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NEIGHBORHOOD CHARACTERISTICS OF FOOD INSECURITY IMPACTING MENTAL HEALTH IN EAST TENNESSEE COMMUNITIES

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To the Graduate Council:

I am submitting herewith a dissertation written by Rochelle Alyssa Butler entitled "NEIGHBORHOOD CHARACTERISTICS OF FOOD INSECURITY IMPACTING MENTAL HEALTH IN EAST TENNESSEE COMMUNITIES." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Counselor Education.

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NEIGHBORHOOD CHARACTERISTICS OF FOOD INSECURITY IMPACTING MENTAL HEALTH IN TENNESSEE COMMUNITIES

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ABSTRACT

This study contributes to a growing body of research in counseling, public health, and psychology that examines how features within neighborhoods affect mental health. The environment in which their clients live directly affects services that counselors provide. Mental health discussions often center at the individual level, but mental health significantly impacts communities a whole. Therefore, the presence of mental health problems in individuals will affect the wider community at varying societal levels. Geographic information Systems, (GIS) will be used to determine which features of built environment associated food insecurity impact mental health and where the correlations between mental health and food insecurity are strongest. The proximity of features defining food insecurity will be used to identify areas that may be vulnerable to mental health issues. The study's research questions will examine conditions of the neighborhood's built food environment that impact mental health and in turn increase allostatic load. The hypotheses of this study assert that positive food choices and a healthy neighborhood food environment will have a positive linear relationship with mental health. The results of this study will increase the use of the geographic information systems within counseling research; inform counselors and policymakers the impact of social determinants on mental health and identify vulnerable geographic subgroups. Counselors and decision makers may choose to use information and findings from this study to develop population-specific interventions.

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CHAPTER 1: THE RESEARCH OBJECTIVE

Introduction

This chapter gives the reader an overview of this study; specifically, how the food environment of neighborhoods affects mental health. Social determinants of mental health will be defined for this study. The reader will also be introduced to the concept of allostatic load. The complex relationships between stress, physical and mental health will be defined through the concept of allostatic load. Discussion ensues on the impacts of the food environment on mental health. The resulting spatial features that affect mental health will be used to predict hot spots of mental health vulnerability. These features and variables will be discussed in detail. The history and definition of these construct will be presented as well as a framework for measuring and understanding the built environment through social determinants of mental health. A statement of the problem and purpose statement will lead to the research objectives and hypotheses for the study. Finally, limitations of the study will be discussed, and various key terms will be outlined for the reader.

Background

The built environment of the neighborhood can be a ‘wicked’ problem for individual health and learning (Taylor & McGlynn, 2009). The interrelated issues impacting positive community development involve elements of poverty, education, and crime (Taylor & McGlynn, 2009). However, neighborhoods that function in healthy productive manners provide protective factors for the individual community members (Taylor & McGlynn, 2009). Therefore, improving the neighborhood or community can be one of the most effective strategies to solve problems relating to individual health and learning.

As a result of research conducted by the World Health Organization (W.H.O.) and its Commission on the Social Determinants of Health, social conditions have a direct influence on health outcomes (Allen, Balfour, Bell, & Marmot, 2014; World Health Organization, 2011). Social determinants of health refer to social and environmental factors that influence individual health. Often, social determinants of health have more impact on an individual's health condition than traditional health services (Allen et al., 2014).

Within sociological research, Putnam and Bourdieu discussed social determinants of health long before W.H.O. identified social determinants of health. Putnam emphasizes how social networks and cohesion of social networks is crucial for healthy communities. Bourdieu emphasizes the resources of networks (Carpiano, 2006). According to Bourdieu, a network of relationships provides links to resources. For an individual to access these resources he/she must have access to the network containing the resources. Putnam also identifies social capital as being part of social networks, but he emphasizes the importance of community-focused networks. Putnam focuses more on the impact of social capitol within communities. Trust and reciprocity of trust form social networks within communities (Ziersch, 2005). Trust and the exchange of trusting expectations have a mutual benefit in developing social networks (Compton & Shim, 2015). Research on developing social capital leads to the research done on social determinants of health. Research on social determinants of health builds upon the relationship between social networks wihin the environment and includes other factors of how people live. Education, workplace conditions, safe living arrangements, and quality nutrition have an impact on social determinants of health within each community. The conditions in which we live impact not just the health of individuals but also of the community (World Health Organization, 2011).

Although there is plenty of research on the physical health outcomes of social determinants of health, there is far less research on the mental health outcomes of social determinants. Some research points to a two way relationship between mental and physical health where one influences the other (Allen et al., 2014). For example, researchers found that chronic stress causes depression via the same biologic pathways that link chronic stress to physical health. The chemistry of the brain controls hormonal responses to stress and influenced the nature of the relationship between stress and health (Hammen, 2005). This two-way relationship can be thought of as allostasis. Allostasis represents the body's adaptation to physical, psychosocial, and environmental stress. Allostasis load represents the long-term result of stress on the body which in turn, results in chronic illness (Logan & Barksdale, 2008).

Research has shown that the main social determinants of mental health are a lack social inclusion, a lack of safety and discrimination, a lack of economic resources within the community and food insecurity (Compton & Shim, 2015). Social inclusion gives people a sense of belonging and gives individuals resources to help them deal with stress. Social inclusion also refers to the availability of resources in the community that promotes trust and cooperation or social capital such as recreation centers, libraries or medical facilities. Safe communities also give individuals a sense of belonging and equitable access to social capital (Parasuraman & Shi, 2014; Strolin-Goltzman et al., 2012). People feel as if they have more control over their lives when they feel safe and valued in their community. Research shows that individuals experience positive mental health and well-being when they feel more control over their lives that comes when they feel safe (Allen et al., 2014; Compton & Shim, 2015; World Health Organization, 2011). Lack of access to economic resources often results in insecurities and poverty (Ziersch, Baum, Macdougall, & Putland, 2005). Therefore, it is difficult to have housing, food, clothing, transportation, and many other things we need to be healthy when economic resources are scarce or individuals are insecure about their economic future (Compton & Shim, 2015).

Although there are many neighborhood variables that affect mental health, the impact of the food environment within a neighborhood on mental health will be the focus of this research. The independent variables chosen for this study will represent features of the built environment that influence the food and economic features of the built environment within neighborhoods. The food and economic variables are part of the social determinants of mental health. Dependent variables will be a measurement of mental health. Since mental health is one factor influencing allostatic load, the allostatic load of individuals is a latent construct within this study.

Because there is often a reciprocal relationship between mental health and social determinants, this study hypothesizes that mental health increases with an increase in positive social determinants of mental health such as food security. Decreased mental health often leads to reduced income and employment, food insecurity, and social isolation that then cycles back to entrenching individuals in poverty and increases the risk of mental disorders (Allen et al., 2014; Compton & Shim, 2015). Therefore, neighborhood features of food insecurity that influence allostatic load measures of mental health will be used to determine areas of mental health vulnerability within a neighborhood.

Theoretical Framework

This research will attempt to understand the complex relationships between features of the built environment within neighborhoods and the health of the community. The focus will be on understanding the impact of specific features of the built environment within the community on mental health. Research regarding the effects of a neighborhood on health and social outcomes has a relatively long history (Oakes, 2004). Ernest Burgess and Robert Park developed the concentric zone theory in the 1920s to explain the divisions of communities based on socioeconomic factors in and out of the city of Chicago. It was the first theory explaining how social groups organized within an urban area. According to the theory, the communities or social groups extend outward from the central business zone of the city. Subsequently, the study finds a relationship between how far one lives from the central business district and economic status. This study will use concentric zones but consider the school as the bullseye to study community or neighboring effects of the population surrounding the school (Anderson & Egeland, 1961; Ernest W Burgess, 1928).

In this research, a public health expose (PHE) paradigm will be used as a theoretical framework. A PHE paradigm provides a conceptual framework to identify and compare relationships between individual health characteristics and health disparities at population levels across communities and over time (Paul D Juarez et al., 2014). The health of the environment links closely to that of individuals (De Silva, McKenzie, Harpham, & Huttly, 2005). A PHE paradigm can address the environmental impacts on individual health. The purpose of an expose is to identify population risk factors in epidemiological studies. Epidemiology identifies patterns and effects of health and diseases in populations. The purpose of a PHE paradigm is to be able to generalize observations from a group of individuals to the entire population. These generalizations can be used for policy and public health choices and decisions (Paul D Juarez et al., 2014).

When making community level decisions, GIS technology, and spatial modeling can help research and community members visualize the environmental factors impacting the community (Barnard & Hu, 2005; McMaster, Leitner, & Sheppard, 1997). Anselin, Syabri, and Kho (2006) state that empirical spatial data analysis that includes mapping and geo-visualization, exploration of data; autocorrelation analysis and/or spatial regression provide visualizations and explanations of patterns in geographic data in a spatially integrated manner. Using GIS and spatial modeling could help counselors identify hotspots of mental health vulnerability and target counseling interventions appropriately within the community. The approach has implications for health care and research but also for providers (Barnard & Hu, 2005; Jung & Elwood, 2010) as pictured in Figure 1.

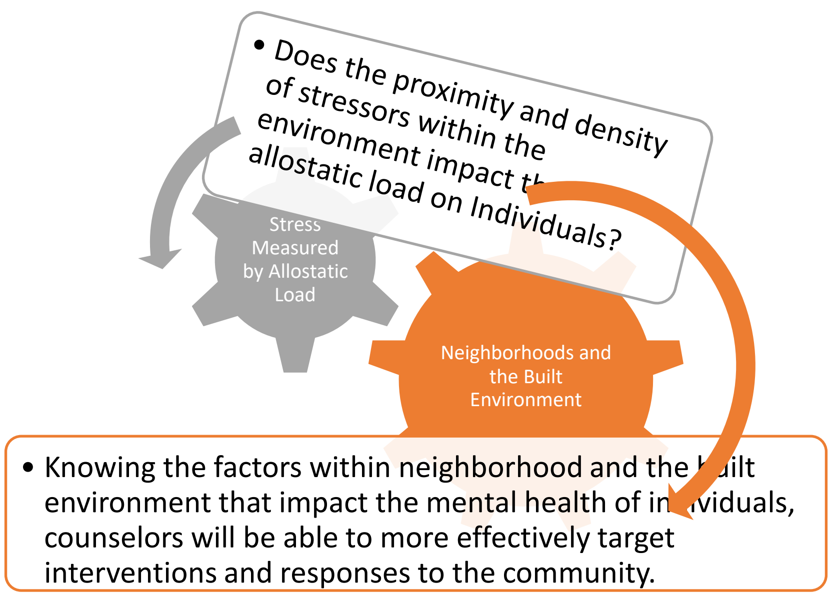

Figure 1: The cyclical action of stress, social determinants of health and allostatic load

Statement of the Problem

Although the promotion of mental wellness and the identification of mental illness is a worthy goal, treatment will be inadequate if we as counselors believe that treatment ends with the clients served. Unless counselors are concerned with the impact that treatment has on the society in which the individual interacts with, the endeavors with the client alone are insufficient. “Unless fundamental change occurs within how our client interacts with his neighborhood, school, environment, culture, and religious and social institutions, our work with individuals is destined to be, at best, only partially successful" (Goodman et al., 2004).

Prilleltensky (1999) articulates that mental health issues do not exist in isolation. Mental health and individual theories of psychology show that an individual's support system and the environment influence an individual's sense well-being. For counseling interventions to be effective, counselors need to engage their clients in treatment. Counseling curriculum teaches counselors that clients own their situation and that they are responsible for their choices. However, macro-level systems influence the nature of the micro-level interaction (Cline, 2003). A combined ownership of the treatment engagement problem at the micro, mezzo, and macro level would be most beneficial to counseling clients. It is important for counselors to recognize the impact that environmental factors have in influencing individuals' well-being. This study will emphasize the importance of the neighborhood and macro-level influences on individual client well-being.

A preliminary analysis of data from the Collaborative Psychiatric Epidemiology Surveys (CPES) (2001-2003) indicates that self-disclosed mental health scores correlate with whether or not the individual saw a professional counselor as demonstrated in Figure 2.

A regression analysis was conducted to see if subjective mental health had a linear relationship with counselor visits for mental health related issues. Mental health rating was entered into the model as dependent upon a counselor visit. The model showed that visits to counselor significantly correlated with subjective mental health. However, the effect size is very small and only predicts 1.4% of the variance in the model. F (1, 1147) = 15.74, p < .001. This leads to the question; what other factors may contribute to mental health?

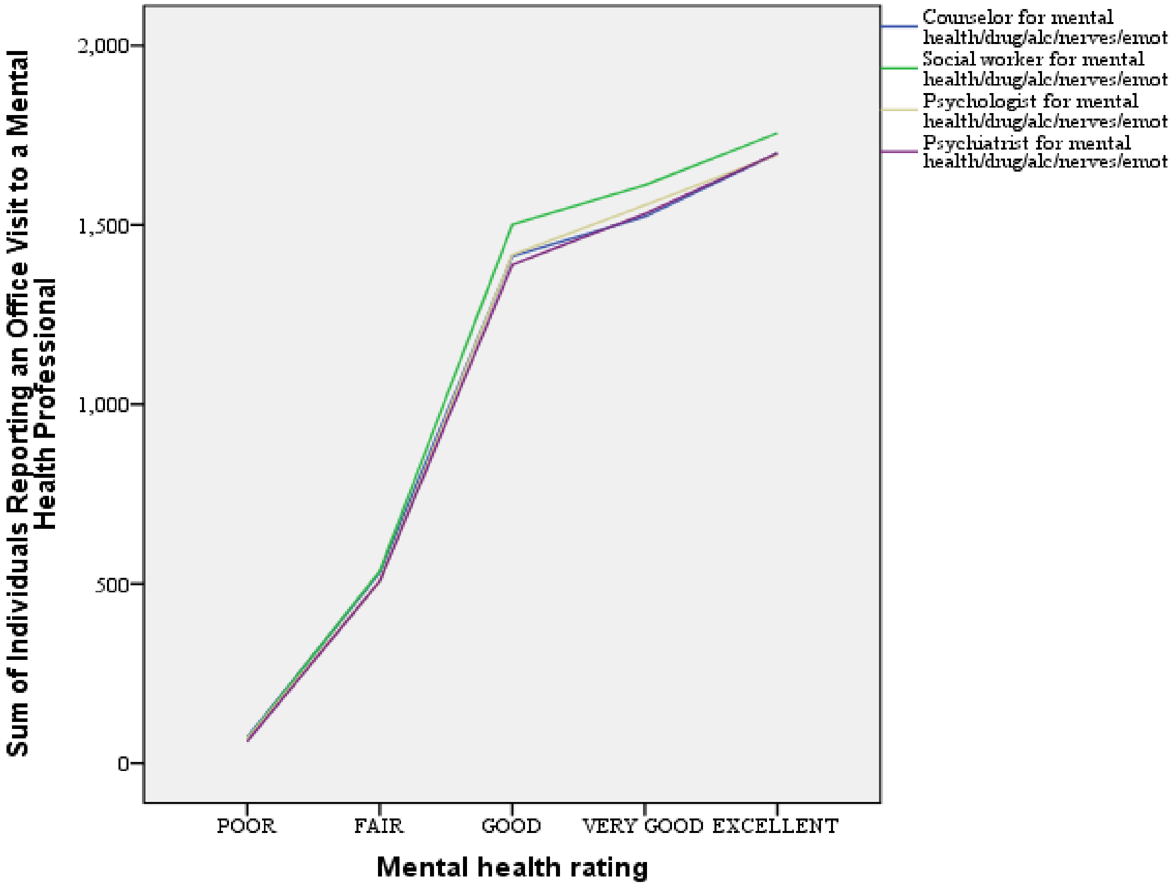

Figure 2: The impact of professional mental health treatment on mental health rating

Although counselors can and should encourage people in the communities they serve to receive mental health care, what can counselors do to promote mental wellbeing outside of the counseling session? Can counselors advocate for stronger neighborhoods to improve the mental wellbeing of all members of the community their serve? To advocate for stronger mental health, counselors need to be aware of what particular neighborhood factors influence the mental health of their community – one of which is food insecurity. Social determinants of mental health articulate food insecurity as one factor influencing the health of individuals.

The social determinants of mental health will be used in this study as a starting point or a theoretical framework to help gauge and determine if there are other community factors or features that can improve the health of the community. Because not all social determinants of mental health could be feasibly studied for this dissertation, this study will focus on one component of the social determinants of mental health – food insecurity within communities and the economic factors influencing food insecurity. This leads to the research questions for this study.

Research Questions

Research Question 1: Is there a negative relationship between purchases of fruits and vegetables within a community and anti-depressant prescription drug use within Tennessee?

H0: There will not be a relationship between purchases of fruits and vegetables within a community and anti-depressant prescription drug use within Tennessee.

H1: There will be a negative relationship between the purchase of fruits and vegetables and mental health.

Research Question 2: Is there a negative correlation between per capita income spent on fruits and vegetables and the use of anti-depressant medication?

H0: There will not be a significant relationship between per capita income spent on fruits and vegetables and the use of anti-depressant medication

H1: There will be a negative relationship between the purchase of fruits and vegetables and mental health.

Research Question 3: Will the density of fast-food restaurants in a neighborhood predict the amount of per capita income spent on fresh fruits and vegetables?

H0: The density of fast-food restaurants in a neighborhood will be unable to predict the amount of per capita income spent on fruits and vegetables

H1: As the number of fast food restaurants in neighborhood increases, the amount of income spent on fruits and vegetables decreases.

Research Question 4: Will the density of grocery stores in a neighborhood predict the amount of income spent on fresh fruits and vegetables?

H0: The density of grocery stores in a neighborhood will be unable to predict the amount of income spent on fresh fruit and vegetables

H1: As the number of grocery stores in an area increases the number of fresh fruit and vegetable purchases increases.

Research Question 5: Will the density of fast-food restaurants in a neighborhood predict the number of people in the community who use a prescription drug for depression?

H0: The density of fast-food restaurants in a neighborhood will be unable to predict the number of people in the community who use a prescription drug for depression.

H1: As the number of fast-food restaurants in a neighborhood increases; the number of people, who use prescription drugs for depression will increase

Research Question 6: Will the density of grocery stores in a neighborhood predict the number of people who use prescription drugs for depression?

H0: The density of grocery stores in a neighborhood will be unable to predict the number of people who use prescription drugs for depression.

H1: As the number of grocery stores increases, the number of people who use prescription drugs for depression decreases.

Significance of Research Question

Often organizations rely on empirical research to make policy changes. Once a model for this research has been satisfactorily built, adjusted, and its output checked; the results can be used by counselors to inform their practice and services provided. It can also give mental health agencies information in risk analyses and decision-making. This work will expand and synthesize current research on social determinants of mental health for local communities in East Tennessee and give policymakers, community members, and mental health clinicians a broader understanding of how the built environment and mental health are interconnected and provide a decision-making tool for mental health interventions.

Method

To answer the research questions, variables will be chosen and operationalized that represent mental health, communities, and the food environment. Subsequently, multiple analyses will be employed. Although this study will use geocoded databases of variables, each research question will require a series of steps and methods. The following section will outline the method for each research question.

Research Objectives

This dissertation will examine the existence and significance of spatial dependencies between neighborhood characteristics and social determinants of mental health. The objectives are to find the associations between mental health and neighborhood characteristics of food insecurity. By using a dependent variable that measures mental wellness within communities and independent variables that measure neighborhood features, a prediction model can be formulated. Mental wellness within communities can be predicted from the neighborhood features. These predictions inform counselors of types of services and interventions a community may need. Finally, the last objective will be to examine spatial variability in anxiety and depression medication use, possible predictors and the relationships between them. These objectives will demonstrate the value of spatial analysis in the counseling field.

GIS technology can be used to build models is to test relationships, find correlations, build models; test hypothesizes and illustrates statistical predictions. Statistical analyses can answer "if" a relationship occurs while GIS helps define "where" the relationship occurs. Statistics and GIS may work in tandem with the exploratory function of mapping spatial data if new questions arise from the research process. Therefore, this study will provide mental health researchers, clinicians, and policy makers with tools and information that can potentially lead to the development of mental health interventions or become a catalyst for policy changes.

Limitations of the Study

Neighborhood measures are often an aggregate measure. Because aggregate measures are a combination of factors that combine multiple socioeconomic characteristics of community members, it is difficult to tease out the factors within individual cases that are specifically related to place of residence. The extent to which aggregated neighborhood construct variables represent each specific individual- within the aggregated community cannot be validated nor viewed as reliable since aggregated data removes individual variability (McCoy, Johnston, & institute, 2001). Therefore, one cannot make conclusions about individuals based on aggregated data. Aggregated data may also depict inaccurate measurements of neighborhood health if neighborhood socioeconomic characteristics do not truly represent the neighborhood construct of interest (Law & Collins, 2013).

Despite the limitations of aggregated data, these early neighborhood studies using census-defined areas have laid the groundwork and provided justification for more detailed and complex studies of neighborhood health effects (Paul D Juarez et al., 2014). By building upon the previous literature, new studies have improved the methodological sophistication and made it easier to tease out and identify the impact that the built environment has on health (Law & Collins, 2013). Recent environmental studies have been designed with more attention to measurement of aggregated data and specific neighborhood attributes. Additionally, more detailed and sophisticated analyses have been used in recent studies (A. V. Diez Roux & Mair, 2010).

Limitations that come from using geo-coded data include spatial autocorrelation and spatial uncertainty within the data (Goodchild, Haining, & Wise, 1992; Haining, 2003). Spatial autocorrelation occurs when the data in neighboring districts is too similar. Although one assumption of spatial analysis is that things that are closer to each other are more similar. However, if the data between nearby neighborhoods is too similar, there is not independence observations within the data set. Most statistical tests assume that the data is a sample of independent observations, meaning that the value of one observation does not affect the value of other observations. Non-independent observations lead to too many false positives in statistical testing (Tabachnick, 2013). Researchers have cited that geospatial data can have issues with spatial coding and the time-based location. Additionally, geospatial data collection protocols and policies lack standardization, and social constructs are not clearly defined (Paul D Juarez et al., 2014). The authors encourage researchers to develop a common informatics structure that supports data sharing at the same time de-identifies personal data. Additionally, the authors encourage protocols for the standardization of data dictionaries and protocols for using restricted data.

This study uses data taken from the ESRI data repository. Census data, ACS data, consumer-spending data, market potential data and business location data are geocoded and stored in the ESRI data repository. The geocoded data from national surveys will be used to define the food consumption, food environment, and mental health constructs. These large national surveys are subject to sampling and non-sampling errors. According to the BLS (2015), differences in the interpretation of questions, the accuracy of the information provided, and mistakes in coding the survey data cause sampling and non-sampling errors. The full extent of the nonsampling errors in the data is unknown. Sampling errors can occur in the data because the data for the surveys used are collected from a sample of the population as opposed to the entire population. Limitations of this study will be discussed in detail in Chapter 2.

Laws enacted to ensure patient confidentiality limit research on public health issues within neighborhoods. HIPPA, The Health Insurance Portability and Accountability Act of 1996 currently prohibits data collected by the National Center for Health Statistics from being displayed in any way that allows individuals to be identified. When research defines very small clusters of living units as neighborhoods, the identity of individuals within that cluster is revealed. Subsequently, HIPPA laws protecting individual identity are violated. Unfortunately, there is not a standardized measurement of small neighborhoods or narrowly defined data. Therefore, many data sets do not include important data related to health. Therefore, it is difficult to study health issues when the data cannot be obtained. To produce quality health related research, more metrics or definitions of neighborhoods need to be developed so research can be completed without violating HIPPA laws (Kulynych & Korn, 2003).

Definition of Key Terms

Definitions of key terms are provided for purposes of having a basic understanding of some of the terminology to be used in the study:

American Community Survey (ACS): - Data on income, education, employment, language, migration, citizenship, marital status, and housing characteristics is obtained from the ACS. The ACS collects and produces population and housing information every year and represents a continuous measurement of population data.

Allostatic load: Allostasis refers to the body's processes that to adapt to stressors. Theories of allostatic load suggest a clear biological pathway between chronic stress and heart disease, obesity and mental health issues.

ArcGIS: A collection of GIS software products built upon a geodatabase that provides a platform for computer based spatial analysis, data management, and mapping. It is a software system for working with maps and geographic information.

Built Environment: The built environment includes the fabricated structures that make up the surroundings. The built environment includes places, spaces, environment conditions created or modified by people. The built environment interacts with the social environment and then affects our health and mental health.

Choropleth Thematic Map: A map which displays georeferenced data with color or symbols defined by specific values. Different colors, shapes and symbols are often used to represent different variations of the variable.

Community: The community defined for this study will be the neighborhood surrounding the elementary school. The people who live within the community defined by the elementary school boundary shape file share values and interactions defined by the school.

Consumer Expenditure Survey (CES): A survey that collects data on the buying habits of American consumers. The data in this survey includes information on spending habits, income, households and the consumer unit (families and individual) characteristics. The U.S. Census Bureau collects the data from the Bureau of Labor Statistics. It is the only Federal survey providing information on consumers' expenditures and incomes within society.

Consumer Expenditure (CEX) data: This is a comprehensive database, developed by ESRI designed to provide data on household expenditures within specific geographic locations. The data combines the latest Consumer Expenditure Surveys (CES) data from the Bureau of Labor Statistics and ESRI's Tapestry Segmentation data to give a picture of specific household expenditures in geographic locations. Data is reported by product or service and includes total expenditures as well as average spending per household.

ESRI: (Environmental Systems Research Institute) ESRI is a developer of geographic information systems (GIS) software. The company produces software that will plot addresses, demographic information, and other geo-coded data. The company was founded in 1969 by Jack and Laura Dangermond (McCoy et al., 2001).

GIS Database: A GIS database is a computer based integration of mapping systems that stores geographically referenced data. Georeferenced data that can be sorted, managed and stored as a group but also be analyzed as individual units. A GIS database includes data about the spatial locations and shapes of geographic features recorded as points, lines, or areas and their attributes. The data also provides a map for display and visual analysis.

Margin of Error (MOE): A measure of the variability within the population estimate due to sampling error. The Census Bureau reports ACS data with a margin of error.

Per capita income: Average income for individuals within a household. Per capita income is calculated from the aggregate income of persons 15 years and older within each household and divided amongst all the household members.

Social Determinants of Health: Environmental and social conditions that collectively impact individual health. The community into which people are born into, live, work, and age include various social determinants of health. However, the local environment is shaped by a wider set of environment forces which include economics, social policies and politics within the broader sense of community. The social determinants of health are mostly responsible for health inequities.

Social Determinants of Mental Health: The social and economic conditions that impact and influence individual mental health risk.

Summary

The primary purpose of this study will validate the idea that the proximity of social determinants of mental health influences the mental wellness and overall allostatic load within a community. Food insecurity, as one of the social determinants of mental health, will be related to the mental health of communities. The hypothesis purports that healthy food choices and healthy food environments correlate positively with positive mental health. Communities with significantly high instances of mental illness and unhealthy food environments correlate and could be considered communities that need specific counseling interventions and policies. This study will present potential interventions for counselors and policy makers related to the findings. A literature review focused on social determinants of mental health, allostatic load, spatial dependencies, and inferential geospatial statistics will follow. Chapter 3 will present the research methodology used in the proposed study with sections focused on the research problem and purpose, research questions and hypotheses, data collection, database construction, data cleaning, and inferential analyses.

CHAPTER 2: LITERATURE REVIEW

Introduction

This chapter will present the existing literature on the relationships between social determinants of mental health and allostatic load. The built environment of the neighborhood will be discussed focusing on the food environment and food choices within the neighborhood boundaries. Subsequently, a discussion will ensue on how the built environment affects mental health within communities. Next, a review of inferential statistics will be presented which will cover the use of regression analysis, correlations, the use of aggregated data, and the use GIS data and mapping systems in research.

Historical Context of Neighborhood Research

Typically, counselors assess mental health or well-being at the individual level. However, many studies indicate that communities have an impact on the mental health of individuals (Baker, 1974; M. Bronfenbrenner, 1970; U. Bronfenbrenner, 1974). For example, the ‘‘Chicago School’’ researchers found that the decay of physical structures in neighborhoods impacted individual mental health problems and environment impacts behavior (Ernest Watson Burgess, 1923; Ernest W Burgess, 1928). Researchers Faris and Dunham specifically noted that a relationship exists between psychosis and the ecological structure of the city (Faris & Dunham, 1939).

Neighborhood research has developed from varying disciplines. Disciplines studying neighborhoods with the intent of improving the individual’s quality of life include sociology, geography, psychology, and social work. Additionally, other academic disciplines study neighborhoods with a broader scope or intent. Such fields may include business and marketing or history. Overall, most these fields have some interest in understanding how neighborhoods affect the individuals that reside within them. Examples include: Social Learning Theory

(Bandura & McClelland, 1977); Theories of Social Capital by Bourdieu and Putnam (Carpiano, 2006); the Concentric Zone Theory; (Ernest W Burgess, 1928); and the Ecological Model by (U. Bronfenbrenner, 1974). Additionally, the theories within social and behavioral sciences are intersecting with theories in public health and epidemiology (Glass & McAtee, 2006).

Since many different fields have demonstrated a research interest in neighborhood effects, a cross-disciplinary approach has emerged. Although cross-disciplinary approaches deepen and enhance understanding of neighborhood effects, it also complicates this area of study. Specifically, defining and applying theoretical approaches to neighborhood research has become complicated by integrating fields of study. It seems that a good starting point to understand this complexity is to apply a broad interpretation of the ecological approach (Faris & Dunham, 1939; Openshaw, 1984; Robinson, 2009).

The ecological perspective provides the researcher with a broad perspective of a neighborhood (Robinson, 2009). Within the ecological perspective, one is looking beyond the individual and beyond the small cluster or micro-behaviors to understand behavior from a larger vantage point or a more distant perspective (Bronfenbrenner, 1979). A range of theoretical approaches from different disciplines has provided an umbrella of conceptualization for neighborhood research (A. V. Diez Roux & Mair, 2010; Elwood & Leitner, 1998; Roy, Hughes, & Yoshikawa, 2012; Sampson & Raudenbush, 1999). These theoretical approaches view neighborhoods from different perspectives or different lenses of vision. The view of the neighborhood viewed through the lens of as functionalist compares roles and jobs within a neighborhood or social attributes. A city planner looks at the neighborhood as a compilation of structures, pathways, and intersections. The neighborhood viewed through the lens of a social worker may see how social attributes contribute to social disorganization. The lens of a sociologist may study class conflict or the culture of poverty. A public health worker may look at the spread of disease within the community and healthy living strategies within a community. Finally, the ecological lens may look at the interactions of systems within a neighborhood and view the neighborhood from a much broader perspective. Although many views of the neighborhood are specific and give a fine-grained picture of neighborhood interactions, they give the ecological researcher more detailed pictures of the systems in which individuals reside (U. Bronfenbrenner, 1974). Small neighborhood factors and changes can often have a broad impact on the systems within the neighborhood. Societal variables and factors outside the neighborhood also directly impact the neighborhood and systems within the neighborhood. The national economy, world events, and public policies will impact individuals, structures, and groups within neighborhoods (Robinson, 2009).

The ecological perspective encourages researchers to consider communities and neighborhoods as impactful on individual's state of mind and well-being. Subsequently, various types of social science researchers have undertaken studies to determine the relationship or impact that neighborhoods have on community behaviors and outcomes. Through various types of research and theoretical perspectives, communities are often defined socially and spatially different. Furthermore, the focus of the study is often different depending on the theoretical perspective and discipline. Studies may focus on interactions between individuals in the community, social dynamics, or focus on structural or organizational components (Bandura & McClelland, 1977; M. Bronfenbrenner, 1970; U. Bronfenbrenner, 1974; Ernest Watson Burgess, 1923; Ernest W Burgess, 1928).

Defining Neighborhood Used for this Study

Burton, Price-Spratlen, and Spencer (1997) review neighborhood measurement methods and discuss the pros and cons of measuring neighborhoods using different definitions. The authors found that within the body of literature, neighborhoods tend to be conceptualized as sites, networks, or cultures of people. The authors suggest that future studies should consider the objective and subjective nature of neighborhoods. Neighborhoods defined from the physical address perspective (census tract) may pose a limitation for certain studies. Additionally, the utility of viewing individuals and neighborhoods as separate and independent systems limits the types of relationships discovered within the findings. Furthermore, the importance of neighborhood processes and changes over time can provide neighborhood studies with a rich source of data.

Coulton, Korbin, Chan, and Su (2001) researched several definitions of neighborhood units and methods to measure neighborhoods. Researchers asked residents to draw maps of their community, and then the researchers compared those results with the census definitions of neighborhoods. The maps drawn by the residents were remarkably different from census-defined boundaries. The definition of community defined by the residents not only covered different geography but produced different social indicator values. However, not all the residents could agree on where their community boundaries started and stopped. This study suggests that researcher defined neighborhood boundaries could be a possible source of bias when studying neighborhood variables (Coulton et al., 2001). Furthermore, people who live in suburbs tend to see neighborhoods existing in larger and clearly defined boundaries than city residents define their neighborhoods (Haney & Knowles, 1978). Therefore, defining a neighborhood based on resident perceptions may not be accurate due to variances in individual perceptions (Coulton et al., 2001).

Previous studies, often defined neighborhoods by census tracts and government-defined boundaries due to convenience and accessibility (Ming Wen & Kowaleski-Jones, 2012). Census tracts are small statistical sections of a county or geographic area that remain the same over a long time so researchers can make statistical comparisons (A. V. Diez Roux & Mair, 2010). Census tracts do not take into account boundaries or behaviors of different social groups and many research studies assume that the elements associated with one's census tract are the main influence on the community or neighborhood (Roy et al., 2012). However, relying on census tracts to understand communities ignores the impact of social relationships within the community (Coulton et al., 2001; Openshaw, 1984). Consider an individual who lives in a geographic census tract whose average demographics include above average income, subdivision living arrangements on large tracts of land, and access to public parks and recreation facilities. This same census tract may include pockets of neighborhoods next to the large subdivision that has lower housing quality, lower average household income and residents who are experiencing transportation issues. Although the same census tract represents both neighborhoods, it is unlikely that both sets of individuals are accurately represented and defined by the census tract data. Thus, one objective of this study is to define neighborhoods by factors which unite the community – such as an elementary school (Roy et al., 2012).

Neighborhood Context of Schools

This study defines the neighborhood to be studied as the school community. Schools are organized communities with a system of shared values (Bryk & Driscoll, 1988). Bird and Little (1986) describe these shared values as “norms of schooling” Norms taught in school provide the framework civility, interaction, and learning within the community. Schools are central to the community and provide the fabric for community interactions and education (Gruenewald, 2003). Within this study, multiple levels of data will be aggregated and compiled for a neighborhood defined by the elementary school district boundaries. This method moves away from treating schools as spatially independent contextual components of a community

(McMaster et al., 1997). Schools and communities unite a neighborhood (Bryk & Driscoll, 1988). These two entities connect and provide multiple layers of supports for all its members its members. The unity seen between the two entities serves as the basis for the definition of a community school that is a place and partnership between resources and individuals (Taylor & McGlynn, 2009).

Neighborhood Health

Previous literature and research revealed that the SES status of neighborhood communities greatly impacts the health status of individuals within the community (Robert, 1998; Ross & Mirowsky, 2001). Studies on neighborhoods indicate that neighborhoods impact heart disease; (Everson-Rose & Lewis, 2005; Mobley et al., 2006; Roux, 2003); diabetes (Ernst, Olson, Pinel, Lam, & Christie, 2006; Rocchini, 2002); obesity (Frank, Andresen, & Schmid, 2004; Giles-Corti, Macintyre, Clarkson, Pikora, & Donovan, 2003) and mental health (M. Wen, Hawkley, & Cacioppo, 2006). However, beyond economic and demographic variables, few studies have examined the additional neighborhood factors or stressors and their cumulative impacts on the health of the community or allostatic load (Ana V Diez Roux, 2001; Duncan & Aber, 1997).

Measuring the health effects of specific neighborhood characteristics is complicated because many of these dimensions are interrelated (Barnard & Hu, 2005; De Silva et al., 2005). There is bound to be multicollinearity between neighborhood variables and interaction effects. Therefore, a crucial issue in the examination of neighborhood effects is to study how individual-level variables are incorporated into conceptual models of the neighborhood (P. D. Juarez et al., 2014). The most common criticism of postulated neighborhood effects is that they result from confounding or confusing individual-level variables.

Society sees disease and illness as an individual experience (Paul D Juarez et al., 2014). However, the behaviors of the individuals collectively demonstrate the impact of the disease on the community and the environment (A. V. Diez Roux & Mair, 2010). Stressors are environmental factors that often have a reciprocal relationship with disease. Environmental stressors can cause diseases and diseases can cause stress within the environment (Flier, Underhill, & McEwen, 1998). Stressors can impact the body and make individuals more susceptible to diseases, and lack of stressors can protect the body (Mirowsky & Ross, 1986). The impact of stress on the body is what researchers have defined as allostatic load (Logan & Barksdale, 2008; Bruce S. McEwen, 2003). This next section will define the construct of allostatic load and the relationship between allostatic load and biological symptoms of mental health. It will also discuss the environmental stressors that affect allostatic load. These environmental stressors are often referred to as social determinants of health (Allen et al., 2014; Compton & Shim, 2015; World Health Organization, 2011).

Allostatic Load

Allostasis refers to the body's processes that help it adapt to stressors (Danese & McEwen, 2012; Logan & Barksdale, 2008; Bruce S. McEwen, 2003). Although stress can be good for the body, too much stress will have taxing effects on the body (Goymann & Wingfield, 2004). During periods of stress, the body tries to remain stable and consistent (Logan & Barksdale, 2008; Bruce S. McEwen, 2003). For the body to remain stable, it releases different hormones that help the body maintain a consistent heartbeat and breathing patterns (Danese & McEwen, 2012). These hormones include adrenaline, cortisol, and glucocorticoids (Bruce S McEwen, 2008). However, the release of these chemicals in the body over long periods contributes to an overload on the body and more wear and tear on the body and brain as it works overtime to try to maintain normal functioning (Danese & McEwen, 2012; Logan & Barksdale, 2008). Specific health outcomes related to allostatic load include depression, anxiety, high blood pressure, heart disease, arteriosclerosis, diabetes, and obesity (Hammen, 2005; Bruce S McEwen, 2008). The next section of this paper will focus specifically on allostatic load related to depression and stress.

Stress impairs the hippocampus region of the brain, which is responsible for verbal and contextual memory (Flier et al., 1998; Hammen, 2005). Subsequently, impaired memory leads to emotional changes and instabilities over time (Bruce S. McEwen, 2003). Since the hippocampus is also responsible for regulating the stress response itself; if the hippocampus becomes impaired due to chronic stress exposure, it is subsequently less able to regulate the stress response, suggesting a mechanism by which individual stressors become allostatic load (Bruce S McEwen, 2008). Higher or sustained stress can have negative consequences on the entire body but also impacts feelings related to depression and anxiety (Flier et al., 1998; Pachter & Coll, 2009). It can also lead to further risky behaviors such as alcohol or drug use, poor eating and unusual sleeping patterns (Barnes et al., 2008). Chronic exposure to stress can result in chronic health and mental health conditions (Lee & Ferraro, 2009).

Measures Allostatic Load

This next section will discuss how allostatic load manifests itself in symptoms of individuals within the community. The impact of allostatic load on the body can be seen in various biological systems that influence health (Danese & McEwen, 2012; Bruce S. McEwen, 2003). Because the systems in the body are strongly connected, stimulation of one allostatic system commonly triggers responses in all allostatic systems (Danese & McEwen, 2012). Three distinct and separate systems of the body often exhibit outward symptoms when allostatic load measures are high (Compas, 2006; Sterling, 2012). The circulatory system often exhibits heart disease symptoms and relating conditions of high blood pressure and high cholesterol (Logan &

Barksdale, 2008). The digestive system shows signs of allostatic load in the form of diabetes, obesity, and digestive issues (Crumeyrolle-Arias et al., 2014). High allostatic load impacts the mental health system within individuals and causes signs of chronic depression or anxiety (Goymann & Wingfield, 2004; Bruce S. McEwen, 2003).

Chronic heart disease and Hypertension

Cardiovascular disease is the largest public health and the most prominent health condition implicated in a person's ability to perform tasks of daily living (Caskie et al., 2010). It is often comorbid in patients with mood and anxiety disorders (Gianaros et al., 2009). Individuals exposed to chronic stressors are more likely to experience cardiovascular disease (Bruce S McEwen, 2008). Stress-related events may cause parts of the brain to be hyperactive and increase in inflammation throughout the body. These metabolic changes contribute to atherosclerosis progression and stimulate the development of cardiovascular disease (Danese & McEwen, 2012; Gianaros et al., 2009).

High blood pressure affects one-third of all US citizens (Centers for Disease Control and Prevention 2011). Chronic stress exposure is a risk factor for hypertension. However, the specific mechanism by which stress impacts high blood pressure is not well understood in the medical field. Research has shown that chronic stress exposure leads to sustained high blood pressure and is almost certainly related to allostatic load (Spruill 2010).

Cholesterol levels and blood pressure measurements are other ways we can measure the body's reaction to stress (Moloney, Desbonnet, Clarke, Dinan, & Cryan, 2014). Our body reacts to stress by releasing catecholamine to adjust heart rate and blood pressure when necessary (Logan & Barksdale, 2008). Nevertheless, repeated surges or changes to blood pressure in the body due to stress accelerates atherosclerosis and produces Type II diabetes (Goymann & Wingfield, 2004). The interaction of these two systems and the results also impact allostatic load. (Bruce S McEwen, 2008) Therefore, the frequency of these variables within each community will be used to measure the impact of heart disease on allostatic load.

Overweight/obesity

The outcome of chronic stress exposure is often an overweight body and obesity, particularly abdominal obesity (Bjorntorp 1987; McEwen 1998). Stress and obesity are further linked because stress may change both eating and physical activity behaviors. The release of glucocorticoids as the result of stress exposure creates a preference for calorie-dense foods (Goymann & Wingfield, 2004). Unhealthy eating is, therefore, a secondary part of the biologic stress response (Dallman et al. 2004). A review of the literature and meta-analysis of longitudinal studies by Wardle et al. (2010) concludes that there is a relationship between chronic stress exposure and central obesity. Burdette and Hill (2008) present evidence that perceived neighborhood disorder positively correlates with obesity among adults. Psychological stress mediates the relationship between obesity and perceived neighborhood disorder(Black & Macinko, 2008). Many studies using obesity as an outcome have suggested that poor food and/or physical activity environments are more likely in disadvantaged neighborhoods(Franco, Roux, Glass, Caballero, & Brancati, 2008; Galvez et al., 2009; Morland, Wing, Roux, & Poole, 2002; Powell, Chaloupka, & Bao, 2007; Roy et al., 2012).

Mental Illness

According to the World Health Organization (W.H.O.), depression is the leading cause of disability and the fourth leading contributor to the global burden of disease (Chisholm, 2006). Over the lifetime, 16.6% of all adults will experience a depressive episode (Kessler et al. 2005). Chronic and acute stress exposures correlate with depressive symptoms and major depression among adults and adolescents (Hammen 2005). Chronic stress increases depression via the same biologic pathways that link chronic stress to physical health. The hormonal responses within the body to stress affect the chemistry of the brain, which triggers anxiety and depression (Hammen 2005).

Stress impairs the hippocampus region of the brain, which is responsible for verbal and contextual memory (McEwen 1998). The impaired memory within individuals leads to emotional disturbances over time (Gerritsen et al., 2011; Toomey & Ecker, 2009). The hippocampus is also responsible for regulating the stress response itself; if the hippocampus becomes impaired due to chronic stress exposure, it might become less able to regulate the stress response, suggesting a mechanism by which individual stressors become allostatic load (McEwen 1998). Because the causal relationship between stress exposure and depression is relatively well known, it is an important outcome for the study of neighborhoods as a source of chronic stress. Graff-Guerrero, Gonzalez-Olvera, Mendoza-Espinosa, Vaugier, and Garcia-Reyna (2004) indicate that physiological changes in body chemistry that cause changes in sleeping patterns, eating patterns, concentration, memory, muscle tension, psychomotor activities would give rise to a diagnosis of a depressive mood disorder or anxiety. Because stress affects many systems in the body and the allostatic load on the body, health and mental health are always affecting the other (Danese & McEwen, 2012; Logan & Barksdale, 2008). One cannot talk about the impact of mental health without talking about how it affects physical health. Therefore, measuring allostatic load, also directly measures the impact and outcome of mental health by measuring the impact of stressors on the body (Bruce S. McEwen, 2003).

For this study, the variable of "Using Prescription Anti-Depressant medication" will be used to represent the mental health construct that impacts an individual's allostatic load. Since mental health is related to physical health, there would be significant multicollinearity if a study used both physical health variables and mental health variables (Logan & Barksdale, 2008; Bruce S. McEwen, 2003).

When measuring mental wellness within the community, this study uses an aggregated measure people within the community prescribed anti-depressant medication. In 2012, 16.0 million Americans were diagnosed with major depressive disorder and 10.9 million received treatment for major depressive disorder (Abuse, 2012). Counseling literature often cites the use of anti-depressant medication as a treatment strategy to have unintended consequences on self-esteem and long-term mental health (Arie Dijkstra, Jaspers, & Van Zwieten, 2008; Gibson, Cartwright, & Read, 2014). Research shows that many mental health conditions improve with counseling treatments and patients often prefer counseling to prescription medication (Mulligan, 2015; van Schaik et al., 2004). However, national data between 2007-2010 indicates that the number of people who visit a primary care doctor for mental health increased from 5.96 people per every 100 go 8.49 people for every 100 (Olfson, Kroenke, Wang, & Blanco, 2014). Currently, primary care physicians are significantly more involved in providing prescription drug treatment for depression (Olfson & Marcus, 2009).

The data relating to anti-depressant is a reliable geocoded measure of mental health available in the population-based data (Ryan, Norris, & Becket, 2005). Since aggregated community data represents the construct of mental wellness, it will be used to obtain an overview of mental health patterns or the prevalence of depression within each community. According to the research, prescription medication usage can be used to look at mental health within communities because it is an accurate and practical measure of the members of the community who struggle with depression symptoms (Aletta Dijkstra et al., 2013). Research by Ryan (2005), pointed out that that using prescription drug use may provide the best standardized information on health conditions (Ryan et al., 2005). Other studies have used prescription drug use of a condition to measure the prevalence of the condition (Aletta Dijkstra et al., 2013).

However, using anti-depressant medication to measure mental health may as a underestimate the actual prevalence of mental illness in the community (Sisnowski, Street, & Braunack-Mayer, 2016). People who choose alternative methods to copy with mental illness will not be represented within the aggregate count of prescription medication users. Individuals who are clinically mentally ill but do not access any treatment services will also not be represented in an aggregate count of anti-depressant medication. Furthermore, this population-based variable measure will not measure the state of well-being for individual community members nor will it measure the results of a particular intervention (Pirl, 2004).

Since allostatic load measures the impact of stressors on health, the next section details the environmental stressors that have the largest impact on health. The definition of health from the World Health Organization's constitution declares that; "health is a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity" (World Health Organization, 2003, p. 7). The intersection between individual health and mental health collide when discussing the impact that the environment has upon both. Social determinants of health define the environmental factors that influence health and mental health of individuals.

Social Determinants of Health

Research has shown that neighborhood factors affect individual development, health, and functioning with both health and mental health (Allen et al., 2014; Compton & Shim, 2015; Strolin-Goltzman, Sisselman, Melekis, & Auerbach, 2014; World Health Organization, 2011). Additionally, having a sense of community was positively associated with lower stress and an increase in both social support and physical activity, which improved health and mental health outcomes (Young, Russell, & Powers, 2004). There are many built features within a neighborhood that foster a sense of community amongst its members (Leventhal & Brooks-Gunn, 2000; Sampson & Raudenbush, 1999). Community members may also experience environmental stressors that detract from a healthy environment. Negative social determinants of health will be discussed further.

Food Insecurity

Food insecurity is defined as ‘‘limited or uncertain availability of nutritionally adequate and safe foods or limited or uncertain ability to acquire acceptable foods in socially acceptable ways” (G. Bickel, Nord, Price, Hamilton, & Cook, 2014). Food shortages, reduction in quality food, reduced intake of food and disrupted eating indicates some degree of food insecurity. In 2014, 31.2% of US children lived in a food insecure household. Interestingly, this current definition of food insecurity does not include hunger (O'Reilly, 2015). The new definition of food insecurity embraces the idea that hunger is an outcome of food insecurity but not a defining feature of the construct. Food insecure individuals are unsure how they will access food for their next meal (Kushel, Gupta, Gee, & Haas, 2006). The Committee on National Statistics stressed the importance of differentiating food insecurity from hunger since the former describes the experience and the latter describes the consequence of food insecurity (Cook, 2013).

Research indicates that children food insecure homes are diagnosed with more mental disorders (Melchior et al., 2012; Whitaker, Phillips, & Orzol, 2006) and experience more emotional, behavioral and cognitive concerns (Alaimo, Olson, & Frongillo, 2001; Howard, 2013; Melchior et al., 2009). Stress, anxiety, and shame result from experience household food insecurity (Burke, Martini, Çayır, Hartline-Grafton, & Meade, 2016).Other studies hypothesize that food insecure individuals do not receive needed medical care because the need for adequate food is a higher priority than medical care (Kushel et al., 2006). Additionally, researchers have found that food insecure children have lower fruit intake (Grutzmacher & Gross, 2011) lower calcium intake (Eicher-Miller, Mason, Weaver, McCabe, & Boushey, 2011; Matheson, Varady, Varady, & Killen, 2002), and higher consumption of unhealthy foods (Rosas, Case, & Tholstrup, 2009; Sharkey, Nalty, Johnson, & Dean, 2012). Food insecure adults are also more likely to report more mental health concerns than other adults (Sharkey et al., 2012). Whitaker et al. (2006) reported that food insecurity is associated with mothers who are depressed or anxious. Additionally, food insecure adults are more likely to be overweight or obese (Franklin et al., 2012), particularly women (Larson & Story, 2010).

Medical researchers have researched how dietary choices impact mood and mental health. Medical studies exposed groups of mice to frequent and reoccurring stress. One group of mice received a high-fat and high sugar diet while being exposed to stress while the other group received a healthier diet while being exposed to stress. The study found that mice exposed to stress while on a high-fat/high sugar diet had a buildup of abdominal fat. Alternately, stressed mice on a healthy diet had little changes in weight. Furthermore, stressed mice on a high fat/sugar diet amassed twice as much abdominal fat in the first two weeks as did unstressed mice eating a healthy diet (Kuo et al., 2007; Young et al., 1997).

Although dietary changes are not recommended as a substitute for professional mental health treatment, they can be a supplement counseling and mental health treatment (Whitlock, Orleans, Pender, & Allan, 2002). Research and evidence do suggest that certain nutrients support emotional well-being, and proper nutrition will improve people's physical and emotional condition. For example, Omega-3 helps improve people's overall mood (Lucas et al., 2014). Tryptophan, an amino acid produces serotonin that influences levels of depression (Hammen, 2005). Magnesium helps the human body produce energy. Some researchers have found that patients who take extra magnesium recover more quickly from depression. Folic acid and vitamin B-12 play an important role in metabolism and production of blood cells components related to dopamine and noradrenalin (Appelhans et al., 2012; Gracey, Stanley, Burke, Corti, & Beilin, 1996). Lack of these chemicals also relates to depression. Increasing a person's levels of folic acid and vitamin B-12 increase the ability to metabolize antidepressant medications.

Pregnant mothers who do not get enough nutrients can double the risk of schizophrenia in their children since nutritional deficiencies can affect neonatal brain development (Brown & Susser, 2008). Folate deprivation can inhibit or alter DNA repair (O'Mahony, Hyland, Dinan, & Cryan, 2011). Folic acid is found in green leafy vegetables and fruits. Vitamin B-12 is mainly found in fish, shellfish, meat and dairy products (O'Mahony et al., 2011). Therefore, proper nutrition does support good physical and emotional health (Appelhans et al., 2012; Lucas et al., 2014; Morland, Wing, & Roux, 2002; Sharkey et al., 2012).

Literature relating the quality of diets to food environment in neighborhoods is prevalent. The physical placement of food stores within neighborhoods does have an impact on food choices (Cummins & Jackson, 2001; Wakefield, 2004). A limited availability of healthy food choices and the perceived convenience of unhealthy foods presents barriers to healthy eating (Glanz, Basil, Maibach, Goldberg, & Snyder, 1998; Gracey et al., 1996; O'dea, 2003). Much of the literature on food retail environments and health indicates that proximity of the food outlet drives consumer's decisions. However, a few recent studies provide differing opinions. Studies by (Cannuscio et al., 2013; Drewnowski, Aggarwal, Hurvitz, Monsivais, & Moudon, 2012) indicate that many consumers in city environments travel to food stores beyond the closest market to purchases groceries. An ecological model of human behavior theorizes that many systems act upon individuals and influence behaviors associated with the local food environment

(Nettle, Gibson, Lawson, & Sear, 2013). However, individual behaviors are influenced by more than just geographic proximity. Although the physical food environment of neighborhoods has been well studied, Story, Kaphingst, Robinson-O'Brien, and Glanz (2008) purports that the social environment influences food choices of individuals. Role modeling, social supports and social norms within a community influence choices and decisions of the individuals living within those boundaries.

Furthermore, it is becoming apparent that the key to identifying disparities in health outcomes including mental health, diabetes, and mental health comes from examining differences in the food environment in neighborhoods (Hill, Wyatt, & Melanson, 2000; Rocchini, 2002). Galvez's research emphasizes that policymakers and health care providers should have a basic understanding of the local food environment to fully understand all the supports and barriers that exist in the clients that they serve (Galvez et al., 2009; Galvez et al., 2008). An understanding of the food environment can lead to healthier lifestyles in the communities. There is a wealth of literature that suggests that examining differences in food store availability help to further understanding of the impact of food choices on mental health (Galvez et al., 2008).

Research has shown that inequities in the availability of different types of food stores do exist by neighborhoods (Black & Macinko, 2008; Franco et al., 2008; Galvez et al., 2009; Powell et al., 2007). The availability of healthy food stores within a neighborhood improves access and diet quality. Research indicates that supermarkets had four times the number of healthy foods than convenience stores (Cummins & Jackson, 2001; Galvez et al., 2008; Sallis, Nader, Rupp, Atkins, & Wilson, 1986). Additionally, research has shown that having a supermarket within a defined community is related to a 32% increase in fruit and vegetable intake (Galvez et al., 2008; Morland, Wing, & Roux, 2002). Since previous research underscores the importance of food availability and consumption, both constructs will be represented within this study to measure the impact of nutrition on mental health.

Economic Instability

People's perceptions of food security are also related to their perception of economic stability. The prevalence of food insecurity inversely relates to household income (Kushel et al., 2006). Affordability of food choices and the availability of money to buy food will impact the dietary choices made within a neighborhood (Eicher-Miller et al., 2011; Glanz et al., 1998; Morland, Wing, & Roux, 2002; O'dea, 2003). The SES of the neighborhood correlates to health outcomes, including mental health (Dupre, 2007; Menec et al., 2010). Neighborhood qualities such as SES and educational or employment opportunities have also been shown to impact racial/ethnic disparities in health (J. Kim, 2011; Liang, Xu, Bennett, Ye, & Quiñones, 2009). The effects of household income on behavior and IQ of children in the home were studied by (Brooks-Gunn, Duncan, Klebanov, & Sealand, 1993; Leventhal & Brooks-Gunn, 2000) The research found that the families who were supportive of each were able to mediate IQ scores.

Social Capital

The positive relationships between people or groups of people within communities make up the definition of social capital (Carpiano, 2006; Delany-Brumsey, Mays, & Cochran, 2014). Putnam believes that common positive social characteristics increase social capital within a community (Adler & Kwon, 2000). Developing more social capital within a community involves building trust amongst community members, developing community cooperation, encouraging a sense of helping others, and providing opportunities for civic engagement (De Silva et al., 2005). Places and facilities within a community that allow people to interact build more social capital. Social capital links individuals with institutions and organizations through services (Parasuraman & Shi, 2014).

Access to facilities and services within a community correlate with to positive mental health and well-being (Bowling, Barber, Morris, & Ebrahim, 2006; Leslie & Cerin, 2008). Furthermore, access to health care facilities reduces neighborhood inequalities in health outcomes (Barnett, Pearce, & Howes, 2006; Hiscock, Pearce, Blakely, & Witten, 2008; Lubans, Aguiar, & Callister, 2010). The World Health Organization, (W.H.O.) has consistently stated that the amount of social capital within a community inversely relates to the health inequalities within the neighborhood (World Health Organization, 2011). The less social capital present in neighborhoods, the more mental health problems are evident (De Silva et al., 2005).

Structural neighborhood characteristics of the built environment shape the social capital within a neighborhood (Suglia et al., 2016). Grocery stores and health food restaurants within neighborhoods provide resources that residents can use to safeguard and improve health (Cannuscio et al., 2013). However, neighborhoods with lower SES typically have more fast food access and limited access to affordable healthy food(Galvez et al., 2008). The social conditions in low-income neighborhoods develop infrastructure related to the development of more fast food restaurants and limited access to affordable healthy food (Kwate, 2008). The interactions and communications within buildings facilities social capital.

Community members who participate in networks within communities build more social capital resources. Social capital provides the community with a cohesive feeling and a sense of belonging (Carpiano, 2006; De Silva et al., 2005). Therefore, the mental health services, groups, and civic organizations within a community are directly related to health and mental health of the community (Brehem and Rahn 1997). Furthermore, social inclusion is directly related to the social capital within an organization.

Housing Instability

Living in deteriorating neighborhoods may have a multitude of direct and indirect effects on the body and the quality of life (Gee and Payne-Sturges 2004). Pevalin, Taylor, and Todd (2008) cite that many research studies support the association between poor housing and poor health. Similarly, Leventhal and Brooks- Gunn (2003) looked at the association between neighborhood residence and mental health outcomes in which census tract data was used to identify participants and found again that poor housing associates with poor health. Kowaleski-Jones (2000) indicated that the impact of residential stability has strong protective effects on child and adolescent risk-taking behaviors. A study by (Galea, Ahern, Rudenstine, Wallace, & Vlahov, 2005) studied the built environment about depression. People who lived in buildings with poor quality exterior were 36% more likely to report depression in the past six months. Residents who had nonfunctioning kitchens or more heat problems were also 40% more likely to report having symptoms of depression in the last six months.

Safety

Living in a neighborhood considered dangerous can add to one's stress level. According to Sampson and Raudenbush (1999) vandalism, litter and graffiti are more apt to make community members fearful and anxious within their neighborhood. Mirowsky and Ross (2003) report that criminal activity in a community or signs of criminal activity increases the residents' feelings of anxiety and depression. Ziersch et al., (2005) find that perceived neighborhood safety is also related to the health of the individual and subsequently the community. Leslie and Cerin (2008) find that the safety and walkability of neighborhoods significantly correlate with mental health within the community. The implication of these findings suggests that crime and safety variables within a neighborhood significantly affect mental health. Additionally, further research indicates that the lack of social capital within a neighborhood is associated with poor health and indirectly associated with crime in the community (Roy et al., 2012).

Additionally, those living in poorer neighborhoods also face other forms of stress that can exacerbate the problem including crime, safety, and neighborhood disorder (Keith, Lincoln, Taylor, & Jackson, 2010). A Chicago study found that perceptions of the neighborhood were associated with mental health and may have a causal effect (Wen et al., 2006). However, data from a Harvard study shows that collective efficacy in neighborhoods is one of the strongest predictors of lower homicide rates, regardless of individual socioeconomic resources (Morenoff, Sampson, and Raudenbush 2001).

To study the impact of the local food environment on mental health, a secondary analysis of public available datasets will be used. The next section defines the data sets and analysis features used in this study.

Analysis Methods

Measuring Spatial Dependencies Using GIS

This study uses a geographic information system (GIS) to define and identify neighborhoods. A GIS system allows the researcher to integrate multiple data sources to analyze environmental factors in a community (Law & Collins, 2013). It is important for the researcher to identify the variables most appropriate for a community studies and risk assessment (Elwood & Leitner, 1998; McMaster et al., 1997). However, the decision as to which variables to choose cannot always be left to the researcher alone. Local community members may have information on the environment that researchers may overlook (McMaster et al., 1997).

GIS technology helps researchers visualize relationships within the context of the neighborhood. Where relationships occur are as important as when and if the relationships exist. Data analysis and models of relationships between variables within the context of the neighborhood are resources that GIS technology can provide researchers. GIS technology provides additional problem solving and analytical tools for researchers and organizations. Understanding the relationship between variables within communities helps researchers understand systemic and structural environmental issues within the population of a community (Rawson, 2011). GIS can expand the scope of traditional research, and in turn, better inform communities and decision-makers.

Mental health issues are often the result of social influences within the environment or community in which the individual lives. Policies aimed at providing mental health interventions are connected to the geographic location of the individuals served (Turk, 2013). GIS is a significantly important tool that can be used to assess the effectiveness of policies and interventions aimed at specific groups or people within specific communities (Rawson, 2011) GIS allows researchers to integrate information from a variety of sources, which allows for spatial analyses to examine the relationship between datasets within the confines of the community. This provides a more accurate and client-specific policy or intervention for specific communities (Yang, Shoff, & Noah, 2013). The visualization of relationships spatially allows traditional statistical analyses to be applied and interpreted in new ways.

GIS helps researchers compute simple circular boundaries to define areas. Within this method, differences between variables inside and outside the area are assessed (Glickman 1994). With this definition of a community, it is easier to analyze health and geographic data because the data is already defined within a geographic context. Spatial models can be created with multiple layers of variables on the geographic surface of the map (McMaster 1990). Subsequently, the models created use standardized variables that give researchers a reliable and replicable spatial method to analyze data and assess risk.

According to Shannon, Bashshur and Metzner (1969), the location and social activities of people are often spatially ordered and distributed. Shannon, Bashshur, and Metzner (1969) introduce research that is concerned primarily with the impact that distance has on individuals receiving medical services. They identify two important studies, Jehlik and McNamara (1952), Ciocco, and Altman (1954), who both independently explore the relationship between distance to a physician and/or hospital and patient care. These studies are significant because they represent the first attempts in health services research to formalize the idea that distance affects access to health services (Shannon, Bashshur & Metzner, 1969).

According to McLafferty (2003), the use of Geographic Information Systems (GIS) in health services research has increased in the past few decades. GIS software enables investigators to input, store, manipulate, analyze, and visualize spatially referenced information. This ability provides the researcher with a set of tools for describing and understanding the spatial organization of health delivery systems (Higgs, 2004). What differentiates GIS from other information systems is that objects in the relational database are stored according to location (Love & Lindquist, 1995). As a result, GIS is an important tool for researchers to use when emphasizing the geographical or spatial dimension of access to health services. More specifically, the technology can be used to evaluate the type and quality of health services available in a given area, the distance and cost to reach those services. Furthermore, GIS visually identifies disparities in access to health services along with various sociodemographic, economic, and geopolitical lines (McLafferty, 2003). The technology offers an advantage over traditional research analytics because of its ability to relate both spatial and attribute data, which in turn provides enhanced integration and interpretation. For instance, GIS spatial pattern analysis employs statistics to describe and model distributions (e.g. central feature, mean center, median center), patterns (e.g. an average nearest neighbor, spatial autocorrelation), and relationships (e.g. ordinary least squares, geographically weighted regression) in spatially referenced data (Rosenshein, 2011). This type of analysis allows health services researchers to evaluate the spatial patterns of diseases for at-risk populations (Foody, 2006). Because of technology's capacity to integrate data with mapping functions, GIS is an influential tool that health services researchers can use to explain disparities in healthcare access and health outcomes (Graves, 2009). In this context, GIS technology can be a valuable problem-solving tool for decision makers to use when allocating resources toward emergent health priorities such as mental health and wellness.

Inferential Statistics

Studies that investigate accessibility to health services typically use statistical methods to test research hypotheses. For example, Fortney et al. (1999) use regression analysis to test the hypothesis that geographic accessibility affects the number of visits patients make to their provider. Also, they use a logistic regression model to determine if geographic distance between patient home and the provider affects the likelihood of being compliant with treatment (Fortney et al., 1999). A study by Nemet and Bailey (2000) evaluates whether healthcare utilization is dependent upon the distance to the provider (Nemet & Bailey, 2000). Luther et al. (2003) use ANOVA to compare the averages of those who have high and low health care access to determine if health care access influences disease mortality and/or child health. Furthermore, Towne, Smith and Ory (2014) use bivariate and multivariate regression analysis to assess differences in distance, utilization, and availability of cancer screening providers in various countries (Towne, Smith & Ory, 2014). These studies indicate that using statistical measures with GIS data are applicable in health-related research to measure the impact neighborhood features on community groups.

Conclusion

The literature describes the mental health consequences of social determinants. The complicated web of social determinants and its impact on health and mental health is difficult to separate. Often, mental health and problems result from more than factors than just genetics or biological makeup. The convergence of time, stress and environment play a role in mental health and health concerns. The impact of allostatic load impacts many health and physical health conditions. The impact that community or the social environment on stress is well documented. Gaining a better understanding of how these social determinants affect individuals and the community helps counselors plan policies and intervention strategies that are specific and targeted to the population served.

One of the most important but under-appreciated factors in mental health is the role of nutrition. The strength of evidence linking diet and mental health continues to grow. More research continues to relate positive nutritional choices to positive mental health management and prevention. Linkages between diet and mental health are strengthening thanks to the many research studies on the relationship between variables within communities. Research studies have examined individual level relationships between mental health and diet as well as population or cultural comparisons between mental health status and food intake.

However, intervention is key to achieving quality health and mental health within the lifespan. Additionally, intervening at the right moment in time with the correct intervention is crucial. Some of the research indicates protective factors such as education, social support, and feelings of mastery and control over one's life can mediate the impact of social determinants. The effects of the community, individual choices, and the opportunities for choices within the community are just beginning to be understood. This study will contribute to the growing body of literature linking diet interventions and mental health. Links between the two areas will help counselors identify interventions that are culturally relevant, and community-based.

CHAPTER 3: METHODOLOGY

Introduction

The impact of social determinants on mental health within neighborhoods can greatly affect the focus of mental health counseling and community initiatives designed to reduce disparities (Allen et al., 2014; Compton & Shim, 2015). The built food environment is one such social determinant mental health and will be used for this study. This study uses population data at the community level to investigate the relationship between the built food environment and mental health within school communities. Visual and statistical representations of the data are provided. Detailed analysis will explore how the food environment within communities influences mental health outcomes. Since food insecurity is one of the social determinants of mental health, this study expects that food insecurity will have a negative impact on mental health.

Although the goal of statistical analysis is to find “if” there is a relationship between variables, the goal of a GIS analysis is finding where that relationship occurs (Law & Collins, 2013). This study used bivariate correlation and regression analysis to determine if relationships exist between food choices and mental health. To determine where correlations are strongest, GIS data was used to conduct geographically weighted regression (GWR). Statistical analyses were used to determine where and why mental health and food insecurity intersect. Additionally, this research used descriptive statistics, cluster analysis, Pearson correlations, ordinary least squares regression (OLS) and geographically weighted regression (GWR) to investigate differences in geographic units. Before any analyses were conducted, the assumptions of the analysis were tested and validated. The first section discusses the variables selected for this study. Independent, dependent and demographic variables are defined and discussed. The next section discusses the data cleaning and preparation. Next, the analysis methods chosen to answer the research questions and finally ethical issues and limitations will be discussed.

Problem and Purpose of the Study

Although the promotion of mental wellness and the identification of mental illness is a worthy goal, treatment will be inadequate if we as counselors believe that treatment ends with the clients served. Counselors need to understand the environment in which their clients live to develop appropriate treatment strategies that meet their clients' goals. To help counselors understand the environment, this study will examine the impact of food environments on mental health within Tennessee school communities.

This dissertation examines the existence and significance of spatial relationships between the food environment, and mental wellness. This study measures mental wellness against food insecurity and if appropriate, develops a model predicting mental health of a community from the food environment. The social determinants of a mental health drive the theoretical underpinning of variables chosen and researched for this study. Therefore, this study examines the availability and proximity of features of the built environment that contribute to mental wellness in the context of allostatic load to better understand the mental health of the client's counselors serve.

Research Objectives

This dissertation examines the existence and significance of spatial dependencies between neighborhood characteristics and one specific social determinant of mental health – food insecurity. The objectives are to find the associations between mental health and neighborhood characteristics of food insecurity. By using variables measuring mental wellness, food availability, food consumption choices, and geographic locational data, counselors could begin to understand the complex relationship that neighborhood and context have on the mental health of clients served. An understanding of the relationship between mental health and the food environment informs counselors on types of services and interventions a community may need in addition to traditional counseling services. These objectives will also demonstrate the value of spatial analysis in the counseling field.

The purpose of using GIS technology to build models is to test complex multivariate hypotheses and illustrate statistical predictions. Therefore, this study will provide mental health researchers, clinicians, and policy makers with tools and information that can potentially lead to the development of mental health interventions or become a catalyst for policy changes

To answer the research questions, a quantitative and geographical approach will be used to determine the interrelationships between built neighborhood factors and measures of mental health. Since schools often serve as the center of a community, neighborhoods for this study will be defined by elementary school district boundaries. Before any geographic variables are entered into the study, a relationship between mental health and food will be established correlations. Finally, neighborhood attributes that contribute to food availability and insecurity will be geocoded and examined. For each neighborhood condition or characteristic, geospatial hotspots will be identified within community school regions.

The secondary data used for this study will be mapped using ArcMap GIS 10.4. Regression and bivariate correlations will be used to examine variables relating mental wellness to food within the neighborhood. The differing results will then be analyzed and studied to ensure the results are valid and reliable.

Data Selection

Data

The data for this study will come directly from ESRI. ESRI provides a comprehensive set of geocoded data on demographics, spending, and business data for mapping and analysis purposes (Law & Collins, 2013). However, the data was collected in various surveys which will be described in the next section. The base map of streets and counties will come from ESRI and the software used to display this data will come from ESRI. An outline of the data to be used is included next to an operational definition of the variables chosen.

Base Map

The ESRI Tennessee topographic base map will be used as a starting point to picture the geographic features within the state of Tennessee including major roads and highways, city and county boundaries. Tennessee was chosen for this study due to the high prevalence of mental health issues within the state and the due to the statistics on unhealthy food consumption. According to national health rankings, Tennessee ranks 49th in the nation with the 2nd lowest number of fruits and vegetables consumed on average per person. Additionally, Tennessee residents disclose they have more poor mental health days than any other state in the nation and ranked 50th on the United Health Foundation Survey (United Health Foundation, 2016). A boundary file that provides the GIS coordinates of the elementary school zones and districts within the state of Tennessee will be brought into the ArcGIS platform and entered on top of the ESRI base map (E. ESRI, 2014). School communities in Tennessee will be used for this study since elementary school district boundaries will define neighborhoods. The SABINS project will provide the geographic coordinates for community school data file.

Community Shapefile

To measure communities, The School Attendance Boundary Information System (SABINS) file will be used (Center) The SABINS provides researchers with GIS-compatible boundary files for school districts within the United States. The data is available through the National Historical Geographic Information System, (NHGIS) web application. NHGIS asks schools to disclose their district coordinates to the project voluntary (Center) NHGIS then takes the boundary information and creates a shapefile which is a standard spatial data file format used in GIS projects (E. ESRI, 2014). The accuracy of the shape file data depends on a voluntary disclosure of each school district. Because some school districts did not disclose their shape file coordinates to the SABIN project, this study will be unable to include those school districts. There were 822 school districts in Tennessee whose coordinates are logged into the SABINS shape file. This will be used as a base for analysis.

Schools are central to many communities and provide the fabric for community interactions and education. Multiple levels of data will be aggregated and compiled for this neighborhood study and will be defined by the elementary school district boundaries. This method moves away from treating schools as spatially independent contextual components of a community (McMaster et al., 1997). Schools and communities unite a neighborhood. These two entities connect and create supports for its members. This serves as the basis for the definition of a community school that is a place and partnership between resources and individuals (Taylor & McGlynn, 2009). For adequate power, a minimum of 200 elementary schools in Tennessee with similar population density characteristics will be used to measure the effect of food insecurity on the mental health component allostatic load.

Data Enrichment

To answer the research questions, the shape file will be enriched with data variables. Data enrichment provides structural knowledge about the spatial and semantical context of the map features and supports complex decision-making and analysis (E. ESRI, 2014). The activity of extracting information about the spatial environment and integrating it into a spatial database is called data enrichment (Law & Collins, 2013). Enriching geometries and shapes with penitent data is part of the relationship modeling process when creating maps (Law & Collins, 2013). Therefore, the shape file will be enriched with data representing mental well-being and healthy eating. The variables and sources are outlined below. The data for this study is stored in the ArcGIS data repository.

Population Data

ESRI's population data integrates data from a variety of sources. ESRI begins by using population estimates uses estimates from the US Census Bureau (ESRI, 2014). Since the population data is only updated every five years, ESRI adds a time series of county-to-county population migration data from other sources (ESRI, 2014). Additional population data used to ensure accuracy is derived from the Internal Revenue Service reports, building permits and housing starts, and residential postal delivery counts. To measure current population changes within census defined block groups, ESRI uses data from Experian; the US Postal Service (USPS), and Metrostudy to validate the results (ESRI, 2014).

The two population variables used for this study from the ESRI database include Population Density POPDENS_CY and Total Population -TOTPOP_CY. The raw ACS data provided by ESRI includes a confidence interval and a MOE (margin of error) statistic (Law & Collins, 2013). Confidence intervals evaluate how close the estimate is to the true mean. ESRI has provided confidence intervals and calculated coefficients of variation for population variables using ACS data (Koo, Chun, & Griffith). The amount of sampling error relative to the size of the estimate is calculated and expressed as a percentage. ESRI defines small confidence intervals as less than or equal to 12% (ESRI, 2014). Evaluation of the MOE will be used to determine if the samples used for this study are reliable estimates of the population.

Results from various studies indicate that ACS data in low-income areas are more prone to sampling error (Folch, Arribas-Bel, Koschinsky, & Spielman, 2014; Spielman & Folch, 2015). ACS data quality has been shown to be less reliable in smaller geographic regions even though the data is often the foundation for social science research (Folch et al., 2014; Spielman &

Folch, 2015). This research study does not define areas based on income, therefore decreasing the sampling error problems seen in studies evaluating areas based on a poverty threshold. Additionally, the regions used for this study will be large enough to be considered reliable. In addition, using caution when interpreting the results will ensure that the sampling error is not biasing the findings. The sampling error will be discussed further in the results section as a limitation of the study.

Income Variables

To estimate income for households, ESRI uses data on income trends from both federal and proprietary sources (ESRI, 2014). Surveys of income used by ESRI include the Bureau of Economic Analysis' local personal income series, the Current Population Survey, and the Bureau of Labor Statistics' Consumer Price Index (E. ESRI, 2014). After forecasting the state income distributions, household income is estimated for counties and then block groups. ESRI's income models correlate the characteristics of households at the block group level with changes in income (ESRI, 2014). This identifies several different patterns of change by household type that are applied to forecast trends in income. ESRI uses the same definition of income that is used by the Census Bureau. Income is defined using statistics from the previous calendar year. Income includes earnings, state or federal aid, retirement income, or investment income. Data on consumer income collected by the Census Bureau includes money received before paying personal income taxes. Per Capita Income and Median Household Income will be the income variables used for this study.

Consumer Spending Data Variables

The Consumer Expenditure Surveys (CEX), 2013−2014, from the Bureau of Labor Statistics (BLS) will be used to estimate current spending patterns within defined communities. The CEX collects data from approximately 7,000 households per quarter for each of the two consumer spending surveys conducted. The two surveys conducted by the CEX include; a Diary Survey detailing daily purchases for households and an Interview Survey detailing general purchases. The Diary Survey requires participants to record consumer purchases for two consecutive weeklong periods. The Interview Survey collects expenditure data from consumers in four quarterly interviews. ESRI integrates data from both surveys into a geocoded dataset to provide a comprehensive database of all consumer expenditures.

The variable giving the average amount of money spent on fresh fruit and vegetables for each household will be used for this study. The data for this variable defines money spent annually within the consumer unit. The consumer unit refers to the family or household. Therefore, the data represents the amount of money each household spends on fruits and vegetables each year. The CEX contains the most recent and comprehensive data available on food spending in U.S. households at the time of this study. Variables used for this study include the amount of money spent at fast food restaurants, the amount of yearly income spent on fresh food and vegetables. Within the 2014 survey data, the average amount of money spent on fruits and vegetables within a consumer unit averaged $769 nationally and $690 in the southern region of the USA. Standard error was 12.06 nationally but 19.70 in the southern region of USA. The coefficient of variation (CV) as calculated by ESRI was 1.57% nationally and 2.86% for the southern region. Since this is less than 12%, ESRI has defined this data as being highly reliable and that the sample represents a good representative of the population as a whole.

Market Potential Variables

Market Potential data within ESRI is an integration of information from consumer surveys completed by GfK MRI (Mediamark Research and Intelligence). GfK MRI's Survey data mainly comes from their yearly "Survey of the American Consumer." MRI surveys 26,000 consumers about behaviors and attitudes related to over 6000 products that consumers use

(Hawes, Rocha, & Meier, 2012). MRI randomly selects participants who are at least 18 years old and living in a private household (Mediamark Research and Intelligence). The annual survey database reflects the responses of 48,000 subjects and every year a new sample is selected (Mediamark Research and Intelligence). The variable indicating how many people used prescription drugs for depression last month is a market potential variables from ESRI. The question on the GfK MRI survey asks participants to self-disclose the medication they are taking for health conditions (Mediamark Research and Intelligence). This variable will be used to measure the mental health of the community.

Business Location Data

Census data on businesses was last collected in 2010. To supplement the census data, ESRI also extracts business data from Infogroup business listings using NAICI industry codes. The Infogroup business list including the business name, location, franchise code, industry classification code, the number of employees, and sales volume. The data originates from phone directory listings, annual business reports; Securities and Exchange Commission (SEC) information; and business listing data from federal, state, and municipal government data. Infogroup verifies the information in telephone interviews. Subsequently, an address list of businesses is then compiled and geocoded to and append 2010 Census Geographic codes via the spatial overlay. The location of fast food outlets and grocery stores will be used to determine if places where healthy and unhealthy foods purchased impact the mental health of the community.

Variable Constructs

Variables used for this study will measure three constructs. The variables will measure mental health, healthy food access, and healthy food utilization. The three constructs are defined as follows. The constructs will be used to associate the findings in this study to the social determinants of mental health and allostatic load as defined in the literature review.

Mental Health

A measurement of mental health used for this study aggregates the number of people who self-identified as using a prescription drug for depression within each community during the 2014 calendar year. ESRI has geocoded data taken from the GfK MRI's survey titled "Survey of the American Consumer." The survey includes two parts; a personal interview, and a product questionnaire. The survey asks participants to disclose which medications they have used in the last 12 months. Upon completion, the interviewer retrieves the completed questionnaire at a specified time and date. Participants do receive monetary incentives for completing the product questionnaire. According to the research, prescription medication usage can be used to look at mental health within communities because it is an accurate and practical measure of the members of the community who struggle with depression symptoms (Aletta Dijkstra et al., 2013). Research by Ryan (2005) has pointed out that that using prescription drug use may provide the best standardized information on health conditions (Ryan et al., 2005).

Food Access

The food environment of a community comprises access and utilization of healthy and unhealthy food. The concept of “access” to food choices will be measured with two variables. The density of grocery stores in the area will measure access to healthy foods, and the density of fast food restaurants in each area will measure access to unhealthy foods. Research has shown that the location and availability of food stores impact how and what people eat (Morland, Wing, Roux, et al., 2002). Supermarkets tend to offer the largest variety of affordable and healthy food choices (Walker, Keane, & Burke, 2010). In contrast, consumption of fast food is associated with unhealthy eating due to the low nutrient content of food and inadequate vegetable and milk food choices (Paeratakul, Ferdinand, Champagne, Ryan, & Bray, 2003, Boutelle, 2007 #195).

Healthy Food Utilization

The utilization of healthy food choices will be measured by the average amount of money spent on fresh fruit and vegetables and the average per capita income spent on fruits and vegetables in a year. The variables from this study come from the consumer expenditure survey. Studies have shown that the consumption of fruit and vegetables indicates healthy eating patterns (McMartin, Jacka, & Colman, 2013). Furthermore, using fruit and vegetable intake as a measure of diet quality is becoming more widely accepted rather than the measurement of micronutrients within diet (Rucklidge & Mulder, 2016). Additionally, other studies have found that mood disorders have a significant association with lower fruit and vegetable consumption (McMartin et al., 2013).

Research Analysis

Three types of analysis will be used for this study. Bivariate correlations, regression, and cluster analysis or hot spot analysis. The descriptions of the analyses to be used will follow.

Bi-Variate Correlations

A bi-variate correlation determines if a possible linear relationship exists between two continuous variables. The correlation coefficient represents the strength of the relationship between the variables studied. The strength of relationship will be calculated as a measurement between the values of -1 and +1. The correlation strength is valued as stronger as the value becomes closer to ±1. A positive correlation coefficient indicates that the variables move in the same direction. As one variable moves up; the second variable moves up. A negative correlation indicates that the relationship is the opposite. As one variable moves up in value, the second variable moves down. Two types of correlation coefficients are often used to measure correlations. The Spearman's rank and Pearson's Correlation coefficient are widely used in research. Spearman's rank is often used when one or both variables are skewed or ordinal.

Spearman's rank is calculated using median values. In contrast, Pearson's Correlation coefficients are calculated using the mean value of variables. Although the Pearson coefficient is appropriate to use when the variables are normally distributed, the Pearson calculation is often affected by extreme values. Therefore, when data is not normally distributed, the Spearman's rank is a more appropriate method to measure correlation. Both tests can be used to determine the strength and direction of the relationships between pairs of variables, but correlation measures do not assess if one variable moves in response to another. In correlations, one variable is not dependent upon the other. Therefore, no predictive conclusions can be drawn from correlations. Thus, relationships identified using correlation coefficients are associations, not causal relationships (Tabachnick, 2013).

Spatial Clusters

Spatial clusters of data will be analyzed using the Hot Spot Analysis tool within ArcGIS (Haining, 2003). The Hot Spot Analysis tool allows the researcher to detect a spatial cluster of statistically significant high or low data concentration within a geographic boundary (McCoy et al., 2001). Locations, where something out of the ordinary has occurred within the data, will be identified. All hot spots detect values that are extreme relative to the mean value. Hot spot analysis is used to compare the distribution of values associated with the geographic features in the feature class to a hypothetical random distribution (Law & Collins, 2013). Hot spot analysis allows the researcher to see where unexpectedly high/low rates of correlation are occurring (Law & Collins, 2013). The Global Moran's I and Local Getis-Ord statistics identify spatial clusters of data. Spatial clustering or hot spot identification occurs when an area of data has a Z-score value larger than 1.96. Therefore, hot spots of mental health and food availability obtained from the analysis will be identified with the spatial locations.

Regression

Regression is a widely used statistical method since it allows the researcher to examine, model and explore data relationships and spatial data. (R. Bickel, 2007). Regression analyses help researchers understand the factors that contribute to the phenomenon being researched. It is most suitable for assessing constructs and evaluating the relationship between the continuous dependent and independent variables. Linear regression models a relationship between a continuous dependent variable and one or more explanatory variables (or independent variables). The advantage of a regression model over correlation is that it asserts a predictive relationship between the two variables and allows for forecasting or predicting. Regression models the past relationship between variables to predict their future behavior. Ordinary Least Square Regression (OLS) formally models a global relationship, quantifies the amount of variation in the dependent variable and establishes statistical significance between the variables being studied.

Analysis Summary

This study will be a secondary analysis of geocoded data to answer research questions related to the relationship between nutrition and mental health in communities. Data will be overlaid onto a boundary map of Tennessee counties and school districts. The data within the elementary school districts will be analyzed to see if there is a relationship between healthy food consumption, mental health and the location of food outlets. A boundary file that provides the GIS coordinates of the elementary school zones and districts within the state of Tennessee will be brought into the ArcGIS platform and then analyzed using SPSS and spatial analyst tools in ArcGIS. The study will use correlations and regression to answer questions about the relationship between mental wellness and nutrition. Each research question will employ a separate analysis as outlined below.

Research Questions

Research Question 1: Is there a negative correlation between the amount of income used to purchase fruits and vegetables and mental health in East Tennessee Communities?

H0: There will not be a relationship between purchases of fruits and vegetables within a community and anti-depressant prescription drug use within Tennessee.

H1: There will be a negative relationship between the purchase of fruits and vegetables and mental health.

A bi-variate correlation will be conducted a Pearson coefficient or Spearman's Rank coefficient will be used depending on whether normality exists in the data. No independent nor dependent variables are necessary for a correlational study. The variable – 'income used to purchase fruits and vegetables' will measure the construct of healthy food utilization. The variable of mental health will be measured by using the variable of "Number of people within a community prescribed anti-depressant medication." The two variables will be used in a bi-variate correlation to determine if a relationship exists in a negative direction.

Research Question 2: Is there a correlation between per capita income spent on fruits and vegetables and the use of an anti-depressant for depression?

H0: There will not be a significant relationship between per capita income spent on fruits and vegetables and the use of anti-depressant medication

H1: There will be a negative relationship between the purchase of fruits and vegetables and mental health.

A bi-variate correlation will be conducted a Pearson coefficient or Spearman's Rank coefficient will be used depending on whether normality exists in the data. No independent nor dependent variables are necessary for a correlational study. The study measures the variable 'per capita income used to purchase fruits and vegetables' against the variable of "Number of people within a community prescribed anti-depressant medication." This bi-variate correlation will be used to determine if there is a negative relationship between the constructs of utilization of income on healthy food choices against mental health.

Research Question 3: Will the density of fast-food restaurants in a neighborhood predict the amount of per capita income spent on fresh fruits and vegetables?

H0: The density of fast-food restaurants in a neighborhood will be unable to predict the amount of per capita income spent on fruits and vegetables

H1: As the number of fast food restaurants in neighborhood increases, the amount of income spent on fruits and vegetables decreases.

A simple linear regression model will be used to determine whether the density of fast food restaurants predicts the amount of income spent on fresh fruits and vegetables.

IV: Density of fast food restaurants

DV: Per capita income spent on fruits and vegetables yearly

Research Question 4: Will the density of grocery stores in a neighborhood predict the amount of income spent on fresh fruits and vegetables?

H0: The density of grocery stores in a neighborhood will be unable to predict the amount of income spent on fresh fruit and vegetables

H1: As the number of grocery stores in an area increases the number of fresh fruit and vegetable purchases increases.

A simple linear regression model will be used to determine whether the density of grocery stores predicts the amount of income spent on fresh fruits and vegetables.

IV: Density of grocery stores in the area

DV: Per capita income spent on fresh fruits and vegetables

Research Question 5: Will the density of fast-food restaurants in a neighborhood predict the number of people in the community who use a prescription drug for depression?

H0: The density of fast-food restaurants in a neighborhood will be unable to predict the number of people in the community who use a prescription drug for depression.

H1: As the number of fast-food restaurants in a neighborhood increases, the number of people, who use prescription drugs for depression will increase

A simple linear regression model will be used to determine whether the density of fast food restaurants predicts the number of people in the community who use a prescription drug for depression.

IV: Density of fast food restaurants in community school area

DV: Number of people in the community who use anti-depressant medication

Research Question 6: Will the density of grocery stores in a neighborhood predict the number of people who use prescription drugs for depression?

H0: The density of grocery stores in a neighborhood will be unable to predict the number of people who use prescription drugs for depression.

H1: As the number of grocery stores increases, the number of people who use prescription drugs for depression decreases.

A simple linear regression model will be used to determine whether the density of grocery stores predicts the number of people in the community who use a prescription drug for depression.

Analysis Tools

Two main tools will be used to analyze the data for this study; ArcGIS and SPSS. The two tools will be described next.

ArcGIS

ArcGIS software will be used as a method of organizing, mapping, analyzing, and displaying the data (Law & Collins, 2013). A GIS shape file of the state of Tennessee and counties, available from University of Tennessee and ESRI, will be used as a base map. SPSS will be used to provide detailed statistical analysis. ArcGIS Pro will be used to organize and process the data. The mapping process will also involve several steps, including (1) the creation of separate layers including a base layer, demographic data, and independent and dependent variable data. Spatial data will be mapped to investigate the hypothetical relationships between variables in all areas of the study. The resulting maps can also be used to develop potential hypotheses and future research objectives.

SPSS

SPSS (Statistical Package for the Social Scientists is a data management and statistical analysis tool (Tabachnick, 2013). SPSS allows users and researchers to undertake a wide range of statistical analyses relatively easily. While this is extremely useful, the researcher still needs to know what analysis is appropriate for the data.

Data Quality

Since this study is proposing the use of large aggregated data for secondary analysis, data cleaning and inspection will be conducted. The presence of incorrect or inconsistent data distorts the results of statistical analyses. Data entry and/or aggregation often impact data quality (Hellerstein, 2008). Employing data cleaning procedures helps researchers identify and correct possible errors in large data sets.

Before analysis of the research questions, frequencies on each variable will be conducted and histograms produced. Checking for missing values or extreme values occur when performing initial frequencies for each variable. Additionally, examining frequencies ensures that missing data is coded consistently throughout the data set. Data will be evaluated for normality and homogeneity of variance.

Ethical Considerations

Ecological Correlations

This study employs ecological correlations within neighborhood communities. The statistical objects being studied are groups of people as opposed to individual people and individual behaviors. The variables represent composites of aggregations of individuals within a neighborhood. This differs from individual correlations where variables are descriptive properties of separate objects. In ecological correlations, the variables are percentages, rates, or means of the entire group (Openshaw, 1984). The ecological correlations compare descriptive properties of groups, and not descriptive properties of the specific individuals who make up the group. In a study that uses ecological correlations, one cannot discover specific individual behaviors(Robinson, 2009). One cannot draw conclusions about individuals within a group based on the ecological data. This study is designed to draw conclusions about the entire group of individuals as opposed to individuals within the group (Openshaw, 1984). Therefore, this study will not generalize the results to specific individual people since we will be using ecological correlations and commit an ecological fallacy. (Klein & Kozlowski, 2000; Robinson, 2009)

Ecological Fallacy

An ecological fallacy occurs when researchers analyze group data and use the results to draw conclusions about individuals in the group. For example, researchers may study 5th-grade classrooms around the country to determine which region fares the best in math achievement tests. If math test scores in Region X were the best in the country, one could not assume that every child in that class is a math genius. Just because that particular class has high math scores does not mean that every specific individual in that class automatically scored the highest on the math achievement test. This study will avoid drawing conclusions about individuals based on aggregated data used in this study.

Aggregated Data

Aggregating data loses information about specific individuals within the groups (Robinson, 2009). Unfortunately, researchers have made erroneous conclusions from aggregated data when they make the association between individual factors and the outcome event among groups (Barnard & Hu, 2005). An error occurs when researchers make an association with ecological data for individuals within each group without accounting for the possible ecological bias (Openshaw, 1984). Often group level statistics reflect an aggregation bias compared to individual or lower level statistics. These issues are now studied using 'multi-level,' or 'mixed' statistical models that take into account different, nested units of analysis (Glick, 1985; Openshaw, 1984).

Researchers analyze differences in groups by recognizing the nested nature of group variables. Researchers can analyze student performance at the student, classroom, school, district, or national level. By including important levels of unit analysis in the study, the validity of the inferences increases and the chances of drawing an ecological fallacy are reduced (R. Bickel, 2007).

Modifiable Areal Unit Problem

Gehlke and Biehl first identified the Modifiable Areal Unit Problem (MAUP) in 1934. The MAUP is a statistical bias in aggregated data influenced by both the means of the aggregated point-based data and the areas into which the data is grouped. Sometimes when grouping data, the aggregation is influenced by the boundaries of the group. The boundaries sometimes overestimate or underestimate the aggregated number due to the impact of the boundaries.

Methods of collection and distribution of data impact aggregated results. If observed data is not aggregated into units following natural breaks of the data under inspection, inaccurate analysis results will follow because the data is biased. One way to treat this kind of bias is to repeat the analysis on alternative aggregation areas. Repeated the analysis for zip codes or block groups in the same area would validate results if MAUP is suspected (Jerrett et al., 2003).

MAUP can also be detected using spatial autocorrelation. Spatial autocorrelation will not eliminate the bias in MAUP. However, it will provide additional insight into the phenomenon from a wider perspective without further aggregating areas (Griffith, 1987). This study will address the modifiable area unit problem by completed spatial autocorrelation with the variables to be used.

Secondary Data Analysis Limitations

The data used for this study is secondary data, and subsequently, the data was not collected to address the specific research questions in this study. Although this is an inherent problem with the secondary analysis of existing data, it poses an issue since the data collected was not collected specifically to test the particular hypothesis in the secondary analysis (Cheng & Phillips, 2014). Another major limitation of the analysis of existing data is that the researchers who are analyzing the data are not usually the same individuals as those involved in the data collection process (Cheng & Phillips, 2014). Therefore, researchers using secondary analysis are not aware of study-specific nuances in the way data was collected, or survey questions were asked of participants (Cheng & Phillips, 2014). The data collection process may be an interpretation the results for specific variables in the data set (Cheng & Phillips, 2014). However, researchers involved in secondary data analysis would not be privy to this information, and it poses a limitation to the study. The number of variables and documentation in large-scale national surveys conducted by government agencies can be daunting and overwhelming. Due to the large nature of such data sets, it is easy for researchers to miss important details. Therefore, it is important for researchers to review the documentation included in secondary analysis datasets carefully. Reviewing information provided about the validity of the secondary data, the data collection process, and previous analyses can mitigate these issues related to secondary data analysis (Cheng & Phillips, 2014).

Summary of the Methodology

To answer the research questions, this study will use data from national surveys and geocoded databases. Regression models will provide answers to the research questions as to how the availability and location of food sources influence food choices and mental health scores. Ordinary least squares regression and geographically weighted regression helped to find answers to the research questions and depict the data in a meaningful way. Spatial features of food availability and food consumption will be used to predict the impact that food has on mental health and subsequently mental health.

CHAPTER 4: RESULTS

Introduction

This chapter describes the results of the study design and methods. The sections begin with a description of dataset characteristics, variable descriptive information and then analysis results.

Data Collection

The school boundary file containing elementary school districts was downloaded from the NHGIS web application and then opened in ArcGIS Map. The shapefile was clipped to include only Tennessee Elementary Schools. The boundary file identified 811 elementary school districts within Tennessee. The shape file was then enriched with data relevant to the study of mental wellness and food insecurity in the community. The following variables were downloaded from ESRI's 2015 database and inputted into each polygon shaped school district:

Median household income

The median income reported by ESRI comes from Census Bureau statistics. Income includes pre-tax income for all individuals 15 years old and over living in the same household. The income statistics cover the past 12 months and is reported in 2014 dollar amounts.

Population density

The population for each community is calculated by dividing the total population count of geographic feature by the area of the feature, in square miles. The geometry of the shapefile features is used to calculate the area of the community.

Total population

ESRI calculates population by combining census counts and the American Community Survey (ACS) five-year averages. The changes in households are modeled from Experian data; the US Postal Service (USPS) data and several additional proprietary sources.

Per capita income

Per capita income is calculated by taking the sum of all the income within each household and dividing by the number of people within each household. The per capita income is then averaged for each area or community.

Grocery stores

A point level data set for the NAICS code 445110 or grocery stores was downloaded from ESRI. The number of grocery stores in each area is then calculated from the point level data. The NAICS code includes stores known as supermarkets and grocery stores. It excludes convenience stores with or without gasoline sales as well as large, general merchandise stores.

Fast Food Restaurants

A point level data set provided by ESRI for the NAICS code 72221 or limited service restaurants. Limited-service restaurants are defined restaurants where customers select items and pay before eating. Additionally, if food is taken out or delivered to the customer's location, the restaurant was considered within the 72221 NAICS code.

Average fruit and vegetable expenditures

The average amount of money that a household spent on fruits and vegetables for the year in 2014 was calculated from the Consumer Spending Index by the Bureau of Labor.

Anti-Depressant Medication

A count of adults using anti-depressant medication within the community was calculated for each area using information fro the GfK MRI "Survey of the American Consumer." Table 1 outlines the initial descriptive data on the variables used in this study.

Table 1. *Range and Mean of Variables within Tennessee Communities*

Variables	N	Range	Mean ± SD
Grocery Store Business	811	0-610	9.12±43.229
Fast Food Restaurants	811	0 – 727	13.06±54.829
Population Density	811	0 – 7983.6	1103±1365.98
Total Population	811	0 – 957,457	15540.6±67915.4
Fruit & Veg Expenses	811	0-2251.72	738.251±270.817
Used Prescription Drug for Depression	811	0 – 39951	856.62±2916.96
Per Capita Income	811	0-71721	23426.2±9086.5
Median Household Income	811	0-159736	44908±20127.2

As the table indicates, there were some school districts with zero statistics. School districts with missing data were eliminated from this study in data cleaning procedures. Because this research focused on the impact of relationships and neighborhoods within school communities, this study used communities where the population density was above the median in the state of Tennessee. The median population density for the state of Tennessee was 453 people per square mile. Only communities where the population density was above 453 people per square mile were used. The median was used as opposed to the mean because median values split the data into two halves and is not affected by extreme values. After eliminating communities with zero data and using communities with population density above the average, 408 communities remained. Frequencies and descriptive data were again calculated for each variable and is summarized in Table 2.

Table 2. *Range and Mean of Variables in High Population Density Communities*

Variables	N	Range	Mean ± SD
Grocery Store Business	408	0-610	10.76±59.814
Fast Food Restaurants	408	0-727	15.58±71.514
Population Density	408	453.3-7983.6	2071.51±1345.7429
Total Population	408	765-957457	17704.66±93727.204
Fruit & Veg Expenses	408	224.05-2251.72	769.0988±326.88
Used Prescription Drug for Depression	408	41-39951	808.27±3907.13
Per Capita Income	408	5231-71721	24664.59±11119.07
Median Household Income	408	159736	46675.02 ±24232.31

Outliers

According to (Tabachnick, 2013) outliers can be identified by visual inspection of histograms or frequency distributions. On initial inspection, outliers were found. Outliers were considered to be any value |3.29| standard deviations above or below the mean (Tabachnick, 2013). Four school districts had extreme values in all of the selected variables used in this study. Additionally, the values were the same for those four communities as outlined in Table 3.

Table 3. *Cases Eliminated from Study Due to Extreme Values*

Variables	Case 33	Case 39	Case 66	Case 92
Grocery Store Business	610	610	610	610
Fast Food Restaurants	727	727	727	727
Population Density	1270.7	1270.7	1270.7	1270.7
Total Population	957457	957457	957457	957457
Fruit & Veg Expenses	884.21	884.21	884.21	884.21
Used Prescription Drug for Depression	39951	39951	39951	39951
Per Capita Income	27004	27004	27004	27004
Median Household Income	47815	47815	47815	47815

It appeared that this was an error that occurred when the data was aggregated. The researcher determined these communities have unreliable data and eliminated them from the study. Research by Osborne (2001) shows that removal outliers can reduce the probability of Type I and Type II errors, and improve the accuracy of estimates. A final data inspection was conducted and is outlined in Table 4.

Table 4. *Description of Variables within Communities Chosen for Study*

Variables	N	Range	Mean ± SD
Grocery Store Business	404	0 - 25	4.83 ± 3.73
Fast Food Restaurants	404	0 - 71	8.53 ± 9.58
Population Density	404	453.3 - 7983.6	2079.43 ± 1350.03
Total Population	404	765 - 32136	8400.18 ± 4426.27
Yearly Fruit & Veg Expenses	404	224.05 - 2251.72	767.96 ± 328.29
Used Prescription Drug for Depression	404	41 - 1667	420.72 ± 243.20
Per Capita Income	404	5231 - 71721	24641.42± 11171.66
Median Household Income	404	10658 - 159736	46663.73± 24352.00

Spatial Autocorrelation

A Moran's index was calculated for the variables to be used in bivariate correlations. Moran's I (Index) is used to measure spatial autocorrelation (Griffith, 1987). Values close to +1 indicate that positive spatial autocorrelation exists and similar values are clustered together. Values close to -1 indicates that dissimilar values cluster together(Anderson & Egeland, 1961).

Spatial autocorrelation helps understand the degree of similar between nearby objects. If there is a strong similar relationship between variables within nearby communities, spatial autocorrelation will identify the strength of the similarity to determine if the communities are too similar to be considered independent from one another. (Goodchild et al., 1992). The Moran's index is used to determine spatial autocorrelation. Moran's Index was calculated for each variable used in this study. The results are summarized in Table 5**.**

Table 5: *Spatial Autocorrelation Values for Variables*

Variables	Moran Index	*p value*	*z* score
Grocery Store Business	.048	.03	2.14
Fast Food Restaurants	.018	.39	.855
Population Density	.21	.00	8.913
Total Population	.06	.01	2.688
Fruit & Veg Expenses	.01	.03	2.08
Used Prescription Drug for Depression	.09	.00	98.05
Per Capita Income	.08	.00	3.46
Median Household Income	0.11	.00	4.88

The table of values shows that seven of the eight variables have significant spatial clustering as evidenced by a significant *p-value*. The value for the Moran Index were calculated near 0 for most all variables. This indicates there is a clustering of both high and low values within each variable. Although some clustering is to be expecting with population data, this might be indicative of a modified area unit problem. The communities studied may be too similar to each other to be considered independent of each other. This limitation will be discussed further within the context of the results.

Descriptive Data

Four hundred and four communities remained for the study and a detailed outline of each school, and the value of each variable per community is provided in Appendix A. Choropleth maps were created and examined to gain an initial understanding of the distribution of each variable across the region. Choropleth maps are included in Appendix B. A summary of the average, range and standard deviation for each variable is included in Table 4.

An exploratory data analysis was conducted to determine if each variable was normally distributed. The results are summarized in Table 5. Results for the Kolmogorov-Smirnov test for normality indicated that the distribution was not a normal distribution. However, the skewness and kurtosis values indicated normality within the data since the values were between /3/ and /10/. Kline (2005) suggests the data could be considered normal if skewness </3/ and kurtosis </10/. A visual examination of the histograms indicated that the data followed a normal curve. Therefore, a Pearson correlation will be used when analyzing bivariate correlations. Table 6 summarizes the skewness and kurtosis values for each variable.

Table 6: *Normality Testing Results*

Variables	Statistic	*n*	*p*	Skewness	Kurtosis
Grocery Store Business	.140	404	.00	1.43	3.28
Fast Food Restaurants	.186	404	.00	2.34	7.74
Population Density	.114	404	.00	1.22	1.35
Total Population	.109	404	.00	1.77	5.62
Fruit & Veg Expenses	.134	404	.00	1.62	3.49
Used Prescription Drug for Depression	.097	404	.00	1.44	3.66
Per Capita Income	.109	404	.00	1.38	2.38
Median Household Income	.143	404	.00	1.62	3.29

Variable Computation

A new variable was calculated for this study. A percent of income spent on fruits and vegetables was calculated. The percent of per capita income spent on fruits and vegetables was calculated by dividing per capita income in each community by fruit and vegetable expenses and then multiplied by 100. The calculation represents how much income per person is spent on fruits and vegetables.

Validity

Since this study used point based data of grocery store and fast food restaurants, the accuracy of the data was tested before analysis. The researcher downloaded addresses from grocery stores and fast food restaurants from the yellow pages for a sample of East Tennessee Communities. These addresses were located in Google Earth and then given x, y coordinate information. Those addressed were subsequently geocoded and entered onto a separate layer map. The results from the manual geocoding layer were overlaid and compared to the map layer containing ESRI's locations of fast food restaurants and grocery stores. The researcher visually inspected the overlaid information and found that ESRI's data was consistently more accurate than the yellow page data.

Results

Research Question 1

Research Question 1: Is there a negative relationship between purchases of fruits and vegetables within a community and anti-depressant prescription drug use within Tennessee?

H0: There will not be a relationship between purchases of fruits and vegetables within a community and anti-depressant prescription drug use within Tennessee.

H1: There will be a negative relationship between the purchase of fruits and vegetables and mental health.

The first research question attempts to answer if there a correlation between purchasing fruits and vegetables and mental health in Tennessee communities. The average amount of money spent on fruits and vegetables per year within each community was $767.96. (M=767.96, SD=328.29) The number of people in Tennessee communities who were prescribed anti-depressant medication averaged 421. (M=420.72, SD=243.20). A Pearson correlation bivariate test was conducted. Pearson's correlational test indicated a significant positive relationship between the two variables, *r* (402) =.34, *p* <.01. Therefore, the null hypothesis was rejected. There is a positive relationship between money spent on fruits and vegetables and high prescription drug use for depression. The results are visualized in a scatterplot seen in Figure 3.

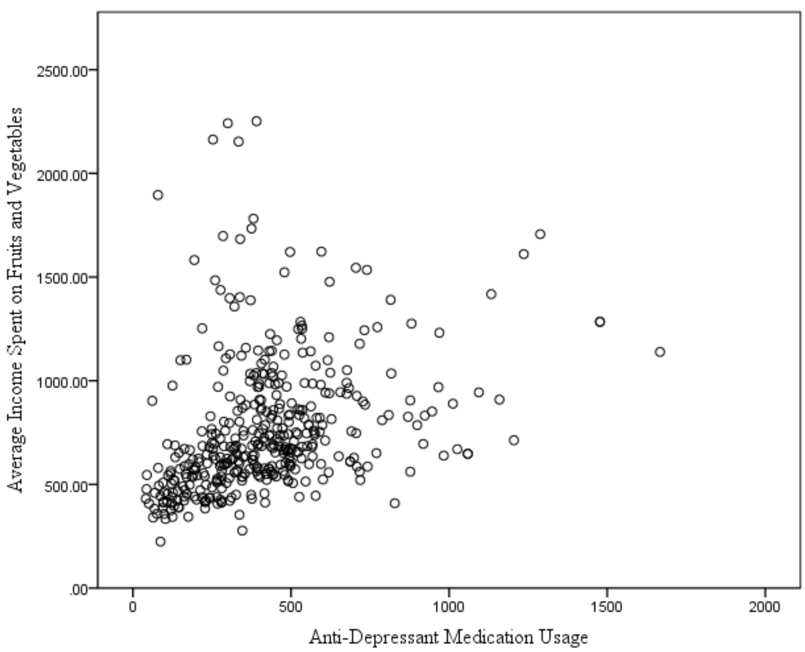

Figure 3. Scatterplot Results of Bivariate Correlation in RQ1

The results from this correlation as seen in Table 7 indicate that household income spent on fruits and vegetables increases as money spent on anti-depression drugs increases. The results of this test do not support the hypothesis. However, it may indicate that if families can afford fruits and vegetables they can also afford prescription medication. The amount of money budgeted towards these items was not factored into the results either. This leads to the next research question, which takes into account the percent of per capita income spent on fruits and vegetables.

Table 7. *Correlation Results of RQ1*

		Fruit and Vegetable Expenditures	Use of Prescription Drug for Depression
1. Yearly Fruit & Veg Expenses	Pearson Correlation	1	.34**
	Sig. (2-tailed)		.000
2. Anti-Depressant Medication Usage	Pearson Correlation	.34**	1
	Sig. (2-tailed)	.000	

**. Correlation is significant at the 0.01 level (2-tailed).

Research Question 2

Research Question 2: Is there a correlation between per capita income spent on fruits and vegetables and the use of anti-depressant medication for depression?

H0: There will not be a significant relationship between per capita income spent on fruits and vegetables and the use of anti-depressant medication

H1: There will be a negative relationship between the purchase of fruits and vegetables and mental health.

This question sought to answer if there was a correlation between per capita income spent on fruits and vegetables and the use of an anti-depressant medication for depression. The average percent of per capita income spent on fruits and vegetables per year within each community was 3.2%. (M=3.18, SD=.37) The number of people in Tennessee communities who were prescribed anti-depressant medication averaged 421. (M=420.72, SD=243.20). The per capita income for each community was divided by the average amount of money spent on fruits and vegetables. This value was then correlated with the number of people who use prescription medication for depression within each community. The Pearson correlation test indicated that *r* (402) = -.42, $p < .05$. The Pearson correlation tests indicated that prescription drug use decreases when the percent of income spent on fruits and vegetables increases. The results can be seen in Table 8 and a scatter plot in Figure 4 visualizes the results.

Table 8. *Correlation Results of RQ2*

		Prescription Drug Use for Depression	Per Capita Income Spent on Fruits and Vegetables
Prescription Drug Use for Depression	Pearson Correlation	1	-.418**
	Sig. (2-tailed)		.000
Per Capita Income Spent on Fruits and Vegetables	Pearson Correlation	-.418**	1
	Sig. (2-tailed)	.000	

**. Correlation is significant at the 0.01 level (2-tailed).

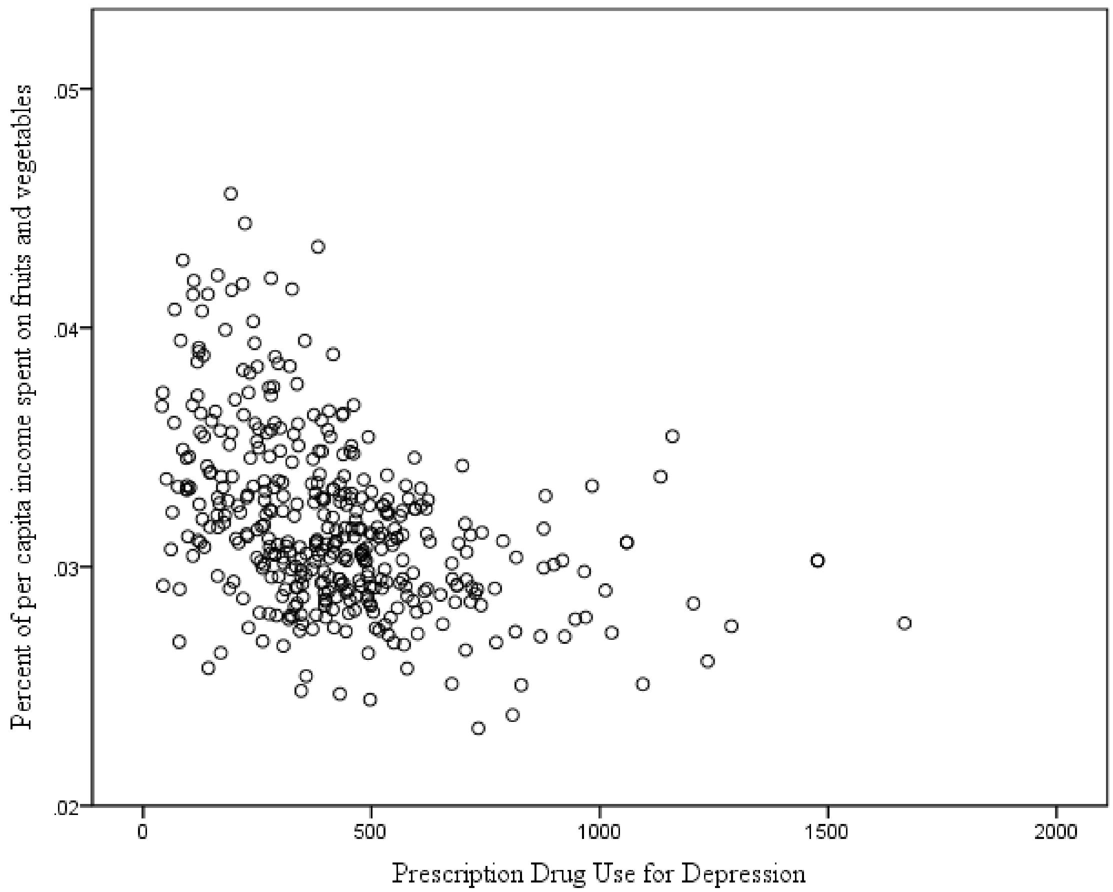

Figure 4. Scatterplot Results of Bivariate Correlation in RQ1

The results of this test show an inverse relationship between per capita income spent on fruits and vegetables and the use of prescription drugs for depression within the communities. In other words, the more income a community spends on fruits and vegetables the fewer community members will be prescribed an anti-depressant for depression. The results of this analysis support the hypothesis that more income spent on fruits and vegetables will have a negative relationship with the number of people within the community who are prescribed medication for anti-depressant medication. Utilization of healthy foods has an inverse relationship with prescriptions for anti-depressant medication within communities.

Cluster Analysis

In order to visualize which areas had strong and weak prevalence of these variables, hot-spot analyses were conducted. Although the presentation of attribute values in the form of choropleth maps was given as part of the descriptive variables, hot spot maps provided more information. The chloroplast maps provided a visualization of variable distributions within each community. However, statistically significant values of high and low counts for each variable were not apparent upon visual examination of the maps. Utilizing the Hot Spot Analysis tool in ArcGIS within the Spatial Statistics Toolbox, analyses were conducted for average fruit and vegetable expenditures, per capita income expenditures on fruit and vegetables, anti-depressant drug use for each community and density of grocery stores and fast food outlets. Each analysis resulted in the creation of an output feature class with standardized scores for each variable. A Getis-Ord Gi* spatial statistic was calculated. The calculation isolates areas that have data which is significantly different from the norm. Areas that had results two standard deviations above the norm were colored red. Areas with two standard deviations below the norm were colored blue. A visual inspection of the data was conducted to see where clustering of data occurred. Interestingly, hot spots for fruit and vegetable purchases typically occurred in the suburbs of Memphis and Nashville as seen in Figure 5. Knoxville had statistically high areas of fast food restaurants while Memphis areas had low areas of fast food outlets. This can be seen in figure 6 and 7 respectively. Also, Knoxville had areas with unusually high amounts of people prescribed prescription drugs for depression and statistically significant cold areas indicating the same areas had very low amounts of per capita income spent on fruits and vegetables. These results can be seen in figures 8, 9 and 10 respectively.

Figure 5. Areas on the outskirts of Memphis and Knoxville had statistically more average income spent on fruits and vegetables

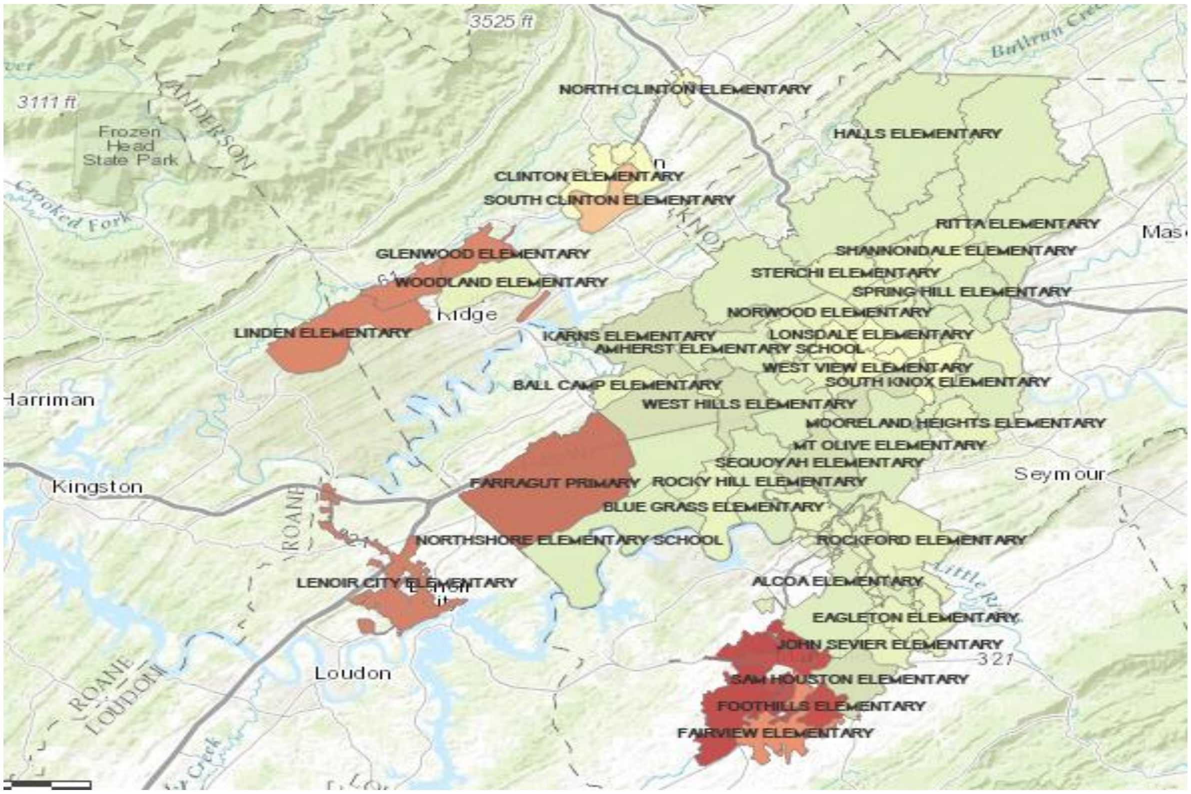

Figure 6. High clusters of fast food restaurants are exhibited around the outskirts of Knoxville

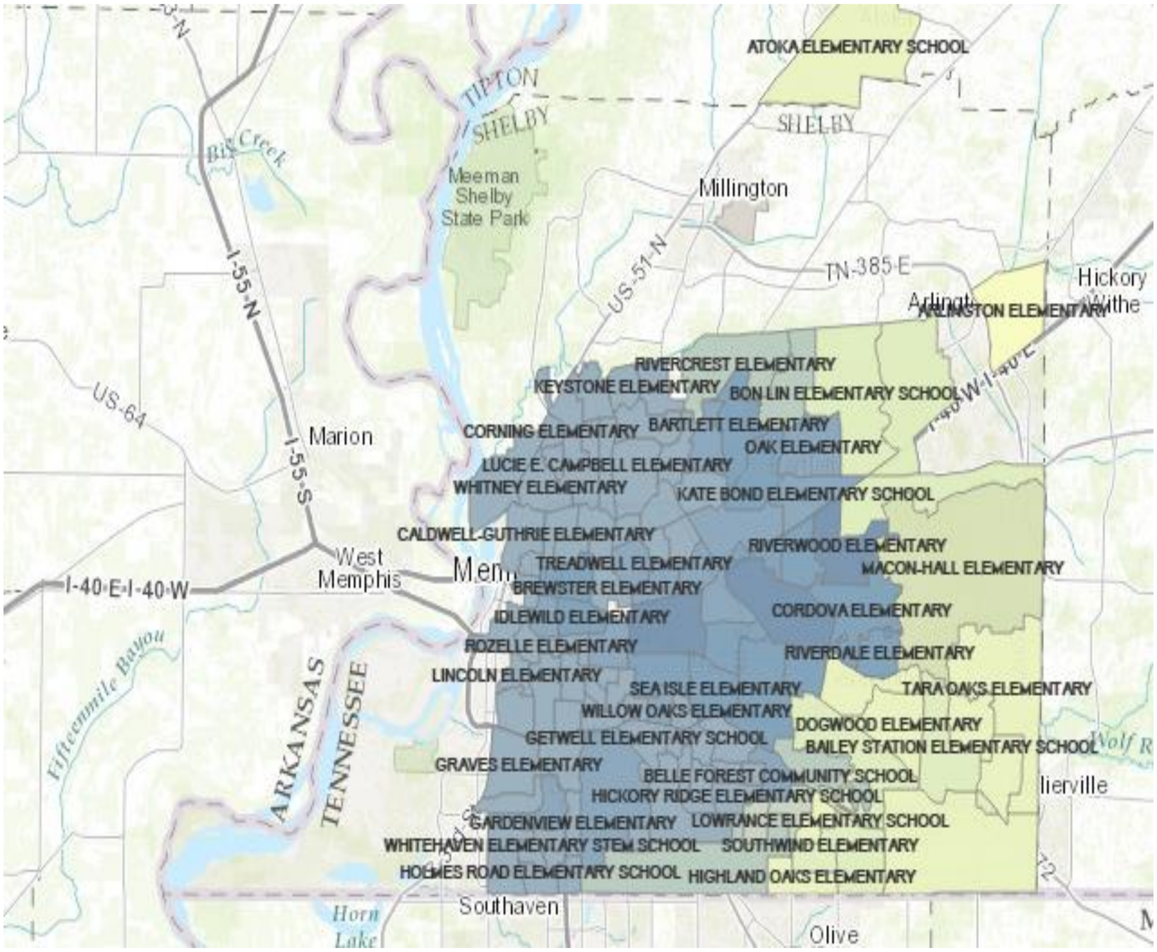

Figure 7. Areas around Memphis have unusually low clusters of fast food restaurants.

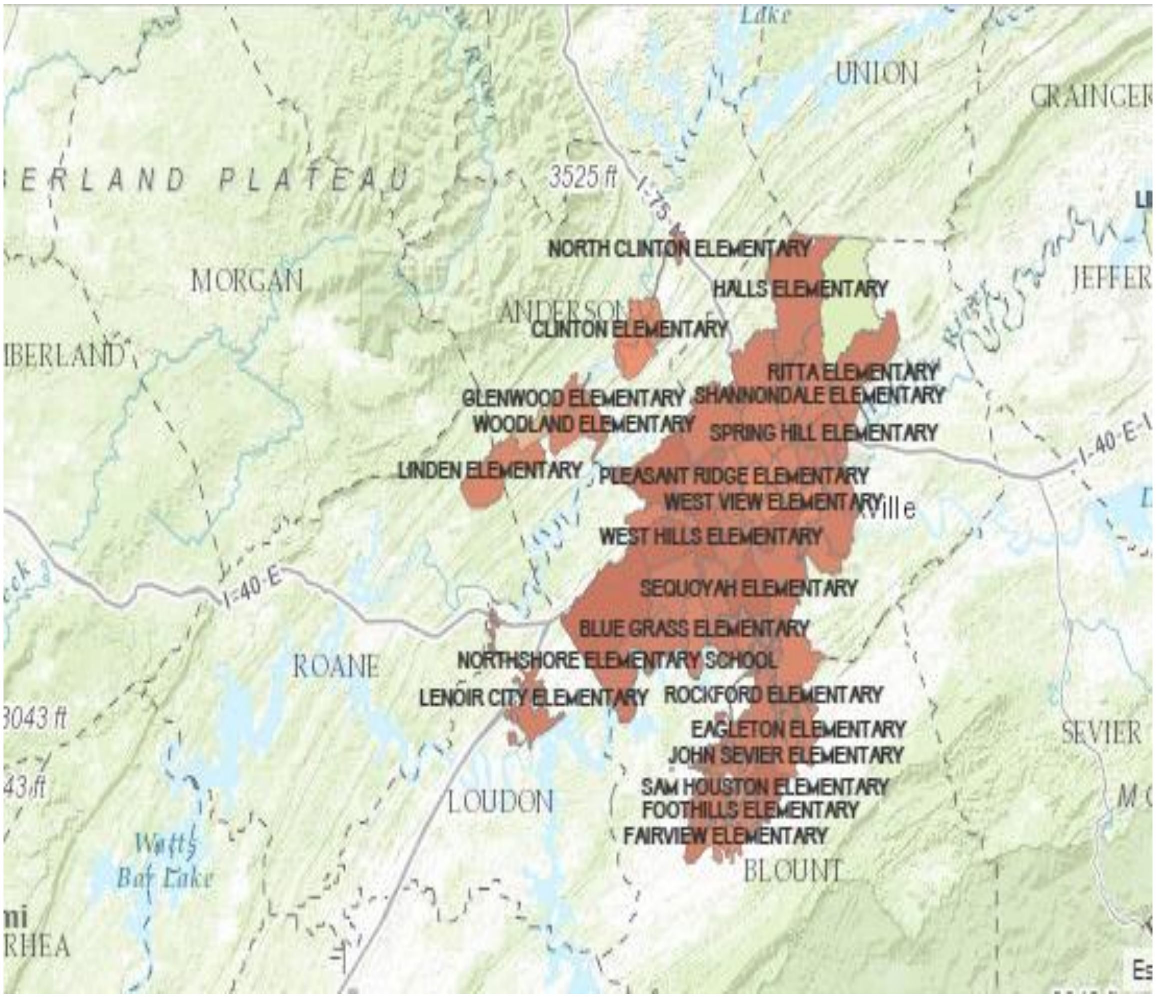

Figure 8. Unusually high clusters of prescription drug use for depression occurred in Knoxville.

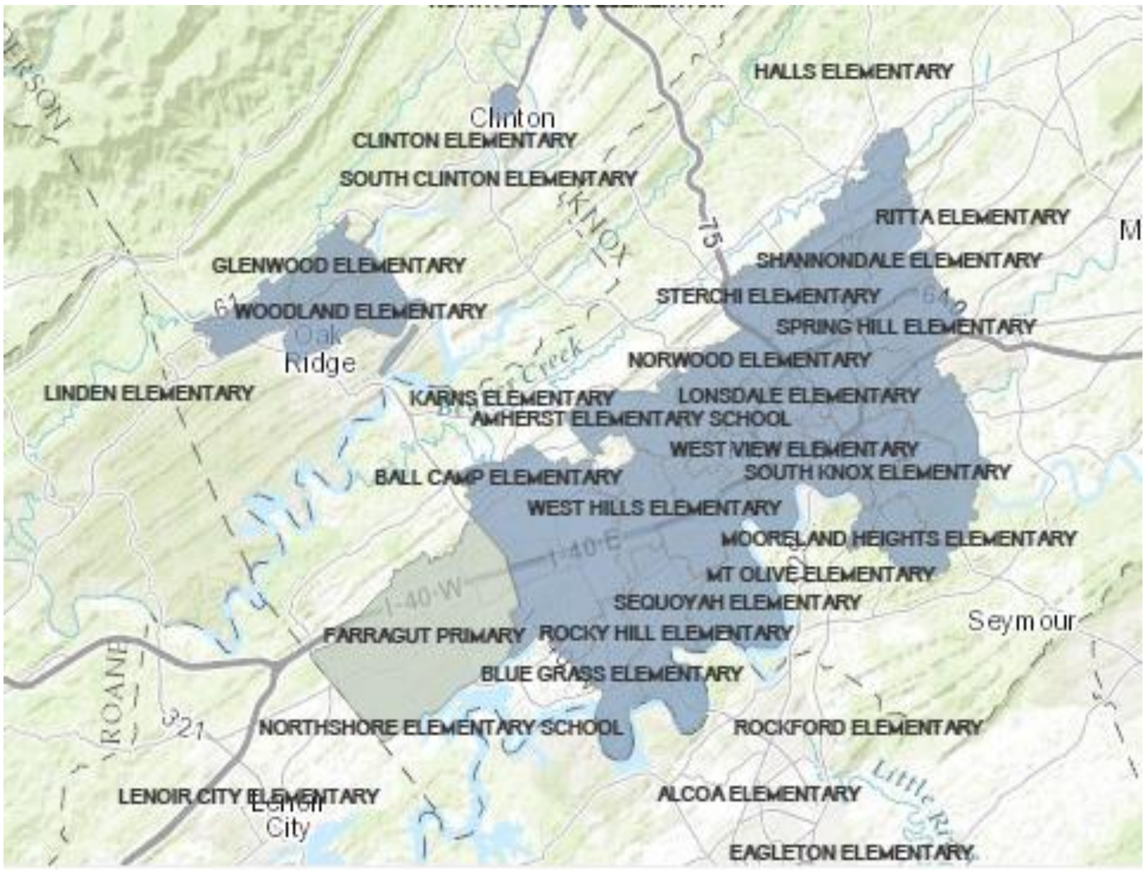

Figure 9. Areas with unusually low amounts of per capita income spent on fruits and vegetables clustered around Knoxville.

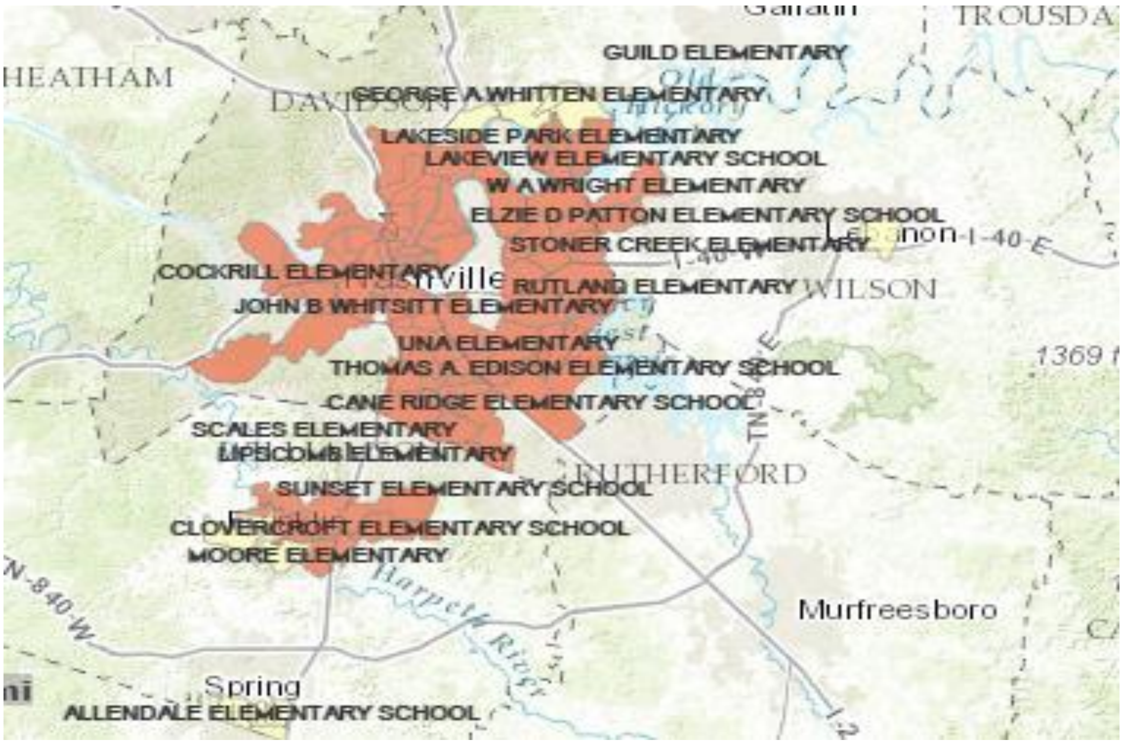

Figure 10. The percent of capita income spent on fruits and vegetables was significantly higher in suburbs of Nashville.

Research Question 3

Research Question 3: Will the density of fast-food restaurants in a neighborhood predict the amount of per capita income spent on fresh fruits and vegetables?

H0: The density of fast-food restaurants in a neighborhood will be unable to predict the amount of per capita income spent on fruits and vegetables

H1: As the number of fast-food restaurants in a neighborhood increases, the amount of income spent on fruits and vegetables decreases.

A simple linear regression model will be used to determine whether the density of fast food restaurants predicts the amount of income spent on fresh fruits and vegetables.

IV: Density of fast food restaurants

DV: Per capita income spent on fruits and vegetables yearly

To determine if the density of fast-food restaurants in a neighborhood predicts the percentage of income spent on fresh fruits and vegetables, a regression analysis was conducted. The average amount of per capita income communities spent on fruits and vegetables was 3.2%. ($M=3.2$, $SD=.37$) The average number of fast food restaurants in each neighborhood was 8.6 ($M=8.6$, $SD=9.6$). The bi-variate correlation indicated that there was a negative correlation between the two variables r (402) = -.37, $p<.01$. Per Cohen (1988), the effect size is medium if r is calculated around 0.3. This correlation indicated that the density of fast food restaurants has a medium effect on average fresh fruit and vegetable purchases within each community. A Normal P-P plot used to verify the normal distribution of variance is included in Figure 11.

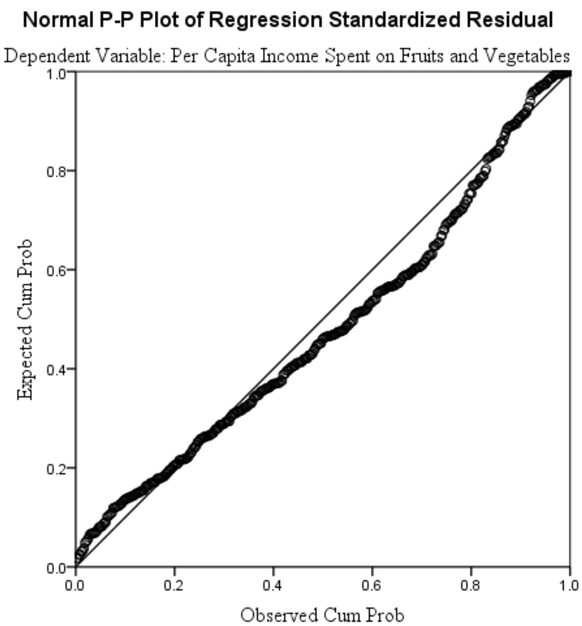

Figure 11. *Normal P-P Plot of Regression Standardized Residual RQ3*

This study hypothesized that less money would be spent on fruits and vegetables if more fast food restaurants dominated the neighborhood. The regression analysis supports this hypothesis F (1, 403) = 62.44, p<.01. The overall model fit was r^2=.13. The number of grocery stores (β = --.37, p <.01) accounted for approximately 13% of the variance in number of community members prescribed anti-depressant medication. From this, we suggest that a prediction model of $\hat{Y} = .03 + -0.16*fast\ food\ density$. For each unit increase of fast food restaurants within an area, the model predicts an average decrease of 0.16 percent of income spent on fruits and vegetables For each standard deviation increase in the amount of fast food restaurants within communities, the percent of per capita income spent on fruits and vegetables decreased by .37, (β =-.37). A summary of the results is depicted in Table 8.

Table 8. *Regression Table RQ3*

		Unstandardized Coefficients		Standardized Coefficients		
Model		*B*	Std. Error	β	t	Sig.
1	(Constant)	3.3	.023		143.25	.00
	Density of Fast Food Restaurants	-.02	.002	-.37	-7.90	.00

a. Dependent Variable: Percent of Per Capita Income Spent on Fruits and Vegetables

Geographically Weighted Regression Results

A geographically weighted regression (GWR) model was calculated along with the linear regression model. GWR captures location relationships between observations and provides more detailed information that which simply are not addressed by a global (OLS) regression model. Using the Geographically Weighted Regression (GWR) tool in the spatial relationships toolset with ArcGIS, a spatially calibrated model was generated. GWR was calculating using an adaptive kernel type bandwidth with cross validation. Since the adaptive approach was selected, bandwidths are specified in terms of nearest neighbors. For this analysis, the GWR converged at 121 nearest neighbors.

The GWR tool gave separate regression coefficients for each of the 404 communities in the sample. These coefficients were mapped as raster surfaces, and the communities were color coded by spatially varying regression coefficients generated using the GWR tool in ArcGIS. Red areas represented regression coefficients more than 2.5 standard deviations above normal and blue areas represented areas with less than 2.5 standard deviations below normal. Shades of variation represent values in between. A map depicting the results is included in the Appendix C. The linear regression model was significant and had a r^2 value of 0.13 (p<.01). Additionally, the GWR model improved on these statistics and increased the model's accuracy to an r^2 value of 0.28 (p<.01). Upon visual examination, it appears as if Knoxville and Nashville had areas with residuals significantly higher than normal while Memphis, Jackson and Chattanooga areas had areas with residuals significantly below normal.

Research Question 4

Research Question 4: Will the density of grocery stores in a neighborhood predict the amount of income spent on fresh fruits and vegetables?

H0: The density of grocery stores in a neighborhood will be unable to predict the amount of income spent on fresh fruit and vegetables

H1: As the number of grocery stores in an area increases the number of fresh fruit and vegetable purchases increases.

The average amount of income spent on fruits and vegetables is 3.2%. The average amount of grocery stores per community is 4.83. A bivariate correlation analysis was conducted before a regression analysis. The bi-variate correlation indicated that the two variables were inversely related to each other *r* (402) = -.16, p<.01. Per Cohen (1988), the effect size is small if *r* is calculated around 0.1. This correlation indicated that the density of grocery stores has a small effect on average fresh fruit and vegetable purchases within each community. A Normal P-P plot used to verify the normal distribution of variance is included in Figure 12.

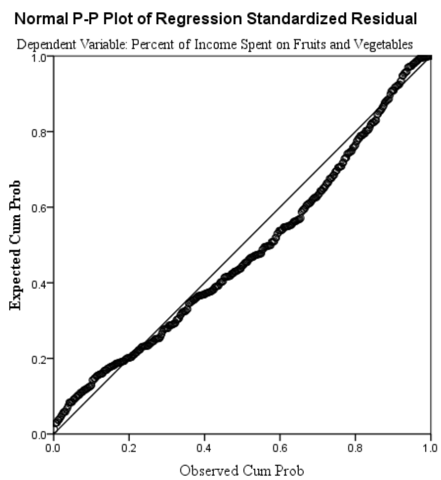

Figure 12. Normal P-P Plot of Regression Standardized Residual RQ4

The regression analysis does not support the hypothesis that as grocery stores increases the average amount of per capita income spent on fruits and vegetables increases *F* (1, 402) = 11.01, *p*<.01. The model significantly indicated that the opposite is true that as the density of grocery stores increases the amount of per capita income spent on fruits and vegetables decreases. The overall model fit was r^2=.03 The number of grocery stores (β = -.16, *p* <.01) accounted for approximately 2.7% of the variance in number of community members prescribed anti-depressant medication. From this, we suggest that a prediction model of Ŷ = *3.26+ -0.16*grocery store density*. For each unit change of grocery stores within an area the model predicts an average decrease of 0.16 percent of income spent on fruits and vegetables. For each standard deviation increase in grocery store density, the change in percent of income spent on fruits and vegetables decreases .16. Table 9 outlines the regression model.

Table 9: *Regression Table RQ4*

		Unstandardized Coefficients		Standardized Coefficients		
Model		*B*	Std. Error	β	t	Sig.
1	(Constant)	3.26	.03		109.06	.000
	Density of Grocery stores	-.016	.01	-.16	-3.32	.000

a. Dependent Variable: Per capita income spent on fruits and vegetables

Geographic Weighted Regression Results

A geographically weighted regression model was calculated along with the linear regression model in order to depict local variations in the relationship between variables. GWR captures location relationships between observations and provides more detailed information that which simply are not addressed by a global (OLS) regression model. Using the Geographically Weighted Regression (GWR) tool in the spatial relationships toolset with ArcGIS, a spatially calibrated model was generated. GWR was calculating using an adaptive kernel type bandwidth with cross validation. Since the adaptive approach was selected, bandwidths are specified in terms of nearest neighbors. For the data, the program has converged at 75 nearest neighbors.

The GWR tool gave separate regression coefficients for each of the 404 communities in the sample. These coefficients were mapped as raster surfaces, and the communities were color coded per spatially varying regression coefficients. These coefficients were mapped as raster surfaces, and the communities were color coded by spatially varying regression coefficients. Red areas represented regression coefficients more than 2.5 standard deviations above normal and blue areas represented areas with less than 2.5 standard deviations below normal. Shades of variation represent values in between. A map depicting the results is included in the appendix. The linear regression model was significant and had a $r^2 = 0.03$ ($p<.01$). However, the GWR model improved on these statistics and increased the model's accuracy to an r^2 value of 0.28 ($p<.01$). A visual inspection of the data indicated that communities that were not close to cities had the residuals significantly higher than urban areas.

Research Question 5

Research Question 5: Will the density of fast-food restaurants in a neighborhood predict the number of people in the community who use a prescription drug for depression?

H0: The density of fast-food restaurants in a neighborhood will be unable to predict the number of people in the community who use a prescription drug for depression.

H1: As the number of fast-food restaurants in a neighborhood increases the number of people who use prescription drugs for depression will increase.

A simple linear regression model will be used to determine whether the density of fast food restaurants predicts the number of people in the community who use a prescription drug for depression.

IV: Density of fast food restaurants in community school area

DV: Number of people in the community who use anti-depressant medication

The following research question sought to answer if the density of fast-food restaurants in a neighborhood predicts the number of people in the community who use a prescription drug for depression. The study hypothesized that an increase in fast food restaurants would predict more people prescribed anti-depressant medication.

The average number of people in each community who were prescribed anti-depressant medication was 421. (M=420.72, SD=243.20). The average amount of fast food restaurants in each community was 8.6 (M=8.53, SD=9.58). A Normal P-P plot used to verify the normal distribution of variance is included in Fig. 13

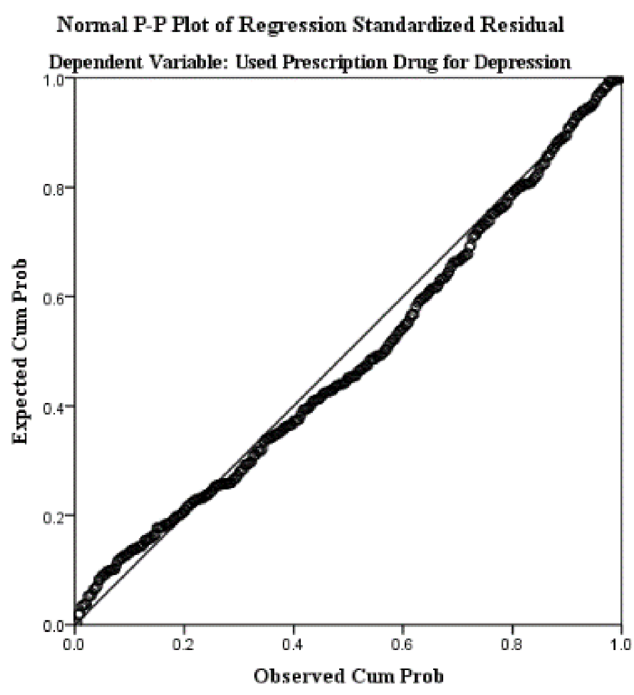

Figure 13. Normal P-P Plot of Regression Standardized Residual RQ5

The results indicate there is a significant and positive correlation between individuals who use prescription drugs for depression and the density of fast food restaurants in their community. r (404) = .67. Per Cohen (1988), the effect size is large if r is calculated above 0.5. This correlation indicated that the density of fast food restaurants has a large effect on the number of people who are prescribed anti-depressant medication wtihin each community. The regression analysis indicated that the number of people within a community who use anti-depressant medication could be predicted from the amount of fast food restaurants in the area. The regression analysis supports this hypothesis: F (1, 402) = 329.13, p <.01. The overall model fit was r^2=.45. The density of fast food restaurants in an area (β = .67, p <.01) accounted for approximately 45% of the variance in the number of community members who are prescribed anti-depressant medication. From this, we suggest that a prediction model of $\hat{Y}$ = *275.30+ 17.04*fast food restaurants*. For each unit of fast food restaurant increase the model predicts an average increase of 17 people prescribed anti-depressant medication. For each standard deviation increase in the density of fast food restaurants the number of community members prescribed antidepressant medication increases .67 since β=.67 While this study cannot conclude that fast food restaurants directly causes more community members to be prescribed anti-depressant medication, the data support the hypothesis that communities with more fast food restaurants will have more community members prescribed anti-depressant medication. The results are summarized in Table 10.

Table 10. *Regression Table RQ5*

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	β	t	Sig.
1	(Constant)	275.296	12.039		22.866	.000
	Density of Fast Food Restaurants	17.039	.939	.671	18.142	.000

a. Dependent Variable: Anti-Depressant Medication Usage

Geographic Weighted Regression Results

A geographically weighted regression (GWR) model was calculated along with the linear regression model. GWR captures location relationships between observations and provides more detailed information that which simply are not addressed by a global (OLS) regression model. Using the Geographically Weighted Regression (GWR) tool in the Spatial Relationships toolset with Arc GIS, a spatially calibrated model was generated. GWR was calculating using an adaptive kernel type bandwidth with cross validation. The GWR tool calculated 392 neighbors. The GWR tool gave separate regression coefficients for each of the 404 communities in the sample. These coefficients were mapped as raster surfaces, and the communities were color coded by spatially varying regression coefficients. The communities were color coded according to spatially varying regression coefficients. Red areas represented regression coefficients more than 2.5 standard deviations above normal and blue areas represented areas with less than 2.5 standard deviations below normal. Shades of variation represent values in between. While the original linear regression model was found to be significant and had an r^2 value of 0.45 ($p <.01$), the GWR model did slightly improve on these statistics and increased the model's accuracy to an r^2 value of 0.47 ($p <.01$). A map of the areas with high and low values is included in the appendix. Upon visual examination, it appears as if Knoxville and Nashville had areas with residuals significantly higher than normal while Memphis, Jackson and Chattanooga areas had areas with standard deviations below normal.

Research Question 6

Will the density of grocery stores in a neighborhood predict the number of people who use prescription drugs for depression?

H0: The density of grocery stores in a neighborhood will be unable to predict the number of people who use prescription drugs for depression.

H1: As the number of grocery stores increases, the number of people who use prescription drugs for depression decreases.

Will the density of grocery stores in a neighborhood predict the number of people who use prescription drugs for depression?

The average number of people in each community who were prescribed anti -depressant medication was 420. (M=419.46, SD=243.11). The average amount of grocery stores in each community was 4.8 (M=4.8, SD=3.7). A P-P plot verified normal distribution of variance as seen in Fig. 14.

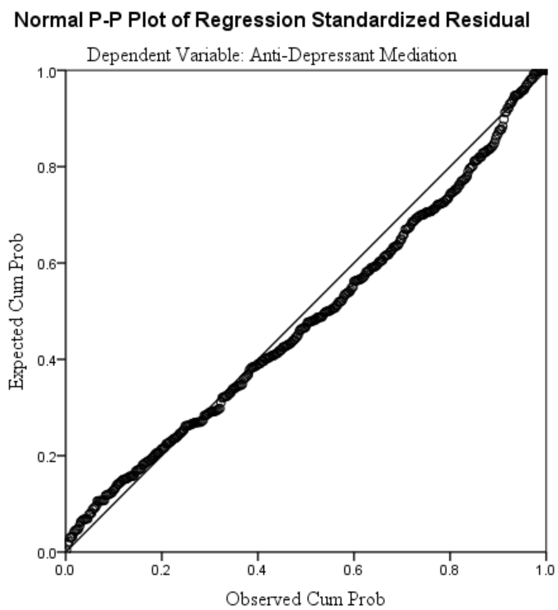

Figure 14. Normal P-P Plot of Regression Standardized Residual RQ6

The results indicate there is a significant and positive correlation between individuals who use prescription drugs for depression and the density of grocery stores in their community, *r* (402) = .41, (p<01.). Per Cohen (1988), the effect size is medium if *r* is calculated above 0.3.

This correlation indicated that the density of grocery stores has a medium effect on the number of people who are prescribed anti-depressant medication wtihin each community. The regression analysis indicated that the number of people within a community who use anti-depressant medication could be predicted from the density of grocery stores in the area F (1, 402) = 80.28, p<01. The overall model fit was r^2=.17. The number of grocery stores (β = .40, p <.01) accounted for approximately 17% of the variance in number of community members prescribed anti-depressant medication. From this, we suggest that a prediction model of Ŷ = *292.07+ 26.63*grocery store density*. For each unit increase of grocery stores in an area, the model predicts an average increase of 27 people prescribed anti-depressant medication. For each standard deviation increase in grocery stores (1 SD), the standard deviation increase of individuals in each community prescribed anti-depressant medication increases by .4 since β=.4. The results can be seen in Table 11.

Table 11. Regression Table RQ6

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	β	t	Sig.
1	(Constant)	292.07	18.12		16.12	.00
	Grocery Store Density	26.63	2.97	.41	8.96	.00

a. Dependent Variable: Anti-Depressant Medication Use

Geographic Weighted Regression Results

A geographically weighted regression (GWR) model was calculated along with the linear regression model. GWR captures location relationships between observations and provides more detailed information that which simply are not addressed by a global (OLS) regression model. Using the Geographically Weighted Regression (GWR) tool in the Spatial Relationships toolset with ArcGIS, a spatially calibrated model was generated. GWR was calculating using an adaptive kernel type bandwidth with cross validation. The GWR tool calculated 55 neighbors. Separate regression coefficients for each of the 404 communities were calculated and then these coefficients were mapped as raster surfaces. The communities were color coded by spatially varying regression coefficients. Red areas represented regression coefficients more than 2.5 standard deviations above normal and blue areas represented areas with less than 2.5 standard deviations below normal. Shades of variation represent values in between. Although the linear regression model was significant and had an r^2 value of 0.17 ($p <$ 01.), the GWR model improved these statistics and increased the model's accuracy to an r^2 value of 0.37 ($p<.01$). A map of the areas with high and low values is included in the appendix. Upon visual examination, it appears as if suburban areas had significantly lower relationships than intercity areas.

Limitations

The results of spatial autocorrelation indicated that all of the data had a significant spatial autocorrelation. This indicates that the data may have a modified area unit problem which is increasing the chance of a Type I error. However, when the geographically weighted regression (GWR) was conducted alongside ordinary least Squares regression (OLS), the regression was still significant. However, the effect size of the relationship was altered. Comparing the results of this study with a similar study using census block groups or zip codes may further enhance or validate these results.

Summary of Results

The first two statistical tests completed compared income spent on fruits and vegetables to use of anti-depressant medication within communities. The first test showed a positive and significant correlation between fruit and vegetable purchases within communities and anti-depressant medication. As purchases of fruits and vegetables increases the use of anti-depressant medication increases. The relationship was significant and positive, but not expected. The hypothesis indicated that anti-depressant medication users would decrease as purchases of fruits and vegetables increased. However, the second correlational analysis supported this hypothesis. In the second correlational analysis, the percent of per capita income spent on fruits and vegetables was correlated with anti-depressant medication. As a percentage of income spent on fruits and vegetables increases, the number of people using anti-depressants decreases

The final four analysis used regression to model the relationship between variables. All four regression models were significant. Table 13 summarizes the results. The first regression analysis projected the amount of per capita income spent on fruits and vegetables based on the amount of fast food restaurants in the area. The model was significant and supported the hypothesis that the amount of per capita income spent on fruit and vegetables decreases when more fast food restaurants are in the area. This regression model accurately predicts changes in average income spent on fresh fruits and vegetables 13% of the time. The next analysis predicted the average amount of per capita income spent on fruits and vegetables by the density of grocery stores within the area. The regression analysis did not support the hypothesis that as grocery stores increases the average amount of per capita income spent on fruits and vegetables increases The model significantly indicated that the opposite is true that as the density of grocery stores increases the amount of per capita income spent on fruits and vegetables decreases. However, the model was only accurate 3% of the time. The next regression analysis supported the hypothesis that as the number fast food restaurants in the area increases, the number of community members who are prescribed anti-depressant medication would rise. The density of fast food restaurants predicted the number of people in the community who were prescribed anti-depressant medication 45% of the time. The regression analysis indicated that the number of people on anti-depressant medication could be predicted from the amount of grocery stores in the area 17%. A summary the statistical findings is included in Table 12. This includes percent of variance explained in each regression analysis, the variance explained in the geographical weighted regression and a visual inspection of the geographical weighted regression to determine if there were areas where the statistical findings were stronger or weaker than others.

Table 12. *Summary of Regression Results*

Research Question	*r*	r^2	GWR r^2	Visual Inspection
Will the density of fast food restaurants in a neighborhood predict the amount of per capita income spent on fresh fruits and vegetables?	-.37	.13	.28	Knoxville and Nashville had areas with residuals significantly higher than normal while Memphis, Jackson and Chattanooga areas had areas with residuals significantly below normal.
Will the density of grocery stores in a neighborhood predict the amount of income spent on fresh fruits and vegetables?	-.16	.03	.28	A visual inspection of the data indicated that communities that were further from cities had residuals significantly higher than urban areas.
Will the density of fast-food restaurants in a neighborhood predict the number of people in the community who use a prescription drug for depression?	.67	.45	.47	Knoxville and Nashville had areas with residuals significantly higher than normal while Memphis, Jackson and Chattanooga areas had areas with standard deviations below normal.
Will the density of grocery stores in a neighborhood predict the number of people who use prescription drugs for depression?	.41	.17	.35	Suburban areas had significantly lower relationships than intercity areas.

CHAPTER 5: DISCUSSION

Introduction

This chapter reviews the first four chapters, which gives a summary of using spatial data to evaluate the impact of the food environment on the mental health of the community. It then provides implications for counselors and provides suggestions for using spatial data to improve counseling interventions, action, and evaluation. Finally, limitations of this study and recommendations for future research are presented.

Literature Review Summary

Spatial measures of food environments and mental health bring attention to the disparities that persist in many East Tennessee Communities. The social determinants of mental health can help theoretically explain some of the factors influencing the health disparities within communities. According to research, the key to identifying disparities in mental health outcomes comes from examining differences in neighborhoods (Hill et al., 2000; Rocchini, 2002). Providers should have a basic understanding of the environment to fully understand all the supports and barriers that exist in the clients that they serve. An understanding of the food environment can lead to healthier lifestyles in the communities they serve.

An ecological perspective was used for this study because the ecological perspective encourages researchers to consider the impact communities and neighborhoods have on individual's state of mind and mental health. The ecological perspective provides the researcher with a broad perspective of a neighborhood (Robinson, 2009). Within the ecological perspective, one is looking beyond the individual to understand behavior from a larger vantage point. This study defined neighborhoods using the elementary school district boundaries. Schools are central to many communities and provide the fabric for community interactions and education. As seen in the literature, the social determinants of health and mental health have a large impact on the well-being of each community. The ecological perspective encourages researchers to consider communities and neighborhoods as impactful on individual's state of mind and well-being.

The impact of nutrition on individual mental health has been documented within the research. Additionally, the issues related to mental health are also intertwined with physical health. Many times, mental illness is studied at the individual level and viewed as an individual problem. However, the behaviors of individuals collectively demonstrate the impact that individual disease and illnesses on the community and the environment. Inversely, the impact of an individual's good health and well-being and the absence of disease in individuals can impact the community, environment, and neighborhood in which individuals interact. The environmental factors often have a reciprocal relationship with physical and mental illness. This can be seen through the concept of allostatic load. Allostatic load is the long-term result of stress on the body.

Methodology Summary

This dissertation examines the existence and significance of spatial dependencies between neighborhood characteristics and one specific social determinant of mental health – food insecurity. The objectives are to find the associations between mental health and neighborhood characteristics of food insecurity. This study incorporates methods and technologies used in other fields of research from a counseling perspective. Although the use of Geographic Information Systems (GIS) technology and geocoding neighborhood factors has been used in public health, sociology, and geography research, the counseling field has yet to widely incorporate the usefulness of these methods to explore problems of interest to this profession. However, there is a need for additional research that considers the interconnectedness of counseling issues that encompass the individual within the context of the environment.

Although the goal of statistical analysis is to find "if" there is a relationship between variables, the goal of a GIS analysis is finding where that relationship occurs (Law & Collins, 2013). This study used bivariate correlation and regression analysis to determine if relationships exist between food choices and mental health. To determine where correlations are strongest, GIS data was used to conduct geographically weighted regression (GWR). Statistical analyses were used to determine where and why mental health and food insecurity intersect. Additionally, this research used descriptive statistics, cluster analysis, Pearson correlations, ordinary least squares regression (OLS) and geographically weighted regression (GWR) to investigate differences in geographic units. Before any analyses were conducted, the assumptions of the analysis were tested and validated.

Findings

Within Tennessee communities used for this study, a relationship between mental health and healthy eating was found. The more per capita income spent on fruits and vegetables the fewer people in the community are prescribed anti-depressant medication. Additionally, the regression model found that as the density of fast food restaurants increases, the number of people who are prescribed anti-depressant medication also increases. This supports previous research on the relationship between healthy eating and mental health. Policy makers and counselors alike who provide services in communities which were identified as hotspot areas of fast food restaurants may benefit from participatory action research projects. Discussions on the impact of fast food restaurants on the mental health of community members may provide valuable insight for counselors providing services and policy makers whose decisions directly impact community members. It is apparent that income and SES plays an important role in these correlations. A regression model using income as a moderator would further enhance the initial correlations and help to explain the role income plays in the relationship between fruit and vegetable purchases and anti-depressant medication. Since the enactment of Affordable Care Act, citizens are required to have health insurance that covers mental health services. Therefore, the cost of prescription medication should not have as much impact on community members as the cost of fruits and vegetables. However, there is still a stigma associated with mental health and a lack of understanding of what health insurance now covers. The cost of prescription medication may indirectly play a role and contribute to the variance between the two variables. Since that was not considered for this study, it poses a limitation for the results.

. One cannot state that purchasing fruits and vegetables causes anti-depressant use to decrease. Even though there is a statistically significant relationship between the two concepts, a researcher cannot rule out the possibility that there are not a third variable affecting the relationship. For example, when per capita income was used to transform the amount of money spent on fruits and vegetables, the correlation changed directions which show that income has a large impact on the behavior of individuals within a community.

A visual examination of the cluster analysis showed significant clustering in certain areas. When the cluster analysis maps are overlaid, Knoxville areas schools showed both high areas of prescription drug use for depression and low averages of per capita income spent on fruits and vegetables. A participatory action research project within areas with high and low clustering area may shed light on the impact of the relationship in local areas and give counselors and policy makers more information on interventions that meet the needs of the community members.

However, the most significant regression analysis concluded that the density of fast food restaurants in an area predicted the number of community members who were prescribed anti-depressant medication. This coupled with the correlation that more per capita income spent on fresh fruits and vegetables reduces the number of community members using anti-depressant medication has significant implications for community leaders, educators, and counselors.

Multiple regression would enhance this study by using more than one variable to model the relationship between fast food restaurants and grocery stores. Additionally, a participatory action research study may be helpful to validate the results of this study. Areas in which there is a high density of fast food restaurants may want to have a discussion with community members to see if the projected impact of fast food restaurants is having the predicted impact on the community. The idea then validates the results and explains what other factors may be present in the relationship between healthy eating and mental health.

The findings of this study support the need to consider neighborhood and environmental interventions in the prevention of mental health. The results indicate that there is a relationship between mental health and healthy eating within Tennessee communities. The density of fast food restaurants within certain communities is highly localized and hot and cold spots of fast food restaurants were identified. These spatial clustering patterns suggest a need for localized counseling interventions related to the food environment. Counselors providing services in areas that are identified as hot spots (i.e., areas with extremely high fast food restaurant density), can pay attention to the neighborhood characteristics and plan or prepare counseling interventions that relate to the food environment. Although counseling interventions often focus on the individual or the family, counselors can be proactive with their clients by identifying neighborhood, and the social culture that impacts the counseling process.

Limitations

The use of one or two variables to measure socio-demographic features in neighborhoods is not enough to understand mental health disparities and capture the unique picture of mental health within a community. Although this study may provide a start to understanding the relationship between the food environment and mental health, implementing multivariate studies into the integration of the mental health counseling planning activities will be useful in guiding health resource allocation, service provision, and policy decisions at the local level.

The data used for this study was aggregated data that includes estimated numbers based on survey and economic models. Unfortunately, it does not fully capture the actual number of people within each community who struggle with mental illness or are impacted by poor food availability and poor food choices. This data represents the estimated number of users about the 2014 estimated local population. Since data available for these specific measurements are aggregated into a group, we as researchers do not know the entire story. Maps, just like any other information graphic, exist to show signals in the noise (Goodchild et al., 1992).

The Modified Area Unit Problem discussed in the literature review may also impact this study. Because community boundaries were drawn as elementary school boundaries, the aggregated estimates may not be accurate. Point based data that falls on the boundary of the community may not be modeled correctly. Furthermore, the data may be duplicated in surrounding communities, which could overestimate the problem especially if the boundary drawn does not reflect the actual community as defined by the people who live in the area.

Using the ethical considerations of this study, readers need to be careful not to conclude erroneous conclusions from this data. Correlation does not necessarily mean causation. Eating unhealthy food does not cause mental illness. Additional variables may influence the relationship between the two variables. Adding more variables may fully explain the impact of healthy eating and mental health within a community. Additionally, drawing the conclusion that all people who are prescribed anti-depressants eat unhealthy foods would be erroneous.

Furthermore, the data for this study only captured one moment in time. It did not capture longitudinal data. Nor did this study capture the neighborhood environment from the participants' childhood living experience. Although one's childhood has been shown to have an impact on mental health, this study can only analyze the current condition of mental health within the community against the current state of food choices made by adults. Although the past may have influenced members in this study, it was not considered as a factor for this research.

Implications

This study saw an inverse relationship between the percentage of income spent on fruits and vegetables and prescription drug use for depression. The number of people prescribed antidepressant medication in communities decrease as more per capita income was spent on fruits and vegetables. Additionally, as fast food restaurants increased in a community prescription medication for depression also increased. Counselors who are serving communities that have a significantly higher rate of prescription drug use for anti-depressant medication, high fast food outlets or low percentage of income spent on fruits and vegetables may want to consider a participatory action research study to understand the impact that these variables have on specific communities. Furthermore, there may be other multiple variate relationships within the community impacting the correlation seen between mental wellness and unhealthy eating locations and habits. Counselors, educators, and community leaders may benefit from having meaningful discussions on the additional variables affecting the bivariate relationship in their specific communities. Subsequently, discussion on how to improve both healthy eating and improve mental health in the community would result from the initial discussion on the findings of this research study.

This study used aggregated data to obtain an overview of mental wellness patterns within communities as related to healthy/unhealthy food access and consumption. Developing mental health outcome measures based on population indicators has unique advantages. This may be particularly helpful for school counselors, community leaders, or other health professionals who want to use aggregated data to influence social determinants of mental health in an attempt to improve counseling outcomes for individuals and the community as a whole.

Integration of cross-disciplinary methods of inquiry can be utilized to broaden the knowledge base of counseling as seen in this study. These results also point to the importance of incorporating mapping technology in the planning of mental health services to best serve the needs of the population within each geographic area. Additionally, these methods can be expanded to: identify target areas for prevention and outreach efforts, provide visual data for policy recommendations, demonstrate need in seeking funding opportunities, and aid in program evaluation efforts. On the community level, the integration of methods brings professionals from varying disciplines together in collaborative work thus realizing more effective and holistic social change.

Implications for Counseling Practice

Since no person can be completely understood apart from his or her defining social context, using neighborhood context to understand individuals guides counselors to see the connectedness between client and system. This eliminates the hyphen between person and environment. Since provision of individual one-on-one counseling sessions is a major role of counselors, it is easy to focus on intrapersonal issues while ignoring ecological problems rooted in the built environmental of the community. Although taking an ecological perspective to counseling often complicates the task of designing interventions, the outcomes of counseling may improve if culture and context are used within the interventions. Ecological focus implies that individuals and their environments are adaptive to each other. Therefore, interventions can be carried out in either person or environment and have a reciprocal impact on the other. The ecological perspective can enable counselors to see clients through a system of lenses that does not separate the person from the environment but requires that they are seen together. Systemic thinking (used in the ecosystems perspective) allows the practitioner to recognize the interconnections present in clients, and thus, consider interventions anywhere in the case.

Effective, evidence-based, and well-coordinated treatments could yield ineffective results if the environment in which the client lives does not support the treatment objectives. From this perspective, the implications of this study inform service providers as to where their programs are most needed in the context of the food environment within communities.

A primary purpose of this study is to identify, propose, and statistically compare the food environment within school communities as it is related to mental health. The overall implications are intended to aid in improving the overall counseling services for individuals within the context of the neighborhood by informing decision making around locations. Identifying differences between the food environment among neighborhoods has clarified how mental health services could be directly impacted by where client's live and work. The identification neighborhoods with unhealthy food environments provide counselors with knowledge of how their well-intended interventions may be unsuccessful if the environment is not taken into consideration during the counseling process. The identification of proximal access to unhealthy foods may give policy makers and counselors suggestions as to where new services may be placed to meet the geographic counseling needs of clients. Specifically, it is hoped that this knowledge will demonstrate the importance of proximal access in service delivery.

Future Research

There is a growing body of literature assessing the geography of fast food in relationship to obesity. Most of the studies have found a positive association between availability of fast food and obesity. More geographical analyses combining food access with food consumption data related to mental health would give counselors more direction on the integration of their services with the community in which they serve. Not only is there is a need for research which connects eating habits and mental health, but also on other social determinants of mental health. Combining data on as many possible potential confounding factors provide a more accurate picture of the community and increase counselor success with clients. Since allostatic load measures show that physical and mental health is connected, more research could be done on counseling interventions that impact both the physical and mental well-being of clients together.

There is a need to direct additional resources toward creating, maintaining, and sharing existing and new spatial data. More spatial data should be collected relating to the social determinants of mental health. If more data is collected, geocoding the data to enable small-scale spatial joining and analysis is most helpful for the communities and services that counselors typically provide. Address-level data, as opposed to city or zip code level, is the most versatile. This type of data can be aggregated up to other scales such as census units or other neighborhood and regional measures. Additionally, if spatial data is gathered over time, the more longitudinal analysis may be conducted.

As there had been little research conducted that incorporates the use of GIS mapping methods and counseling, the possibilities for future research in this area are overwhelming to consider. Future studies of this nature could consider the objective and subjective nature of neighborhood definitions, the pros and cons of viewing clients and neighborhoods as independent systems, and the value and importance of connections within neighborhoods and the process in which those develop. Additionally, a mixed methods approach would compare objective physical space of census tract with subjectively perceived boundaries as reported by individuals or groups. This would demonstrate the utility of the social address perspective versus a more individualized and subjective method.

This research study and much of the research on communities and the built environment have focused on bivariate relationships (Maantay, 2002). However, it is important for research to consider a variety of variables within each community or environment and their relationship to each other within the community. Examining how a convergence of neighborhood factors including income, educational attainment of community members, race, residential tenure, access to mental health services, crime, and the food environment may provide a complete picture as to the interventions counselors can provide outside of the counseling office.

Future research should examine the impact of the environmental on specific counseling interventions.

Because aggregated statistical data was used for this study, local knowledge from community members and community-based organizations should be used to validate this data before policy changes take place. Local knowledge about risks, assets, and solutions can contribute to spatial understandings of the data presented in this study. Community-based participatory research is one often-cited approach for incorporating local knowledge.

Conclusion

Although the promotion of mental wellness and the identification of mental illness is a worthy goal, treatment will be inadequate if we as counselors believe that treatment ends with the clients served. Unless counselors are concerned with the impact that treatment has on the society in which the individual interacts with, the endeavors with the client alone are insufficient.

Counselors should not only consider the food environment of the clients in which they serve, but also the other environmental factors that impact treatment and the counseling services provided. The counseling services provided do not only include what goes on between counselor and client but also includes interventions about where the client and community intersect. Recognizing that places are what people make of them suggests a more active role for schools in the creation community policy and intervention.

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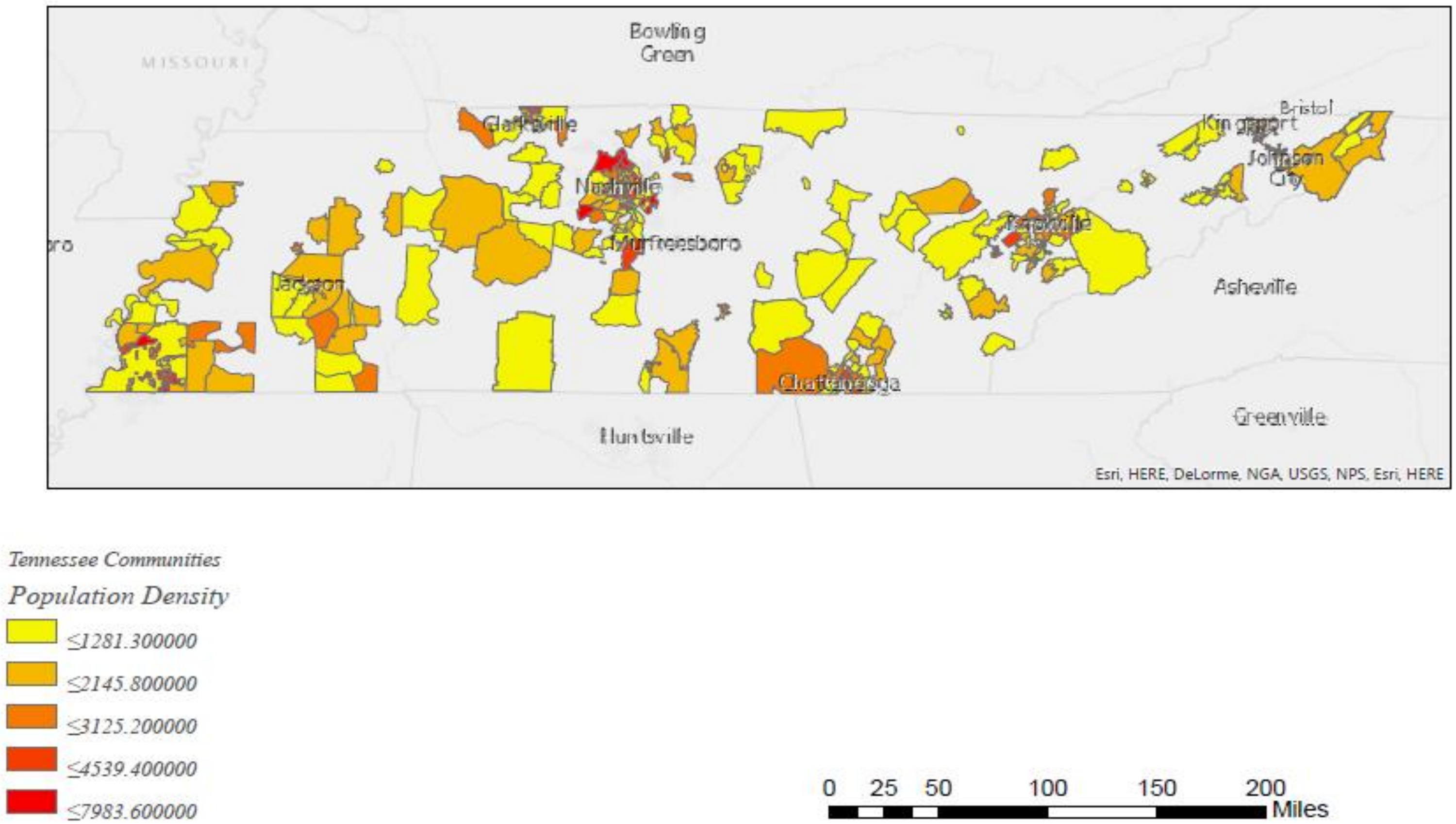
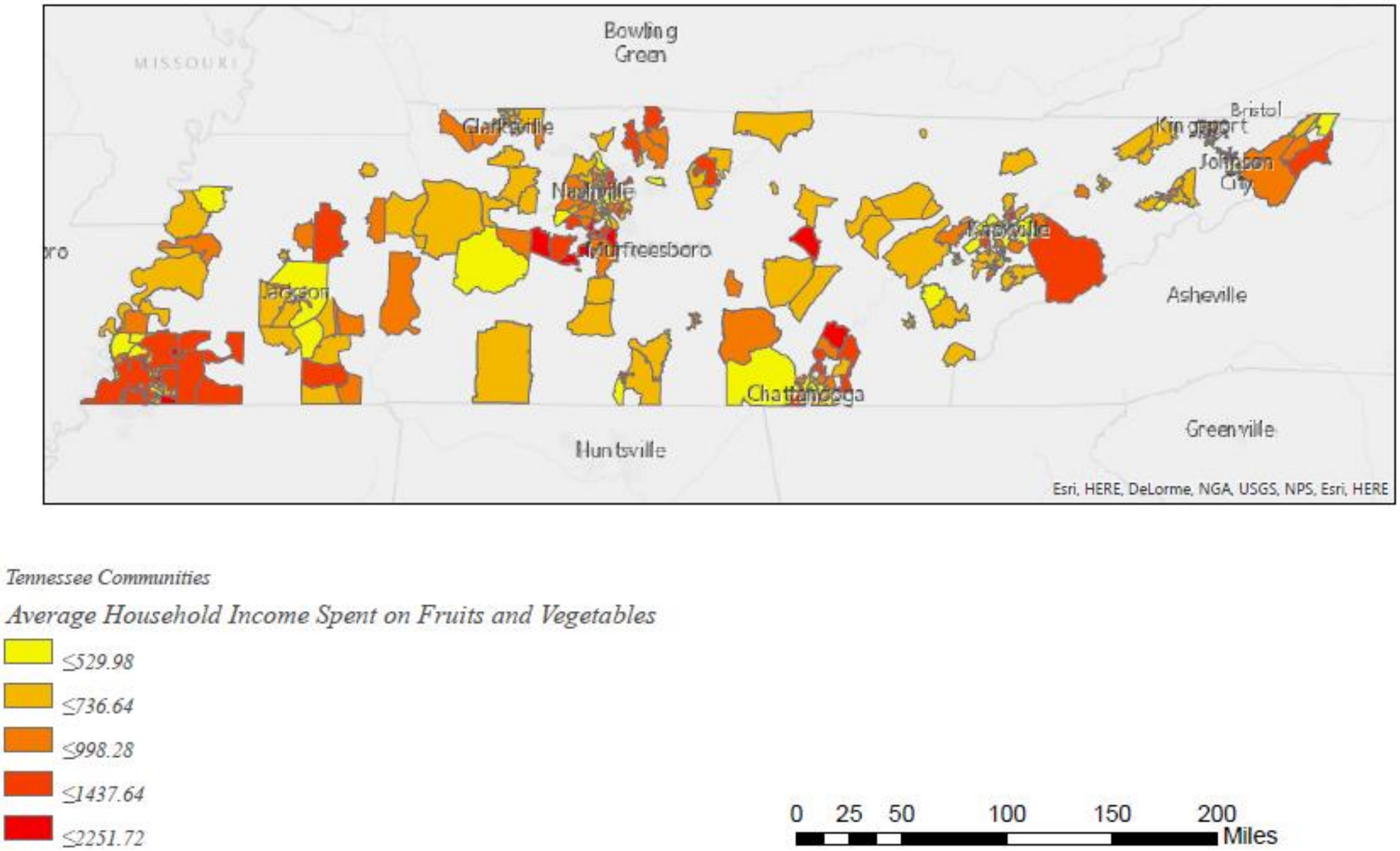
APPENDICES

Appendix A: Spatial Depiction of Variables

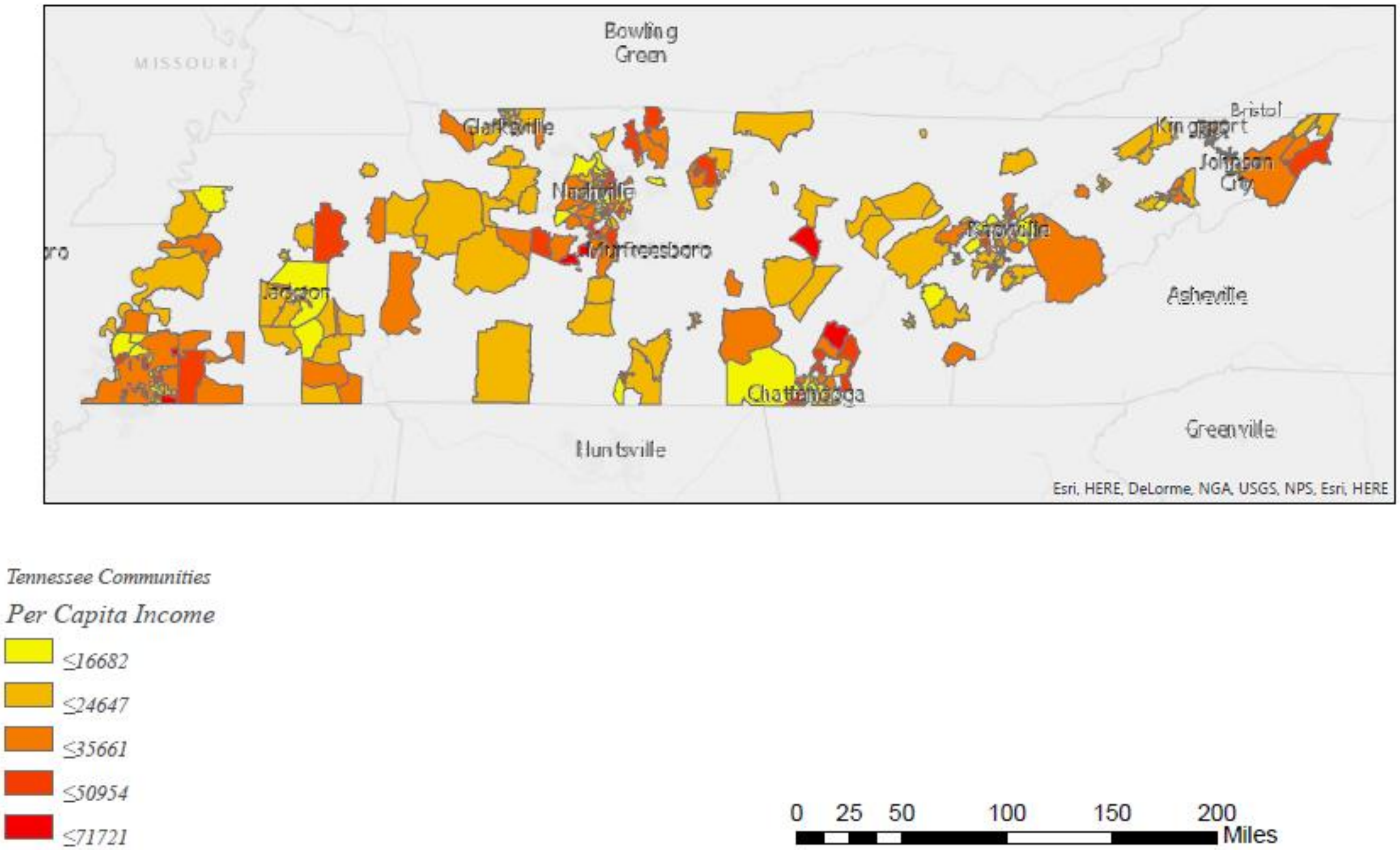
Population Density in Tennessee Communities



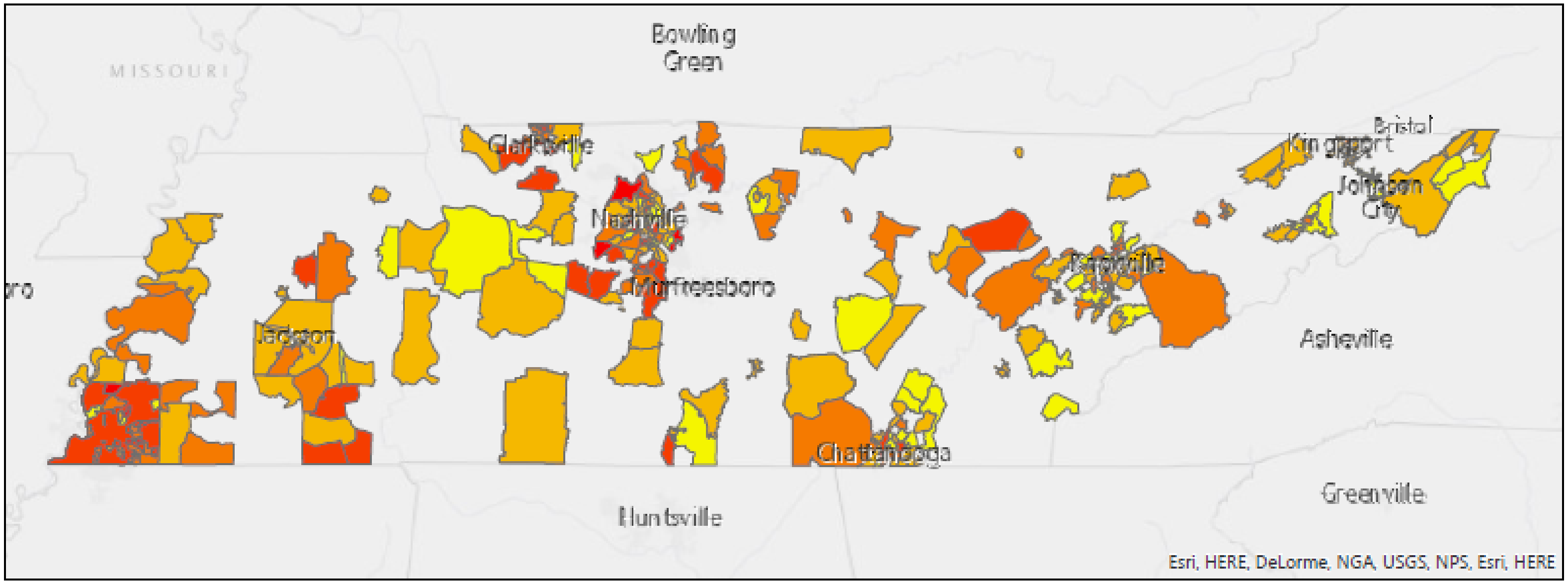
Average Household Income Income Spent on Fruits and Vegetables in Tennessee Communities



Per Capita Income in Tennessee Communities



Percent of Per Capita Income Spent on Fruits and Vegetables in Tennessee Communities



Tennessee Communities

Percent of Per Capita Income Spent on Fruits and Vegetables

≤2.867336

≤3.139347

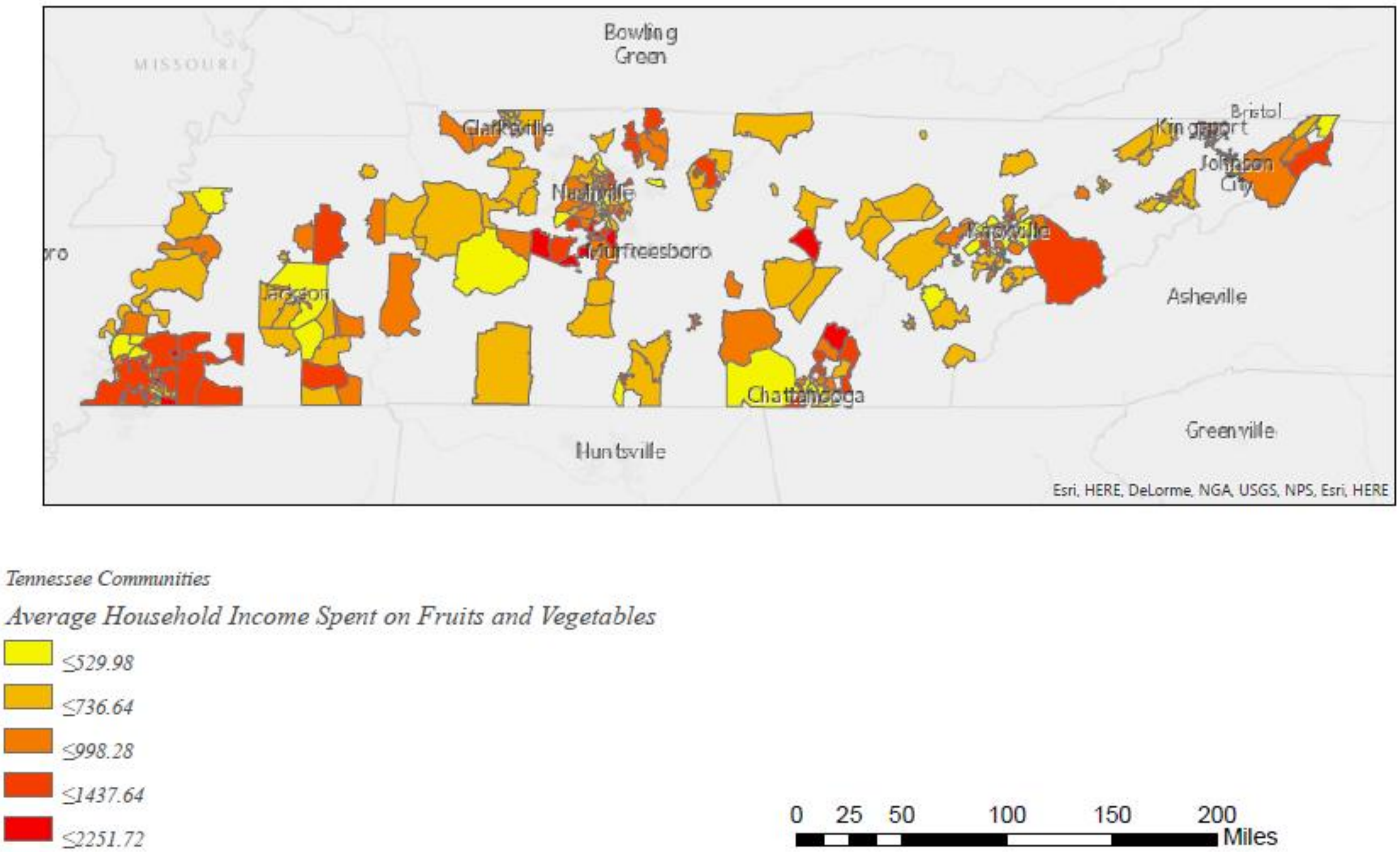
≤3.422666

≤3.822687

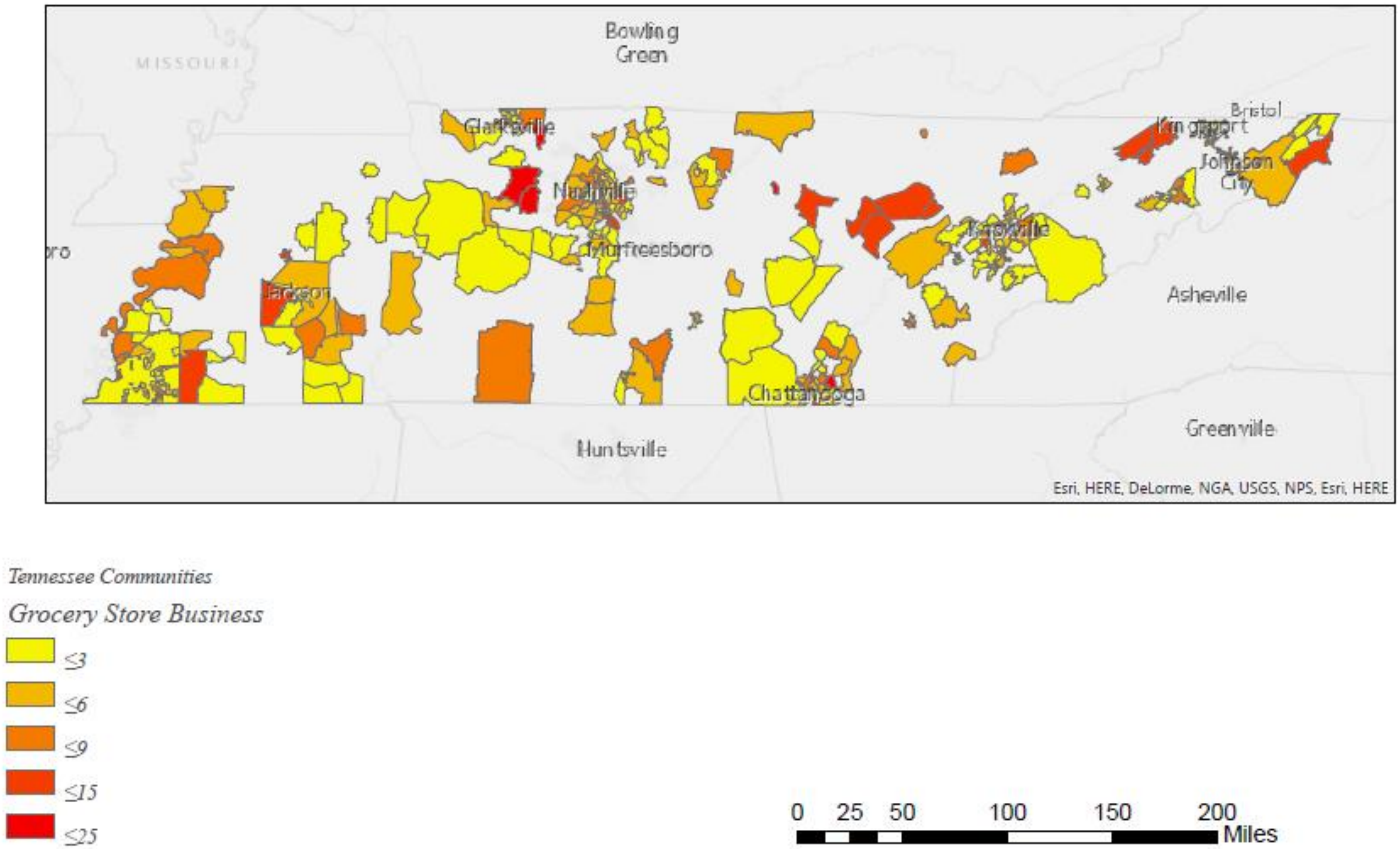
≤4.560993

0 25 50 100 150 200 Miles

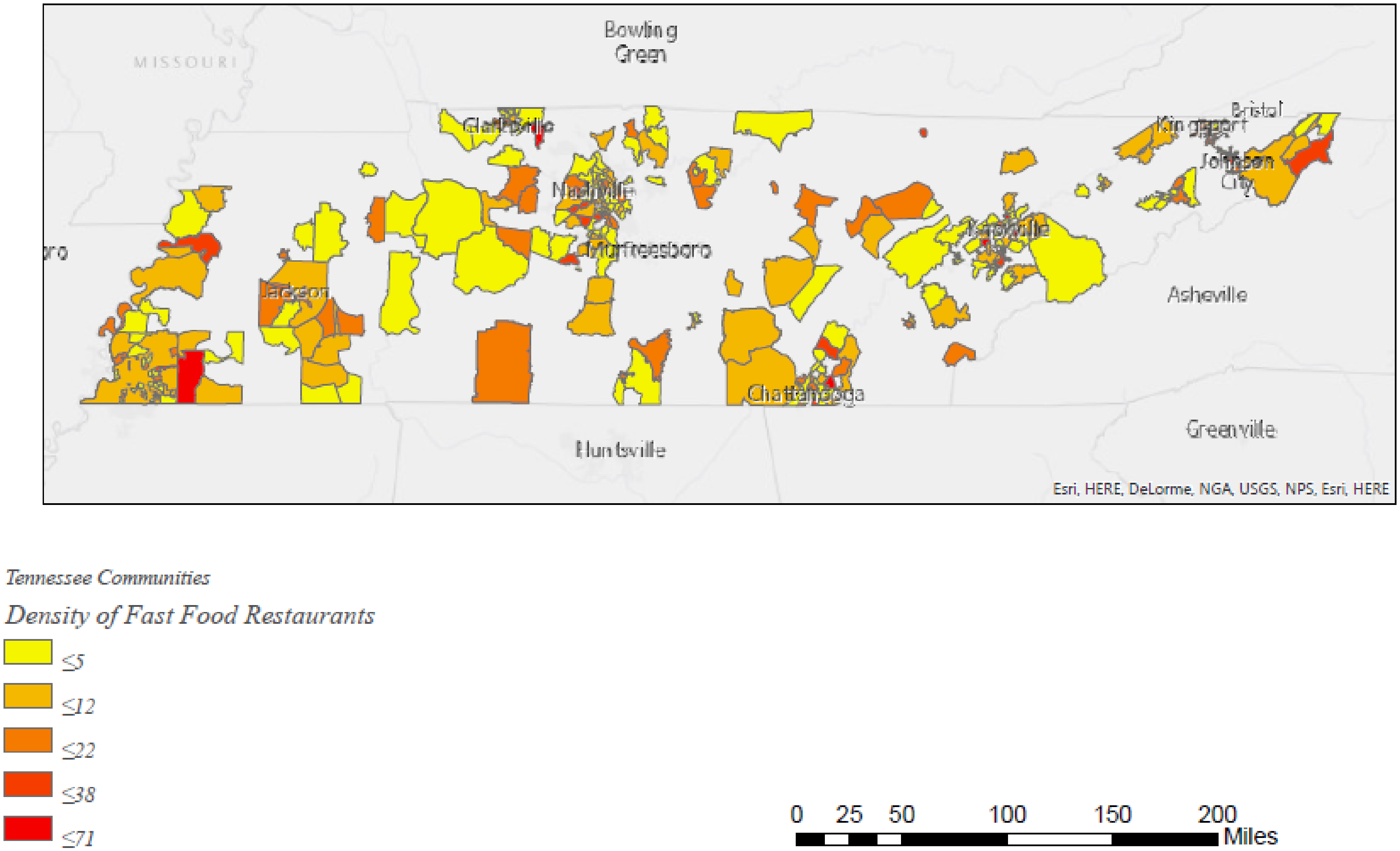
Average Household Income Income Spent on Fruits and Vegetables in Tennessee Communities



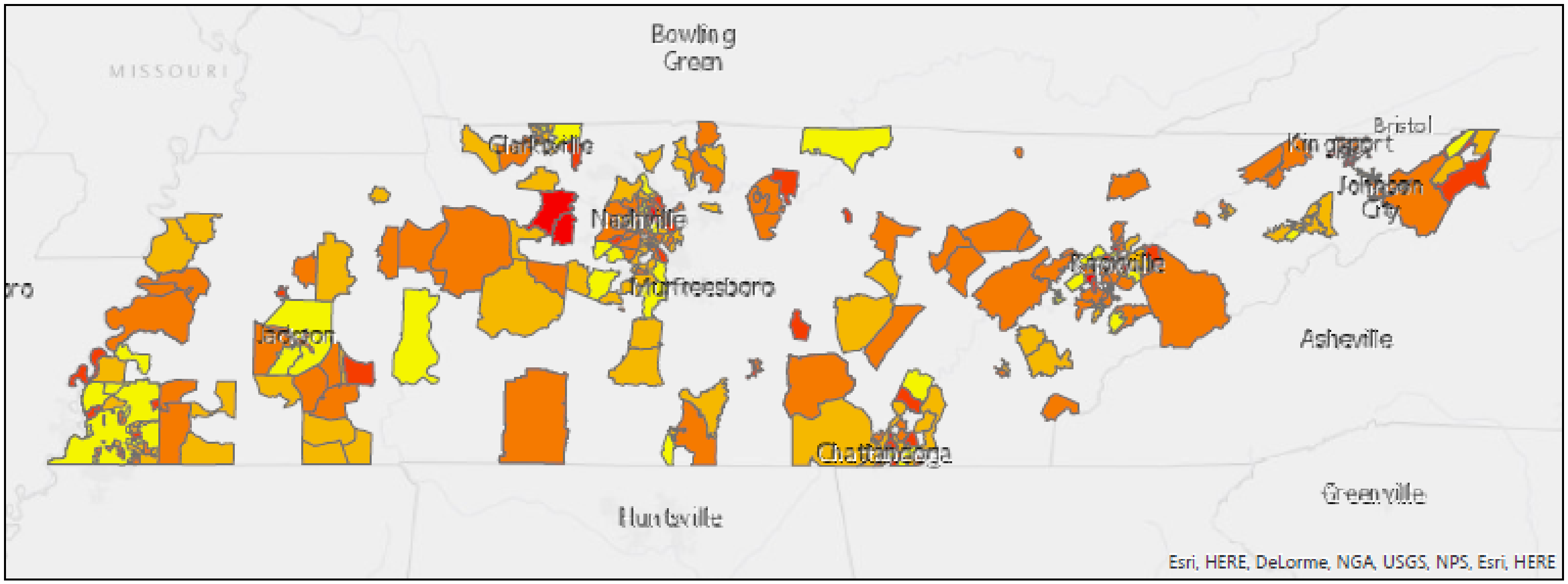
Grocery Store Density in Tennessee Communities



Fast Food Density in Tennessee Communities



Number of Community Members Who Used Prescription Drugs for Depression in Tennessee Communities



Tennessee Communities

Number of Community Members Who Used Prescription Drug for Depression

≤235

≤410

≤628

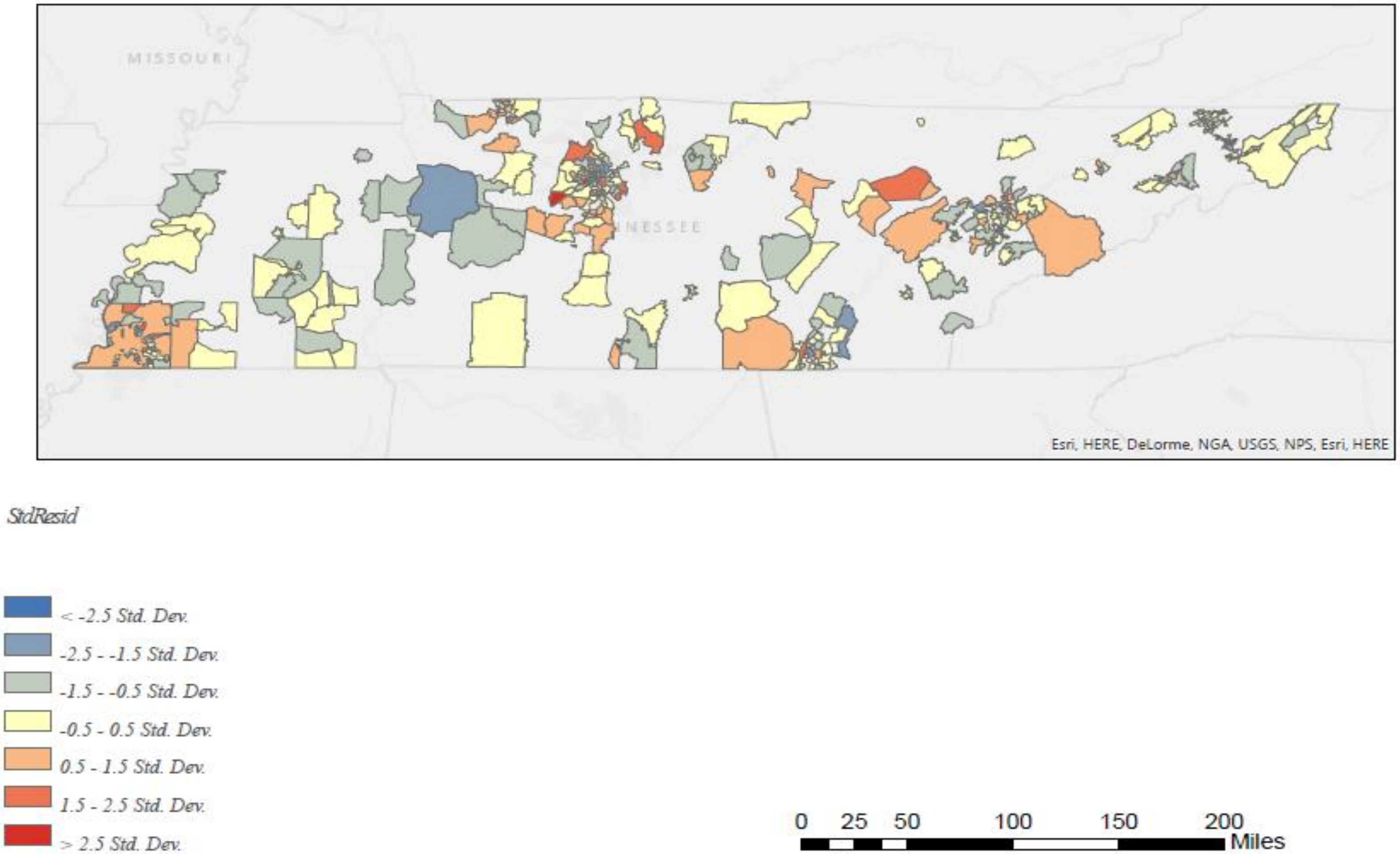
≤983

≤1667

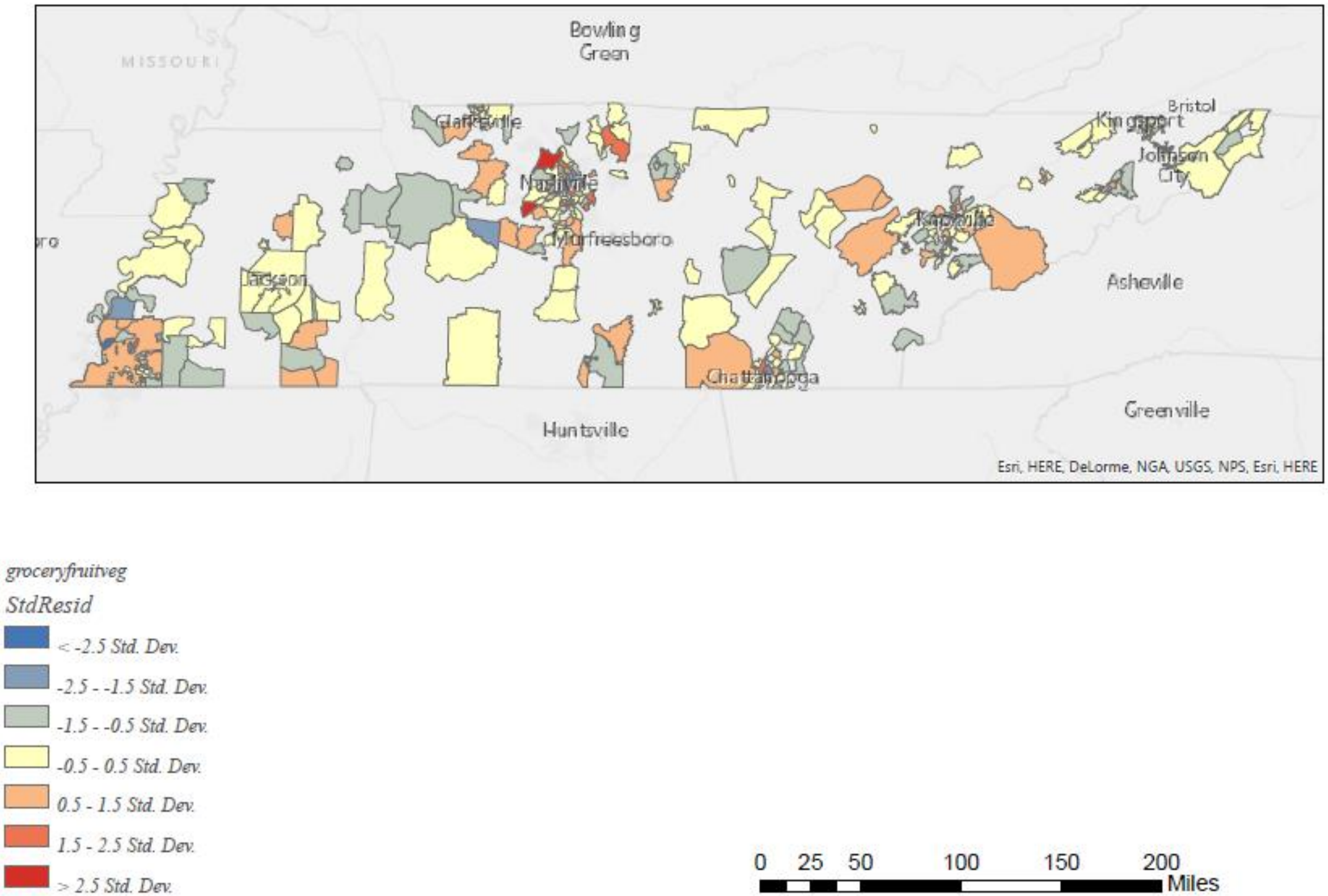
Appendix B: Geographic Weighted Regression

Geographically Weighted Regression

Research Question 3: Will the density of fast-food restaurants in a neighborhood predict the amount of per capita income spent on fresh fruits and vegetables?

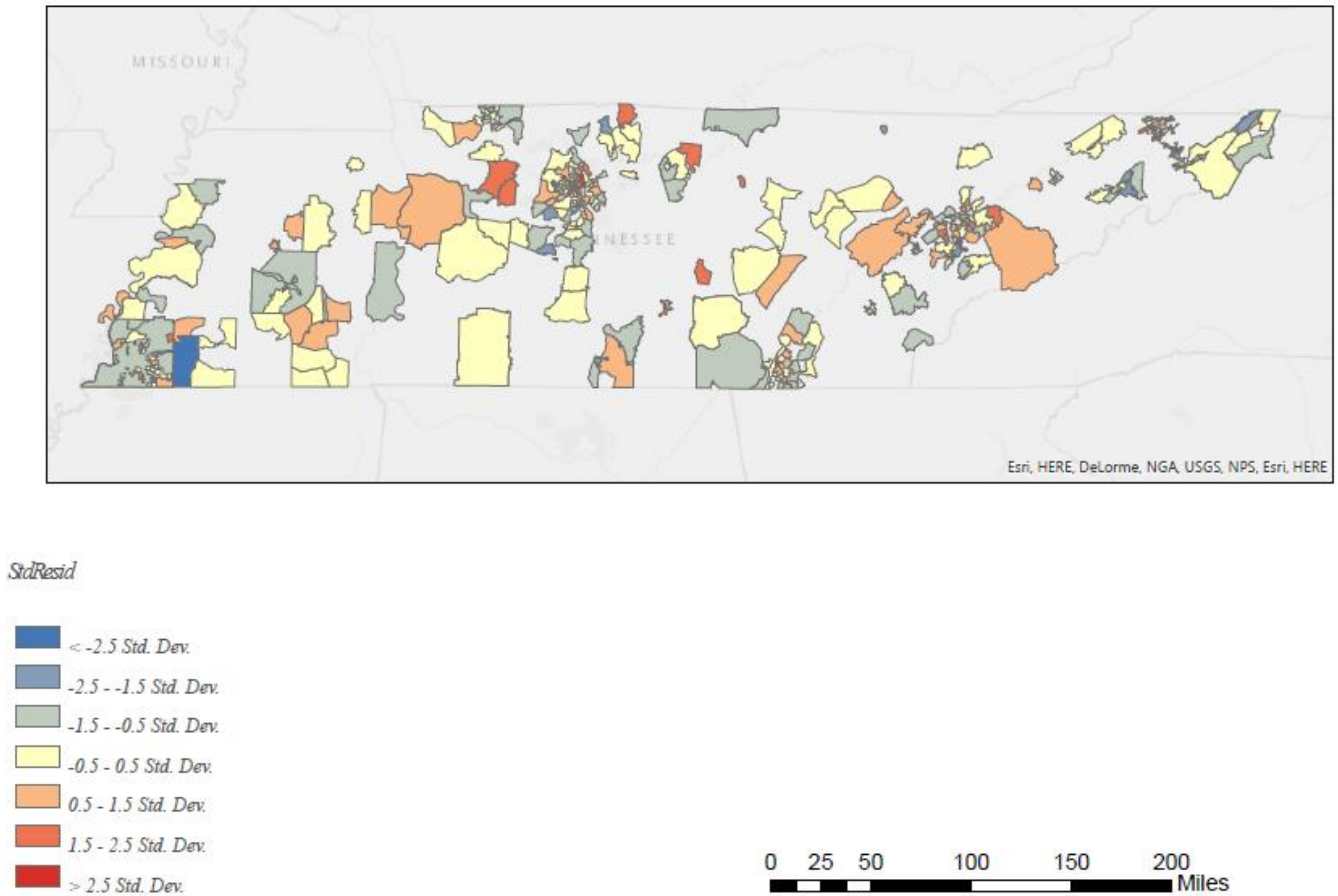


Research Question 4: Will the density of grocery stores in a neighborhood predict the amount of income spent on fresh fruits and vegetables?



Geographically Weighted Regression

Research Question 5: Will the density of fast-food restaurants in a neighborhood predict the number of people in the community who use a prescription drug for depression?



Geographically Weighted Regression

Research Question 6: Will the density of grocery stores in a neighborhood predict the number of people who use prescription drugs for depression?

VITA

Rochelle Alyssa Butler was born in Valparaiso, Indiana on August 26, 1970. After finishing high-school in 1988, she studied elementary education at Valparaiso University. In May 1992, she received a B.S. degree in elementary education with a liberal arts business minor. After teaching 2nd grade for 4 years, she was accepted into the Master's Program at Colorado State University. In 1999 she received a Master of Education (M.Ed.) degree in Education and Human Resource Studies with a concentration in counseling and career development. After working in the counseling field, she began the doctoral program in Counselor Education at the University of Tennessee in 2012 and completed her PhD in 2016.