003; U.S. Census Bureau 2010; U.S. Department of Health and Human Services 2015; OMB 2015). Most importantly, the ways in which rural and urban areas are delineated influence healthcare planning and the research that shapes it in myriad ways (Humphreys 1998b). Designating service center locations, allocating healthcare resources, and determining need by measuring service utilization are central objectives in public mental health promotion that are impacted by rural-urban classification methods.

The objective of this research is to develop an alternative differentiation of rural and urban areas that consists of more than population statistics and considers the spatial aspects of land use and land cover (LULC). Remotely sensed LULC data, in combination with population and community resource measures, will be employed to create an index to classify rural locations in Oklahoma. This rural-urban classification scheme will be utilized specifically for the purpose of exploring geographic patterns in mental health. The research is guided by the following questions: How can remote sensing data be used to calculate rurality for the purposes of medical geography? How much impact does rurality have on mental health patient rate patterns in Oklahoma? Does the rurality index more effectively contribute to explanations of mental health patient rate patterns than the census defined rural variable? To provide context for this study, an overview of rural mental health is offered followed by a critique on evolving definitions of rurality. Next, the justification and methodology for the creation of a spatially explicit rurality index is explained. Finally, remotely sensed data is included in a statistical analysis of the impact of rurality on the spatial patterns of mental health in Oklahoma.

Rural Health and the Measurement of Rurality

Trends in Rural Mental Health Research

Rural health and mental healthcare literature discussing physical barriers to access, resource availability, and negative health outcomes have concentrated on analyzing travel time to care, prevalence of mental disorders, and availability of mental healthcare facilities or physicians (White 1986; Ricketts 1999; Fortney et al. 1999; Fortney, Owen, and Clothier 1999; Arcury et al. 2005a; Arcury et al. 2005b; Chan, Hart, and Goodman 2006; Thomas et al. 2009). Due to confidentially, data limitations, chosen methodologies, and time/cost constraints, many studies utilize aggregated health records and preexisting classifications of rurality (Goldsmith et al. 1994; Lin et al. 1996; Holzer, Goldsmith, and Ciarlo 1998; Ricketts 1999; Caldwell, Jorm, and Dear 2004; Ellis et al. 2009; Thomas et al. 2009; McCarthy et al. 2012; Cummings, Wen, and Druss 2013). Larger geographic areas and broader populations are analyzed by examining relationships between socioeconomic characteristics of rural areas and mental health or service patterns at the census tract, census block, zip code, or county levels. Aggregating data maintains patient confidentiality, and the data are more feasibly acquired from public health organizations at this scale. Additionally, the majority of this rural population health research also uses broad, predefined, and generally accepted rural-urban definitions to analyze population health or healthcare service patterns (Caldwell, Jorm, and Dear 2004; Eberhardt and Pamuk 2004; Ellis et al. 2009; Thomas et al. 2009; McCarthy et al. 2012; Cummings, Wen, and Druss 2013).

Studies commonly rely on rural-urban definitions from federal agencies such as the U.S. Census Bureau, Office of Management and Budget (OMB), or U.S. Department of Agriculture (USDA), and each delineate urban and rural places differently as shown in Table 1 (Philo, Parr, and Burns 2003; Johnson-Webb et al. 1997; Eberhardt and Pamuk 2004; Cromartie and Bucholtz 2008; U.S. Census Bureau 2010; OMB 2010; McCarthy et al. 2012; OMB 2013; Department of Health and Human Services 2015; U.S. Census Bureau 2015; USDA 2016; USDA 2017).

Table 1. Rural definitions from Federal Agencies

Federal Agencies	Rural-Urban Defining Methods	Common Uses for Rurality Measures
Office of Management and Budget (2013)	Defines metropolitan areas as encompassing central counties with one or more urbanized areas of 50,000 people or more. Non-metropolitan counties are considered rural. Non- metropolitan counties consist of micropolitan areas comprised of 10,000 or more persons and noncore counties which include all remaining rural areas.	Researchers and practitioners who study economic, social, and health conditions in rural America
U.S. Census Bureau (2010)	The Census Bureau recognizes two types of urban areas: 1) Urbanized Areas (UAs) consisting of 50,000 people or more and 2) Urban Clusters (UCs) consisting of between 2,500 and 50,000 people. All population, housing, or territories not located within urbanized locations are considered rural. (Less than 2,500 people and lacking a densely developed core of census tracts/census blocks).	Frequently utilized for health research and to decide if a facility qualifies for certain programs as a rural health clinic.
U.S. Department of Agriculture (2017)	Uses an administrative boundary concept by utilizing municipal borders to determine urbanity. Three main categories are defined: 1) Urban areas with populations ranging from 2,500 to 49,999, 2) Rural towns with fewer than 2,500 people, and 3) Open countryside, Locations not within delineated city jurisdictional areas are considered rural.	Used to determine eligibility for rural development and assistance programs.

Multiple rural-urban classification schemes can lead to different populations included as rural (Cromartie and Bucholtz 2008; U.S. Census Bureau 2015; USDA 2017). As noted by Cromartie and Bucholtz (2008), America’s rural population ranges from seven to 49% depending on the definition. Thus the definition of rurality affects the way we study rural health because areas may appear to have fewer resources, lower access, or higher physician shortage based on the rural-urban taxonomy selected (Humphreys 1998a; Humphreys 1998b). For example, Eberhardt and Pamuk (2004) identified higher suicide rates among rural residents utilizing OMB classifications, but the results may have varied if a different rural definition was used. Due to the effects on research outcomes, selecting a suitable rural definition is challenging, but important for decision makers as they design policies or choose where to allocate resources (Cromartie and Bucholtz 2008).

Many rural-urban classifications primarily consider population size or density. Bachrach (1985) suggests that census classifications of urban–rural and metropolitan–non-metropolitan derived from population counts within political bounds are useful for many basic statistics and standard studies but are less germane to grounded human realities. Furthermore, Gregoire and Thornicroft (1998) asserted that the concept of rurality encompasses not just population density but also the social context, physical environment, and land use. Therefore, many scholars propose creating indices that consider multiple factors to avoid problematic, simplistic, or inconsistent rural depictions (Hart, Larson, and Lishner 2005; Ocaña-Riola and Sánchez-Cantalejo 2005; Mountrakis, AvRuskin, and Beard 2005; Prieto-Lara and Ocaña-Riola 2010; Li, Long, and Liu 2015).

Rural Indices

Four decades ago, Cloke (1977) created a rurality index using principal components factor analysis for socioeconomic variables, and since then, other studies have used similar statistical techniques to classify rurality using an index (Harrington and O'Donoghue 1998; Ocaña-Riola and Sánchez-Cantalejo 2005; Prieto-Lara and Ocaña-Riola 2010; Li, Long, and Liu 2015). Ocaña-Riola and Sánchez-Cantalejo (2005) emphasized that only considering a single variable to measure rurality, such as the population or population density, truncates the complex idea down to a rural/urban dichotomy by selecting arbitrary cut-off points that may not be applicable across all settings. Instead, research suggests combining multiple variables to capture the dynamic economic, educational, demographic, employment and/or land use of rural areas to provide a better measure of rurality (Murray et al. 2004; Mountrakis, AvRuskin, and Beard 2005; Prieto-Lara and Ocaña-Riola 2010; Li, Long, and Liu 2015). For this reason, rural indices may be created specifically for a particular region or purpose based on the selection, availability, or applicability of economic, land use, or socio-demographic measures. The goal of these indices is not only to capture a more accurate measure of current rural settings, but also to adapt to changing rural patterns over time (Li, Long, and Liu 2015).

One shortcoming of rural indices is that they often do not include spatial components, such as distance to resources, physical features, or land cover. The small number of studies that have attempted to capture spatial characteristics of rural areas in indices (Table 2) have predominantly included distance to population centers or proximity to various resources as a variable indicating remoteness (Weinert and Boik 1995; Mountrakis, AvRuskin, and Beard 2005). One such study by Murray et al. (2004) applied the Accessibility/Remoteness Index of Australia (ARIA), an accepted geographic measure of remoteness, to mental health survey reports to reveal that two measures of wellbeing were negatively correlated with reduced service accessibility. However, beyond the examples in Table 2, few spatial methods have been used to delineate rural areas, and the inclusion of LULC data is rare (Nielsen and Johansen 2009). Additionally, few rural indices have been utilized to better understand health disparities (Weinert and Boik 1995; Murray et al. 2004).

Table 2. Indices measuring rurality or remoteness that include a spatial component.

Authors	Index	Purpose	Indicators	Spatial Components
Cleland and Mushitz (1991)	Connectedness Index	Measure rurality with a variable including distance to a metropolitan area, a proxy for spatial connectedness,to analyze communities' access to resources for the resolution of local issues.	Proximity to a metropolitan area & 9 socioeconomic & demographic variables.	A measure of adjacency is the spatial component. The measure is a distance variable-- proximity to a metropolitan area.
Weinert and Boik (1995)	The Montana State University (MSU) Rurality Index	Measure of rurality considering access to healthcare.	County level population & distance to emergency care for individual Montana residents.	Only included resource availability as a spatial consideration.
Leduc (1997)	General Practice Rurality Index (GPRI) for Canada	Measure of rurality for general health practice	6 variables: remoteness measured from a referral center, remoteness from an advanced referral center, population, acute care hospital presence, amount of general practitioners, and number of specialists.	Used travel time and distance to centers
Murray et al. (2004)	Accessibility/ Remoteness Index of Australia (ARIA)	Explore effects of rurality on mental health survey reports of distress, disability and wellbeing.	Remoteness values for 11,340 populated localities are based on the road distance to populated locations & service centers.	Distance between urban areas is only spatial characteristic included.
Mountrakis, AvRuskin, and Beard (2005)	Spatial Rurality Index (SRI)	Measuring a hierarchy of network connections (transportation, infrastructure, & resource networks) to identify more isolated places with less infrastructure & classify them as rural.	GIS used to create a connectivity cluster of indicators and an access to service cluster of indicators that were combined into a single rural index.	Concept of rural was reduced infrastructure measured by the presence of networks (nodes) and degree of network (node) connectivity. The degree of accessibility was measured by calculating the absence or distance to a particular service.
Nielsen and Johansen (2009)	Distance Index prepared through GIS	Measured the level of rurality	An index was created by calculating the number of rural communities that have to be passed to get to urban areas.	LULC data & GIS is used to classify rural areas then the "level of rural rurality" is assessed with an index that includes the number of rural communities traveled through to reach areal units classified as urban area.
Chi (2010)	Developability Index	Identifies the proportion of lands available for development at minor civil division level in Wisconsin.	Water, wetland, tax-exempt lands, slope, and built-up lands were included in an index measuring undeveloped areas	Land use and land cover data were used to identify land for development

Although a growing number of rural indices integrate spatial variables and GIS, remote sensing techniques are not frequently utilized (Nielsen and Johansen 2009; Chi 2010). Remotely sensed data are acquired from a sensor that is not in contact with the phenomenon being studied. Typically, these data consist of images acquired via satellite or aircraft. LULC information are classified from these images based on the Earth's reflected or emitted electromagnetic radiation in one or more fields of the electromagnetic spectrum (Jensen 2009; Campbell and Wynne 2011). Agriculture, wetlands, forests, watersheds, and barren areas can be classified using remote sensing techniques and compared to the dense infrastructure of urban landscapes (Yuan et al. 2005; Homer et al. 2015). Thus, remote sensing is commonly used to collect and analyze LULC data in order to study urbanization trends and differentiate rural land uses (Gong and Howarth 1990; Jianquan and Masser 2002; Yuan et al. 2005; Martinuzzi, Gould, and González 2007).

By using remote sensing to locate land cover that has varying degrees of infrastructure, rural locations can be classified by their physical and infrastructural characteristics and not just population alone. The utility of including remote sensing information in rurality indices has clear implications for rural mental health research. In this study we will combine measures of community resource availability, population density, and remotely sensed LULC data to create a rurality index to be used for analysis of mental health patterns in Oklahoma.

Study Area

Oklahoma is the study area for this research due to its poor health outcomes, high percentage of mentally ill, and large proportion of rural areas (Figure 1) (Mental Health America 2015; Oklahoma Health Improvement Plan 2015). Additionally, the state faces multiple social, economic, and demographic obstacles that research links to poorer mental health outcomes including increased rates of incarceration, domestic violence, unemployment, uninsured residents, poverty, and a statewide shortage of psychiatrists (Wetrz 2011; Vieth 2013; Oklahoma Health Improvement Plan

2015; Green 2016; HRSA 2016). Using remotely sensed data to aid in defining rural Oklahoma areas can provide a clearer understanding of what areas in the state should be classified as rural based partially on LULC. Moreover, identifying the impact of rurality, socioeconomic, and demographic variables on spatial patterns in mental health issues can shed light on possible community characteristics increasing vulnerability to higher mental illness rates throughout the state.

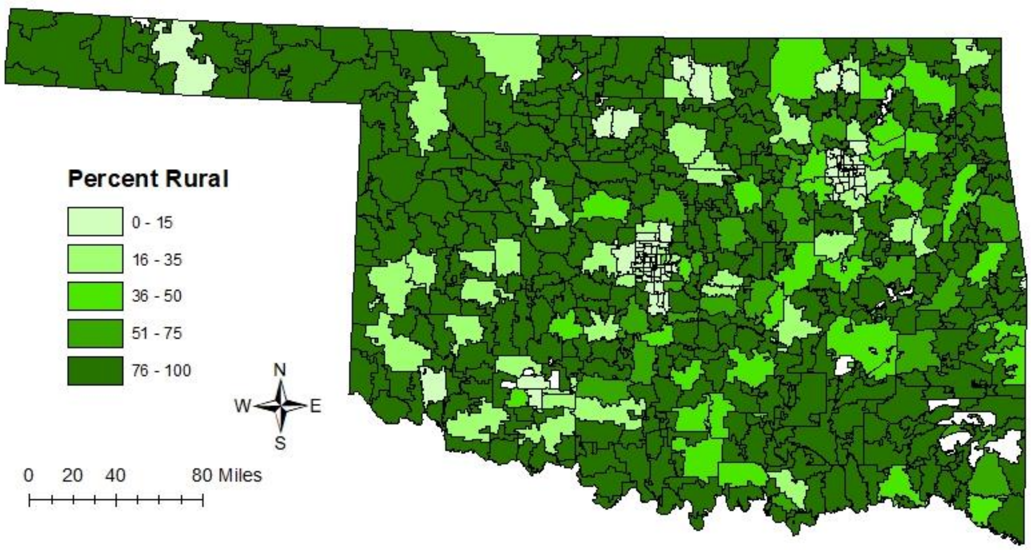

Figure 1: Percent rural per zip code based on the U.S. census definition of rural.

Data and Methods

Data

Mental health data for this study were acquired from the Oklahoma Department of Mental Health and Substance Abuse Services (ODMHSAS) and consist of all patients admitted into ODMHSAS affiliated care from 2011-2014. Cases were listed using a unique numerical identifier and zip code of residence to protect confidentiality. In this study 290,655 individual cases were aggregated into 648 zip codes based on residence. However, four zip codes were later discarded due to lack of data availability. Patients who listed a PO Box as their residence were assigned to the nearest zip code for analysis. Subsequently, ODMHSAS patient rates per 100,000 people were calculated for each of the 644 zip codes and used as the dependent variable for the regressions (discussed below).

Next, socioeconomic and demographic data obtained from the U.S. Census Bureau's 2010 Census and 2014 American Community Survey (ACS) were collected at the zip code level. ACS 5-year estimates for zip codes were chosen because they are the most recent data, yield a larger sample size, and match the mental health data time frame. Twenty-eight variables quantifying population characteristics including: race/ethnicity, educational attainment, income, employment status, health insurance coverage status, marital status, female-headed households, percent in the labor force, percent of the population 65 years or older, percent living below poverty, percent supported by public assistance, and percent of vacant housing in a zip code were selected due to possible associations with poor health outcomes as noted in the literature (Ricketts 1999; Wainer and Chesters 2000; Arcury et al. 2005a; Mohatt et al. 2006; Council of Economic Advisors 2010).

Additionally, I created the community opportunities rate variable, which broadly depicts available community resources and infrastructure. The variable was constructed from the number of schools, religious organizations, and civic organizations per 1,000 people in a zip code. The schools and organization data were obtained through a yellow page scraper tool designed with an algorithm to extract selected business information from the Yellow Pages directory. The measure also can represent opportunities for social networking and connectedness, which has been linked with improved health outcomes (von Reichert, Cromartie and Arthun 2014; Glanz 2015).

In addition to the mental health and socio-demographic variables, LULC variables in this study were obtained from National Land Cover Database (NLCD) (Homer et al. 2015). NLCD 2011 has a spatial resolution of 30 meters and classification is based on a decision-tree using 2011 Landsat data (Homer et al. 2015). From the NLCD dataset, four urban land classifications were combined to represent all developed or urban land types: Developed Open Space, Developed Low Intensity, Developed Medium Intensity, and Developed High Intensity. All other land cover classifications were combined to represent undeveloped land cover. The proportion of each zip code's land area classified as undeveloped and the percent of undeveloped LULC within a 20-mile radius around each zip code are variables included in the rural index (discussed below).

Rural Index (RI)

To address the first research question about how remote sensing data can be used to calculate rurality for the purposes of medical geography, a rurality index (RI) is created using principal components analysis (PCA) (Figure 2). PCA is a statistical technique that reduces a larger number of variables into a smaller number of components based on interrelationships (Everitt and Dunn 1993; Vyas and Kumaranayake 2006). PCA mathematically generates uncorrelated indices that are linear weighted combinations of the original variables (Vyas and Kumaranayake 2006). The population density per square mile of each zip code calculated from U.S. census data, the community opportunities rate, the percent of each zip code's land area classified as undeveloped, and the percent of undeveloped LULC within a 20-mile radius of each zip code are entered into the PCA to create the RI. The percent of undeveloped LULC within a 20-mile radius is included to consider the environmental characteristics of nearby locations. Literature suggests that about 20 miles or less is a commonly accepted distance traveled to acquire non-emergency healthcare (Probst et al. 2006; Yen 2013; McGrail, Humphreys, and Ward 2015). Including LULC characteristics from surrounding areas in this index also reduces the impact of edge effects that zip code boundaries artificially impose. Thus, it may prevent skewed results based on overgeneralizations or overestimations of rural populations. For example, some individuals may be located in a relatively rural zip code, but may have better physical access to a mental healthcare provider because they reside next to an urban area with multiple providers in an adjacent zip code.

Regression Techniques

To analyze the impact of rurality on mental health, RI and the socioeconomic and demographic variables are entered as independent variables into a stepwise multiple regression model to best explain variations in spatial patterns of ODMHSAS patient rates. Regression methods are employed to expose causal or predictive relationships between the dependent mental health variable and the independent variables representing community characteristics (Getis 2008). Stepwise regression is a semi-automated global regression technique where at each step, when a variable is added into the model, all variables in the model are tested to determine if their significance has been reduced below a specified tolerance level. If a variable becomes insignificant with the addition of new variables, it is automatically removed from the model (Montgomery, Peck, and Vining 2015). Therefore, this method allows for selecting the most parsimonious model to explain ODMHSAS patient rate patterns.

Next the stepwise regression model residuals are mapped to identify if there are clustered residuals signifying possible spatial autocorrelation. Moran's I is computed for the residuals of the global model to confirm spatial autocorrelation. If residuals are spatially autocorrelated, further testing will be completed to determine whether the independent variables in the model have a consistent relationship with the dependent ODMHSAS patient rates variable in both geographic and data space using the Koenker (BP) Statistic Analyses (Koenker, 1981). If the statistic returns a significant result indicating non-stationarity, the variables are appropriate candidates for geographically weighted regression (GWR).

If applicable, GWR will be conducted to account for spatial autocorrelation and non-stationarity issues (Fotheringham, Charlton, and Brunsdon 1997; Fotheringham, Brunsdon, and Charlton 2003). GWR is employed to show the locational variance in explanatory power of the independent demographic and socio-economic variables by creating a regression equation for each unique location in the study area. GWR has the capability to model spatially-varying relationships between dependent and independent variables where global regressions may fall short in extrapolating local differences. Furthermore, the significance of the spatial variability in each local parameter estimate is examined by model comparison. To test the geographical variability of a coefficient, the Akaike Information Criterion (AIC) of a fitted GWR model is compared to the AIC of a model in which only a selected coefficient is fixed and the other coefficients are maintained the same as they are in the fitted GWR model. If the original fitted GWR is superior than the difference between the AIC values of the two models will appear negative. Negative values of Difference of AIC indicate spatial variability and the need to include the variables as local, while positive values suggest variables should be run as global in the model (Fotheringham, Charlton, and Brunsdon 1997; Fotheringham, Brunsdon, and Charlton 2003). Next, the AICs of the potential GWR models will be compared to the AIC computed for the global models to determine whether the GWR models have a superior fit. A lower AIC indicates that a model is a better fit (Akaike 1973).

Assessing RI Effectiveness

Finally, RI effectiveness is tested by comparing, the ability of RI to contribute explanation to the spatial patterns in ODMHSAS patient rates and the explanatory power of the census defined percent rural per zip code variable (Figure 2). The same regression procedures are performed with the census percent rural variable substituted in place of RI. The census-derived variable is selected for comparison because it is a rural definition frequently utilized for health research. The results of the global regression and GWR including RI are compared to global and local regressions including the census percent rural variable to find if RI contributed to a better understanding of ODMHSAS patient rate patterns.

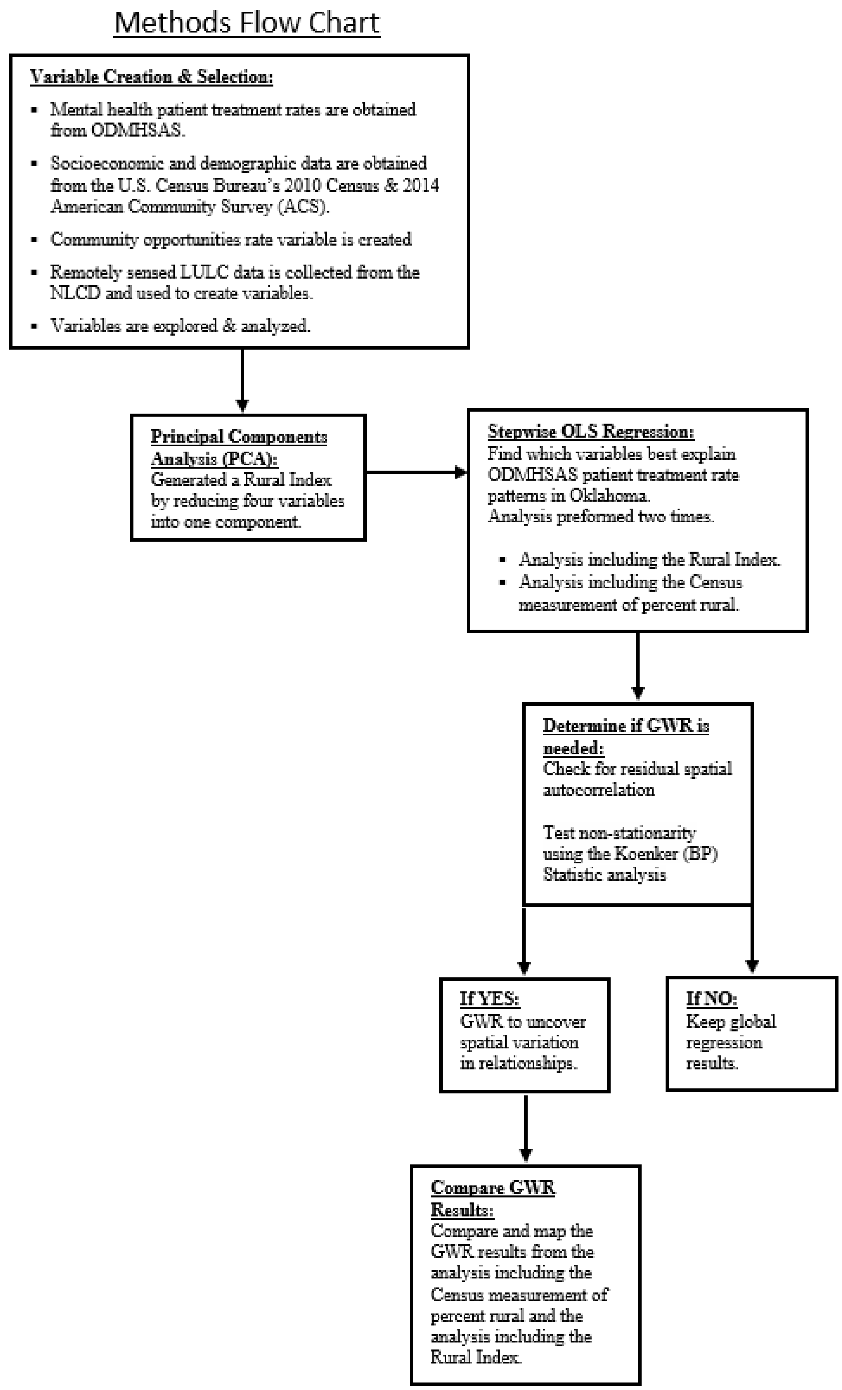

Figure 2: Flow chart of methods used in this study.

Results

PCA generated one component consisting of percent undeveloped per zip code, percent undeveloped inside the 20 mile buffer, population density per square mile, and community opportunities (Table 3). The four variables in this component combined to explain about 64% of the variation in the data. This component was selected as the RI because it had the highest Eigenvalue of 2.554, which is above the generally accepted Kaiser Criterion threshold of 1, and it had the highest percent of variance at 63.851%.

Table 3. The rural index component created through PCA.

Rural Index Component	**Component Matrix**
Percent Undeveloped	.961
Community Opportunities Rate per 1,000	.133
Population Density per Square Mile	-.909
Percent Undeveloped in 20 Mile Buffer	.889

*Bartlett's test of sphericity was significant at .000 and the Kaiser-Meyer-Olkin Measure of Sampling Adequacy statistic of .626 indicates the proportion of variance in the variables may be caused by underlying factors.

Next, the RI was entered into a global stepwise regression along with 28 socioeconomic, demographic, and environmental variables. The stepwise regression produced 11 possible models describing the variation in ODMHSAS patient rates throughout Oklahoma. Of those 11 models, RI was a significant variable lending explanatory power in six models. The most parsimonious global model yielding the highest R^2 included six variables to explain 38.5% of the variation in ODMHSAS patient rates. Variables influencing higher ODMHSAS patient rates included increasing percentages of the population classified as: not in the labor force, unemployed, African American, uninsured, and living alone. Additionally, RI was the only variable that had a negative relationship with patient rates in the model. RI is inversely related to ODMHSAS patient rates, thus as rurality increased, patient rates decreased in Oklahoma zip codes. This unexpected inverse relationship could indicate that rural Oklahoma residents experience better mental health despite previous research suggesting rural populations have increased mental illness vulnerability. However, it is likely that fewer rural residents may seek care from ODMHSAS services based on literature suggesting that barriers to physical access, clinic availability, financial accessibility, or low social acceptability for mental health service acquisition may impede rural residents mental health service use (Jones, Parker, and Ahearn, 2009; Smalley et al. 2010; Smalley and Warren 2012; U.S. Department of Health and Human Services 2015; Jensen and Mendenhall 2018).

Table 4. Most parsimonious stepwise regression model.

Model 8	Standardized Coefficients Beta	t	Sig.
(Constant)		1.467	.000
% Not in Labor Force	.298	8.163	.000
% African American	.230	6.605	.000
% Live Alone	.220	6.342	.000
Rural Index Component	-.148	-3.969	.000
% Uninsured	.146	4.344	.000
% Unemployed	.127	3.756	.000

To compare the utility of RI to the census percent rural variable, the same procedures were conducted, and stepwise regression techniques were run with the census variable and the 28 socioeconomic and demographic variables. The census percent rural variable did not explain any significant variation in the first nine of 11 models generated and contributed little explanation to ODMHSAS patient rate patterns in the last two models. Moreover, the regression including the independent variables from the first global stepwise regression model and the census percent rural variable substituted for the RI yielded an R^2 of .367. This model explained slightly less than the model including the RI, however, it is important to note that the census percent rural variable contributed the least of the variables included in the model (Table 5). The inverse relationship between rurality and ODMHSAS patient treatment rates is apparent in both models, but RI provided more power of explanation.

Table 5. Stepwise regression model with the census rural variable with the original variables significant in the stepwise regression with RI.

Independent Variables	Standardized Coefficients Beta	t	Sig.
(Constant)		2.243	.000
% Not in Labor Force	.283	7.766	.000
% Live Alone	.241	7.073	.000
% African American	.240	6.865	.000
% Uninsured	.155	4.582	.000
% Unemployed	.122	3.557	.000
% Rural	-.113	-3.067	.000

Mapping regression residuals, computing Moran's I, and conducting Koenker (BP) Statistic Analyses (Koenker 1981) on the model results including RI confirmed that the variables in the model would be appropriate candidates for GWR due to significant non-stationarity. The same procedures performed on the global regression results of the model including the census percent rural variable indicated that the independent variables would also benefit from GWR analysis. Therefore, GWR was conducted on the same set of variables entered in each of the global regression models. An adaptive bandwidth was selected because zip codes are not regularly sized and spaced throughout the state. Adaptive bandwidths are preferred over fixed bandwidths, which may not identify subtle local variations in urban areas where data are geographically clustered (Charlton, Fotheringham, and Brunsdon 2009). Additionally, the bi-square kernel was selected because it has a distance decay weighting function and assigns zero weights to observations outside of the bandwidth so that distant zip codes characteristics have no impact (Charlton, Fotheringham, and Brunsdon 2009).

GWR results from both models greatly increased the power of explanation for ODMHSAS patient rate patterns throughout Oklahoma. The R^2 of the model including RI improved from .385 to .684, while the census percent rural variable model improved from .367 to .641. Additionally, the GWR models had significantly lower corrected AICs, signifying that these have a better fit than the global regressions. Interestingly, in the model with RI, the index showed spatial variation in its relationship with patient rates and was run as a local variable. In the second GWR model, the census percent rural variable did not have local variation in its relationship with patient rates and was run as global. The fact that the index had spatial variation in its relationship with ODMHSAS patient rates, may signify that RI is capturing different aspects of rurality and subtle differences that the census variable is incapable of portraying. Maps of the GWR model results reveal the zip codes in which variations in ODMHSAS patient rates are best explained (Figures 3-4).

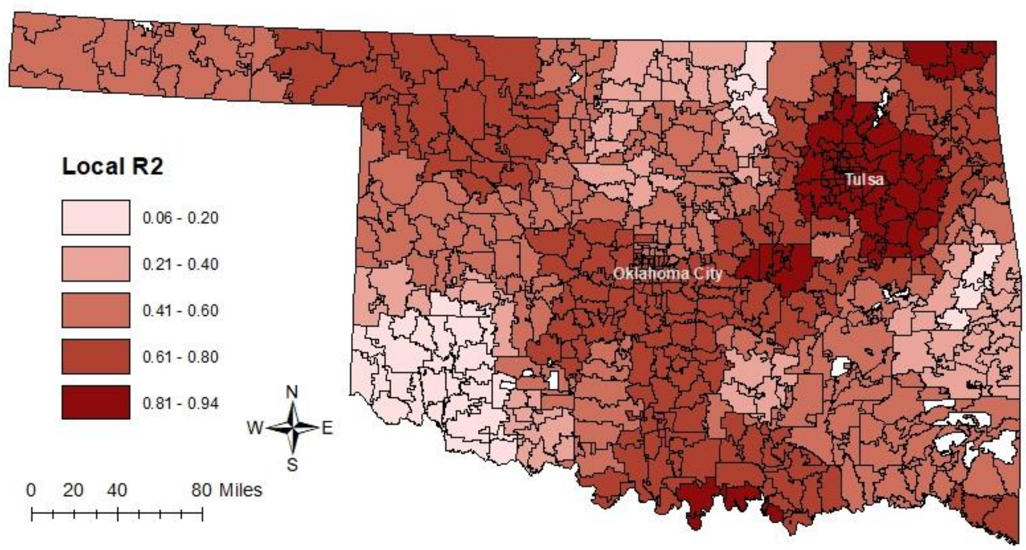

Figure 3. Mapped local R^2 from the GWR model including the RI component (Table 4).

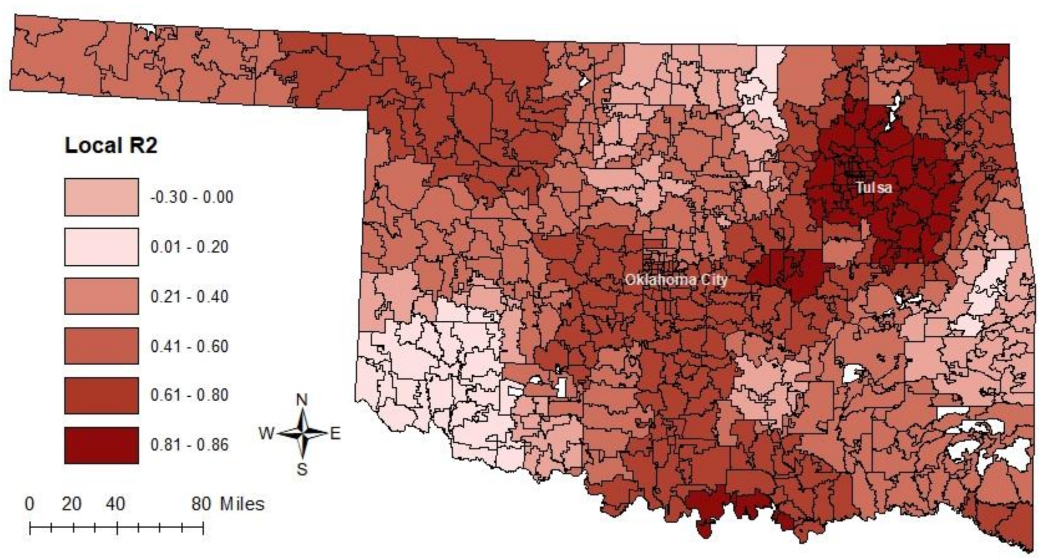

Figure 4. Mapped local R^2 from the GWR model including the census percent rural variable (Table 5).

Overall, the GWR model with RI explained 68% of the variation of ODMHSAS patient rate patterns, while the model with the census percent rural measure explained only 64%. The maps (Figures 3 and 4) illustrate that both models had the highest explanatory power (over 81%) for ODMHSAS patient rates in the Tulsa area. The GWR model with RI also explained between 61% to 80% of variation in many predominantly rural classified areas in Central and Northwest Oklahoma (Figure 1) and explained up to 94% in some northeast, southcentral zip codes. The model using the census percent rural variable was less successful in explaining patterns in many of the same zip codes in these regions by about 20%. The biggest improvement in explanation using RI was in the northeastern areas of the state where the model including RI explained between 80% to 94% of the variation in ODMHSAS patient rates, while the model with the census percent rural variable explained less than 40% (Figures 3-4).

Discussion

Considering aspects of LULC may lend understanding to how spatial components of the environment and rurality can impact population issues. This study offers a rurality index including remotely sensed LULC data to measure disparities in mental health, which most previous studies have not done. While this particular study tested the rurality index for a medical geography application, these methods can be expanded to investigate different population issues and their relationship to rurality. RI added spatial considerations to the definition of rurality and helped explain how rurality impacts mental health patterns in Oklahoma. Notably, one limitation of this study is that Oklahoma's true mental illness disease burden is difficult to represent through ODMHSAS data as patients who sought treatment from Native American tribal clinics, Indian Health Services, or at other commercial or private mental health facilities are not included in that dataset. Also, reduced proximity to mental health clinics, rural attitudes toward mental health, stigma, and fewer resources for rural residents may result in rural patients not seeking treatment as often as urban residents. Therefore, mental illness may be underreported in more remote locations.

Although those limitations are important to acknowledge, this work contributes to the overall body of rural mental health research by utilizing remote sensing data to help classify rural areas for the purpose of analyzing the impact of rurality on mental health patient rates. In previous mental health research, most studies utilizing remotely sensed data concentrated on exploring the built environment's impact on mental health by measuring access or distance to green space in urban areas (De Vries et al. 2003; Maas et al. 2009; Van den Berg et al. 2010; Richardson and Mitchell 2010; Beyer et al. 2014). However, research suggests that open space in congruence with sparse infrastructure, physical isolation, low population density, service inaccessibility, and personnel shortages can hinder health in rural areas (Bachrach 1985; Ricketts 1999; Mohatt 2006). Bacharach (1985) described space as a major impairment to providing a complete array of mental health services in rural America. Importantly, this study provides a possible way to consider how sparse infrastructure and the environment can impact mental health in more rural settings, which has been largely ignored by remote sensing applications.

Another contribution of RI is that it takes into account the infrastructure of nearby areas in defining rural locations. Often, spatial studies of health examine the characteristics within areal units and compare them to neighboring areas without considering how adjacent areas might be impacting those characteristics. Including LULC characteristics within 20 miles of each zip code decreases the bias that the superimposed boundary lines of zip codes introduce. Notably, there is still some bias present because a 20 mile boundary was selected. Nevertheless, including the features of surrounding areas within a distance supported by the literature is an improvement upon many prior rural indices, which may neglect to consider the influence nearby infrastructure may have. This component of the index may also prove a crucial consideration for applications beyond health. For example, the characteristics of neighboring locations is an aspect important to research investigating service use patterns and resource availability.

The RI improved explanation of the variations in ODMHSAS patient rates compared to the census variable. Locations with more dispersed populations or places with more inclusive mental health case data may especially find RI applicable. If data are available at a smaller spatial unit, RI could also be implemented at a much finer spatial scale because NLCD data derived from Landsat imagery is available at a 30 meter resolution. Therefore, studies conducted at a smaller scale may potentially yield more pointed results. Ultimately, the considerations presented in this article should be addressed in future research and it is imperative that general definitions of rurality not be blindly employed without initial exploration.

Conclusion

The disparate disease burden and healthcare access obstacles facing remote populations exemplify why mental disorders are identified as a top rural health priority (Bolin et al. 2015). Understanding possible contributors to poor mental health and targeting areas vulnerable to these conditions is especially important for Oklahoma where the disease burden is among the highest in the nation, many areas are underserved, and budget cuts continue to reduce funding (Vieth 2013; Oklahoma Health Improvement Plan 2015; Cosgrove 2015; HRSA 2016; KOCO 2016). Having a more nuanced and spatially explicit measurement of rurality is crucial for future rural health investigations and aids in ensuring limited resources target the right locations (Murray et al. 2004). This study suggests that part of the explicit definition of rurality should include LULC characteristics. Including the LULC of areas, a measure of social resources, population density, and the LULC of nearby locations in RI created a more holistic and multidimensional definition of rurality. Philo, Parr, and Burns (2003) encouraged researchers to explore definitions of rurality appropriate to the study of mental health. This study accomplishes that with its creation and application of RI. When entered into a GWR model with socioeconomic and demographic characteristics, RI helped explain over 68% of the variations in ODMHSAS patient rates and in some rural regions of Oklahoma explanation increased to over 81%. RI proved superior to the commonly accepted census percent rural variable which lent less descriptive power to spatial patterns of ODMHSAS patient rates. Thus, RI provides a multifaceted spatially considerate way to define rurality and contributes to the investigation of the intricate relationship between rurality and mental health in American communities.

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CHAPTER V

CONCLUSION

Mental health is a pressing issue for the economy and societal well-being of Oklahoma, the United States, and the world (CDC 2005; Substance Abuse and Mental Health Services Administration 2015; World Health Organization 2011; Oklahoma State Department of Health 2014; Oklahoma Health Improvement Plan 2015; Mental Health America 2015). Each of the three articles focuses on the ways in which the places that people live may impact the mental health of the population. Broadly, this research contributes to how geographic perspectives can be utilized to examine mental health. More practically, these studies analyze mental health treatment patterns in Oklahoma and attempt to identify places and populations that may be vulnerable to mental illness. Pinpointing groups or areas that may suffer mental disorders at higher rates could help guide the state in how to best allocate already strained resources. In rural Oklahoma this appears to be particularly important.

Currently, Oklahoma is ranked 46th in overall health and is ranked among the highest states for mental distress and lack of insurance (United Foundation 2016). Moreover, throughout the U.S., mental illnesses have massive economic costs for individuals, health organizations, and governments (Insel 2008). With Oklahoma's recent budget cuts to mental health care (KOCO 2016), it is crucial to efficiently and effectively use available funds to maximize care for individuals throughout the state. Beyond the conditions in Oklahoma, monetary costs associated with poor mental health, premature mortality linked to mental illness, and high rates of disability and mortality caused by mental disorders are growing concerns around the world (World Health Organization 2011). The need for improvement in mental health and overall wellbeing is vital. Therefore, for a broader

public health initiative it is imperative to address mental health disparities that plague communities.

These studies each support the proposition that communities' characteristics in both the social and physical environment may exacerbate stress and mental health concerns for individuals (Macintyre and Ellaway 2003; Galea et al. 2005; Cooper et al. 2009; Lorenc et al. 2012; Barahmand, Shahbazi, and Shahbazi 2013; Halpern 2014; Barr 2014). Each study attempts to identify these determinants' connection to the spatial patterns of ODMHSAS mental health treatment records in communities throughout the state.

Article 1 Overview

The first article identifies how mental health patient rates and poor mental health days differ among places categorized by similar SES. Using a public health social ecological framework which postulates that individuals are deeply embedded in their neighborhoods, broader communities, and environments, zip codes were statistically grouped by their similar place characteristics to determine if different types of communities suffered disparate amounts of mental health concerns (Golden and Earp 2012). The social ecological approach allows this research on mental health to go beyond the immediate patient to the broader environmental context (Golden and Earp 2012). This approach meshed well with the spatial techniques in medical geography and enabled public health concerns to be conceptualized differently with an emphasis on how place matters to mental health. This study also investigated which race/ethnic groups in Oklahoma are more prone to reported mental illness within these similar community environments.

Findings reinforced previous literature suggesting that areas classified as lower SES experienced poorer health outcomes (Kawachi and Berkman 2003; Evans 2003; Murali and Oyebode

2004; Diez Roux and Mair 2010; Halpern 2014). Specifically, this study found that areas with greater rates of poverty combined with community SES indicators like higher levels of unemployment, increased rates of uninsured, higher proportions female-headed households, large percentages of renters, lower levels of educational attainment, and reduced numbers of high income earning households may be environments that increase residents' vulnerability to poorer population mental health in the form of average PMHD and overall patient rates. Additionally, Hispanics were most likely to appear underserved while Native American consistently sought more treatment for mental health issues in Oklahoma. Importantly, the results point to areas and groups that need to be further investigated to learn more about what preventative programs could be put in place to better address the mental well-being of these populations. This has practical implications for the betterment of mental health in Oklahoma communities.

Article 2 Overview

The second article in this dissertation located zip codes with increased poor mental health measures including ODMHSAS patient rates, depression rates, other behavioral disorder rates, developmental issues, emotional disorders, and PMHD. This research employed global and local regression models to identify what social and economic factors are driving each of these poor mental health patterns throughout regions of the state. Unlike the first article that grouped zip codes with similar SES, this article focused on local patterns within each zip code through the use of GWR. These techniques were performed on zip codes throughout the state as well as separately for urban and rural zip codes.

Regression results for urban areas and rural areas revealed that the independent SES variables that significantly help explain mental health patterns in rural areas differ from urban locations. For example, in urban areas, the percent of the population with income over $100,000 was not present in any regression models, but in rural Oklahoma, areas with higher rates of developmental disorders and behavioral disorders were associated with areas of reduced proportions of residents earning over $100,000. Similarly, the percent of the population that was uninsured or unemployed added little understanding of poor mental health patterns in urban areas, yet increased the strength of several mental health regressions at the statewide and rural levels of analysis. There were also slight differences between Oklahoma City and Tulsa urban areas. Notably, the percent who are renting housing only added explanation to the depression rates, developmental disorder rates, and emotional disorder rates' regression models in the Tulsa area and did not contribute to mental health pattern explanations in Oklahoma City, rural Oklahoma, or at the statewide level.

Overall, these findings support the notion that indicators of low SES, including unemployment, lack of insurance, single female headed household, and housing tenure characteristics such as renting corresponded to areas with higher stress and identified them as possible contributors to poor mental health (Kawachi and Berkman 2003; Evans 2003). Moreover, this research offered important insight on how these relationships may vary in different settings. Mapping the results from GWR visibly illustrated for which zip codes the relationships are the strongest, thus pointing researchers, public health planners, and mental health practitioners to areas that would be prime places to target for further examination.

Oklahoma zip codes exhibit diverse place characteristics, therefore it is not surprising that there are differences in disease rates within these diverse places. Urban regressions offered significantly high levels of explanations for SES, demographic, and environmental characteristics related to poor mental health. Regressions failed to adequately explain these relationships within rural zip codes. Therefore, the characteristics that seem to be driving poor mental health in urban communities must be more closely assessed to identify measures to alleviate some of the stress that may contribute to mental distress. Rural areas, on the other hand, must be analyzed further to find if there are other community variables associated with poor mental health in these locations that this study did not capture or if it is an issue of lack of mental health service access or availability.

Article 3 Overview

The third article explores rural mental health patterns further. Previous research reveals that rural residents may have unique challenges and be particularly at risk for poor mental health (Human and Wasem, 1991; Roberts, Battaglia, and Epstein 1999; Mohatt et al. 2006; Smalley et al. 2010; Smalley and Warren 2012; Jensen and Mendenhall 2018). Specifically, this study concentrated on aspects, complications, and issues of rural classification innate to the of study rural mental health. Scholars emphasize that the way rurality is categorized can impact and alter the research results (Johnson-Webb et al. 1997; Philo, Parr, and Burns 2003; Wakerman 2004; Hart, Larson, and Lishner 2005; Coburn et al. 2007; Cromartie and Bucholtz, 2008). Thus, this classification demands consideration, and commonly accepted rural-urban classification schemes must be examined to determine if they are appropriate for the purpose of each study.

In this article, I constructed a spatially explicit rurality index (RI) that included remotely sensed land use land cover (LULC) data. The inclusion of LULC data can capture physical environmental aspects of remote and urbanized locations that traditional rural definitions may ignore. If different zip codes are included in rural or urban categories, this could impact how we interpret the intricate relationships between place characteristics and mental health issues in rural areas. Therefore, this new rural classification scheme was employed to learn more about statewide mental health patterns and their relationship with rurality. It was apparent that rural mental health patterns could not be clearly explained by place characteristics in article 2. Therefore, using an alternative way to classify rural areas that concentrates on more than just population density, as the predefined census rural-urban classifications used in article 2 did, can offer a broader perspective. GWR models of socioeconomic and demographic variables including the RI were performed on Oklahoma zip codes. These results were compared to the local GWR results using the census percent rural variable to ascertain if RI is a preferable measure. Although in this case RI only slightly improved explanatory power, the importance of this study is the critical attention to a more detailed definition of rurality and the inclusion of spatial variables in the index.

In conclusion, all three articles analyzed mental health through a spatial lens, and in doing so have placed an emphasis on how location may impact mental health. As Oppong and Harold (2009) explain, adverse societal and economic conditions do not affect all areas uniformly, thus some Oklahoma zip codes and community environments appear to be more vulnerable to poor mental health. These articles also served to highlight what place characteristics seem to be prompting poor mental health patterns. Understanding more about how place is entangled with mental illness can potentially shed light on more targeted approaches and offer insight into what preventative community-level measures can be taken to foster residents' psychological well-being throughout the state. Additionally, the methods that these articles propose could be adapted to analyze other areas in the U.S. for a broader impact. Consequently, examining mental health from a medical geographic perspective can offer a way to connect human health outcomes to their surrounding environments (Meade 2010). Our surroundings are the stage at which health behaviors are acted out and the place where health services and interventions are designed. Understanding that human health is situated within places is a crucial realization that can dramatically alter the way mental illness is evaluated and improve population mental health. In the future, the spatial aspects mental health and healthcare must be a continued focus for the betterment of Oklahoma communities and broader society.

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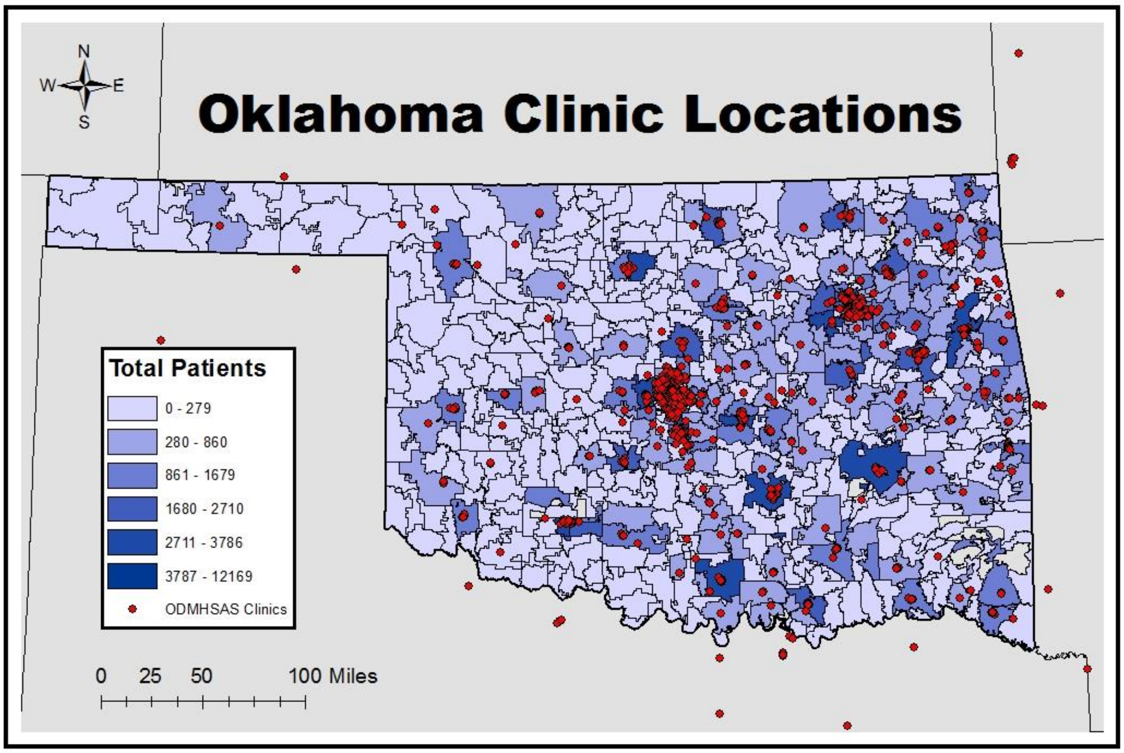
APPENDIX



ODMHSAS Affiliated Clinic Locations in Oklahoma Zip Codes

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