A Geospatial Analysis of Income Level, Food Deserts and Urban Agriculture Hot Spots

by

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To those individuals that dare to challenge the collective way of life in an effort to live true to their beliefs.

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Acknowledgments

I will be forever grateful to my family for their endless support of all of my adventures.

Abstract

Since the turn of the twenty-first century, concerns with disparities in food access and food consumption have been a growing topic for scholars and activists alike (Reisig and Hobbiss 2000; Whelan et al. 2002). The incorporation of agriculture in urban settings is one possible remedy to sustain population growth and increasingly high demands for food. Green spaces can help high-risk communities gain access to fresh, organic produce and reduce the presence of food deserts. However, within the spectrum of sustainability socioeconomic factors play a critical role in a community's access to healthy organic foods. Although various studies associate an increase in access to food with the implementation of urban agricultural practices (LeClair and Aksan 2014), social exclusion remains a dominant obstacle in the successful integration of Urban Agriculture (henceforth: UA) in communities facing food insecurities (Meenar and Hoover 2012; Tiarachristie 2013). By expanding on the research and data collected by CultivateLA, this study assesses the relationship between clusters of different types of UA practices in LA County based on income levels to determine possible overlaps with food deserts in underserved communities. Using the geospatial analysis methods of Hot Spot Analysis, Buffers, and Directional Distribution to test the bivariate hypotheses, the pattern demonstrated by each of these phenomena, UA sites and food deserts, reveals that there is a significant statistical difference between them based on income levels within LA County. The findings indicate that a higher number of UA sites are located in neighborhoods with low percentages living under poverty, while 85% of neighborhoods with high percentages living below poverty are designed as food deserts. These results provide spatial statistical evidence of how these phenomena overlap, providing a platform for further exploration by city planners and other policy makers to remedy limited access to healthy foods in high-risk areas.

Chapter 1: Introduction

Over a decade into the new millennium, humanity continues to face the dilemma of sustaining high demands for food as population grows. Concerns with disparities in food access and consumption have been a growing topic for research and development within a variety of academic and professional fields, as well as governmental agencies efforts (Reisig and Hobbiss 2000; Whelan et al. 2002). Within the spectrum of sustainability, socioeconomic factors play a critical role in a community's access to healthy organic foods. One remedy to this issue is the incorporation of agriculture into densely populated urban settings. Although various studies associate an increase in access to food with the implementation of urban agricultural practices (LeClair and Aksan 2014), social exclusion remains a dominant obstacle in the successful integration of Urban Agriculture (henceforth: UA) in communities facing food insecurities (Meenar and Hoover 2012; Tiarachristie 2013). The following chapter presents the existing conditions, problems and objectives to food access addressed in this thesis.

1.1 Food Environment

The Center for Disease Control (CDC) defines the food environment as "the physical presence of food that affects a person's diet; a person's proximity to food store locations; the distribution of food stores, food service, and any physical entity by which food may be obtained; or a connected system that allows access to food" (Center for Disease Control 2015). Moreover, the CDC further explains that the term food environment is also used to describe a communities' collective local food landscape as well as the nutritional quality. The reference to a neighborhood's food environment is useful when describing the retail or physical aspects of food (presence and accessibility to food stores and markets) and the consumer impact (healthiness and affordability). Understanding the full scope of a neighborhood's food environment enables a thorough analysis of the conditions that affect the way communities feed themselves. More so, the food communities select can be influenced by a full range of other factors, like taste, price, convenience, knowledge and availability (Glanz et al. 1998). When deficiencies emerge in one of the components of the food environment, other aspects are affected like overall public health which in turn can have an economic impact (Bader et al. 2010).

1.2 Food Deserts

11.5 million people, or 4.1 percent of the total U.S. population, live in low-income areas more than 1 mile from a supermarket. Neighborhoods with low access to affordable fresh food sources that make up a healthy full diet are considered food deserts (CDC 2010). Alternatively, these areas have an increase access to unhealthy cheap food. This phenomenon has been linked to obesity and diet related health problems which pose a risk in a communities' overall public health as well as impacting the economic stability on both the micro and macro level (USDA 2009).

As more public resources and attention are given to the identification and assessment of food desert, the way the qualifying variables are defined have a determining factor in the outcome of the analysis. Two methods of assessment are primarily implemented: information obtained by geographic information systems (GIS) and surveying/observation (LeClair and Aksan 2014). Research on this topic shows that there still remains disparity in determining all the available resources for food access in high poverty neighborhoods (Raja, Ma, and Yadav 2008; LeClair and Aksan 2014; Short, Guthman, and Raskin 2007).

Geographic Information Systems (GIS) technology is already widely used in the daily lives of most urban city dwellers (Li 2004). In regards to the methods of measurement of food access, as suggested by LeClair and Aksan (2014), there is a great need to rethink the methods employed to define areas that lack nutritious and affordable food which are classified as food deserts. Between navigating streets to locating the nearest resource, basic user-friendly geospatial tools are just a smart phone away. In performing a geospatial analysis and establishing the nature of the relationship between food desert hot spots and urban agricultural hot spots based on income level, municipalities can allocate resources to remedy food access issues in high risk areas.

1.3 Urban Agriculture (UA) as an Alternative

In support of this growing movement, Olivier De Schutter (2014), the Special Rapporteur on the right to food for the United Nations (UN), states that the push to focus food production towards rebuilding local food systems making them decentralized and flexible benefits both local producers as well as consumers. According to a study conducted by the non-profit Conservation Law Foundation (CLF), urban agriculture (UA) can positively affect a community in multiple ways, including reducing carbon footprints, producing micro businesses, and serving communities (CLF 2012). Initially, UA alleviated the environmental strain on dense urban cities. The CLF study explains, UA does so by reducing the demand for imported produce, improving domestic water use through gray water systems, and reducing pollutants in the atmosphere with the establishment of roof gardens (CLF 2012).

By creating open green spaces, communities can also better identify with their surroundings, producing a greater desire to care for the land. Green spaces can help high-risk communities gain access to organic, fresh produce, dismantling food deserts. However, within the spectrum of self-sustainability, socioeconomic factors play a critical role in a community’s access to healthy organic foods. Although various study associate an increase in access to food with the implementation of urban agricultural practices (LeClair and Aksan 2014), social exclusion remains a dominate influence in the successful integration of UA in communities facing food insecurity (Meenar and Hoover 2012; Tiarachristie 2013).

1.4 Objective of this study

The purpose of this thesis is to conduct an analysis examining the relationship among income levels, food desert hot spots, and urban agricultural hot spots in Los Angeles (LA) County, California by expanding existing studies of each topic. As an emerging social movement, urban community-based agriculture such as Community Supported Agriculture (CSA), farmer's markets, and community gardens have the potential to remedy Food Deserts (Meenar, Hoover 2012). Cultivate Los Angeles (http://cultivatelosangeles.org/) published a study highlighting the state of LA's UA practices in LA County. Although they were able to collect data and categorize existing practices, the scope of their analysis is limited. There is an opportunity to expand on this research and find the relationship between socioeconomic levels and food justice through the participation in UA. This study aims to monitor the accessibility of fresh produce within dense urban communities based on their income level and highlight disparities in areas indicated as food deserts, which may inform policy and accommodate lack of access.

This thesis examines the relationship between clusters of different types of urban agricultural practices in LA County based on income levels. By expanding on the research and data collected by Cultivate LA, this research investigates possible overlaps with food deserts in underserved communities. Initially, it is important to explain why UA is a relevant research area in relations to food security by analyzing the positive effects on the community level. Using the economic datasets provided by the US Census Bureau, the study established which communities are under served due to economic hardship. The study then compares proximity to food retailers, which provide the criteria for a food desert. Lastly, it is beneficial to understand the relationship between dense urban populations and the concentration of urban agricultural practices when outlining their utility, which in turn can inform policy to remedy limited access in high risk areas. The study aims to show how income levels directly affect the implementation of urban agriculture while highlighting the disparity in high risk urban demographics which are largely surrounded by food deserts and have limited access to affordable healthy foods.

The subsequent chapters of this thesis is as follows. A review of existing research and studies related to food access, UA, and food deserts is covered in Chapter Two. The same chapter will examine variables utilized in previous studies to classify food deserts and their relevance to this study. Chapter Three outlines the study area, data sources for this analysis and any modifications applied to the datasets, and the methodologies implemented in order to assess the relationship between clusters of different types of urban agricultural practices in LA County based on income levels to determine possible overlaps with food deserts in underserved communities. An analysis of the results of the methodologies used is examined in Chapter Four including their shortcomings. Lastly, Chapter Five reviews the findings of this thesis and includes recommendations for future research.

Chapter 2: Background and Literature Review

The importance of understanding the dynamics of food environments, as expanded in Chapter 1 of this thesis, determines the conditions of a community's overall food choices and diet quality (USDA Food Environment Atlas 2015). Concentrations of distinct occurrences such as UA and food deserts within a demographic area can serve as an indicator of the food environment for that neighborhood. This chapter expands on existing research regarding urban agricultural practices, criteria for determining food deserts, and remaining obstacles for high-risk populations to food access relative to disparities based on income, availability of resources and inequality (Bader et al. 2010; Meenar and Hoover 2012; Tiarachristie 2013; Cohen and Reynolds 2014; Reynolds 2014). The different areas of research outlined in this chapter set the criteria for this study and establish the parameters for this research. The studies mentioned in this chapter investigate how these different phenomena affect selected demographics, but miss to connect and examine the spatial statistical relationship between income and these food environment occurrences.

2.1 Urban Agriculture

UA is much more than a farmer's market or the distribution of fresh produce by Community Supported Agriculture (CSA). UA is the roof garden with a chicken coop that help supply fresh eggs and vegetables to residents in apartment complexes. It is the school garden that teaches students photosynthesis and how things can grow with care and maintenance. Moreover, it is an opportunity to reduce the environmental impact on the already limited resources on the planet while providing a chance of economic growth through established micro-businesses (Rogus and Dimitri 2014; Vitiello and Wolf-Powers 2014; Ackerman et al. 2014). This trend of growing food locally is not new, but as Schutter (2014) from the United Nations stated, it has the potential to remedy food scarcity. This thesis aims to analyze the correlation of the increasing popularity of growing food in dense yet diverse urban settings based on income levels, and provide an analysis to delineate relationships between high concentrations of food deserts and a lack of implemented urban agricultural practices in LA County.

2.1.1 Defining UA

As defined by Bailkey and Nasr (2000), UA involves the growing, cultivating and distribution of food locally in and around a village, town, or city. There are two types of places UA sites develop in: intra-urban areas, which are within a city, and peri-urban areas, which are rural communities in the outskirts of cities, towns or villages (RUAF Foundation 2015). Schutter (2014) mentioned in his report that the high demands for imports of goods by wealthy countries is a driving force for the poverty around the world. He expressed that humanitarian relief should shift into supporting impoverished countries to develop the ability to be self-sustaining and revert to a locally invested production of resources. In order to remedy the effects of globalization, countries must revert to local resources as well as a local mindset.

Although UA offers the potential for strengthening the social ties of a community, it dominantly facilitates two major roles for the communities involved; food security and the potential for economic stimulation by creating new job opportunities (Ackerman et al. 2014; US EPA 2013; Heumann 2013). Food security means having both adequate quantity and quality of food for a household. If either factor is compromised this can lead to health issues and is an indication of economic difficulties. The conditions for low access to healthy foods may vary, for example low access in rural areas consists of a different set of conditions than low access in urban areas. The implementation of UA in low access areas has shown to be a viable method to improve the availability of healthy foods to these communities (LeClair and Aksan 2014).

Several studies show that UA has proven to be a staple income for developing countries (Zezza and Tasciotti 210). However, UA does not contribute strongly to job creation in the United States (Vitiello and Wolf-Powers 2014; Cohen and Reynolds 2014). Issues with land use, local food policy and the seasonal nature of UA limit the capacity for steady income flow, although it can serve as a supplemental income in some areas (Angotti 2014). Nonetheless, UA can economically impact a community by increasing the availability of staple foods for a household which in turn alleviates some of the strain on resources for other expenses (Ackerman et al. 2014).

2.1.2 Perspectives on UA

Several analyses have emerged regarding the benefits and curation of UA throughout the world. The book by Mougeot (2005) is one of the first accounts of analysis for UA across multiple countries with diverse socio-political and economic systems. The book concentrates on strategies to incorporate urban farming through urban planning. The countries reviewed include Argentina, Botswana, Côte d'Ivoire, Cuba, France, Togo, Tunisia, the UK, and Zimbabwe. There is a growing interest in the United States to participate and implement UA, however, there still remains a large deficit of analysis of this phenomenon, especially regarding the socioeconomic component of participation. Mougeot's study provides examples of case studies and examine existing research to formulate evidence for the relationship between income and food environments. Moreover, this association highlights that areas like food deserts dominate in low-income communities and UA practices dominate in high-income communities in developing countries, which is the aim of this thesis to investigate.

When observing international examples of urban agricultural implementations in a community, Australia serves as a great site to explore, as it is socially and economically similar to areas within the United States. In a study by Mason and Knowd (2010) they investigate the development and effects of UA specifically in Sydney, Australia. The article explains how a population's health is affected by urban sprawl, large corporate supermarket food dominance, obesity, and globalization. The study shows how UA can diminish those effects in the developed world and reflects upon the increasing demand for locally grown agri-food. However, the study does point out the challenge that most cities face in the ability to consolidate the high demand that industrialization provides versus the growth capacity of UA practices.

Changing perspectives from a global scale to the United States, California has considerable qualities for analysis. The state produces the most amount of food in the United States and at the same time has two of the top five most densely populated cities in the country, San Francisco and Los Angeles (US Census Bureau 2010). Interests in UA within these dense cities has increased over the years reaching households through farmers markets, community gardens, CSAs and even farm to table restaurants (Surls et al. 2015). CultivateLA is a collection of UA sites throughout Los Angeles County. Each site was confirmed, mapped and classified as a community garden, farm, nursery, or school garden. This data is focused on Los Angeles County and not the whole state of California, making it a good basis to start gathering urban agriculture data for a targeted study area. The data collected does incorporate an Agriculture Density Index, which measures the concentration of agriculture in various cities throughout the county (Cultivate, 2013). Their findings include:

- 761 School Gardens
- 211 Nurseries
- 171 Farms
- 118 Community Gardens

Total: 1,261

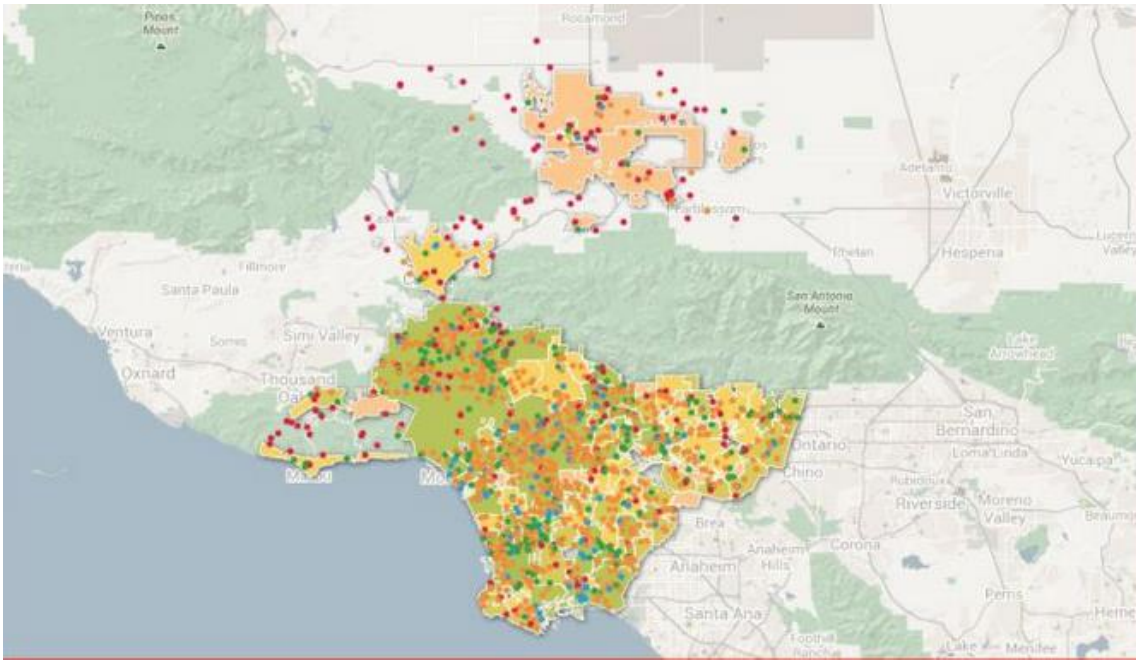

Figure 1 Map of UA Sites Courtesy of CultivateLA

2.1.3 GIS Prior Study Shortcomings and Current Study Implications

The 2012 case study for UA in Boston conducted by The Conservation Law Foundation and CLF Ventures, Inc. (henceforth: CLF) creates a tangible analysis of the multi-dimensional impact of UA in a high population, low open space city. This case study analyzes job creation, economic benefits, environmental impacts, and health benefits for establishing 50 acres of UA in the city of Boston. It is a very thorough investigation and provides the logistical procedures needed to implement a citywide program, including policy barriers and opportunities. It is an excellent account of how a city can establish a program that can holistically collect and assess the impact of UA. Currently, city officials have not picked up this program and UA remains random and scattered throughout the city. This study serves as an example of research being invested in the creation of UA practices within cities but there is a lack of analysis of social exclusion and other dominant obstacle in the successful integration of UA in the communities within these cities facing food insecurities (Meenar and Hoover 2012; Tiarachristie 2013).

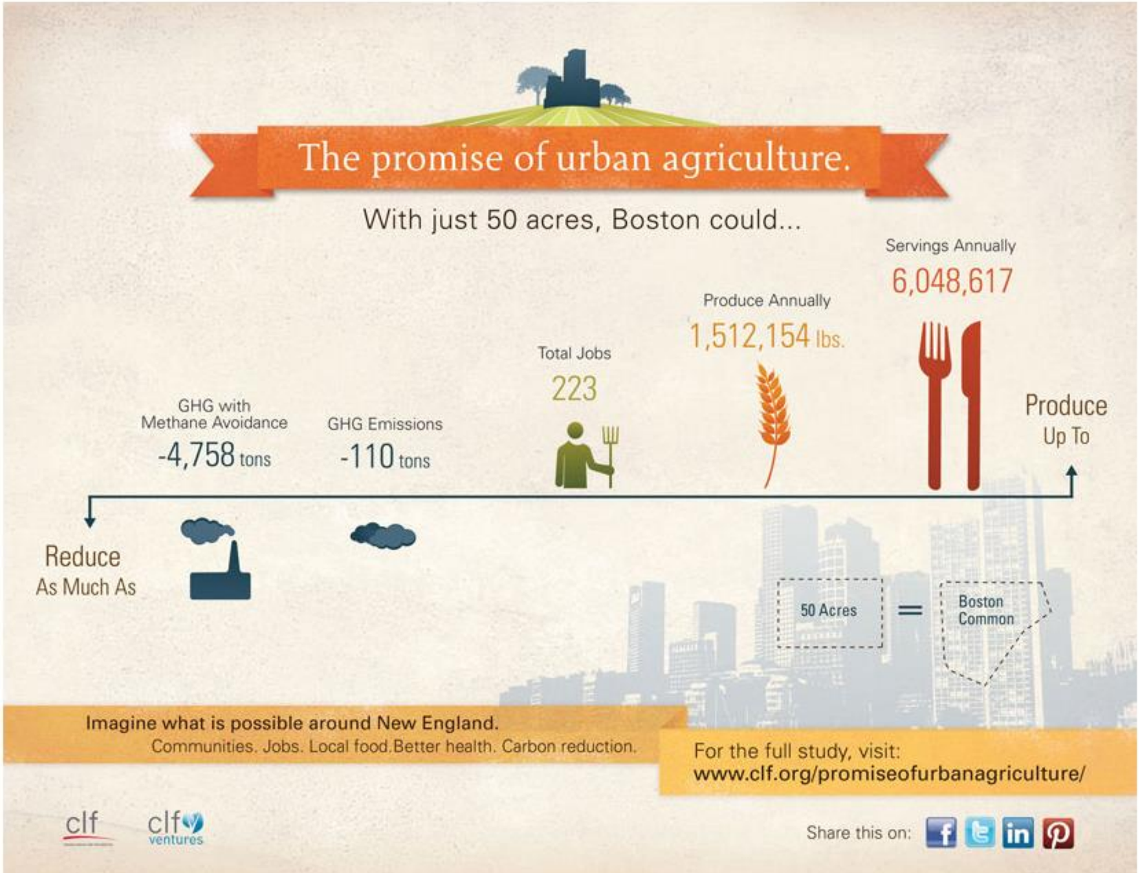

Figure 2 CLF Infographic Detailing the Growing Green Report for Boston

Similar to the assessment conducted for the city of Boston, the case study and report conducted in collaboration by Urban Design Lab, The Earth Institute, and Columbia University gives a comprehensive analysis of the potential of establishing a citywide UA program in New York City (Ackerman, 2012). However, unlike the Boston case study, this report provides geospatial representation of waste management, potential roof top gardens, and water conservation through storm water collection. It is an extensive working model that incorporates the full logistical life cycle of a citywide UA implementation.

Currently a separate organization, although heavily influenced by the previous study, Five Boroughs (http://www.fiveboroughfarm.org) is executing its Phase III of UA throughout 5 boroughs in New York City (NYC). The program works independently to establish a citywide plan to enhance the sustainability of NYC. Phase I was the developmental stage of policies and matrices to boost and expand UA in NYC. Phase II brought about a partnership with NYC Department of Parks & Recreation to implement and measure the impact of UA practices in the city. This includes a 28% increase of food producing farms and gardens in the last 2 years. Currently in Phase III, the project aims to serve as an adaptable model for UA implementation in cities by releasing a Data Collection Toolkit. This document is made available online and provides instructions on how to collect data from UA sites and directs registered urban farmers to the affiliated website: http://farmingconcrete.org/barn/ (2015) to input their results. The results are then visualized through a web map. This project is creating a platform to adapt UA practices within multiple cities and even incorporates community development and empowerment as one of its goals. However, the project lacks investigation of the relationship between socioeconomic obstacles that emerge due to the range of income and varied poverty levels within the city (Cohen and Reynolds 2015).

Chiara Tornaghi from the University of Leeds, UK (2014) published an article calling for a critical geography of UA. As a growing trend with positive implications, Tornaghi claims that there is a need to increase investigation on the topic. In doing so, areas of inequality can be addressed. For example, food cultures and consumption habits in urban areas can be mapped and analyzed to determine desired foods as well as bring awareness to possible health risks. Currently there is a lack of investigation of the full life cycle of UA. The areas affected by UA are connected, influenced and dependent of each other, creating a life cycle of the practice. Buying locally grown food not only has a socioeconomic impact by creating micro businesses, but the reduction of importing food to a region has environmental consequences as well. Likewise, it affects the public health of a community.

2.2 Food Deserts

As more public resources and attention is given to the identification and assessment of food desert, the way the qualifying variables are defined have a determining factor in the outcome of the analysis. Two methods of assessment are primarily implemented; information obtained by geographic information systems (GIS) and surveying/observation (LeClair and Aksan 2014). Research on this topic shows that there still remains disparity in determining all the available resources for food access in high poverty neighborhoods (Raja, Ma, and Yadav 2008; LeClair and Aksan 2014; Short, Guthman, and Raskin 2007). Further research implies that small food retailers, bodegas and corner stores may be easier to reach and cater to distinct food cultures. However, issues of exclusivity of ethnicities and affordability still limits neighborhood’s access to healthy food. The following sections of this chapter examine the methodology used to assess food deserts in previously published articles, and define the following variables for this study: access to healthy foods, travel time, access to a vehicle, and methods to outline income levels.

2.2.1 Accessibility

Accessibility to fresh, healthy and affordable foods is a dictating factor in determining if a neighborhood is a food desert. A study conducted by Shaffer (2002) indicates 2.3 times more supermarkets per household in Los Angeles County in high-income neighborhoods when compared to low-income neighborhoods. The disproportion is further highlighted by ethnicity; largely white neighborhoods have 3.2 times as many supermarkets as black neighborhoods and 1.7 times as many as Latino neighborhoods. (Shaffer 2002). Although this study is over ten years old and demographic changes are possible to have taken place, it does indicate a measurable disparity of access to affordable healthy foods, specifically for low-income demographics.

The research conducted in this thesis will match the criteria established by the United States Department of Agriculture (USDA) Economic Research Report Number (ERR) 140 to define which areas within Los Angeles County are considered food deserts. The report considers an area as having low access to food sources when at least 500 people and/or 33 percent of the tract population resides more than 1 mile from a supermarket or large grocery store in urban areas, and more than 10 miles in rural areas (USDA 2012). Data extracted from the USDA's Food Access Research Atlas provides aggregated figures to expand the degree of limited access based on availability of food sources. The data expands the criteria defined by ERR140 areas to 20 miles away from a large food store. Unfortunately, since this data is aggregated and is at a larger unit scale, it does not enable a detailed analysis of affected demographics.

2.2.2 Travel Time and Access to Transportation

A study conducted by Inagami's et al. (2006) on the body mass index (BMI) of low-income neighborhoods and the locations of healthy food supplies confirmed that the longer the distance traveled to reach a grocery store, the higher BMI in high poverty neighborhoods within Los Angeles County. Individuals that traveled more than 1.75 miles to a market weighted about 5 more pounds then those who had shorter travel times. Access to a vehicle is an important factor and a potential barrier for households to obtain healthy affordable foods. An alternative method of reaching supermarkets or large grocery stores is public transportation. Using public transit to buy food supplies, especially for demographics that can only afford to go once a month to make purchases, can be difficult considering the amount of time and load it requires (USDA 2012). Having access to a private vehicle alleviates the potential of community members within a food desert to purchase low quality foods at a nearby vendor.

Since travel time is an important factor for access to healthy foods, the parameters of vehicle accessibility used in the methodology of this thesis are based on the research conducted by the USDA. The criteria established by the USDA's Food Access Research Atlas (2015) regarding the percentage of vehicle availability within a community, classify the variable low vehicle access if:

- at least 100 households are more than ½ mile from the nearest supermarket and have no access to a vehicle; or
- at least 500 people or 33 percent of the population live more than 20 miles from the nearest supermarket, regardless of vehicle access (Food Access Research Atlas 2015).

2.2.3 Criteria of Income Level

The USDA ERR 140 report characterizes poverty levels as low-income tracts within the US Census block groups based on two criteria; a poverty rate equal to or greater than 20 percent, or a median family income that is 80 percent or less of the metropolitan area and/or statewide median family income (USDA 2012). This criteria is identical to the process used by the Food Access Research Atlas.

2.3 Food Justice

One of the positive outcomes of UA, which has been touched upon repeatedly by the previously mentioned studies, is the nutritional benefit of growing food locally. In 2013, Assembly Speaker John A. Perez (D-Los Angeles) delivered an editorial regarding his invested interest for his district to develop and incorporate UA. He provides statistical support for UA in Los Angeles County, as well as highlighting the economic benefits to Angelino communities in deflating food deserts. Overall, this article serves as a reference point for the legislative climate in support of or against the use of public open spaces for the cultivation of food (Perez, 2013).

A new social movement has emerged to tackle scarcity and access to food, it is called Food Justice (FJ). In an effort to fight for the right to healthy fresh food, the FJ movement uses active participation techniques to ensure that the responsibility as well as the benefits of food systems is shared equitably. This includes how food is grown, processed, transported, distributed, and consumed (Gottlieb and Anupama 2010). The FJ movement covers a wide range of food inequalities ranging from farmer's rights to transparency of labeling food. Through activism and grassroots efforts the over-industrialized food system, which has reached a global capacity, can increase cultural awareness of food rights. UA practices are a possible alternative to defend FJ, however, issues of discrimination and relevance still dominate in low-income areas when establishing UA sites.

2.3.1 Issues with Discrimination

While city planner and government agencies may be on board to implement UA practices in their communities, broader social and economic issues must be address prior to executing a plan of action (Surls et al. 2015). In order to fully understand the social and cultural context of food and avoid exclusion, open dialogue with the community must be take place before implementing a solution (Short, Guthman, and Raskin 2007; Raja, Ma, and Yadav 2008; Hu et al. 2011; LeClair and Aksan 2014). For example, there are certain foods that are forbidden for one ethnic group, while for another the way food is prepared and served may hold a cultural significance. Each restriction or guideline is a key component to the way communities consume food.

Social exclusion or marginalization is a term used to describe groups within a society that are systematically prevented from full access to the rights, opportunities and benefits that are normally available to other groups within the society. These rights are fundamental parts of society assimilation and include housing, employment, healthcare, civic engagement, education, and more. When inequality can stunt progress and stability social exclusion not only affects the individuals being excluded, but the society as a whole (Silver 1994). One can conclude that social exclusion is a form of discrimination, since it constitutes the unfair treatment of a group versus another group. However, intention plays a role in regards to the type of discrimination that social exclusion falls into. Unintentional discrimination may still be considered unlawful behavior. One form of unintentional discrimination is owned as disparate impact discrimination, which is when an employer or other agent creates practices that have an inequitable unfavorable effect on persons in a protected class (Civil Rights Act of 1964).

Social exclusion based on income level, race and ethnicity are contributing factors to the limitations for access to healthy affordable food for underserved communities. The same study conducted by Inagami's et al. (2006) confirmed that Supermarkets in Los Angeles County located in low-income neighborhoods are less likely to stock healthy foods than stores in higher-income areas. The study collected data by performing random interviews of individuals residing in high poverty neighborhoods and census tract data to determine the location of supermarkets versus high poverty neighborhoods. They then performed statistical analysis using multilevel linear regression models that resulted in this disparity. Additionally, a 2003 study by Sloane et al. conducted a comparative analysis of available healthy affordable food in dominantly African American neighborhoods versus wealthier neighborhoods with low concentration of African Americans in the Los Angeles Metropolitan area. The study results show that in a high poverty predominantly African American community in Los Angeles, 3 out of 10 food stores lacked fruits and vegetables, while nearly all of the stores in predominantly white high income areas sold fresh produce.

As criticized in the 2013 report by Giovania Tiarachristie, UA sites are glorified as a tool for empowerment in underserved communities; however, her research shows through qualitative analysis that lingering racism and race-class issues still remain. She conducted a study investigating an UA revitalization project in a low-income neighborhood in Harrisburg, Pennsylvania. The article highlights a lack of communication and knowledge base of the demographics prior to carrying out the revitalization plans, creating conflict with the existing community. The project also failed to take into consideration the food culture of the neighborhood in question, creating more waste than healthy food access. Tiarachristie's article reinforces the need to analyze and quantify emerging patterns and relationships between the popularity of UA practices, the reality of food deserts and how income plays a deciding factor of participation.

2.4 UA and Food Desert Research in Los Angeles County

In the fall of 2011 the U.S. Department of Agriculture (USDA) awarded a $29,000.00 grant to the Los Angeles Neighborhood Land Trust (LANLT) in an effort to address health issue related to access to healthy food and support local food system. The funding expands the People's Garden Initiative by developing educational resources and programs related to UA by supporting and establishing new community gardens in underserved areas (Marketing Weekly News 2011). Prior research for Los Angeles County devoted to investigating the topics of food security and improving access to healthy foods sources for neighborhoods designated as food deserts focuses primarily on the criteria of food deserts, and explores the potential value of UA to improve conditions (Los Angeles Food Policy Council 2012; Hingorani and Chau 2013; Jackson et al. 2013). However, there is a lack of investigation on the spatial statistical relationship between income levels and these two existing component of the food environment in the county.

The 2011 research report by Longcore et al. addresses the issue of a lack of citywide coordination for the implementation of community gardens as a method to remedy issues of food access in Los Angeles County. The report documents a project to develop a municipal strategy to guide decision makers on prioritizing which high need neighborhoods would benefit the most in fostering community gardens. The strategies include identifying the "landscape of need" which catalogues the neighborhoods with the greatest need for healthy affordable foods; "potential siting considerations" or areas that are ill advised for the overall health of those involved to establish new community gardens; and "landscape of opportunity" which maps the most favorable areas to establish a new community garden. Each map is made available for public use as a .kmz file and accessible to view for free through Googles Earth (Longcore et al. 2011).

The criteria selected for the exclusion and inclusion of potential areas to establish new community gardens are of particular interest. The categories selected to avoid establishment of a new garden include: transportation infrastructure, like freeways and rail lines; gasoline service stations; and areas designated as contaminated with hazardous substances and pollutants, like Superfund sites. Overall health and safety is the major consideration for excluding areas, which from a policy and planning perspective is critical. Likewise, favorable areas for establishing new gardens are largely community centered, such as schools, parks, places of worship, and publicly owned vacant parcels (Longcore et al. 2011). Although this study creates a great starting point to analyze optimal land use to identify areas of critical needs and where to establish UA sites to remedy this need, a broader analysis is needed to fully understand the socioeconomic dynamics of these areas. Moreover, using the same methodology to expand the analysis with other types of UA sites like farmers markets, farms and nurseries can prove to be an essential tool for policy makers when faced with decision on implementing services.

A study conducted by Ruelas et al (2011) highlights the effects of farmer's markets in low income urban communities in East and South Los Angeles from 2007-2009. The study collected anonymous qualitative information for a period of two years to examine and track the use of farmers markets and develop a demographic profile. The dominant demographic for each market studied were Hispanic women with an income level less than $15,000 a year. The majority of responders lived within a 4 mile radius of the market and expressed a satisfaction with the access to healthy food options. This study highlights the potential of UA sites, farmers markets in particular to stimulate, to reach underserved demographic groups although still at a disadvantage regarding distance. The study is limited to measurements of market utilization impact and satisfaction and lack quantitative analysis of the role of farmers markets for these communities. This thesis addresses the quantitative analysis on a broader scale by statistically examining the concentrations of incidents within a geographical area that appear over time, and therefore providing valuable data regarding which demographics gain access to these healthy food sources.

Chapter 3: Methodology

This chapter explains the selection of the study area, the data sources for this study, and the methods used to test the bivariate hypotheses; the relationship between established UA sites and food deserts in LA County based on poverty levels. The primary geoprocessing functions of ArcGIS Desktop used to analyze the bivariate hypotheses are explored through the use of Spatial Autocorrelation, Hot Spot Analysis, Buffers, and Directional Distribution Analysis to examine if there is a relationship between the mean incomes of each phenomena. Once the data is prepared, consolidated and preliminary analysis is conducted, then the statistical significance can be determined by performing a Hot Spot Analysis of these features. An analysis of the pattern demonstrated by each of these phenomena; UA sites and food deserts, can reveal if there is a significant statistical difference between income levels for these neighborhoods.

3.1 Study Area and Scale of Analysis

Los Angeles County was selected for this analysis due to its size; estimated population in the county as of 2014 was 10,116,705 which is about a quarter of the total population of the whole state of California (United States Census Bureau 2015). It is an urban area with a diverse range of ethnicities and incomes, which enables a large enough study area to uncover patterns but still serve as a controlled variable. Due to the range and flexibility of food cultures within the county, there is a higher chance to identify multiple clusters or patterns of food access inequality based on the criteria outlined by the USAD's (2009) report on food access. Some of the factors highlighted in the study include travel time to affordable food suppliers and overall cost of food. Figure 3 is a map displaying the block groups of the selected study area of Los Angeles County.

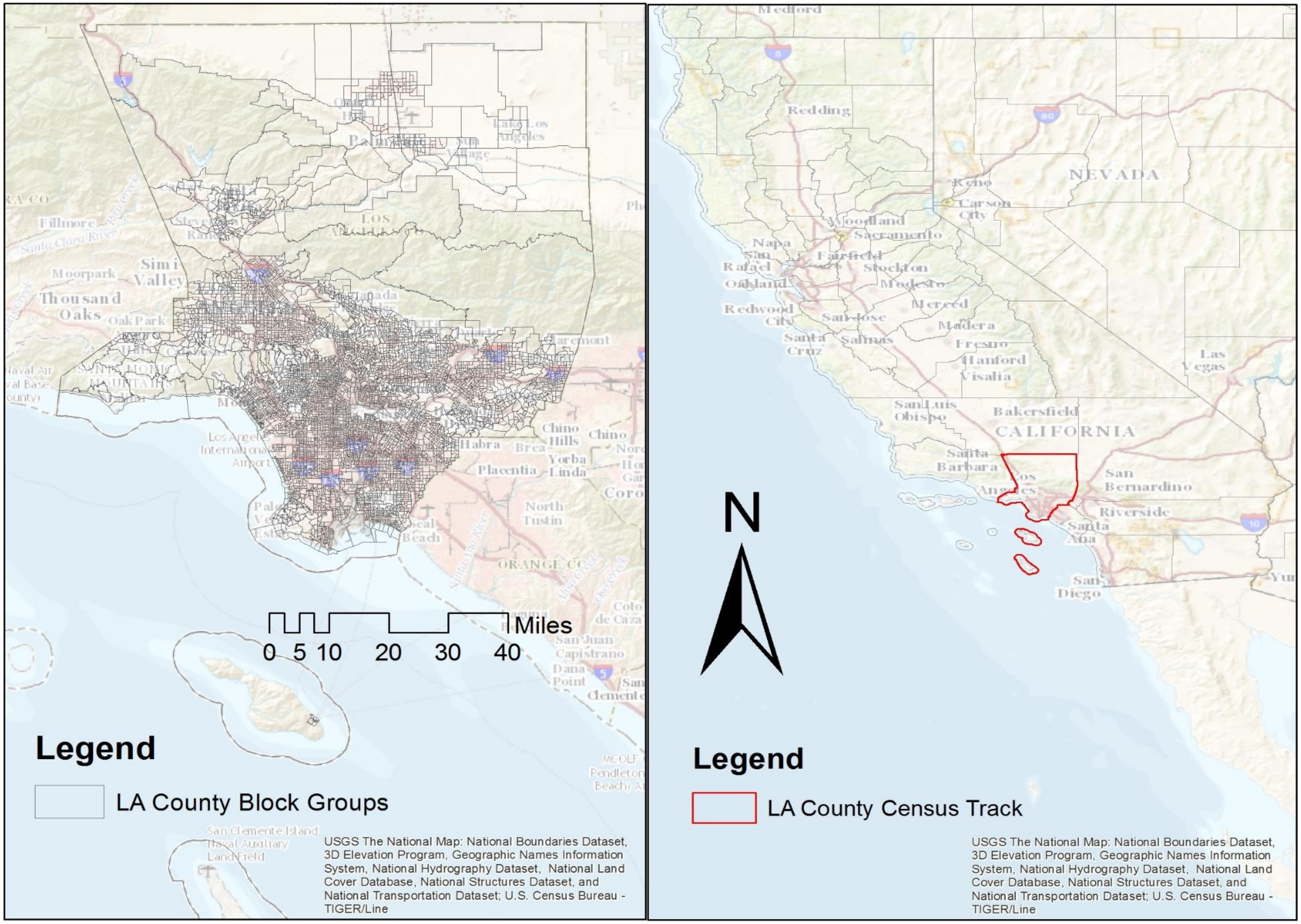

Figure 3 Map of Study Area: Los Angeles County

3.2 Data and Sources

Table 1 Summary of Required Spatial Dataset

Dataset	File type	Data type	Details	Source	Temporal resolution of the dataset
Urban Agricultural site in LA County	Excel .xlsx	Point feature class	All captured locations of school gardens, nurseries, farms and community gardens	CultivateLA	Data up to date through July 2013
USDA Farmers Market Directory	Excel .xlsx	Point feature class	All registered locations of farmers markets in the US	United State Department of Agriculture	Data up to date through July 2015
Demographics profile	Shapefile	Point feature class	Demographic data of US and Puerto Rico including commuting, poverty, and income.	US Census Bureau	Based on 2010 Census TIGER/Line Shapefiles and the 2010 Census Summary
Food Access Research Atlas	Excel .xlsx	Polygon feature class	Accessibility to sources of healthy food. Individual-level resources that may affect accessibility. Neighborhood-level indicators of resources.	United State Department of Agriculture	Based on 2010 census tract polygon
Census block groups	Shapefile	polygon feature class	All block groups units within California	US Census Bureau	Boundaries published 2010 and ACS estimations valid through 2013
TIGER/line street network files	Shapefile and .dbf	polyline feature class	Street network within California	US Census Bureau	Published January 12, 2014
Los Angeles Urban Area	Shapefile	polygon feature class	Case study area	US Census Bureau	Boundaries valid as of 2010
Prevalence of Childhood Obesity, 2008	Shapefile	polygon feature class	Concentration of child obesity	LA County Enterprise GIS	Based on 2008 data figures

Table 2 Summary of Required Software

Software	Manufacturer	Function	Access
ArcGIS Desktop 10.3.1	*Esri*	• Data Manipulation and Analysis ▪ Geoprocessing Functions ◆ Overlay analysis ◆ Proximity analysis ◆ Table analysis and management ◆ Surface creation and analysis ◆ Statistical analysis ◆ Selecting and Extracting data	USC GIST Server

Los Angeles County has a robust collection of diverse datasets that are readily available for public and academic use made available by the LA County GIS Data Portal, Los Angeles County Department of Regional Planning and academic institutions which serve as a reservoir for GIST data. In addition, private entities have gathered and prepared a series of datasets on a large range of topics that are available for a minimal cost. For the sake of continuity and efficiency, the majority of data sources implemented in this study are provided by the US Census Bureau and other governmental agencies, with the exception of data provided by CultivateLA. The latter dataset is a research study conducted in association with an academic institution (UCLA 2013) and therefore reassured the integrity and accuracy of the information.

The datasets utilized for this analysis provide geocoded point features of UA sites within the county. These points include locations of farms, school gardens, and community gardens. This data was supplied by CultivateLA and its usage has been authorized, including the expansion of the existing dataset. In addition to the data provided by CultivateLA, point features provided by the United States Department of Agriculture (USDA) Farmer's Market Directory for each registered market in LA County were extracted from the dataset and combined with the layer from CultivateLA to create a single layer. Since both layers are projected using

GCS_North_American_1983 XY coordinate systems, their geodatabases were combined using Microsoft Excel and a feature class was generated using the XY table tool in ArcGIS, as Figure 4 demonstrates. This process was executed without any issues.

If UA is going to serve as a remedy to food access disparities, then the value of these designated sites must be taken into account in order to measure the impact they have on the surrounding demographics. Not all types of UA sites have the same value in regards to productions and accessibility. Based on the data provided by CultivateLA, the most prevalent type of UA site throughout LA County is school gardens which total 761 out of 1,261 sites or 60%. School gardens may produce some amount of food which may supplement the diet of the students who tend to them. As published by the research conducted by CultivateLA (2013) there is a string of benefits for the children involved with school gardens ranging from better behavior to improved test scores. However, school gardens remain small in scale and restrict access to the general public.

This presents a problem when conducting exploratory analysis on accessibility of resources. The other sites captured by CultivateLA may have some forms of restrictions as well, like membership fees for community gardens. The data provided by CultivateLA does not confirm if the captured sites are open to the general public nor any additional restrictions. Since the possibility of restrictions are not confirmed for any of the sites, this study will include school gardens within the analysis. Further research is recommended in order to fully assess the extent of accessibility for all types of UA sites.

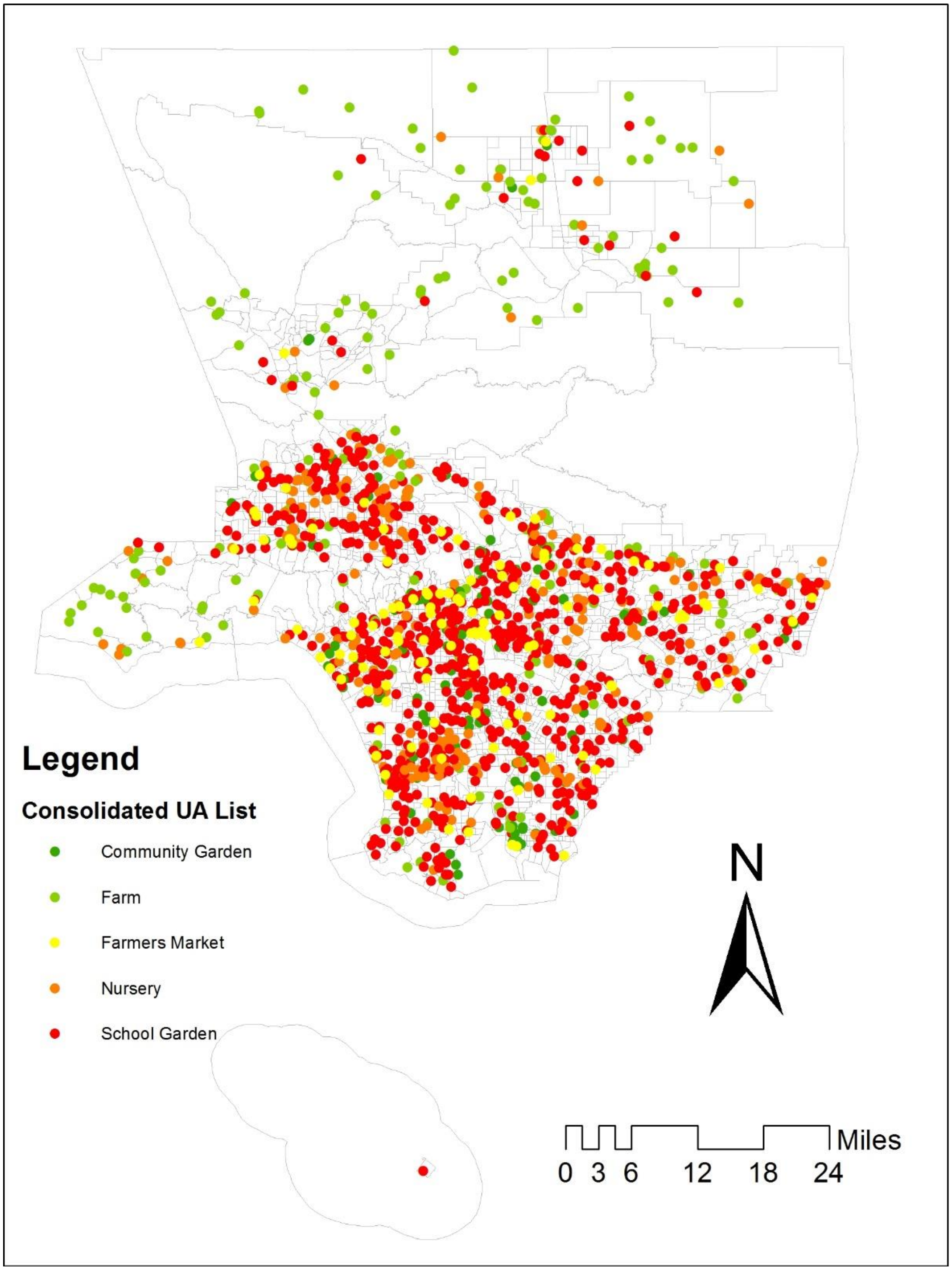

Figure 4 Map with Consolidated Point Features of UA Sites: Los Angeles County

3.3 Methodology

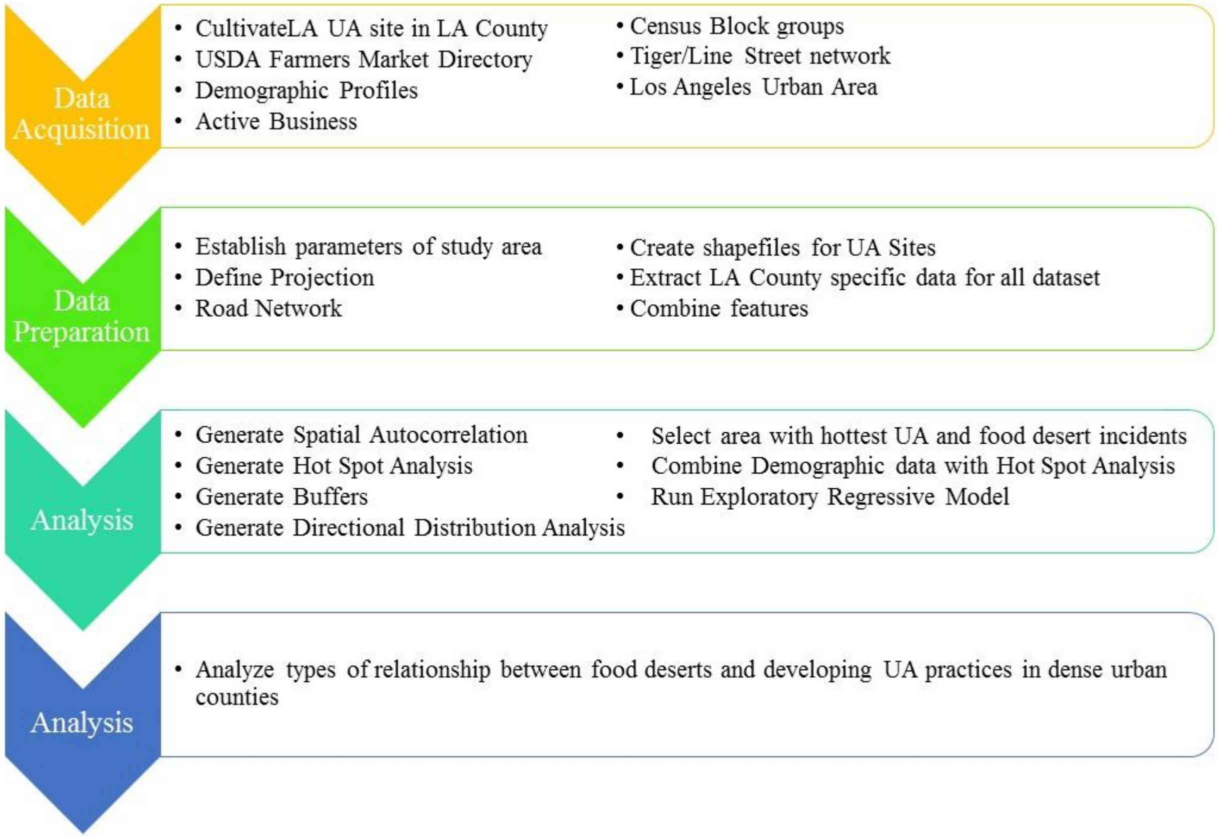

Figure 5 Summary of Workflow

3.3.1 Spatial Autocorrelation and Hot Spot Analysis

Once the layers are combined, a Spatial Autocorrelation analysis is generated in order to establish the nature of the pattern expressed with the set of features and the associated attributes. Establishing the spatial correlation of these features confirms if there is a significant statistical pattern. This in turn can provide important information to policy makers or interested agencies when implementing a new program to address issues of access to healthy foods. The Spatial Autocorrelation tool from the Spatial Statistics toolbox uses the Global Moran's I function to calculate the Z score value for the consolidated UA dataset to determine if the null hypothesis is either accepted or rejected. Patrick Alfred Pierce Moran defines Moran's I equation as (1950):

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2} \qquad (1)$$

where is the number of spatial units indexed by and ; is the variable of interest ; is the mean of ; and is an element of a matrix of spatial weights.

Secondly, the Hot Spot Analysis function is run from the Spatial Statistics toolbox to reflect hot and cold clustering of UA point features. Our eyes and minds naturally try to find patterns, regardless if they exist or not. A hot spot analysis tool can provide a statistical confirmation of concentrations of incidents within a limited geographical area that appear over time. Therefore, quantifying the spatial pattern of UA sites and food deserts in Los Angeles County by running a hot spot analysis can provide valuable data regarding which demographics gain access to these healthy food sources. Before generating the analysis, a spatial weights matrix needs to be created. Providing a weight for each feature is required to establish an accurate statistical measure of the data. This study used an inverse distance weighted strategy for neighboring features to reflect the variation of their influence. Additionally, in an effort to further explore the pattern created by this dataset, it is important to highlight an Average Nearest Neighbor summary of the combined UA sites layers which shows significant amount of clustering with a negative z-score of -50.468. This indicates low values clustered in the study area.

The spatial weighted matrix (SWM) file generated was applied to account for the conceptualization of spatial relationships and the distance method implemented is Euclidean distance, which is calculated with the following equation:

D = sq root [(x1–x2)**2.0 + (y1–y2)**2.0] (2)

Concentration levels, or hot spots, are highest in the south and southwest regions of the county, which are the most densely populated regions of the county.

The next set of data to incorporate into the analysis is demographic information for LA County from the US Census Bureau. The unit of analysis for this layer is census block groups. This dataset provides a larger range of demographic information for the entire USA for the last 5 years, including information on commuting, poverty, and income in Geodatabase table format. The information provided within this dataset will later be combined with a selected region with the hottest concentrations of UA and food desert to serve as explanatory variables when conducting an Exploratory Regression analysis and further regression modeling. This layer delineates the median income levels for both hot spots of UA sites as well as food deserts.

The feature attributes extracted for Los Angeles County from the US Census Bureau data table include income, commuting and housing characteristics. This data was then joint to the dataset from the USDA's Food Access Research Atlas. The USDA provided this dataset for download on their website which provides an analysis of food deserts throughout the US (2015). The tables are easily joined since they shared the same GEOIDs, although a new field for each table was created and the integers of the GEOID fields were copied over. The study characterizes low-income tracts within the US Census block groups based on two criteria: a poverty rate equal to or greater than 20 percent, or a median family income that is 80 percent or less of the metropolitan area and/or statewide median family income (USDA 2015). This study defines low access to food sources or living far from a market where ½ mile distance was used in urban areas and 10 miles was used in rural areas. Additionally, the parameters used by the Food Access Research Atlas will be utilized, henceforth defining low vehicle access if at least 100 households are more than ½ mile from the nearest supermarket and have no access to a vehicle.

3.3.2 Buffers & Directional Distribution Analysis

To understand the spatial extent and the regional movement of local food systems in Los Angeles County, Proximity toolsets were implemented to determine the contiguity of features. The Buffer tool is frequently used in studies utilizing geographical information systems (GIS) to measure accessibility in Food Environments (Charreire et al. 2010). This study used a series of buffers to delineate categories of Low Access to food sources as outlined by the USDA's Food Access Research Atlas; within ½ -10 miles. Additionally, a Directional Distribution Analysis tool from the Spatial Statistics toolbox is applied to both the dataset for UA and food deserts to determine if there is a relationship to any particular feature by highlighting their distributional trends. In order to ensure that the desynchronization of UA and food deserts is represented in a clear scale appropriate to the analysis conducted by this research, the County level will not be the scale of analysis. Rather, smaller unites of analysis and study areas will be selected based on the results of the hot spot analysis. This will therefore take into account the mountainous divide within the geography of the county, which accounts for the limited population.

Prior to executing both analyses mentioned above, the data from the Food Access Research Atlas was examined to explore the validity of the comparative analysis. The frequencies of populations living far away from affordable food sources by ½-10 miles in LA County totaled to 12.8% of the total population in 2010 census. Low income neighborhoods with low access to food total 6.5 percentage of the population and low income tracts for the county total 48%. The results of the analysis will be discussed in the next chapter.

3.4 Regression Modeling

Regression modeling is the first step to further understand what factors may lead to the spatial patterns of UA and food deserts and inform decisions to better equip underserved communities with fresh and affordable food sources. Based on the previously conducted analysis, one region was identified for further exploration. The block with the “hottest” collection of both US sites and classified as a food desert area is selected for an Exploratory Regression analysis. Once selected, the data associated with the block group is extracted and combined with the demographic data from the US Census Bureau. The dependent variable selected for the analysis is neighborhoods with Low Access to food sources within ½-10 miles, as previously used throughout this study. 9 explanatory variables were tested and transformed to a continuous 0-1 scale.

Table 3 Summary of Explanatory Variables

Explanatory Variables
Population Density
Percentage below Poverty
Percentage under 17
Percentage over 65
Access to vehicle
Median Income
Employment Status
Access to Health Insurance
Food Sources/UA

The following method was used to determine the weight for the population density, population below poverty, age and obesity features. The highest and lowest values for the following features in the selected block group were identified and given a scaled value of 0 for the lowest and 1 for the highest. All other values were adjusted to fall within the 0-1 scale. Access to vehicle, Employment status and access to health insurance were valued as 0 = no and 1 = yes. Household with income levels at or below poverty ($42,420 per year) received a score of 1 while incomes above received a score of 0. Lastly, areas within 1+ mile of a food source and

UA sites receive a score of 1 and areas closer to a food source are scored 0. The results of the variables and parameters tested will be discussed in the following chapter.

The results of the exploratory analysis will then be used to determine what combination of variables can yield a viable Ordinary Least Squares (OLS) model. If the exploratory analysis does not yield a viable model, the variables with the highest significance and the model with the highest adjusted R^2 (Adj R^2) values will be modeled using the OLS Regression tool.

Chapter 4: Results

Chapter 4 documents the results of the spatial analysis conducted to test the bivariate hypotheses to examine if there is a relationship between UA sites and food deserts in LA County based on poverty levels through the use of Spatial Autocorrelation, Hot Spot Analysis, Buffers, Directional Distribution Analysis and Regression Modeling. There exists limited studies and analysis for LA County on how both phenomena affect each other. The data utilized in this analysis were described in the previous chapter, including how they were obtained, prepared, and the defined criteria for analysis. An analysis of the pattern demonstrated by UA sites and food deserts can reveal if there is a significant statistical difference between income levels for these neighborhoods.

This chapter highlights the spatial patterns or autocorrelation and examines which block groups in LA County have the highest or lowest concentration of UA and food deserts. Section 4.1 reviews the results of the hot spot analysis of Urban Agriculture sites in the county as well as making a comparison with areas within the county of high levels of poverty. Food desert hot spots are examined in section 4.2 as well. Buffers and the directional distribution for selected areas where each of these phenomena intersect are further explored in section 4.3. An exploratory regression model is executed for the dependent variable of block groups that are identified as low income and low access to healthy food resources within 0.5-10 miles contained by the county. The results are reviewed in section 4.4. Lastly the collective results of these exploratory analysis are reviewed in section 4.5.

4.1 Hot Spot Analysis Urban Agriculture and Poverty

The results from the hot spot analysis of UA sites indicate the statistically significant clusters of these occurrences. A total of 1,438 weighted features were analyzed. Figure 6 shows concentration levels, or hot spots, are highest in the south and southwest regions (Metro or Central LA, West Side, and parts of San Fernando) of the county with a small clustering in the north east region (Antelope Valley). These areas are the most densely populated regions of LA County, as Figure 7 confirms, therefore justifying the results of a high concentration or “hottest" incidents of urban agricultural practices. The resulting map in Figure 6 classifies the sites using the GI Z-scores, separating each by the confidence percentage. The table below illustrates the criteria of the z-score and p-values used to determine the confidence level in this analysis.

Table 4 Z-score and P-value Confidence levels

z-score (Standard Deviations)	**p-value (Probability)**	**Confidence level**
< -1.65 or > +1.65	< 0.10	90%
< -1.96 or > +1.96	< 0.05	95%
< -2.58 or > +2.58	< 0.01	99%

The coldest sites are ten in total and are shown in the map of Figure 6. There are three sites in the South Bay area and seven between the Metro and San Fernando Valley region of the county. When comparing poverty levels for the neighborhoods these sites are located, the areas are close in proximity to neighborhoods considered below poverty levels. This outcome show that there is a low probability that UA sites will emerging in low income neighborhoods. There a total of 198 hottest UA sites with very minimal overlap in areas living below poverty, which again reinforces that UA sites are less likely to emerge in low income neighborhoods.

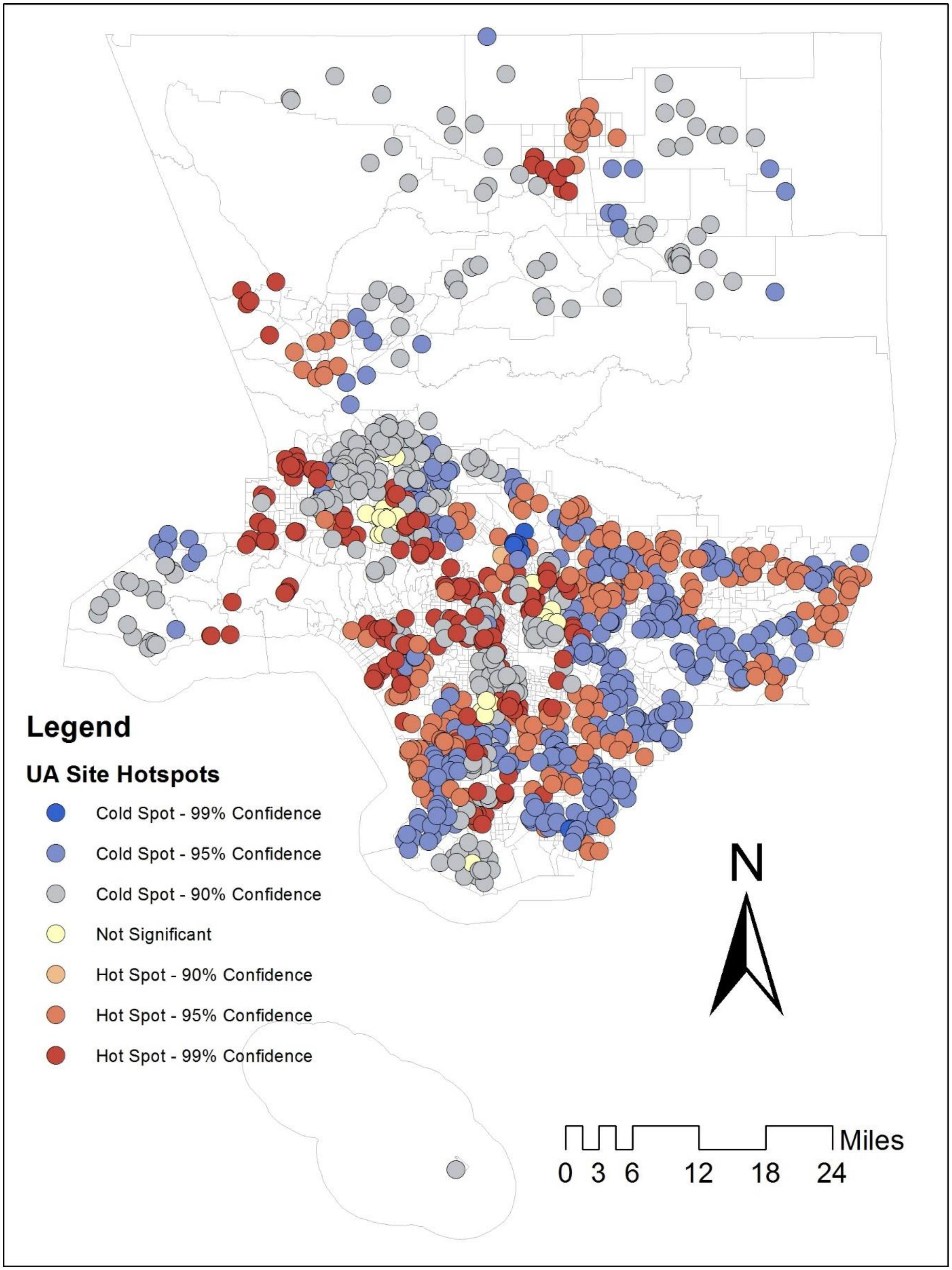

Figure 6 Hot Spot Analysis of UA Sites

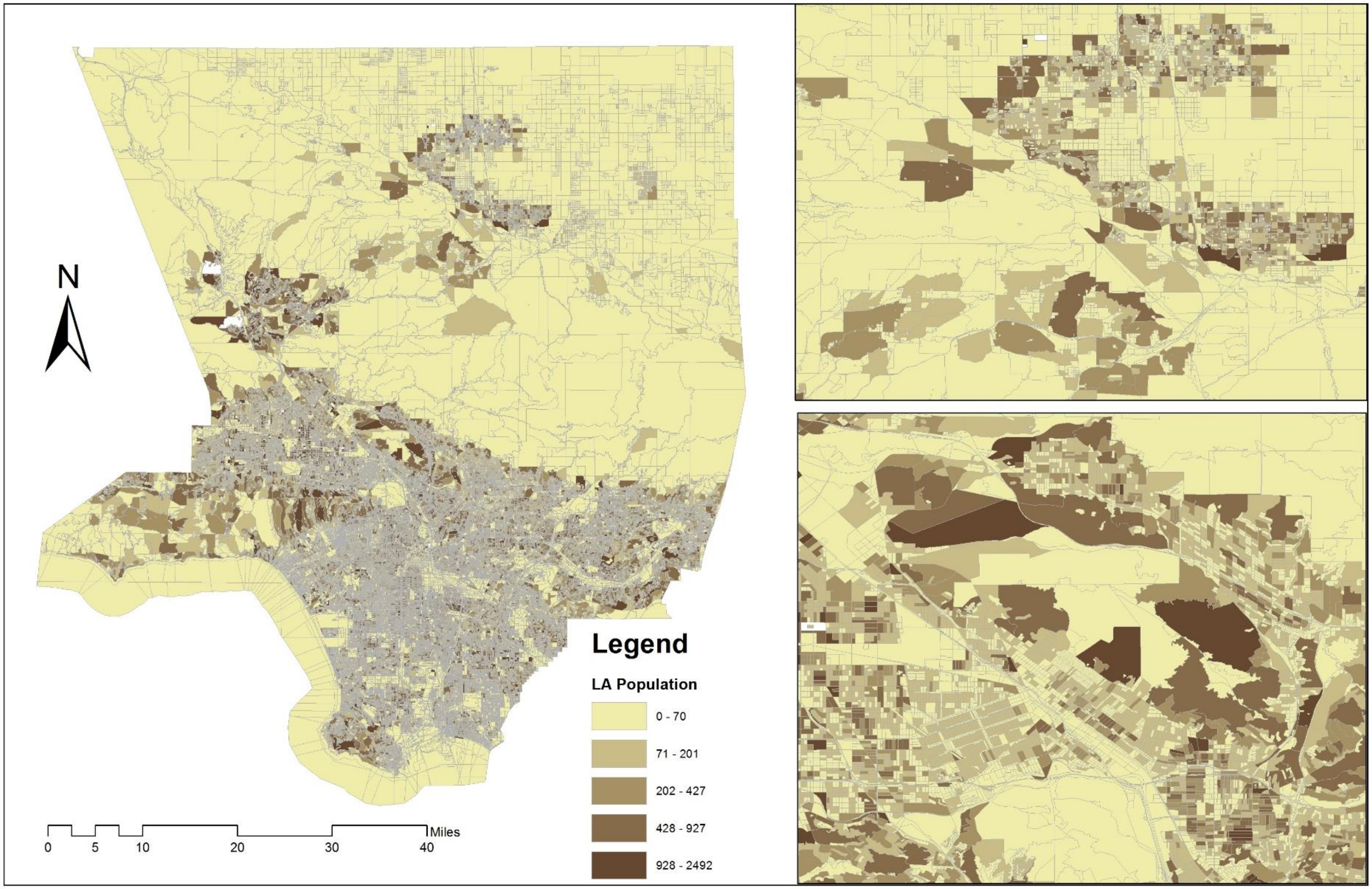

Figure 7 Population Density for LA County

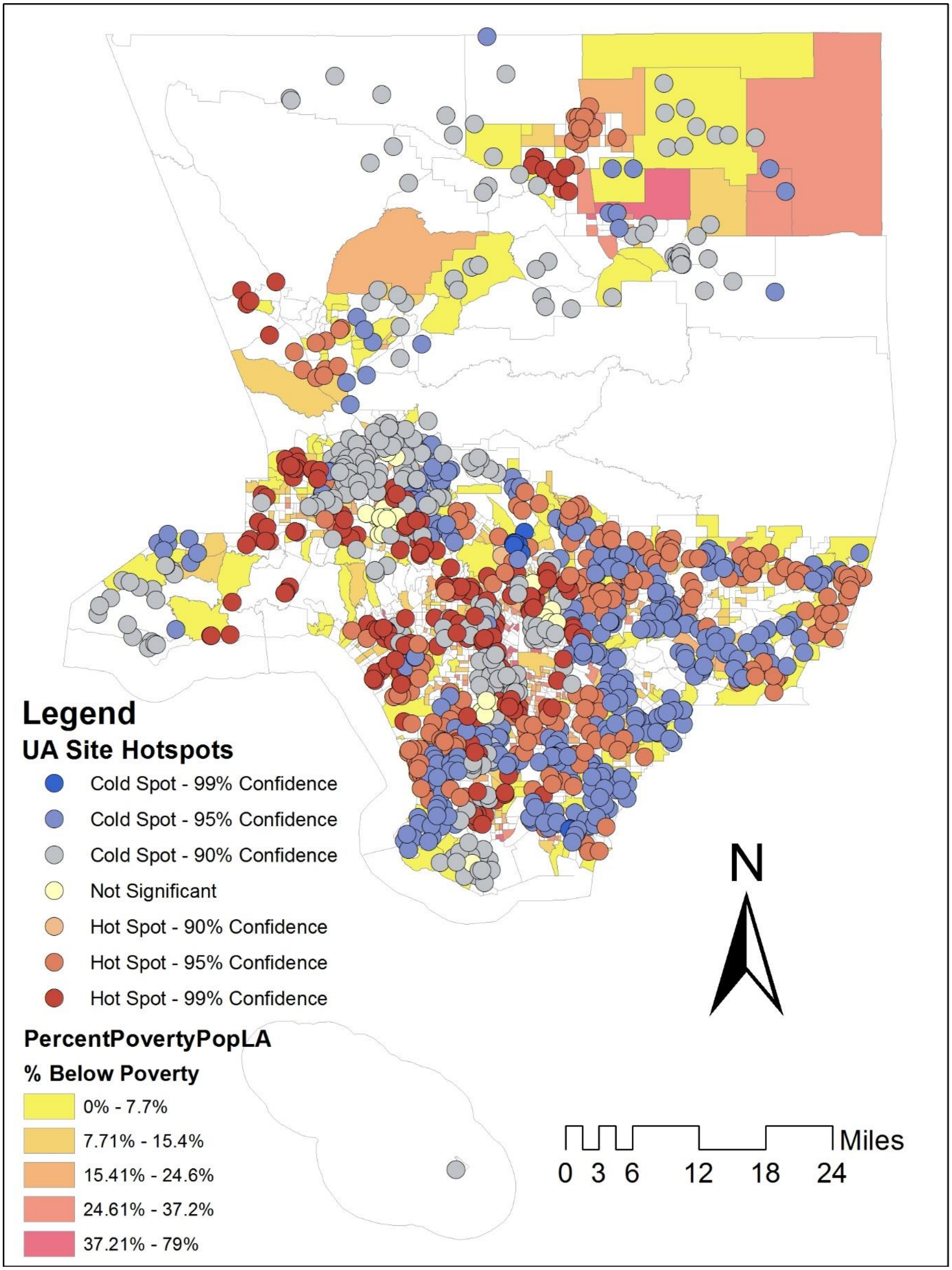

Figure 8 Comparison of UA Site Hot Spots & Percentage of Poverty for LA County

In an effort to understand how the pattern of UA sites affects neighborhoods with the greatest needs, a layer depicting percentage of poverty within LA County was added. Figure 8 shows the resulting map. The layer represents census tracts with population that falls below poverty levels by a range of percentage starting from 0%-7.7% and scaling up to 79%. This map shows the overlap between poverty levels and the weight of probability of UA sites within the county. Figure 9 below enlarges the north east, Antelope Valley region, to highlight the dynamics of these patterns and shows the relationship between both layers. Several of the hottest UA sites fall within regions above poverty levels with very minimal sites within the highest indicated tracts. The results of further analysis exploring the nature of the relationship between these two factors is reviewed in the sections below.

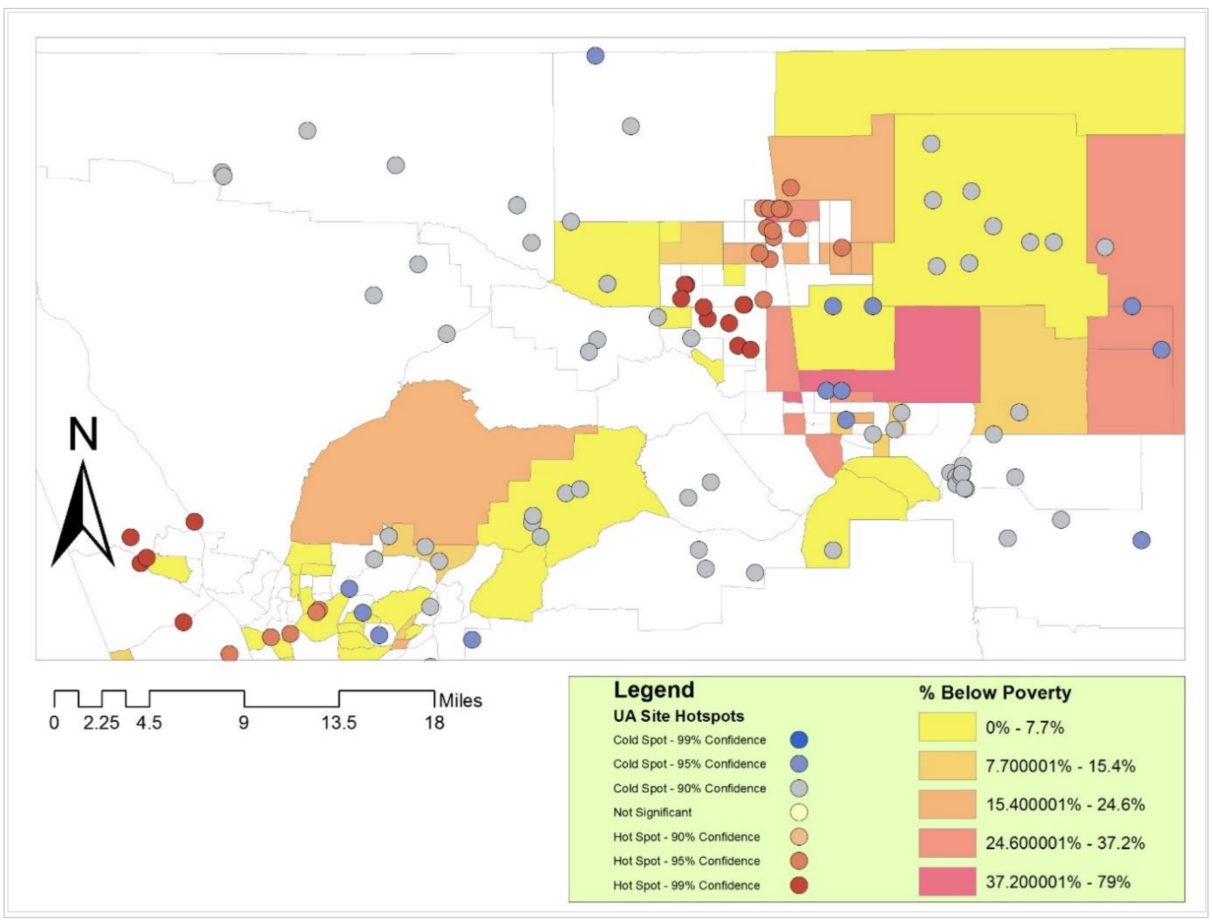

Figure 9 Antelope Valley Region Comparison of UA Site Hot Spots & Percentage of Poverty

4.2 Hot Spot Analysis Food Deserts and Poverty

As explained in Chapter 3 the parameters of the data provided by the Food Research Atlas utilized in this study are based on dense urban neighborhoods, therefore two possible classification were tested in this analysis. Figure 10 shows the census tracts that are classified as Low Income and Low Access to healthy food sources by 1-10 miles. Due to the scale of this analysis and the population density in certain regions of LA County, census tract classification fails to fully capture the nature of how these demographics interact with this space. The second classification, represented in Figure 11 and utilized for the remainder of this analysis, is Low Income and Low Access to healthy food sources by 0.5-10 miles.

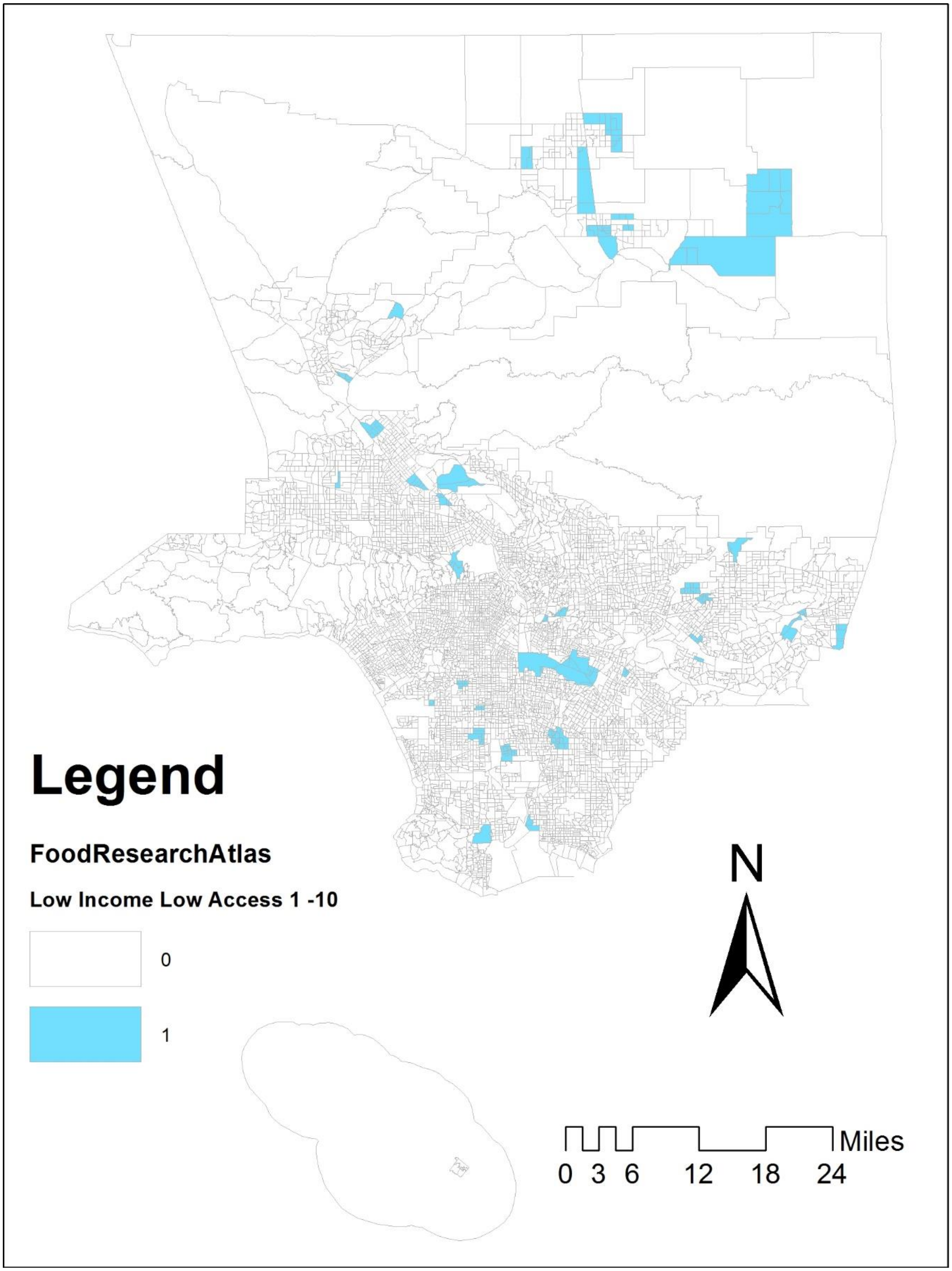

Figure 10 Low Income & Low Access to Food Source 1-10 Miles

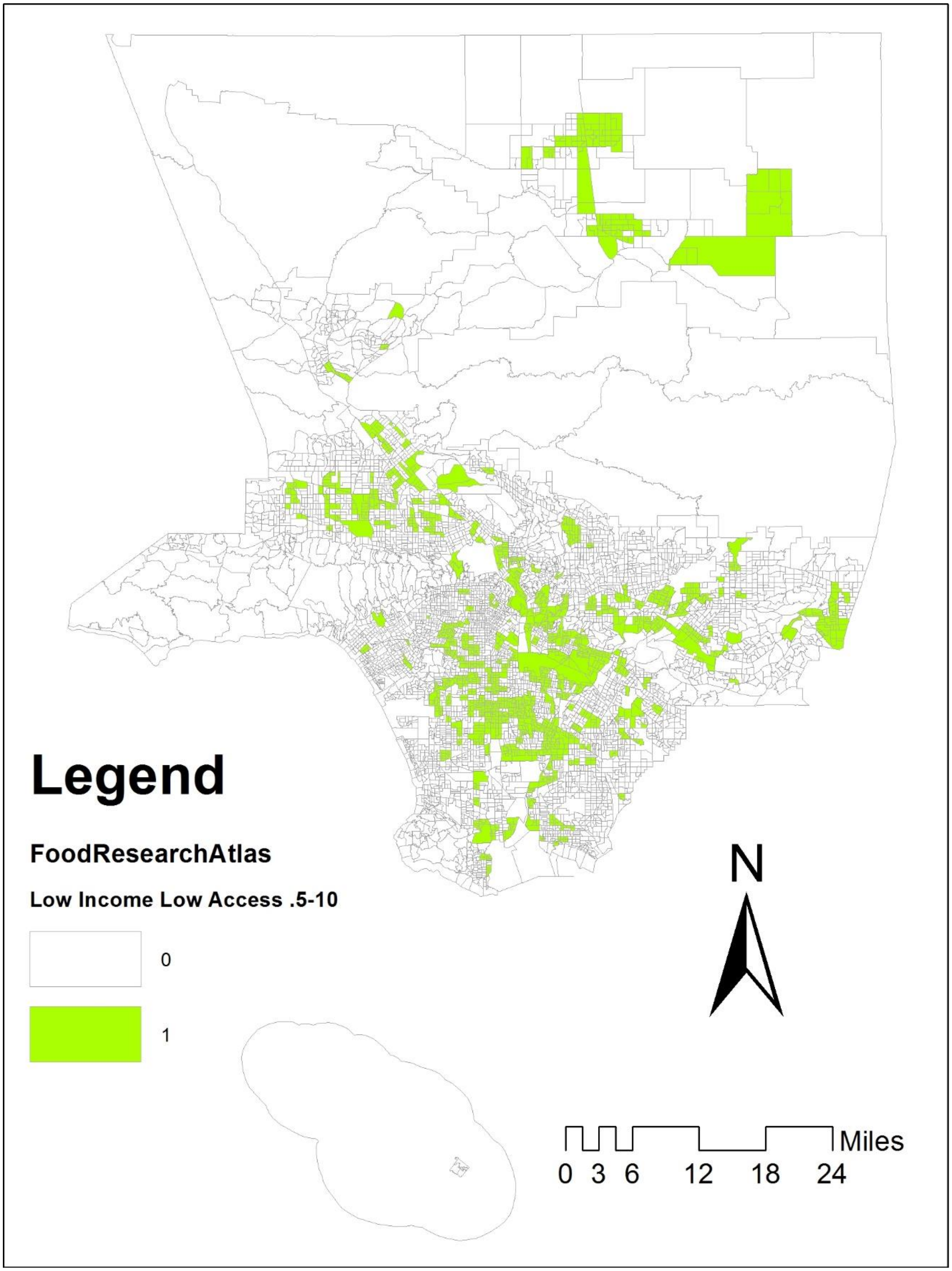

Figure 11 Low Income & Low Access to Food Source 0.5-10 Miles

The results from the hot spot analysis of the census tracts classified as food deserts also represent the statistically significant clusters of this phenomena. Figure 12 indicates that concentration levels, or hot spots, are highest in the south and south central regions (Metro or Central LA, East Side, South Central, and parts of San Gabriel Valley) of the county with a small clustering in the north east region (Antelope Valley). Once again, as Figure 7 shows, these areas are the most densely populated regions of LA County, and justifying the results of a high concentration or “hottest" potential for food deserts to emerge. The resulting map in Figure 12 uses the same classification parameters as used in the hot spot analysis for UA sites.

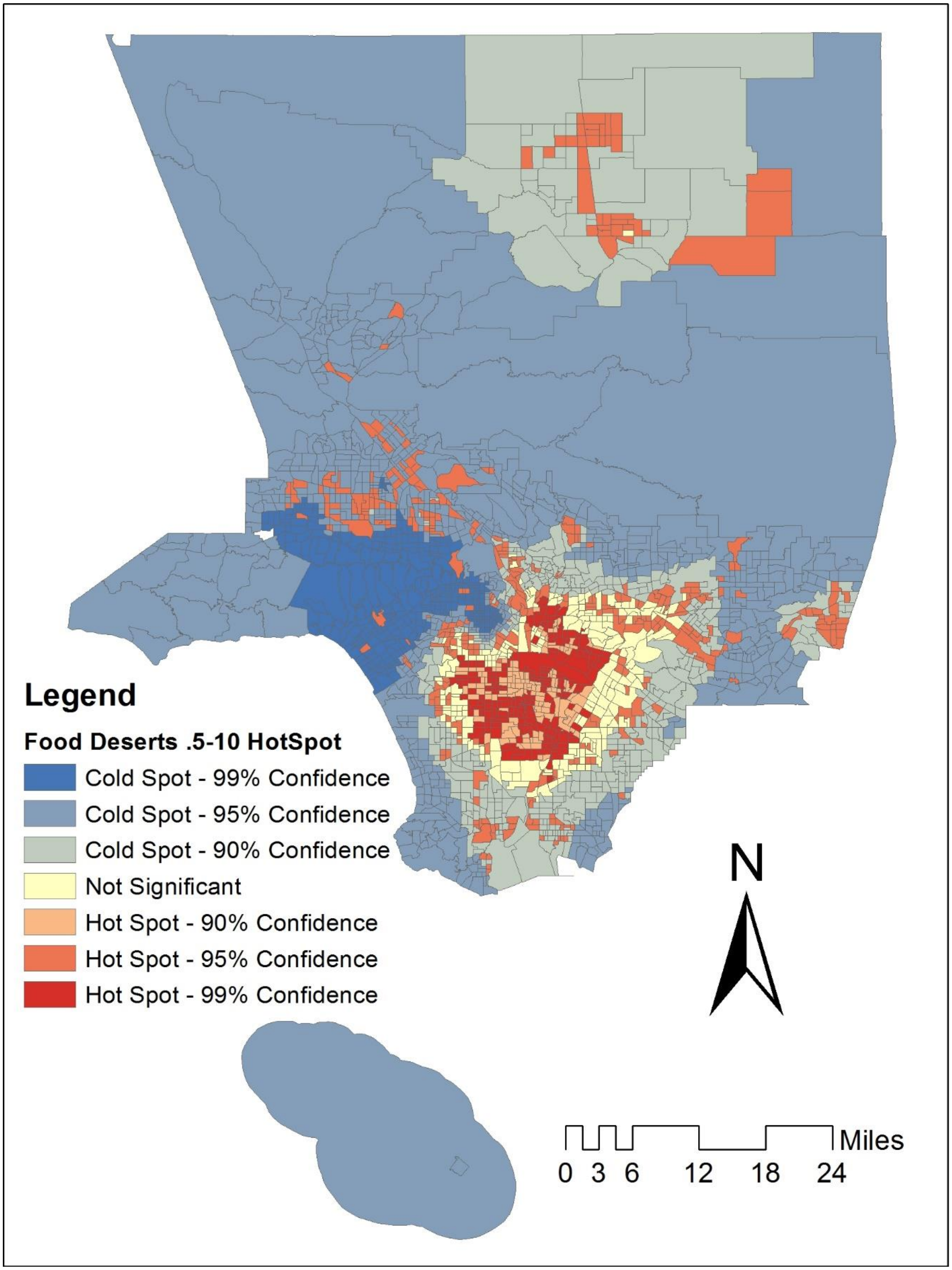

Figure 12 Food Desert Hot Spot Analysis

As previously applied to the hot spot analysis of UA sites, the layer with the neighborhoods with percentages of below poverty neighborhoods within LA County was compared to the layer representing low income and low access tracts within .5-10 miles of healthy food sources. Figure 13 is the resulting map representing the overlap between these two layers. The south and south central regions of the county have the greatest quantity of overlap between food desert neighborhoods and high percentages living below poverty. Out of the 176 neighborhoods with high percentages of demographics living below poverty, 151 are also classified as food deserts, which is 86% of the total. The north east, Antelope Valley region was enlarged in Figure 14 to show the relationship between both layers as it was done with UA sites. There are several food desert areas that overlap with the layer below poverty. Considering that low income is a criteria for establishing regions considered as food deserts in this study, it is expected for areas to overlap. However, it is worth mentioning that the areas overlapping did not have the highest percentage below poverty as classified by the layer. Further analysis was conducted and will be reviewed in the sections below.

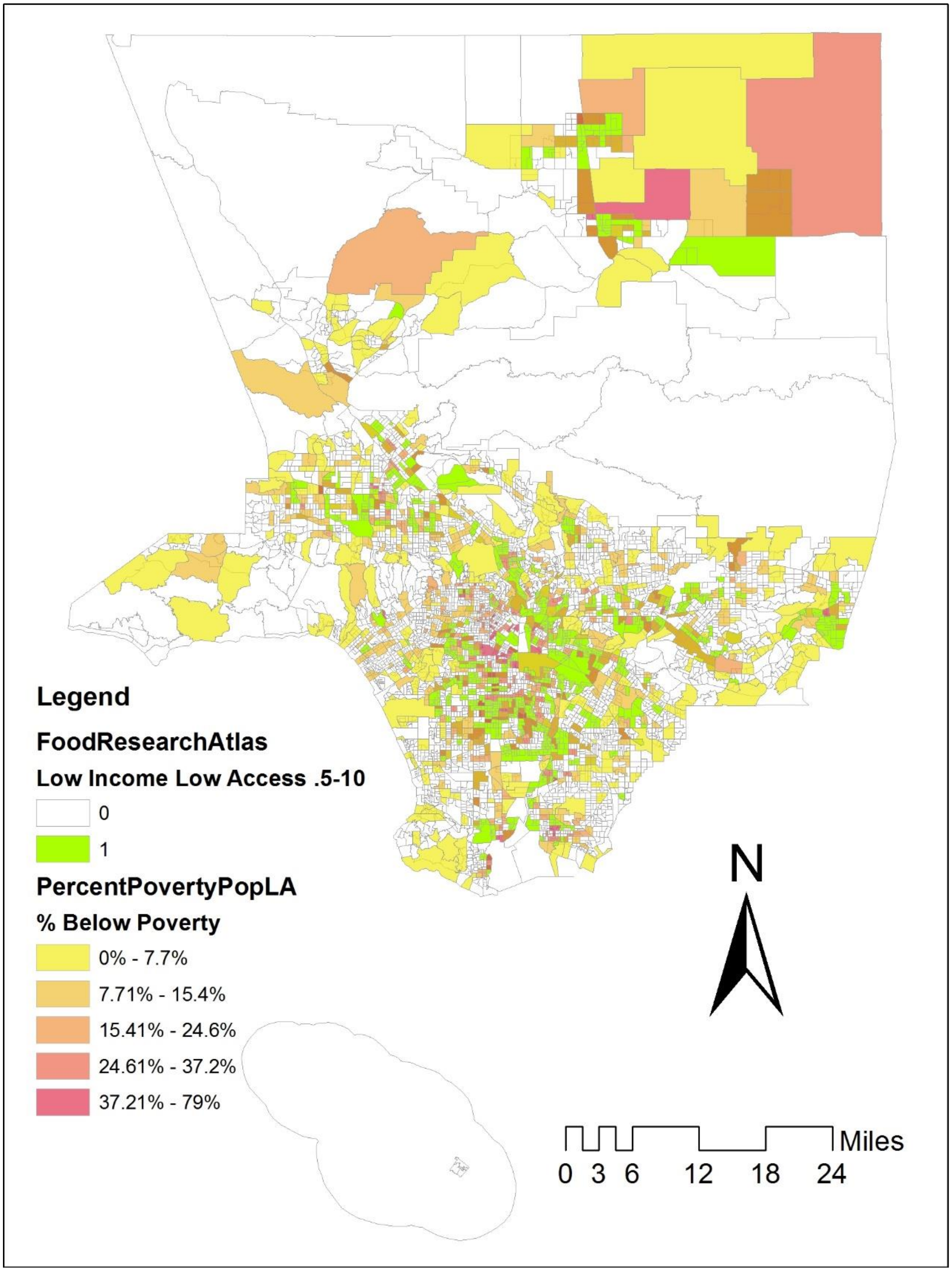

Figure 13 Low Income & Low Access to Food Source & Percentage Below Poverty

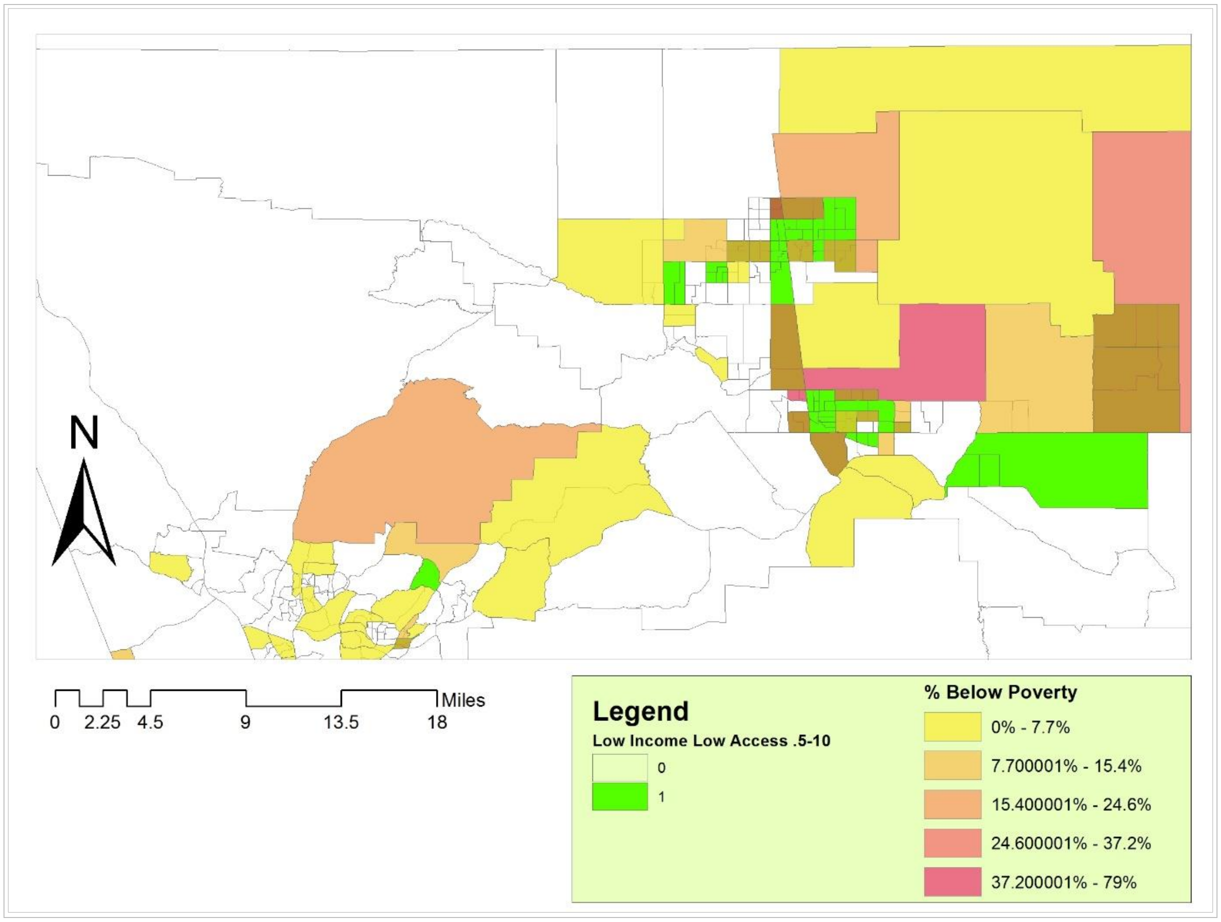

Figure 14 Antelope Valley Region Comparison of Food Desert & Percentage Below Poverty

4.3 Buffer and Directional Distribution

The Antelope Valley region was selected for further analysis. A multi-ring buffer was applied to the hottest UA sites. Four distances were selected to emulate the ranges associated with the criteria for food deserts established by the USDA's Food Access Research Atlas; 0.5, 1, 5, and 10 miles. These buffers assist in outlining the ease in access to healthy foods based on the food desert hot spots. Figure 15 shows the results of the buffers. Three out of the nine sites selected for the buffers are within 1 mile or less of the food desert hot spots, with the majority at a distance of 5 miles or more. It is worth noting that within that same figure, several warm UA sites are actually within the hottest food desert regions. As Figure 16 shows, the majority of those sites are school gardens and may have limited accessibility by the surrounding community, which is not a component provided by this study. Further analysis is recommended in order to establish which UA sites actually allow the surrounding neighborhoods to access their resources.

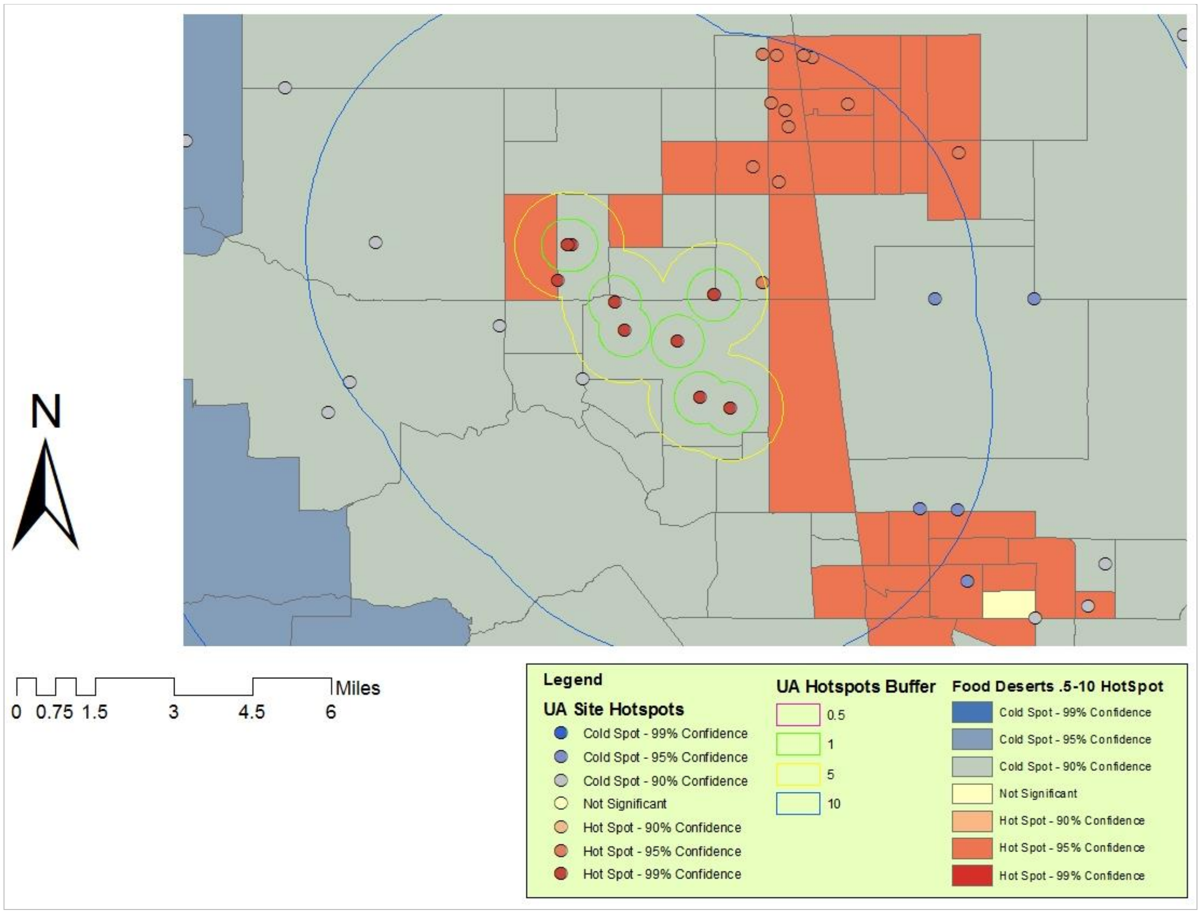

Figure 15 Buffer of Hottest Sites in Antelope Valley Region Based on Food Desert Hot Spots

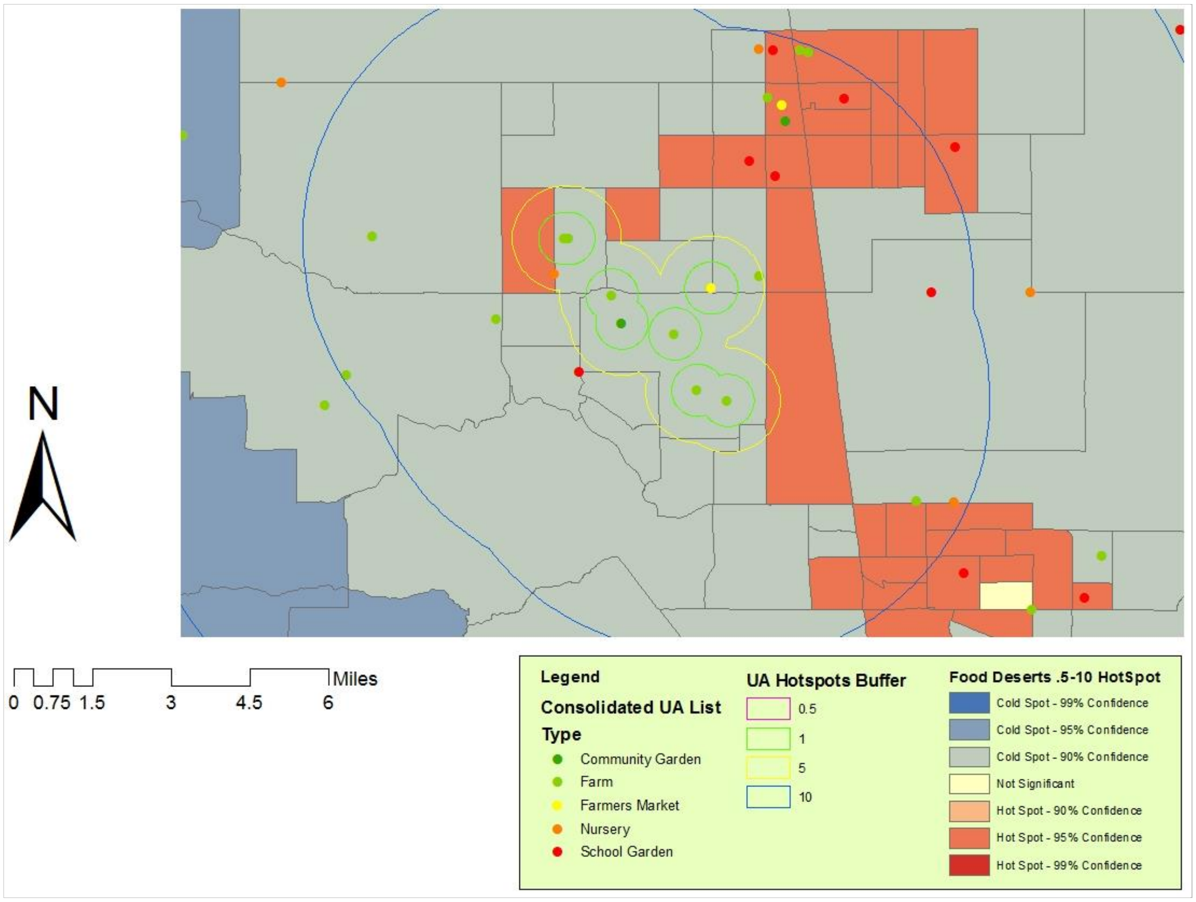

Figure 16 Buffer of UA Sites in Antelope Valley Region Based on Food Desert Hot Spots

Three new feature classes were created for both the hot spot analysis (UA sites and Food deserts) showing the directional distribution of the mean center for each based on the results of the hot spot analysis results. These layers summarizes the spatial trends within each feature to further reveal possible relationships. The study areas selected for UA sites include Antelope Valley, San Fernando Valley and part of West LA, and the remaining south east regions of the county. Once the data for each study areas was exported and added to the map, a directional distribution analysis was executed for each. Figure 17 shows the three directional ellipses for UA sites. The ellipses confirms a south and east bias for the Antelope Valley region, a south and west bias for the San Fernando and West LA region, and a deeper south and east bias for the remaining regions of the county. The directional distribution for food deserts shown in Figure 18 highlights a south and west bias for the Antelope Valley and San Fernando/West LA regions, while the remaining regions of the county show a similar bias like the UA features of south and east.

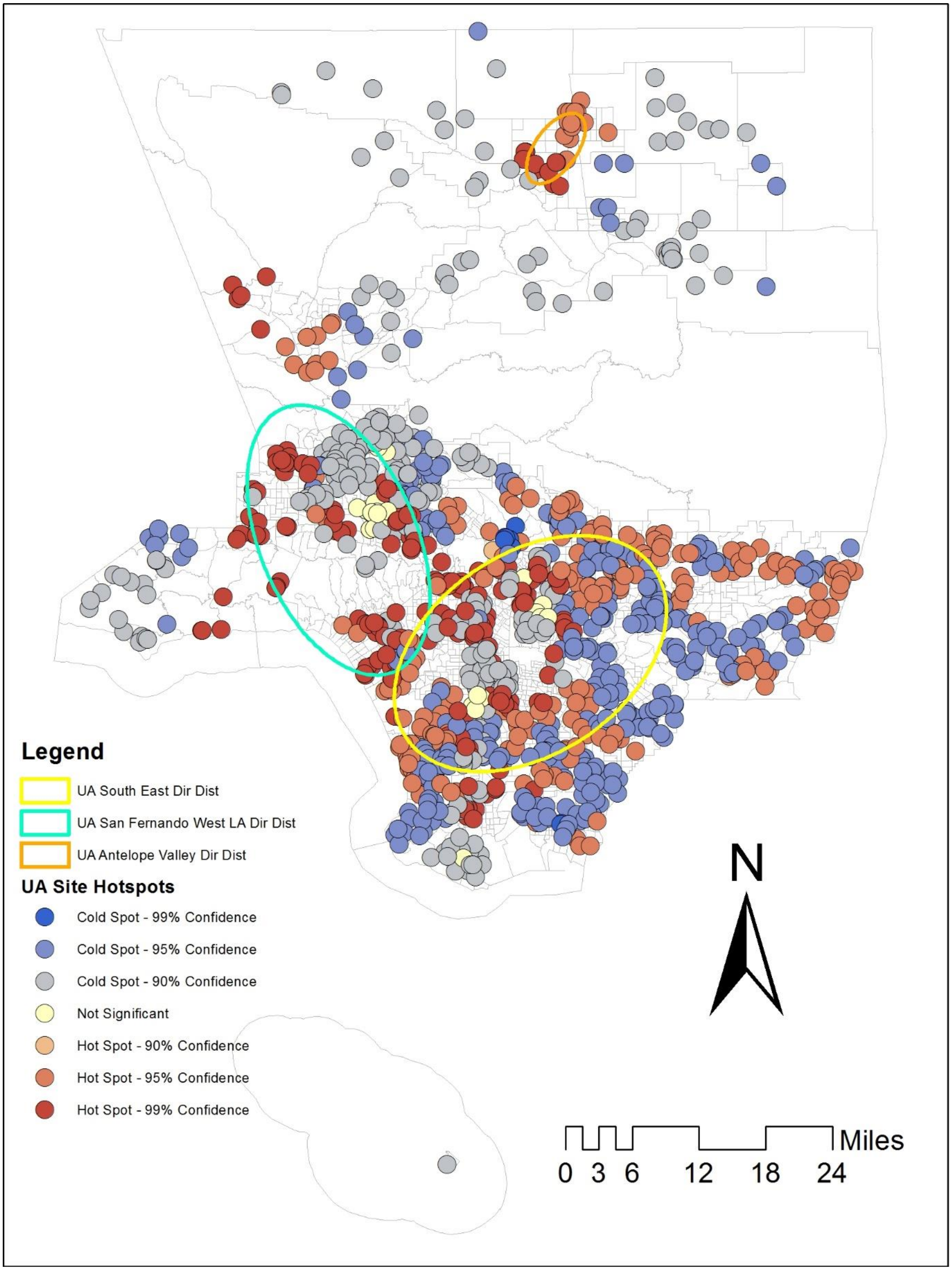

Figure 17 Directional Distribution of UA Hot Spots

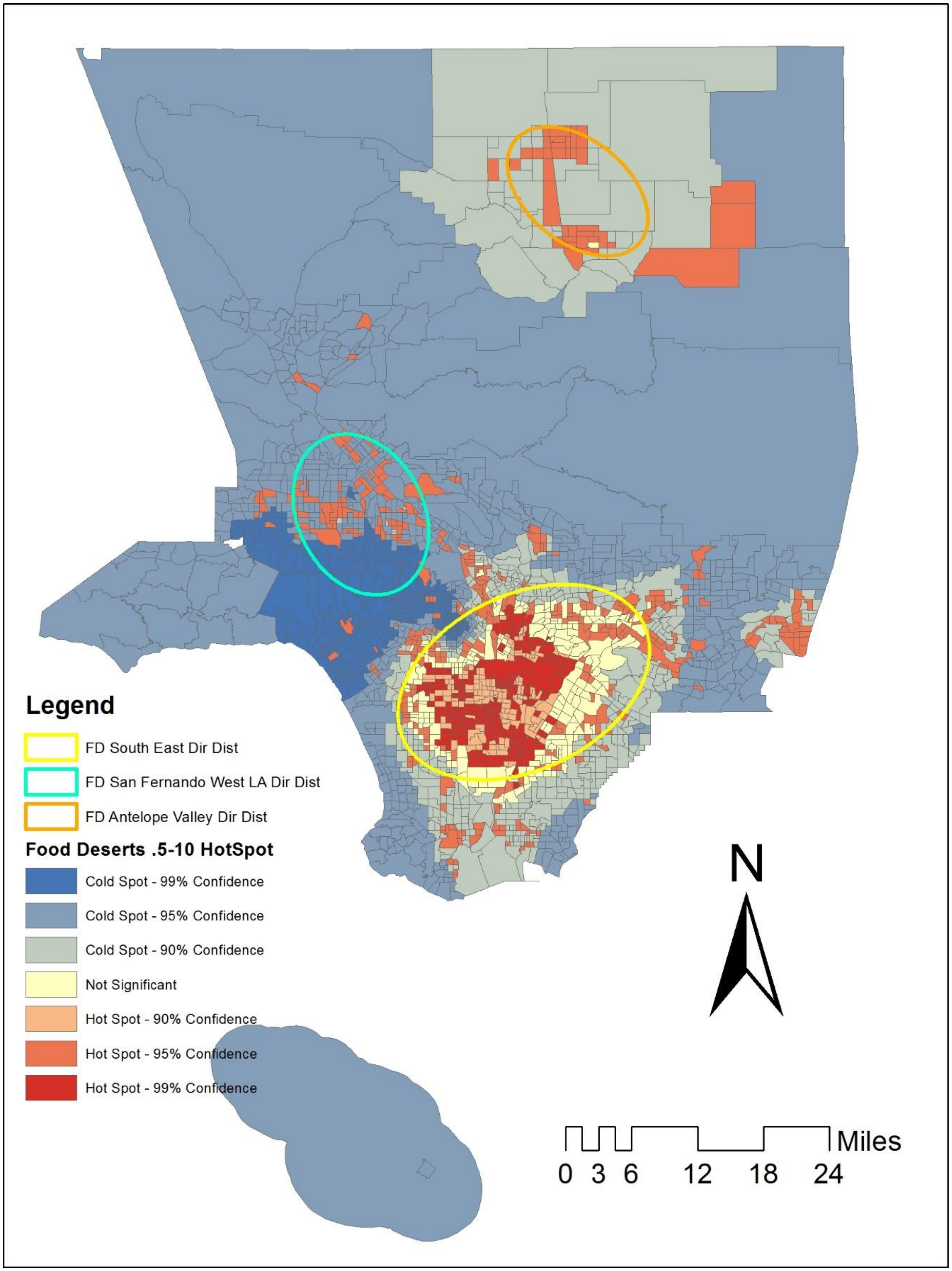

Figure 18 Directional Distribution of Food Deserts Hot Spots

4.4 Regression Modeling

4.4.1 Outcome of Exploratory Regression Model

Although a wide range of demographic variables were provided by US census block groups, the results of the exploratory regression models did not provide a single passing model. The maximum number of explanatory variables indicated in the analysis was 9. The full raw report for the model outcome is in Appendix B and shows the results of the ninth tested potential summary from the output report provided by ArcGIS. The highest Adj R^2 tested was 0.73. This figure represents the amount of correlations between the dependent and independent variables ranging between values of 0-1. The Adjust R^2 value of 0.73 is not substantially low and provides the basis for further exploration through OLS modeling. Appendix B also shows a summary for each section, which confirms that there is no viable model.

Table 5 shows the figures of the Exploratory Regression Global Summary, which list the results of the five diagnostic tests for a passing model. Further examination of this section of the report reveals low passing percentages. All the models have a value of 0.00 for both the Jarque Bera p-value (JB) and Spatial Autocorrelation p-value (AS). This indicates non-normally distributed model residues and significant spatial autocorrelation impacting the results. Further exploration of these outcomes will be reviewed in the results of the OLS regression modeling.

Table 5 Highest Adjusted R-Squared Results

Percentage of Search Criteria Passed				
Search Criterion	**Cutoff**	**Trials**	**# Passed**	**% Passed**
Min Adjusted R-Squared	> 0.50	1,010,894	220,731	21.84
Max Coefficient p-value	< 0.05	1,010,894	169,872	16.80
Max VIF Value	< 7.50	1,010,894	371,174	36.72
Min Jarque-Bera p-value	> 0.10	1,010,894	0	0.00
Min Spatial Autocorrelation p-value	> 0.10	30	0	0.00

The most revealing section of this report is the Summary of Variable Significance. This section highlights the consistency of variable relationships by confirming the percentage of statistically significant for each candidate explanatory variable. Table 6 presents the significance of each variable explored. The variables with the highest and most consistent % of significance were derived from the same dataset provided by the USDA's Food Research Atlas. The % of significance varied thereafter from data obtained from the US Census demographics tracts. Not having health insurance for individuals 18-64 years of age had a high % of statistical significance throughout the analysis but was not a consistently strong predictor. Therefore, not having health insurance can be considered a factor when combined with additional variables to explain the phenomena of food deserts. Income per capita had a high statistical significance and maintained a stable negative variable relationship. Similarly, households that received public assistance had a high statistical significance and maintained a stable positive variable relationship. Overall these figures assist in evaluating which demographic has a higher possibility of explaining or predicting areas that are food deserts.

Table 6 Summary of Variable Significance

Variable	% Significance	% Negative	% Positive
LA1_20MILES.LATRACTS_HALF Low Access Tracts within 0.5 miles	100.00	0.00	100.00
LOW INCOMETRACTS Low Income Tracts	100.00	0.00	100.00
LA1_20MILES.LAHUNVHALF Vehicle access, housing units without and low access at 0.5 mile	100.00	0.00	100.00
X27_HEALTH_INSURANCE.B27010E50 No health insurance coverage age: 35-64	99.27	34.93	65.07
X27_HEALTH_INSURANCE.B27010E33 No health insurance coverage age: 18-34	94.59	34.19	65.81
X19_INCOME.B19001E1 Per Capita Income	83.08	86.44	13.56
LA1_20MILES.POP2010 Population, tract total	82.48	46.59	53.41
X22_FOOD_STAMPS.B22010E2 Household Received Food Stamps/Snap In The Past 12 Months	82.25	10.05	89.95
X19_INCOME.B19001E5 Household Income In The Past 12 Month $20,000 To $24,999	80.22	40.78	59.22
X23_EMPLOYMENT_STATUS.B23025E4 Employment Status For The Population 16 Years And Over: Employed	79.90	89.74	10.26
X17_POVERTY.C17002E1 Ratio Of Income To Poverty Level In The Past 12 Months: total	79.01	27.48	72.52
X19_INCOME.B19001E3 Household Income In The Past 12 Month $10,000 To $14,999	77.77	40.42	59.58
X23_EMPLOYMENT_STATUS.B23025E2 Employment Status For The Population 16 Years And Over: In Labor Force	76.96	65.10	34.90
X19_INCOME.B19001E4 Household Income In The Past 12 Month $15,000 To $19,999	73.70	51.39	48.61
X19_INCOME.B19001E2	72.90	49.34	50.66

Household Income In The Past 12 Month $20,000 To $24,999			
X27_HEALTH_INSURANCE.B27010E17 No health insurance coverage age: < 18	71.61	12.79	87.21
X01_AGE_AND_SEX.B01001E1 Sex By Age: Total	71.07	35.69	64.31
X23_EMPLOYMENT_STATUS.B23025E7 Employment Status For The Population 16 Years And Over: Not in Labor Force	68.57	65.02	34.98
X23_EMPLOYMENT_STATUS.B23025E5 Employment Status For The Population 16 Years And Over: Unemployed	67.49	10.94	89.06
X01_AGE_AND_SEX.B01001E26 Sex By Age: Female	65.29	21.7	78.63
X01_AGE_AND_SEX.B01001E2 Sex By Age: Male	59.81	57.51	42.49
X27_HEALTH_INSURANCE.B27010E66 No health insurance coverage age: 65 +	26.49	60.39	39.61

The summary of Multicollinearity between the independent variables shows that there is a significant similarity in the poverty, income, employment status, and age and sex data from the US census. These results indicate redundancy of the explanatory variables which in turn can indicate an over counting bias within the model, creating an unreliable model. Although the report shows that the types of explanatory variables provided in this analysis are not strong enough to create a viable model through this method of regression modeling, further analysis through OLS can examine a global model to identify and measure the relationship of factors that lead to food disparity in the county.

4.4.2 OLS Regression Model

The model selected for further regression analysis had the highest Adj R2 and the lowest Akaike Information Criteria (AICc). Table 7 lists the nine variables for the model and the results of the corrected AICc, JB, Koenker's studentized Breusch-Pagan p-value (K(BP)), the Variance Inflation Factor (VIF), and the residual (SA).

Table 7 Highest Adjusted R-Squared Results

AdjR2	AICc	JB	K(BP)	VIF	SA	Model
0.73	-1150.51	0.00	0.00	4.29	0.00	+LA1_20MILES.LATRACTS_HALF +LA1_20MILES.LOWINCOMETRACTS -LA1_20MILES.POP2010 +LA1_20MILES.LAHUNVHALF -X19_INCOME.B19001E4 -X19_INCOME.B19001E5 -X27_HEALTH_INSURANCE.B27010E50 +X01_AGE_AND_SEX.B01001E1 - X23_EMPLOYMENT_STATUS.B23025E7

Figure 19 displays the output map of residuals from the OLS analysis of the above selected variables. Issues arise when comparing the results from this map with the results to the map of Low Income & Low Access to Food Source 0.5-10 Miles in Figure 11. The areas in blue indicated locations whose actual value are lower than the model estimates, those areas are not designated as food deserts in Figure 11. Neutral areas are regions with low population which have little statistical relevance for this analysis. However, If the residuals in the red areas are locations with actual values higher than the model estimated but are in actuality the locations designed as food deserts by the Food Research Atlas dataset, then there seems to be a disconnect with the explanatory variables in explaining their relationship between Low Access and Low Income neighborhoods 0.5miles to 10 miles from healthy food sources.

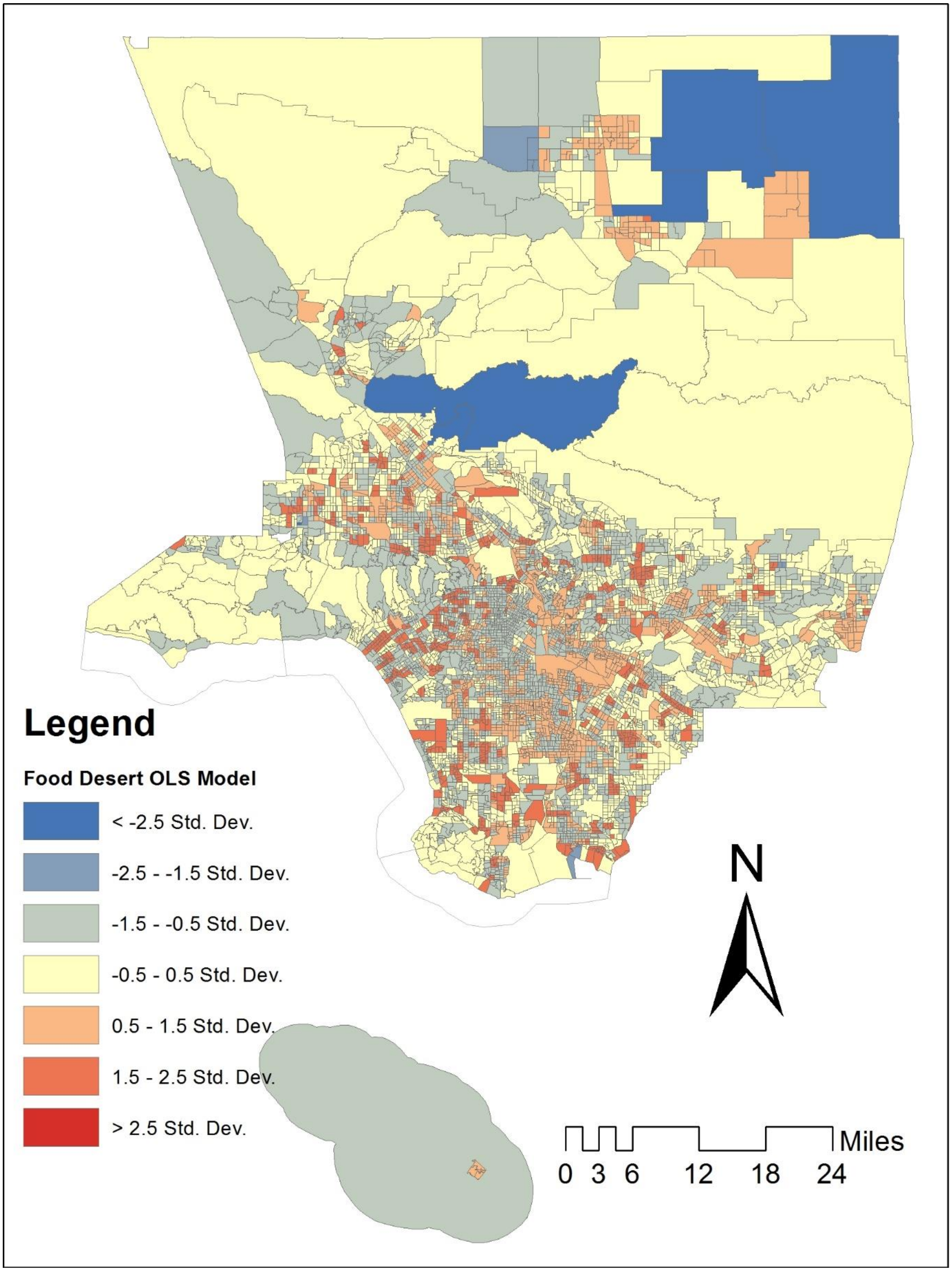

Figure 19 Map of OLS Residuals of Selected Variable from Exploratory Regression Model

Appendix C has the full output report of the OLS regression model. Included in the results of this report is a summary of the model variables. The results show that the model explains 73% of how these variables predict or influence food deserts. All variables proved to be statistically significant and had a VIF below 7.5 showing a low redundancy. The model the residuals proved not to be normally distributed, indicating a biased model.

Additionally, several graphs (Figure 30) are made available for each explanatory variable and the dependent variable. The graphs support the results from report by visualizing the issues within the model. The graphs of the variables distribution and relationships highlight the issues with outlines in the data. The histograms show skewed distributions by several variables. Lastly, scatterplots of the variable distribution and relationships are linear but are not diagonal, so they do not to represent a positive or negative relationship. Figure 31 in Appendix C shows the histograms graph of residuals for OLS model's over- and under predictions and confirms that the model is bias due to the fact that residuals are not normally distributed. Overall the OLS regression modeling enables further understanding of the influence of income, population density, access to a vehicle, health insurance coverage, age and gender plus employment status to the emergence of food deserts.

4.5 Review of Findings

When combining both hot spot layers for UA sites and food desert neighborhoods, the data suggests that their patterns match. This means that there is an overlap between hot spots of UA sites and hot spots of food deserts, both can be found within heavily populated regions of Los Angeles County. Figure 28 maps both layers. Although the concentration of hot and cold features seem similar, different information is revealed after further analysis of the datasets.

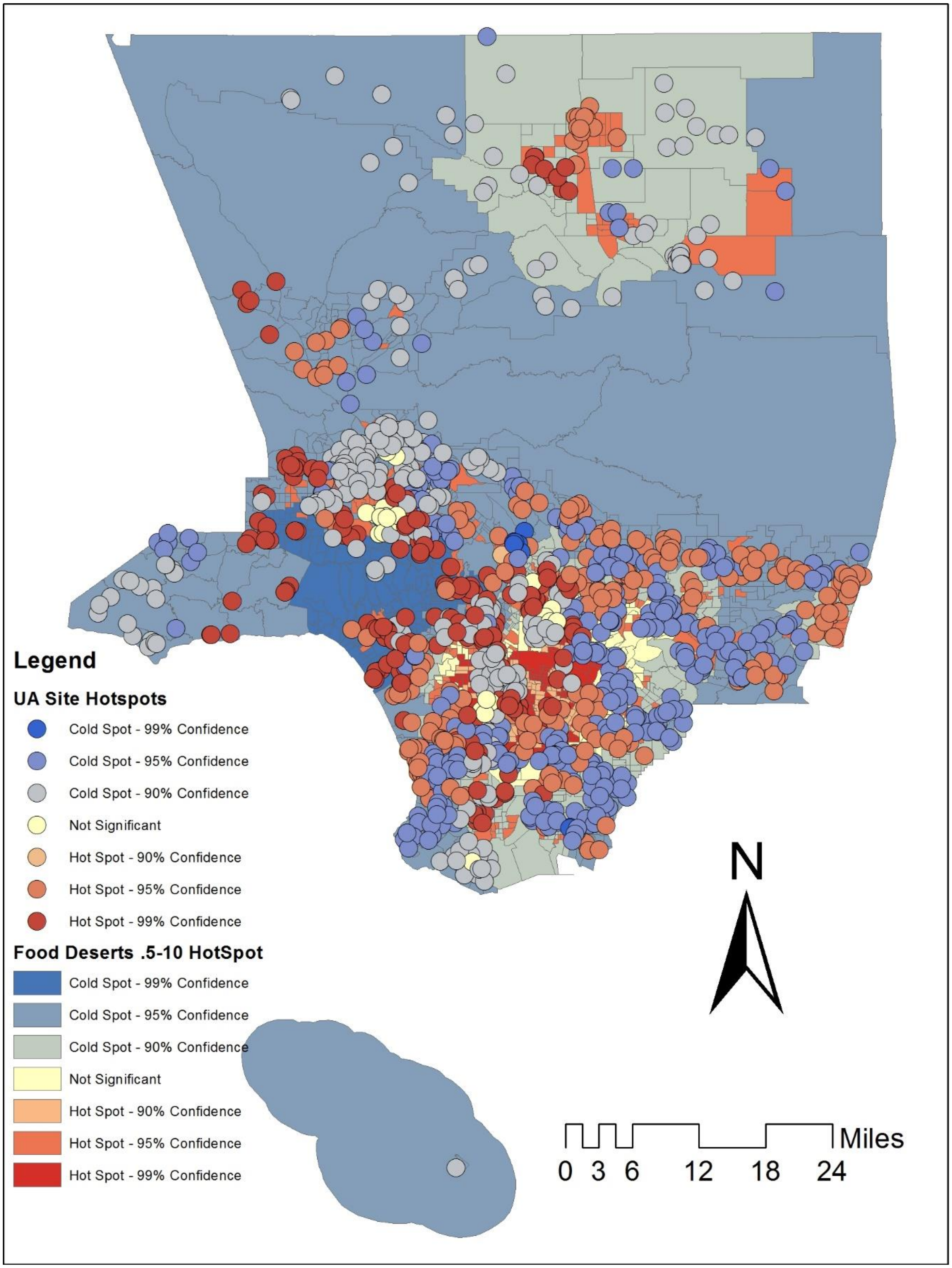

Figure 20 Combined Hot Spots for UA site & Food Deserts

4.5.1 Overlap in Hottest Spots for UA and Food Deserts

After selecting and exporting the hottest features from the UA hot spot analysis, all features from the food desert hot spot layer that contain the specified UA sites were selected and exported as well. Figures 29 and 30 show a majority of low value food desert features that contain the "hottest" UA sites. Statistically, the highest values of UA sites and lowest values of the food deserts fall within the same spatial location. This finding, ultimately indicates a stronger likelihood that a UA site will emerge in neighborhoods that are not food deserts.

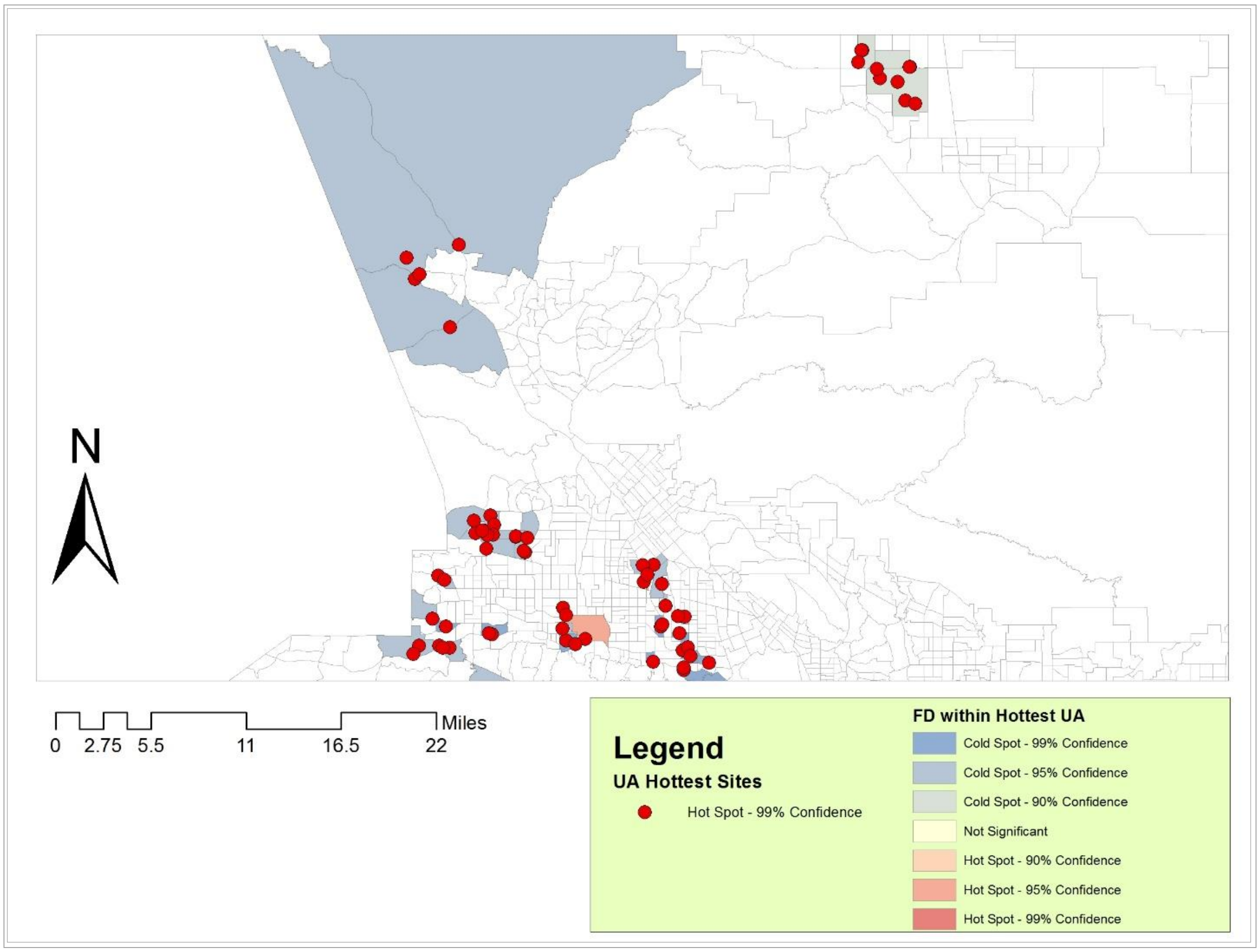

Figure 21 Northern County Hottest UA Sites in Relationship to Food Desert Hot Spots

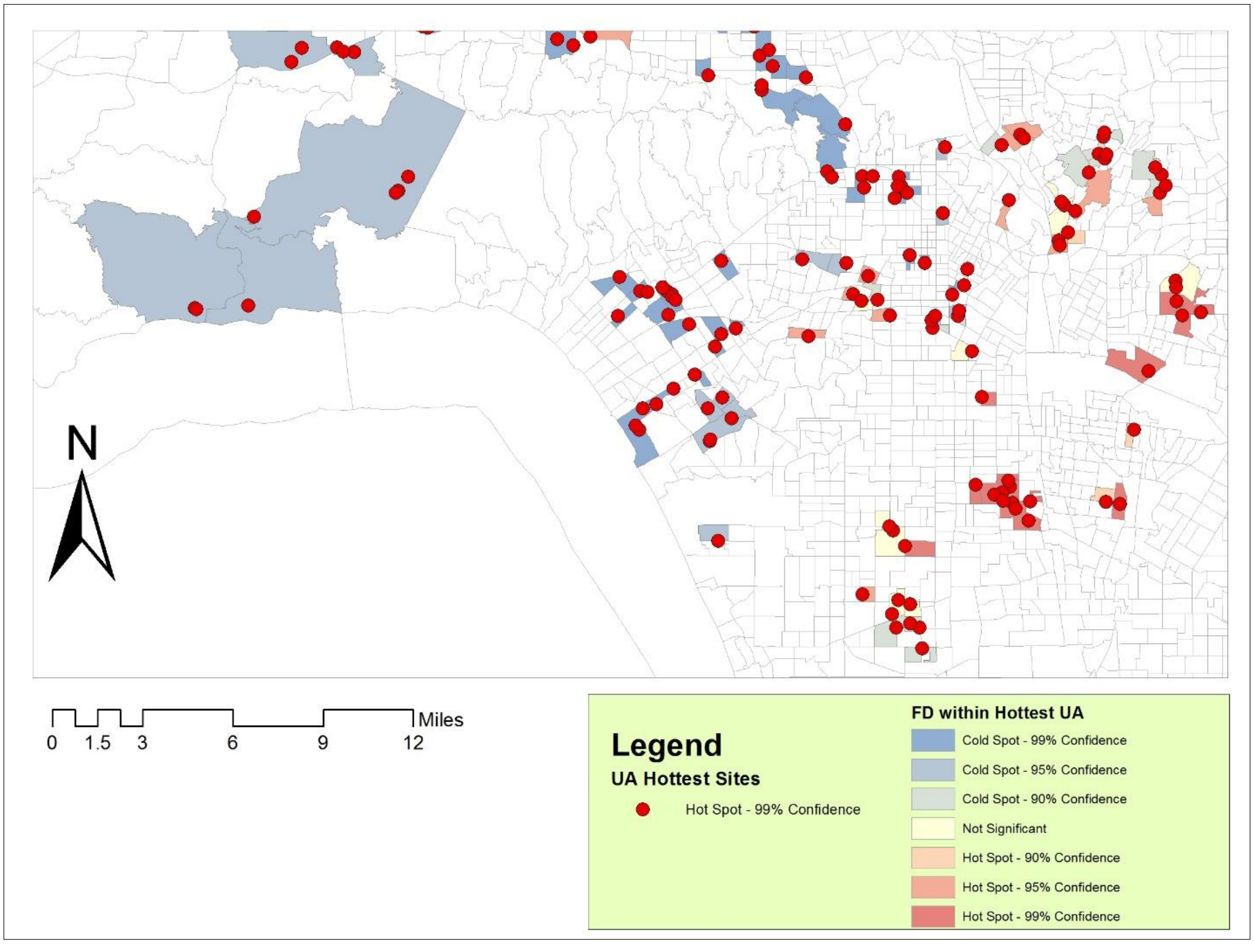

Figure 22 Southern County Hottest UA Sites in Relationship to Food Desert Hot Spots

However, the last figure in this chapter, Figure 31, reveals that further examination of this data is required in order to fully understand the nature of the relationship between these phenomena. When combining the hot spot analysis of UA sites with the Low Income Low Access .5-10 miles food desert layer, there are UA sites that geographically fall within the neighborhoods that are classified as food deserts. These sites are not the "hottest" UA sites, but have a 95% confidence rating. This results show that there are some healthy food resources in high need areas. However, as indicated previously in section 4.3 of this chapter, the types of UA sites can determine if the surrounding neighbors have access to those resources or if they are limited to a selected group.

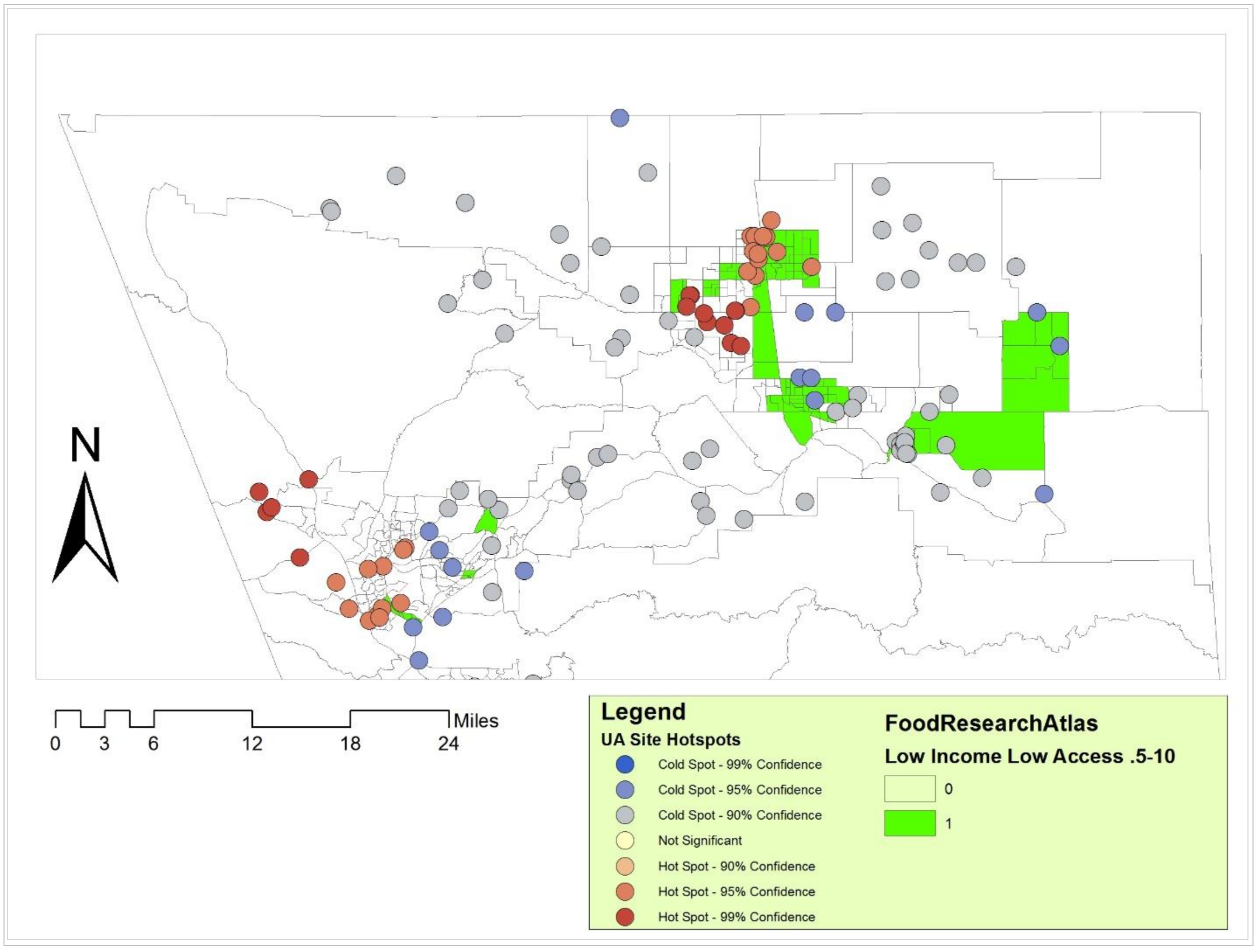

Figure 23 Northern County UA Hot Spots in Relationship to Food Desert Locations

Chapter 5: Discussion and Conclusion

The concluding chapter of this study provides a concise summary of the findings regarding the hot spot analysis of UA sites and food deserts within Los Angeles County, in what direction these patterns are distributed, and the results of the exploratory regression modeling. In addition, the significance of these findings are discussed in reference to this study and to the topic of food justice at large. The study concludes by reviewing the limitations of this research and suggest future research to enhance the comprehension of phenomena and patterns related to this field.

5.1 Summary of Findings

The hot spots analysis conducted on the UA sites shows high concentration of UA sites in the north east region or Antelope Valley region and in the south and south western regions of the county. These areas hold the highest population density in the county, so frequency of these sites will be more common than in less populated regions. Although the hot spot analysis for food deserts is based on the same conditions of population density, the highest concentration of food deserts resulted in the south, south central, central LA and San Gabriel Valley areas with some weight given to the Antelope Valley region. Further analysis of these findings indicated that a higher number of UA sites are located in neighborhoods with low percentages living under poverty. However, 85% of neighborhoods with high percentages of the demographic living below poverty are designed as food deserts.

The directional distribution of the UA sites hot spot analysis show the three directional ellipses with a south and east bias for the Antelope Valley region, a south and west bias for the San Fernando and West LA region, and a deeper south and east bias for the remaining regions of the county. The directional distribution for the food desert hot spot analysis, shows a south and west bias for the Antelope Valley and San Fernando/West LA regions while the remaining regions of the county show a similar bias like the UA features of south and east. Further analysis of these features demonstrated, after comparing the overlap of the hottest UA sites with the food desert features that UA sites are more likely to emerge in areas not designated as food deserts.

The Antelope valley region was selected as a study area to further explore the potential of UA sites to serve as healthy food sources for neighborhoods designated as food desert. Using the distances established by the USDA’s Food Access Research Atlas; .5, 1, 5, and 10 miles, a buffer was applied to the UA site features in that region. The majority of these sites are at a distance of 5 miles or more from neighborhoods designated as food deserts, while a third of the sites are within 1 mile or less.

The results of the exploratory regression analysis did not designate a viable model due to high instances of multicollinearity between the independent variables. The highest multicollinearity occurred with data on poverty, income, employment status and age/sex. The highest resulting Adj R2 of this exploration yielded 0.73. The model with the highest Adj R2 and lowest AICc was selected for further exploration through OLS regression modeling. The results confirmed that the all the explanatory variables are statistically significant but the model’s residuals proved not to be normally distributed, indicating a biased model. Overall the OLS regression modeling enables further understanding of the influence of a variety of variables to the emergence of food deserts.

5.2 Significance of Findings

Los Angeles County has a wide range of demographics living within the region. Within the county the broad spectrum varies from extremely affluent neighborhoods to areas housing populations living below poverty, without access to resources like healthy affordable foods. Food environments and food cultures emerge, as dominant groups take root in an area. Understanding the full scope of a neighborhood’s food environment includes defining what kind of food sources surround these regions, how close are these food sources, and how much time it takes to travel to and from as well as which mode of transportation is used like public transit or an owned vehicle. These details can enable a thorough analysis of the conditions that affect the way communities feed themselves. Urban agriculture is propelled as a way to supplement the access to healthy food options in dense urban settings by creating pockets of resources grown locally by the groups that are at the highest risk.

The findings in this study confirm that the UA sites are more prominent in areas that are not considered food deserts, are above poverty level, and already have access through different means to healthy affordable food sources. These results provide spatial statistical evidence of how these phenomena overlap with each other, providing a platform for further exploration. Additionally, the results from this exploratory analysis confirm the existence of a disparity in the successful integration of UA in communities facing food insecurities due to socioeconomic exclusion. In order for UA to serve as a remedy against disparities in food access, then it is critical to understanding why these sites are prominent in areas that already have access to healthy food sources and not in neighborhoods classified as food deserts. Existing literature on each of these topics; UA and food deserts, continue to explore the individual impact of these food environment phenomena. However, the exploration conducted in this thesis examines the relationship shared by each element and how income influences their development. This study hopes to encourage city planners and other policy makers at different government levels to further assess the relationship of how healthy food practices are being applied and understand why certain practices are not taking shape in areas that need it the most.

5.3 Study Limitations and Future Research

5.3.1 Limitations

It is worth noting that this analysis contained instances of areas with low income and low access food desert neighborhoods with UA sites within their block group in LA County. In order to fully understand the nature of access within UA sites in the county, further information is required. Different types of UA sites may allow or restrict access to participate, collect and benefit from the food sources they grow. For example, a school garden may restrict access of their harvest to students and their families. A community garden may require its participants to rent a lot within their boundaries, creating an economic barrier for individuals who already experience financial hardships. Weights should be given to different types of UA sites to clearly outline if they are indeed “accessible” to neighboring communities and to which degree. This study did not have access to those details based on the information provided by CultivateLA or the USDA’s Farmers Market locator.

As mentioned previous in this chapter, the exploratory regression analysis did not produce a reliable model for the dependent variable of low access, low income food desert neighborhoods within .5-10 miles distance, due to the diversity and quality of the data provided for this analysis. Expanding the data collected in this analysis can provide additional factors to help determine independent variables that can serve as indicators to this occurrence. Lastly, one challenge faced in this study includes the scale of the data utilized in the variety of analyses. Although the majority of the demographic data was made available in the smallest scale possible; block groups, the majority of the datasets for food deserts were in the census tract scale. This hindered the process of analysis by limiting the details in scale for specific neighborhoods affected. The information provided by these datasets had to be outsourced through different sources causing inconsistencies and potential for errors.

5.3.2 Future Research

This study provided a quantitative analysis to illustrate the patterns of UA sites based on income and the influence that food deserts have on the emergence of these sites. However, future analysis to understand the reasoning why these sites are more dominant in certain demographics over others requires qualitative research. For example, surveying and interviewing of sites where UA programs failed can reveal missing components and provide avenues to previous mistakes. Another beneficial area to expand on is a qualitative exploration of food sources in the region in particular. Some neighborhoods where large grocery stores chains are not readily accessible actually have small independent convenience or corner stores that may provide a limited amount of culturally relevant food sources. This factor may provide further information on food cultures for high risk demographics. Likewise, it may play a crucial preliminary role before establishing an UA site to determine which type is the best fit for the neighborhood it will serve.

In addition to assessing and providing weight to alternative food sources, specific areas of Los Angeles County have high numbers of mobile healthy food choices such as certain food trucks and fruit vendors. These small scale, isolated, and sometimes moving sources are not calculated into this analysis but do provide potential healthy food choices. An exploration of the demographic scale these features supply as well as the quantity of individuals that benefit from them is worth exploring, with the expectation of some hybrid implementation of these practices to remedy the growing dilemma of scarcity of access to healthy food sources.

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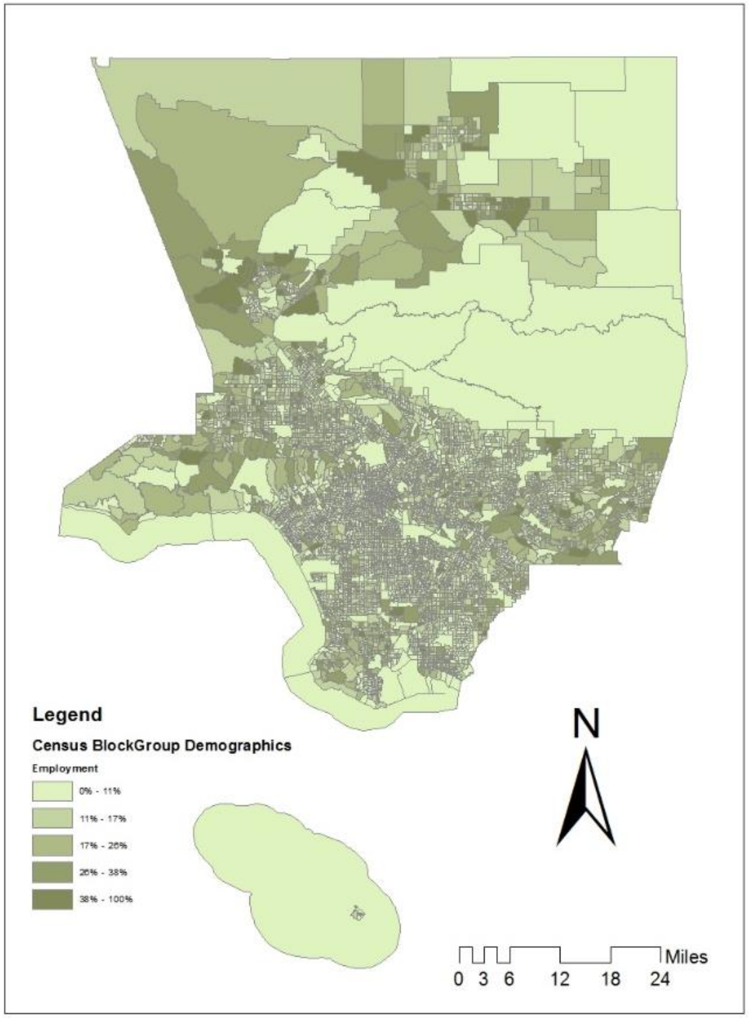
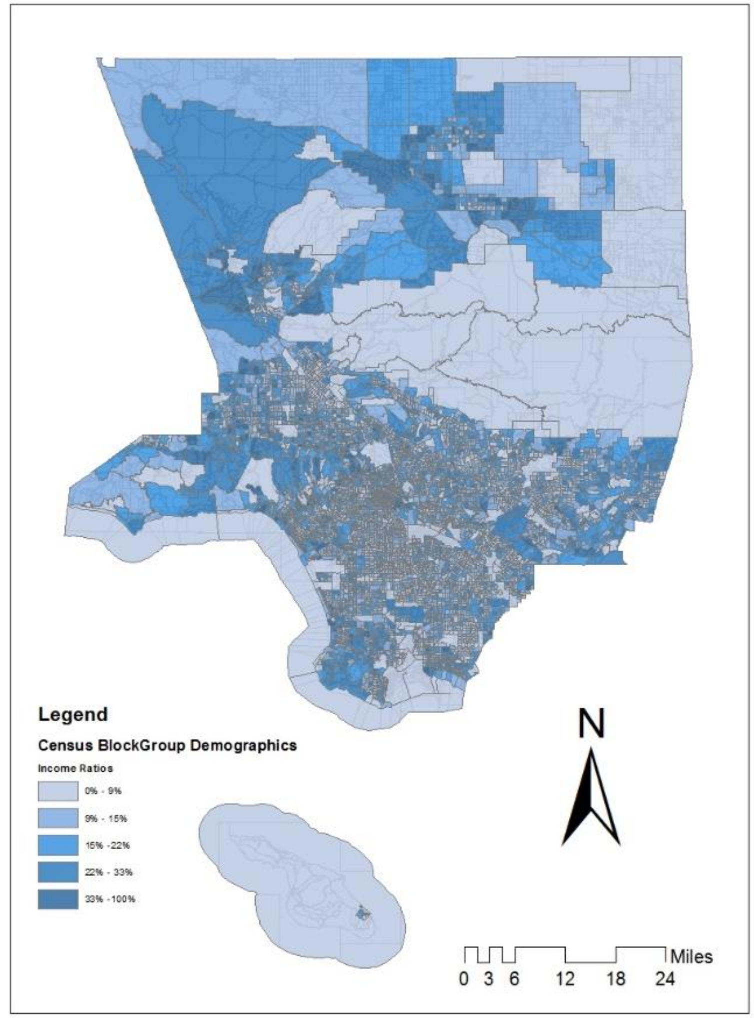
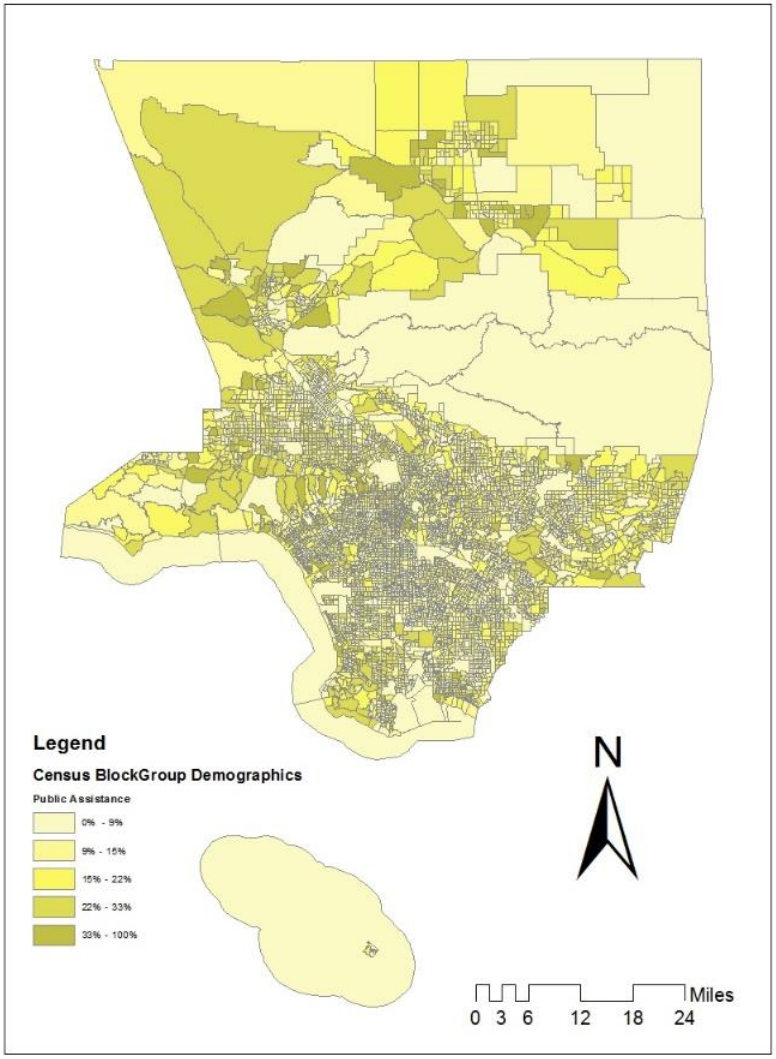
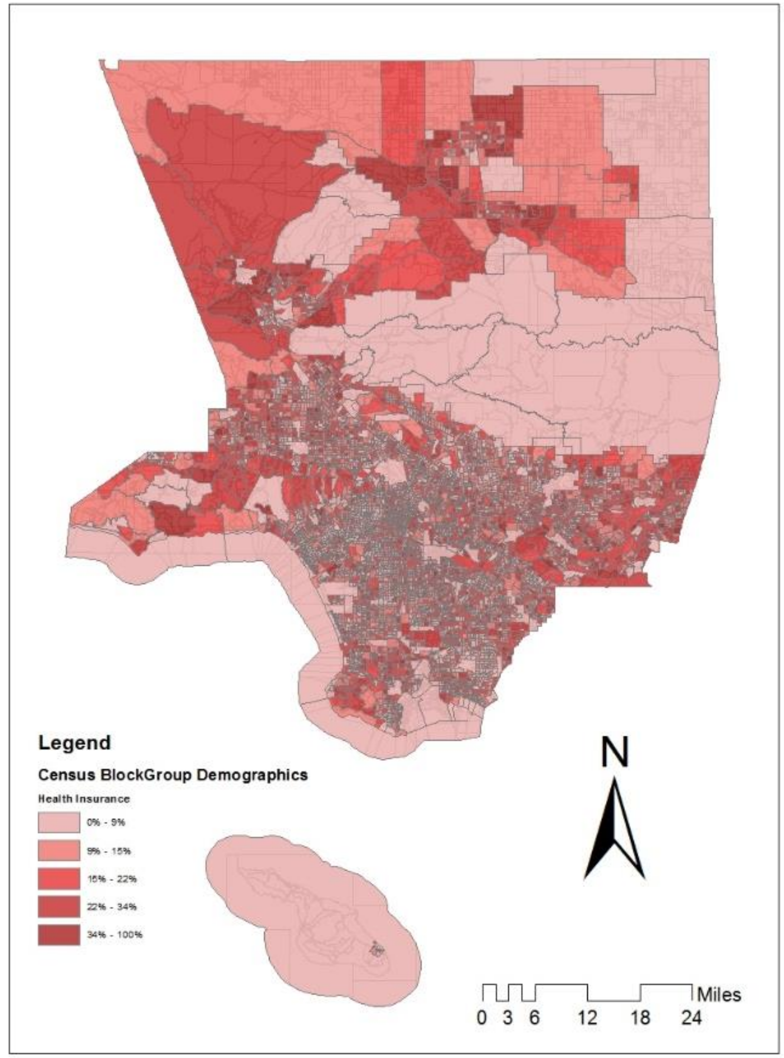
Appendix A: Maps of Demographic Data Utilized in Analysis



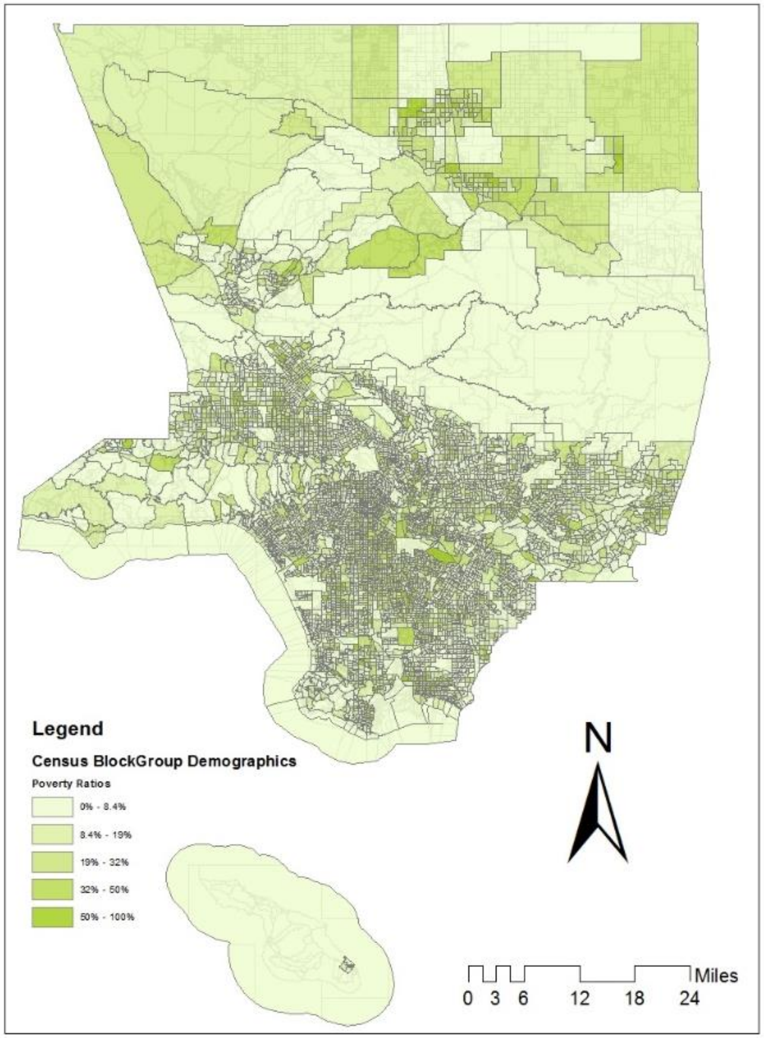


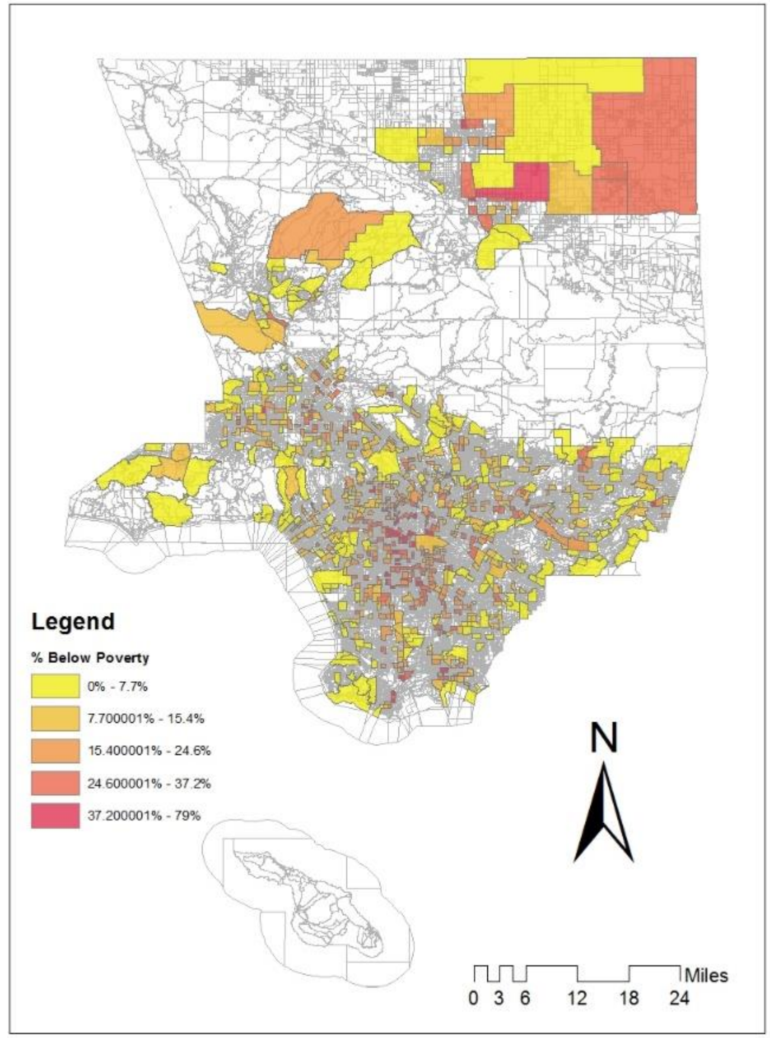
Figures 24 & 25 Census Block Group Demographic Data for Employment & Income Ratios





Figures 26 & 27 Census Block Group Demographic Data for Public Assistance & Health Insurance





Figures 28 & 29 Census Block Group Demographic Data for Poverty Ratios & Percentage Below Poverty

Appendix B: Exploratory Regression Models – Raw Results

****
Choose 1 of 22 Summary
Highest Adjusted R-Squared Results
AdjR2 AICc JB K(BP) VIF SA Model
0.38 4196.06 0.00 0.00 1.00 0.00 +LA1_20MILES.LOWINCOMETRACTS***
0.20 5840.77 0.00 0.00 1.00 0.00 +LA1_20MILES.LAHUNVHALF***
0.16 6195.65 0.00 0.00 1.00 0.00 +LA1_20MILES.LATRACTS_HALF***
Passing Models
AdjR2 AICc JB K(BP) VIF SA Model
****
Choose 2 of 22 Summary
Highest Adjusted R-Squared Results
AdjR2 AICc JB K(BP) VIF SA Model
0.72 -802.78 0.00 0.00 1.07 0.00 +LA1_20MILES.LATRACTS_HALF***
+LA1_20MILES.LOWINCOMETRACTS***
0.52 2527.47 0.00 0.00 1.02 0.00 +LA1_20MILES.LOWINCOMETRACTS***
+LA1_20MILES.LAHUNVHALF***
0.39 4097.32 0.00 0.00 1.28 0.00 +LA1_20MILES.LOWINCOMETRACTS*** -
X27_HEALTH_INSURANCE.B27010E50***
Passing Models
AdjR2 AICc JB K(BP) VIF SA Model
****
Choose 3 of 22 Summary
Highest Adjusted R-Squared Results
AdjR2 AICc JB K(BP) VIF SA Model
0.73 -1077.07 0.00 0.00 1.41 0.00 +LA1_20MILES.LATRACTS_HALF***
+LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF***
0.72 -843.66 0.00 0.00 1.33 0.00 +LA1_20MILES.LATRACTS_HALF***
+LA1_20MILES.LOWINCOMETRACTS*** -
X27_HEALTH_INSURANCE.B27010E50***
0.72 -827.86 0.00 0.00 1.08 0.00 +LA1_20MILES.LATRACTS_HALF***
+LA1_20MILES.LOWINCOMETRACTS*** -
X23_EMPLOYMENT_STATUS.B23025E7***
Passing Models
AdjR2 AICc JB K(BP) VIF SA Model
****
Choose 4 of 22 Summary
Highest Adjusted R-Squared Results
AdjR2 AICc JB K(BP) VIF SA Model
0.73 -1114.69 0.00 0.00 1.43 0.00 +LA1_20MILES.LATRACTS_HALF***
+LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** -
X27_HEALTH_INSURANCE.B27010E50***

0.73 -1112.14 0.00 0.00 1.45 0.00 +LA1_20MILES.LATRACTS_HALF*** +LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E4***
0.73 -1106.81 0.00 0.00 1.42 0.00 +LA1_20MILES.LATRACTS_HALF*** +LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E5***
Passing Models
AdjR2 AICc JB K(BP) VIF SA Model
****
Choose 5 of 22 Summary
Highest Adjusted R-Squared Results
AdjR2 AICc JB K(BP) VIF SA Model
0.73 -1128.46 0.00 0.00 1.52 0.00 +LA1_20MILES.LATRACTS_HALF*** +LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E4*** -X27_HEALTH_INSURANCE.B27010E50***
0.73 -1124.94 0.00 0.00 1.45 0.00 +LA1_20MILES.LATRACTS_HALF*** +LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E4*** -X19_INCOME.B19001E5***
0.73 -1124.93 0.00 0.00 1.45 0.00 +LA1_20MILES.LATRACTS_HALF*** +LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E2*** -X27_HEALTH_INSURANCE.B27010E50***
Passing Models
AdjR2 AICc JB K(BP) VIF SA Model
****
Choose 6 of 22 Summary
Highest Adjusted R-Squared Results
AdjR2 AICc JB K(BP) VIF SA Model
0.73 -1133.64 0.00 0.00 1.68 0.00 +LA1_20MILES.LATRACTS_HALF*** +LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E4*** -X19_INCOME.B19001E5*** -X27_HEALTH_INSURANCE.B27010E50***
0.73 -1132.91 0.00 0.00 1.55 0.00 +LA1_20MILES.LATRACTS_HALF*** +LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E2** -X19_INCOME.B19001E4*** -X27_HEALTH_INSURANCE.B27010E50***
0.73 -1131.48 0.00 0.00 1.56 0.00 +LA1_20MILES.LATRACTS_HALF*** +LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E3** -X19_INCOME.B19001E4*** -X27_HEALTH_INSURANCE.B27010E50***
Passing Models
AdjR2 AICc JB K(BP) VIF SA Model
****
Choose 7 of 22 Summary
Highest Adjusted R-Squared Results
AdjR2 AICc JB K(BP) VIF SA Model

0.73 -1139.93 0.00 0.00 4.10 0.00 +LA1_20MILES.LATRACTS_HALF*** +LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E4*** -X27_HEALTH_INSURANCE.B27010E50*** +X01_AGE_AND_SEX.B01001E1*** -X23_EMPLOYMENT_STATUS.B23025E7***
0.73 -1139.29 0.00 0.00 2.91 0.00 +LA1_20MILES.LATRACTS_HALF*** +LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E4*** -X27_HEALTH_INSURANCE.B27010E50*** +X01_AGE_AND_SEX.B01001E26*** -X23_EMPLOYMENT_STATUS.B23025E7***
0.73 -1138.60 0.00 0.00 1.91 0.00 +LA1_20MILES.LATRACTS_HALF*** +LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E2*** -X19_INCOME.B19001E4*** -X27_HEALTH_INSURANCE.B27010E50*** +X23_EMPLOYMENT_STATUS.B23025E5***

Passing Models

AdjR2 AICc JB K(BP) VIF SA Model

****

Choose 8 of 22 Summary

Highest Adjusted R-Squared Results

AdjR2 AICc JB K(BP) VIF SA Model

0.73 -1147.07 0.00 0.00 4.22 0.00 +LA1_20MILES.LATRACTS_HALF*** +LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E4*** -X19_INCOME.B19001E5*** -X27_HEALTH_INSURANCE.B27010E50*** +X01_AGE_AND_SEX.B01001E1*** -X23_EMPLOYMENT_STATUS.B23025E7***
0.73 -1146.28 0.00 0.00 2.99 0.00 +LA1_20MILES.LATRACTS_HALF*** +LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E4*** -X19_INCOME.B19001E5*** -X27_HEALTH_INSURANCE.B27010E50*** +X01_AGE_AND_SEX.B01001E26*** -X23_EMPLOYMENT_STATUS.B23025E7***
0.73 -1144.17 0.00 0.00 4.15 0.00 +LA1_20MILES.LATRACTS_HALF*** +LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E2** -X19_INCOME.B19001E4*** -X27_HEALTH_INSURANCE.B27010E50*** +X01_AGE_AND_SEX.B01001E1*** -X23_EMPLOYMENT_STATUS.B23025E7***

Passing Models

AdjR2 AICc JB K(BP) VIF SA Model

****

Choose 9 of 22 Summary

Highest Adjusted R-Squared Results

AdjR2 AICc JB K(BP) VIF SA Model

0.73 -1150.51 0.00 0.00 4.29 0.00 +LA1_20MILES.LATRACTS_HALF*** +LA1_20MILES.LOWINCOMETRACTS*** -LA1_20MILES.POP2010** +LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E4*** -

X19_INCOME.B19001E5*** -X27_HEALTH_INSURANCE.B27010E50*** +X01_AGE_AND_SEX.B01001E1*** -X23_EMPLOYMENT_STATUS.B23025E7***
0.73 -1149.60 0.00 0.00 3.04 0.00 +LA1_20MILES.LATRACTS_HALF*** +LA1_20MILES.LOWINCOMETRACTS*** -LA1_20MILES.POP2010** +LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E4*** -X19_INCOME.B19001E5*** -X27_HEALTH_INSURANCE.B27010E50*** +X01_AGE_AND_SEX.B01001E26*** -X23_EMPLOYMENT_STATUS.B23025E7***
0.73 -1149.52 0.00 0.00 4.24 0.00 +LA1_20MILES.LATRACTS_HALF*** +LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E2** -X19_INCOME.B19001E4*** -X19_INCOME.B19001E5*** -X27_HEALTH_INSURANCE.B27010E50*** +X01_AGE_AND_SEX.B01001E1*** -X23_EMPLOYMENT_STATUS.B23025E7***

Passing Models

AdjR2 AICc JB K(BP) VIF SA Model

****

** Exploratory Regression Global Summary (LA1_20MILES.LILATRACTS_HALFAND10) **

Percentage of Search Criteria Passed

Search Criterion	Cutoff	Trials	# Passed	% Passed
Min Adjusted R-Squared	> 0.50	1010894	220731	21.84
Max Coefficient p-value	< 0.05	1010894	169872	16.80
Max VIF Value	< 7.50	1010894	371174	36.72
Min Jarque-Bera p-value	> 0.10	1010894	0	0.00
Min Spatial Autocorrelation p-value	> 0.10	30	0	0.00

Summary of Variable Significance

Variable	% Significant	% Negative	% Positive
LA1_20MILES.LATRACTS_HALF	100.00	0.00	100.00
LA1_20MILES.LOWINCOMETRACTS	100.00	0.00	100.00
LA1_20MILES.LAHUNVHALF	100.00	0.00	100.00
X27_HEALTH_INSURANCE.B27010E50	99.27	34.93	65.07
X27_HEALTH_INSURANCE.B27010E33	94.59	34.19	65.81
X19_INCOME.B19001E1	83.08	86.44	13.56
LA1_20MILES.POP2010	82.48	46.59	53.41
X22_FOOD_STAMPS.B22010E2	82.25	10.05	89.95
X19_INCOME.B19001E5	80.22	40.78	59.22
X23_EMPLOYMENT_STATUS.B23025E4	79.90	89.74	10.26
X17_POVERTY.C17002E1	79.01	27.48	72.52
X19_INCOME.B19001E3	77.77	40.42	59.58
X23_EMPLOYMENT_STATUS.B23025E2	76.96	65.10	34.90
X19_INCOME.B19001E4	73.70	51.39	48.61

X19_INCOME.B19001E2	72.90	49.34	50.66
X27_HEALTH_INSURANCE.B27010E17	71.61	12.79	87.21
X01_AGE_AND_SEX.B01001E1	71.07	35.69	64.31
X23_EMPLOYMENT_STATUS.B23025E7	68.57	65.02	34.98
X23_EMPLOYMENT_STATUS.B23025E5	67.49	10.94	89.06
X01_AGE_AND_SEX.B01001E26	65.29	21.37	78.63
X01_AGE_AND_SEX.B01001E2	59.81	57.51	42.49
X27_HEALTH_INSURANCE.B27010E66	26.49	60.39	39.61

Summary of Multicollinearity*

Variable	VIF	Violations	Covariates
LA1_20MILES.LATRACTS_HALF	1.55	0	--------
LA1_20MILES.LOWINCOMETRACTS	1.86	0	--------
LA1_20MILES.POP2010	1.11	0	--------
LA1_20MILES.LAHUNVHALF	1.44	0	--------
X17_POVERTY.C17002E1	32.73	313540	X01_AGE_AND_SEX.B01001E26 (88.61), X01_AGE_AND_SEX.B01001E1 (88.61), X23_EMPLOYMENT_STATUS.B23025E2 (75.83), X23_EMPLOYMENT_STATUS.B23025E4 (56.50), X01_AGE_AND_SEX.B01001E2 (39.67), X23_EMPLOYMENT_STATUS.B23025E7 (17.69), X19_INCOME.B19001E1 (8.94)
X19_INCOME.B19001E1	10.99	36006	X23_EMPLOYMENT_STATUS.B23025E4 (15.10), X23_EMPLOYMENT_STATUS.B23025E2 (13.06), X17_POVERTY.C17002E1 (8.94), X01_AGE_AND_SEX.B01001E1 (5.31), X01_AGE_AND_SEX.B01001E26 (3.62), X01_AGE_AND_SEX.B01001E2 (2.27), X23_EMPLOYMENT_STATUS.B23025E7 (1.30)
X19_INCOME.B19001E2	1.94	0	--------
X19_INCOME.B19001E3	1.96	0	--------
X19_INCOME.B19001E4	1.81	0	--------
X19_INCOME.B19001E5	1.67	0	--------
X27_HEALTH_INSURANCE.B27010E17	1.76	0	--------
X27_HEALTH_INSURANCE.B27010E33	3.35	0	--------
X27_HEALTH_INSURANCE.B27010E50	3.21	0	--------
X27_HEALTH_INSURANCE.B27010E66	1.08	0	--------
X01_AGE_AND_SEX.B01001E1	121.78	282385	X17_POVERTY.C17002E1 (88.61), X01_AGE_AND_SEX.B01001E26 (66.43), X01_AGE_AND_SEX.B01001E2 (66.43), X23_EMPLOYMENT_STATUS.B23025E2 (59.39), X23_EMPLOYMENT_STATUS.B23025E4 (51.54), X23_EMPLOYMENT_STATUS.B23025E7 (14.56), X19_INCOME.B19001E1 (5.31)
X01_AGE_AND_SEX.B01001E2	30.02	159997	X01_AGE_AND_SEX.B01001E1 (66.43), X17_POVERTY.C17002E1 (39.67), X23_EMPLOYMENT_STATUS.B23025E2 (32.38), X23_EMPLOYMENT_STATUS.B23025E4 (28.87), X01_AGE_AND_SEX.B01001E26 (14.92), X23_EMPLOYMENT_STATUS.B23025E7 (6.33), X19_INCOME.B19001E1 (2.27)

X01_AGE_AND_SEX.B01001E26 32.13 217910 X17_POVERTY.C17002E1 (88.61), X01_AGE_AND_SEX.B01001E1 (66.43), X23_EMPLOYMENT_STATUS.B23025E2 (44.18), X23_EMPLOYMENT_STATUS.B23025E4 (37.64), X01_AGE_AND_SEX.B01001E2 (14.92), X23_EMPLOYMENT_STATUS.B23025E7 (6.33), X19_INCOME.B19001E1 (3.62)
X23_EMPLOYMENT_STATUS.B23025E2 87.55 241171 X17_POVERTY.C17002E1 (75.83), X23_EMPLOYMENT_STATUS.B23025E4 (66.43), X01_AGE_AND_SEX.B01001E1 (59.39), X01_AGE_AND_SEX.B01001E26 (44.18), X01_AGE_AND_SEX.B01001E2 (32.38), X19_INCOME.B19001E1 (13.06), X23_EMPLOYMENT_STATUS.B23025E7 (9.92)
X23_EMPLOYMENT_STATUS.B23025E4 67.18 207017 X23_EMPLOYMENT_STATUS.B23025E2 (66.43), X17_POVERTY.C17002E1 (56.50), X01_AGE_AND_SEX.B01001E1 (51.54), X01_AGE_AND_SEX.B01001E26 (37.64), X01_AGE_AND_SEX.B01001E2 (28.87), X19_INCOME.B19001E1 (15.10), X23_EMPLOYMENT_STATUS.B23025E7 (9.90)
X23_EMPLOYMENT_STATUS.B23025E5 2.37 0 --------
X23_EMPLOYMENT_STATUS.B23025E7 12.58 24457 X17_POVERTY.C17002E1 (17.69), X01_AGE_AND_SEX.B01001E1 (14.56), X23_EMPLOYMENT_STATUS.B23025E2 (9.92), X23_EMPLOYMENT_STATUS.B23025E4 (9.90), X01_AGE_AND_SEX.B01001E26 (6.33), X01_AGE_AND_SEX.B01001E2 (6.33), X19_INCOME.B19001E1 (1.30)
X22_FOOD_STAMPS.B22010E2 2.70 0 --------
* At least one model failed to solve due to perfect multicollinearity.
Please review the warning messages for further information.

Summary of Residual Normality (JB)
JB AdjR2 AICc K(BP) VIF SA Model
0.000203 0.549768 2168.540247 0.000000 2.693563 0.000000 +LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** +X17_POVERTY.C17002E1*** -X19_INCOME.B19001E3*** -X19_INCOME.B19001E4*** -X19_INCOME.B19001E5*** +X27_HEALTH_INSURANCE.B27010E17** -X27_HEALTH_INSURANCE.B27010E50*** -X27_HEALTH_INSURANCE.B27010E66
0.000189 0.549274 2175.574646 0.000000 2.471783 0.000000 +LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** +X17_POVERTY.C17002E1*** -X19_INCOME.B19001E3*** -X19_INCOME.B19001E4*** -X19_INCOME.B19001E5*** -X27_HEALTH_INSURANCE.B27010E50*** -X27_HEALTH_INSURANCE.B27010E66 +X23_EMPLOYMENT_STATUS.B23025E5
0.000184 0.549273 2175.592594 0.000000 12.962272 0.000000 +LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** +X17_POVERTY.C17002E1*** -X19_INCOME.B19001E3*** -X19_INCOME.B19001E4*** -X19_INCOME.B19001E5*** -

X27_HEALTH_INSURANCE.B27010E50*** -
X27_HEALTH_INSURANCE.B27010E66 +X01_AGE_AND_SEX.B01001E1

Summary of Residual Spatial Autocorrelation (SA)
SA AdjR2 AICc JB K(BP) VIF Model
0.000000 0.731520 -1150.509021 0.000000 0.000000 4.290658
+LA1_20MILES.LATRACTS_HALF***
+LA1_20MILES.LOWINCOMETRACTS*** -LA1_20MILES.POP2010**
+LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E4*** -
X19_INCOME.B19001E5*** -X27_HEALTH_INSURANCE.B27010E50***
+X01_AGE_AND_SEX.B01001E1*** -
X23_EMPLOYMENT_STATUS.B23025E7***
0.000000 0.731482 -1149.602202 0.000000 0.000000 3.041721
+LA1_20MILES.LATRACTS_HALF***
+LA1_20MILES.LOWINCOMETRACTS*** -LA1_20MILES.POP2010**
+LA1_20MILES.LAHUNVHALF*** -X19_INCOME.B19001E4*** -
X19_INCOME.B19001E5*** -X27_HEALTH_INSURANCE.B27010E50***
+X01_AGE_AND_SEX.B01001E26*** -
X23_EMPLOYMENT_STATUS.B23025E7***
0.000000 0.731478 -1149.518998 0.000000 0.000000 4.244403
+LA1_20MILES.LATRACTS_HALF***
+LA1_20MILES.LOWINCOMETRACTS*** +LA1_20MILES.LAHUNVHALF*** -
X19_INCOME.B19001E2** -X19_INCOME.B19001E4*** -
X19_INCOME.B19001E5*** -X27_HEALTH_INSURANCE.B27010E50***
+X01_AGE_AND_SEX.B01001E1*** -
X23_EMPLOYMENT_STATUS.B23025E7***

Table Abbreviations
AdjR2 Adjusted R-Squared
AICc Akaike's Information Criterion
JB Jarque-Bera p-value
K(BP) Koenker (BP) Statistic p-value
VIF Max Variance Inflation Factor
SA Global Moran's I p-value
Model Variable sign (+/-)
Model Variable significance (* = 0.10, ** = 0.05, *** = 0.01)

Appendix C: Ordinary Least Squares (OLS) Results

Table 8 Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	-0.372731	0.010955	-34.023140	0.000000*	0.013365	-27.887779	0.000000*	--------
LATRACTS_HALF	0.478818	0.007152	66.952908	0.000000*	0.009610	49.825228	0.000000*	1.490116
LOWINCOMETRACTS	0.662076	0.006884	96.172641	0.000000*	0.007981	82.958325	0.000000*	1.542347
POP2010	-0.000005	0.000002	-2.332716	0.019678*	0.000002	-2.349286	0.018824*	1.096390
LAHUNVHALF	0.001052	0.000060	17.508036	0.000000*	0.000059	17.776475	0.000000*	1.389980
INCOME.B19001E4	-0.000376	0.000109	-3.460513	0.000559*	0.000114	-3.296599	0.001001*	1.481767
INCOME.B19001E5	-0.000357	0.000117	-3.053649	0.002283*	0.000117	-3.047284	0.002331*	1.439334
HEALTH_INSURANCE.B27010E50	-0.000130	0.000031	-4.163121	0.000037*	0.000030	-4.326989	0.000019*	2.361647
AGE_AND_SEX.B01001E1	0.000029	0.000007	4.042121	0.000061*	0.000007	4.246849	0.000027*	4.290658
EMPLOYMENT_STATUS.B23025E7	-0.000066 *	0.000016	-4.042439	0.000061	0.000015	-4.477739	0.000010*	2.916849

OLS Diagnostics

Input Features:	FoodResearchAtlas	Dependent Variable:	LA1_20MILES.LILATRACTS_
Number of Observations:	6420	Akaike's Information Criterion (AICc) [d]:	-1150.509021
Multiple R-Squared [d]:	0.731896	Adjusted R-Squared [d]:	0.731520
Joint F-Statistic [e]:	1944.293572	Prob(>F), (9,6410) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	14343.351097	Prob(>chi-squared), (9) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	2523.123131	Prob(>chi-squared), (9) degrees of freedom:	0.000000*
Jarque-Bera Statistic [g]:	618.291075	Prob(>chi-squared), (2) degrees of freedom:	0.000000*

Figure 30 OLS Model Diagnositc Results

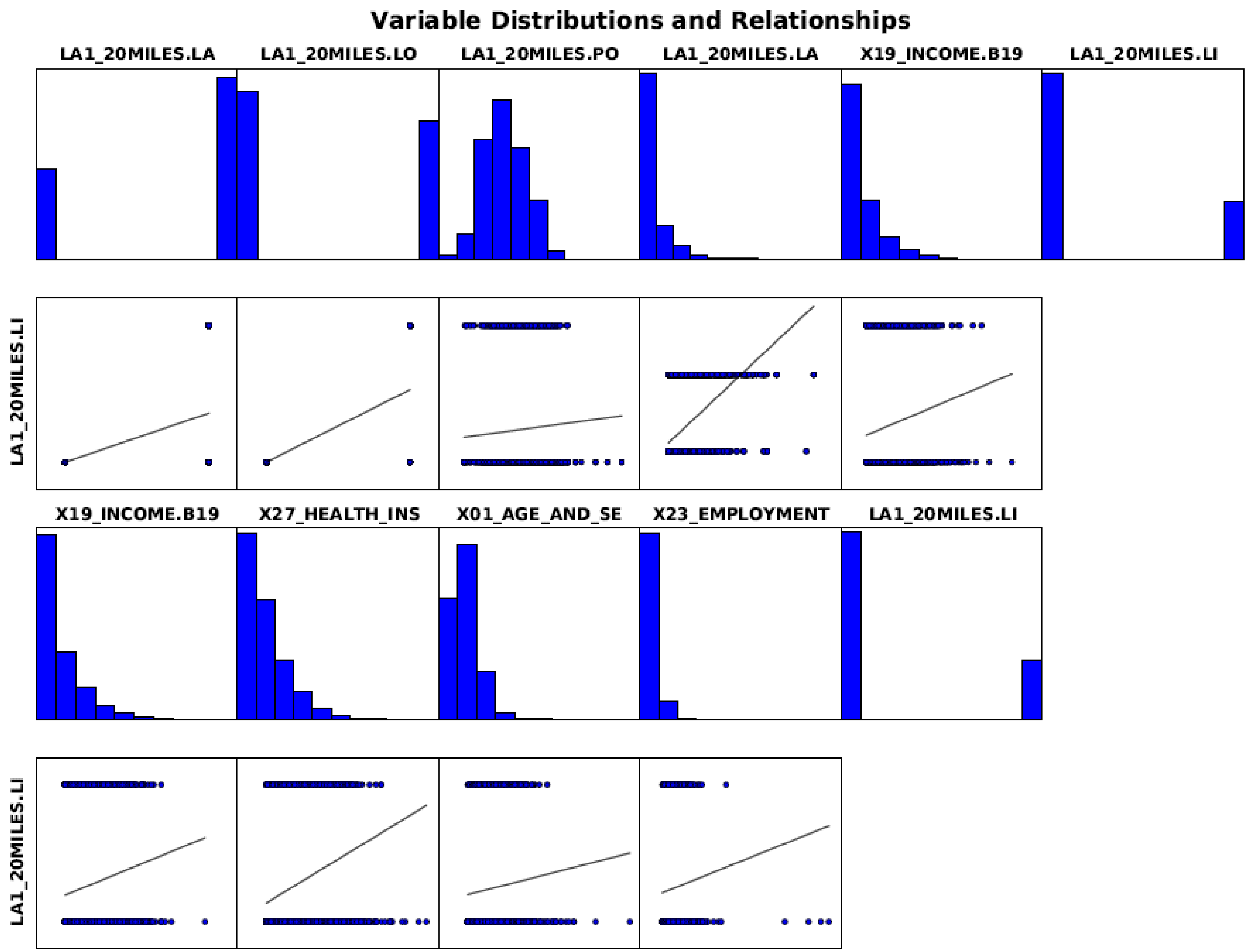


Figure 31 Histograms & Scatterplots for explanatory variable & dependent variable

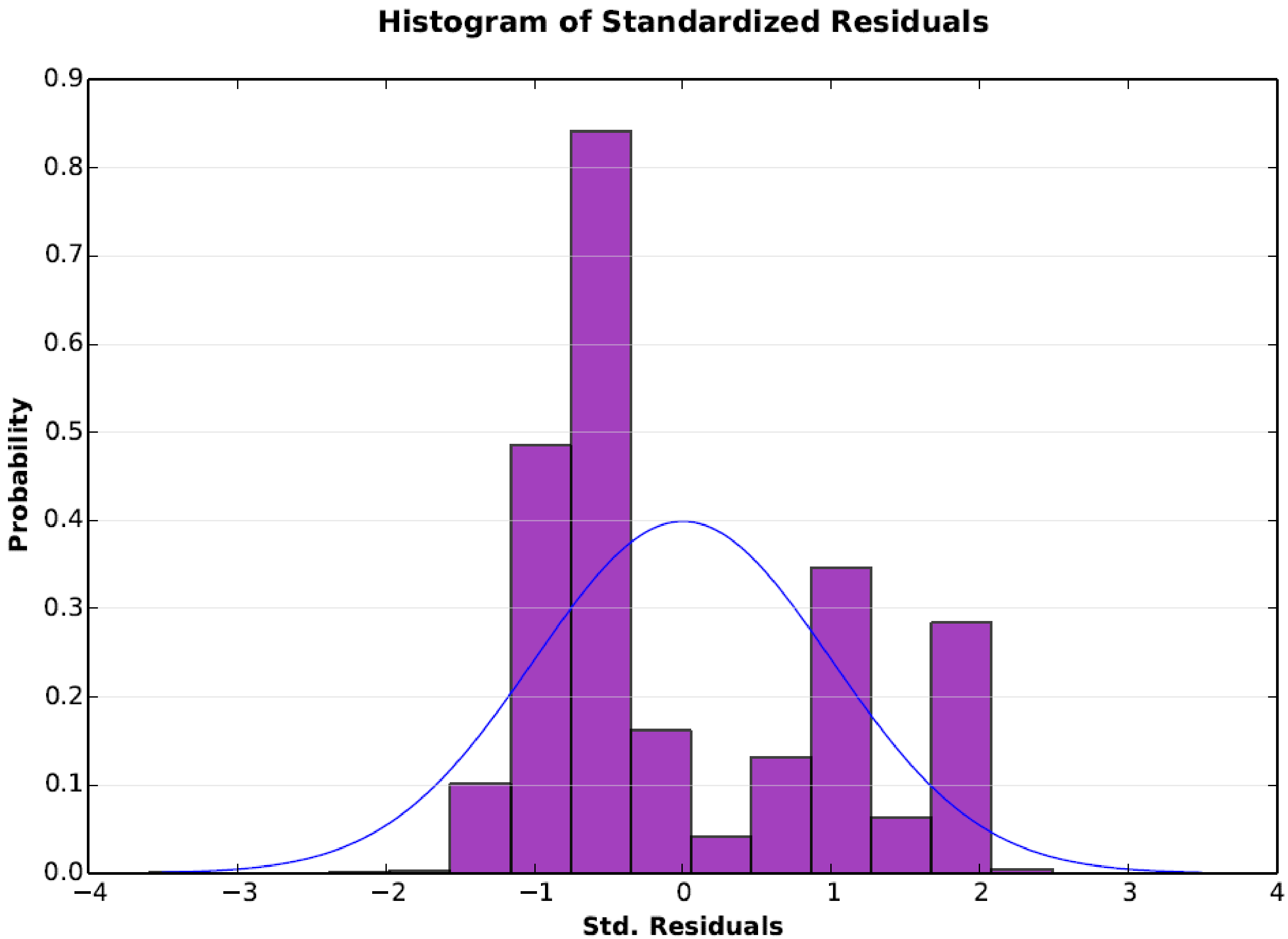


Figure 32 Histograms of Residuals for OLS Model

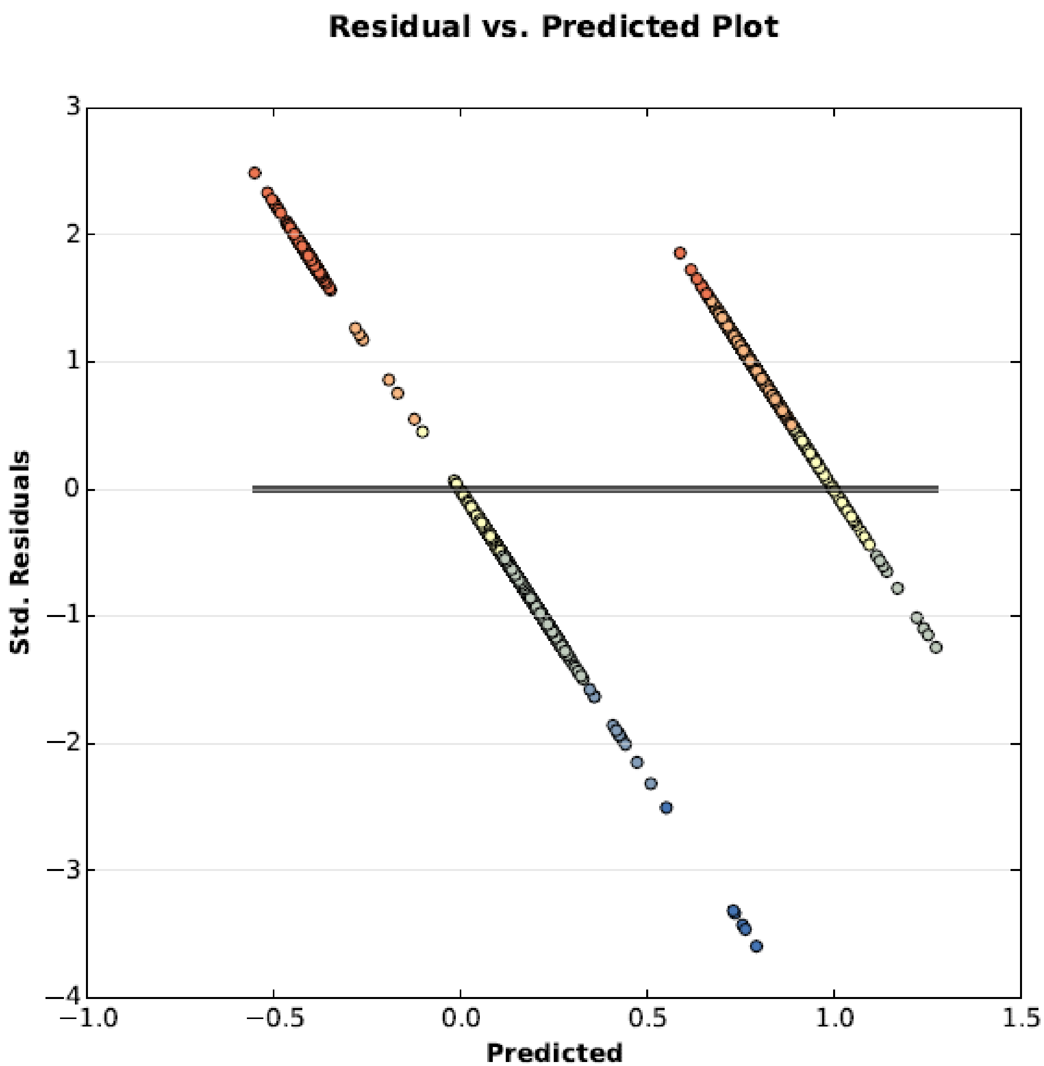


Figure 33 Graph of Residuals in Relation to Predicted Dependent Variable Values for OLS Model