Spatial Patterns of Food Accessibility Across Lane County, Oregon in 2015-2016

by

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A Thesis Presented to the
Faculty of the USC Graduate School
University of Southern California
In Partial Fulfillment of the
Requirements for the Degree
Master of Science
(Geographic Information Science and Technology)

May 2017

To all my relations, thank you.

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Acknowledgements

I would like to express my sincere gratitude to my mentor, Professor Wilson, for direction setting and providing the guidance needed to drive the vision. Also, I am grateful to the other members of my Thesis Guidance Committee, Drs. Warshawsky and Swift, for their commitment to teaching the science of spatial thinking. The faculty of the Spatial Sciences Institute encouraged and supported me while preparing for and completing the project and I would like to thank all of them for their assistance. I am grateful to the Lane County GIS Department for sharing high quality data that supported this research. Esri products and platforms including InfoGroup's Dun and Bradstreet Business Data made the project possible.

List of Abbreviations

ACS	American Community Survey
CBG	Census Block Group
CDC	Centers for Disease Control
CSA	Community Supported Agriculture
DA	Dissemination Area
ERS	Economic Research Service
FFQ	Food Frequency Questionnaire
GIS	Geographic Information Systems
GPS	Global Positioning System
GRS	Geodetic Reference System
MBP	Market Basket Price
MSA	Metropolitan Statistical Area
NAICS	North American Industrial Classification System
RHFA	Relative Healthy Food Access
SES	Socio-Economic Status
SEDAC	Socioeconomic Data and Applications Center
SNAP	Supplemental Nutrition Assistance Program
SQL	Structured Query Language
UK	United Kingdom
US	United States of America
USDA	United States Department of Agriculture
WHO	World Health Organization

Abstract

This analysis of the local food environment in Lane County, OR aimed to investigate inequalities associated with access to healthy food. The findings suggest that the problem is complex and is not simply a lack of healthy food stores. Retail food environments evolve quickly and research approaches to evaluate the phenomena are nimble with advanced technology and high quality data. Spatial access to healthy food is a key factor for dietary decisions. Previous research linked diet related diseases in disadvantaged communities to disparities in food access. Disadvantaged residents were associated with low access to healthy food outlets and high access to unhealthy food stores. Neighborhood food access was tracked through statistical analysis of economic and demographic characteristics that were collected in the federal census. This analysis quantified the food environment in Lane County, Oregon. The primary assessment measured residential proximity to five different food store types over the road network in Esri's Network Analyst. The distances were aggregated into Census Block Groups to determine whether access to healthy food decreased in disadvantaged neighborhoods. This research aimed to fill the gap in the literature for distance-based food access analyses using residential address points at a local scale. This work employed systematic methods that addressed food retail dispersion across heterogeneous space to determine food outlet presences and absences at various distance bands across the study area. This research contributes to methodological developments that would eliminate the standard practice of compartmentalizing urban and rural food environment research into silos that are evaluated separately. The primary finding of the study was that neighborhoods in Lane County characterized as high deprivation with higher minority compositions had better access to healthy food store types. Future research should consider the affordability of healthy foods and include farmers' markets, roadside stands, and community supported agriculture.

Chapter 1 Introduction

Local food environments describe local food purchasing and the types of food available in the area. These places collectively determine people's access to the foods they eat. Food access is simply the distance between people and healthy affordable foods (Morland 2015). This study examined existing conditions of food deserts and identified potential access to healthy food in Lane County, Oregon. Measuring food environments evolved from early food desert studies conducted in the UK where researchers mapped disparities in food access and affordability in the late 1990s and early 2000s (Donkin et al. 1999, Cummins and McIntyre 2002). Research conducted by Cheadle et al. (1991) and Morland et al. (2002) supported the theory that people living in the US are used to making food choices based on local supermarket options and that geographical disparity for healthy food intake can be found in neighborhoods that were characterized by lower incomes and higher composition of minorities.

1.1 Food Access Matters

Food accessibility influences diet and health (Morganstern 2015). It impacts food security at the basic level of geographic distance travelled to obtain food. Food security is one of the principal public health challenges currently facing the nation (Gundersen 2013). Food insecurity affected 16.1% of Oregonians from 2012-2014 despite decreased unemployment over the same period (Oregon Center for Public Policy 2015). Food security has been defined by the World Health Organization (WHO 2015) as the state of all people having access to "sufficient, safe, and nutritious" food to support healthy active lifestyles. The state of food security, in Oregon, by the numbers has remained steady since Smith (2003) examined the state food environment through the lens of comparative hunger incidence statistics affecting the nation at a rate of 3% and Oregon disproportionally at 5.8%. Smith (2003) considered location and economic inequality as possible drivers of greater incidences in Oregon than the nation. Food access was operationalized by the US Department of Agriculture (USDA) as a function of food security (Rabinowitz 2014).

A growing body of empirical evidence strongly suggests neighborhood food environments at the local level are complex associations between many factors that are multidimensional, including the quality and quantity of food stores which, in turn, influence food consumption and related health outcomes (Glanz 2009, Luan et al. 2015, Moore and Diez Roux 2005). The health outcome most often cited in food access studies is obesity because it is a risk factor related to other chronic diseases, such as diabetes and high blood pressure (Abdullah et al. 2010). Researchers are interested in obesity because it disproportionally affects people in the US living in rural areas, low-income neighborhoods, and areas that are more ethnically diverse (Zenk et al. 2015).

1.1.1. Geographical Measurements and Food Environments

Apparicio et al. (2008) and Charreire et al. (2010) defined geographical access as the ease of reaching food sources or services. Their research embraced the complexity of multidimensional phenomena of access, such as food deserts. Areas in the US that are considered “food deserts” are areas with limited access to fresh healthy foods. The USDA was tasked by the US Congress to identify and eliminate existing food deserts through a series of studies funded by the 2008 Food, Conservation and Energy Act. The first in the series measured areas with low food access and determined these areas frequently suffered disproportionately from poverty. Food desert characteristics in urban areas differ from their rural counterparts based on factors like public transportation options and private vehicle ownership. Food deserts in areas where population densities are lower tend to have higher minority populations. Rural areas with rapid population growth tend to pull with them buying power and supermarkets (Dutko et al. 2012).

Five dimensions of food access were defined as availability (food supply), proximity, affordability, diversity (types of food venues), and perception (Charreire et al. 2010). Proximity deals primarily with distances between the location of the food venue and the person. Hereafter food venues are referred to as supermarkets or smaller food stores such as fast food or convenience stores. Often models are built in which the residential location is represented as a point of origin and supermarkets serve as the destination point. Food accessibility models may examine distance to the closest supermarket, average distance to all supermarkets, and the number of supermarkets within a given distance or travel time (Apparicio et al. 2008).

Food environments are dynamic and change rapidly. They are complex. Glanz et al. (2005) suggested that within food environments, nutrition environments exist which contribute to obesity in children and adults in the US Nutrition environments are any place that people consume food. Work, school, and other organizations in addition to meals eaten at home make up an individual or family food environment. Restaurant nutrition environments are of interest because available foods may be higher in sugars and fats and overall may not promote health. Research in this area suggests neighborhood characteristics are associated with food purchasing behaviors.

Neighborhoods that may be considered food deserts have few options nearby to obtain fresh healthy foods. Food swamps are neighborhoods saturated with more fast food than fresh food options. Policy makers have recognized that accessibility to food options influences people’s food choices (Block et al. 2004, Luan et al. 2015, Gallagher 2008). Therefore, community level socioeconomic characteristics, race and ethnicity, and health outcomes are featured in many food access discussions (Alnasrallah 2012, Glanz et al. 2005, Morganstern 2015, Morland 2015).

1.2 Motivation for the Study

The primary motivation of this study was to fill in the empirical gaps for large scale food environment assessments in Oregon. Having the ability to strategize and implement innovative solutions to identify areas with low food access is efficient and cost effective using a GIS. Large-scale finer grained studies are appropriate to address community issues at the neighborhood level. The USDA investigated food deserts nationally at the census tract level (Ver Ploeg et al. 2009). Finer grained studies are emerging in communities as technology allows for higher quality datasets with increased precision and accuracy. This research aims to provide insight to scalable mixed methods distance-based food access research using GIS techniques.

Only 27% of the studies reviewed by Charreire et al. (2010) utilized the distance by road or street network. Additionally, only 19% of food desert studies reviewed by D'Acosta (2015) were aggregated at the level of census block group (CBG). Appropriate map units at the neighborhood level are essential for meaningful research to guide food retail interventions. Oregon communities armed with actionable information can then evolve to meet food security needs. Lane County is an example of an area lacking large scale empirical analyses exclusively examining food access. Food for Lane County conducted an assessment in 2012 that examined the urban core as well as the two flanking urban clusters of Florence and Oakridge (Hummel 2012). The Lane County GIS Department created a web map application to serve results from health analyses that includes results for food accessibility mapped at the census tract level.

1.3 Study Objectives

This study focused on creating a current (i.e. 2015-2016) snapshot of the local food environment in Lane County, Oregon to identify disparities that may exist for food access in neighborhoods with low incomes and higher minority populations. The goal is to better understand the relationship between socioeconomic characteristics, demographics and food stores. The study determined: (1) whether or not neighborhood deprivation has an impact on food access; and (2) whether communities with higher minority compositions experience disparities in food accessibility.

It is necessary to determine whether or not food deserts exist in Lane County, OR. If food deserts exist it is then necessary to evaluate the sites and situations of the phenomena. The social variable comparison examined whether or not equitable food access exists across the study area. The presence and absence analysis is a precursory step for further RHFA examining food swamps. The main research goal is to provide organizations current information and tools for shaping food policy to increase food security for Lane County residents.

1.4 Lane County, Oregon: The Study Area

Lane County is the administrative unit that formerly encompassed all of southern Oregon (Card and Lane County Historical Society 2008). The study area covers 4,722 square miles but some areas are uninhabitable due to steep terrain. It is situated at the southernmost end of the Willamette Valley (Figure 1). The population in the county was estimated from the American Community Survey (ACS) to be 358,337 in 2014 (U.S. Census Bureau 2015a).

The county is bounded by mountains on three sides: The Coastal Range to the west, the Cascade Range in the east, and the Calapooyah Mountains in the south. Three level 3 ecoregions blanket the county from west to east: (1) the Coastal Range; (2) the Willamette Valley; and (3) the Cascades Range (U.S. Environmental Protection Agency 2015). The Willamette Valley is the central ecoregion and contains most of Oregon's population. It stretches northward from Douglas County towards the most densely populated area in the state, the greater Portland Metropolitan Statistical Area (MSA) (Card and Lane County Historical Society 2008).

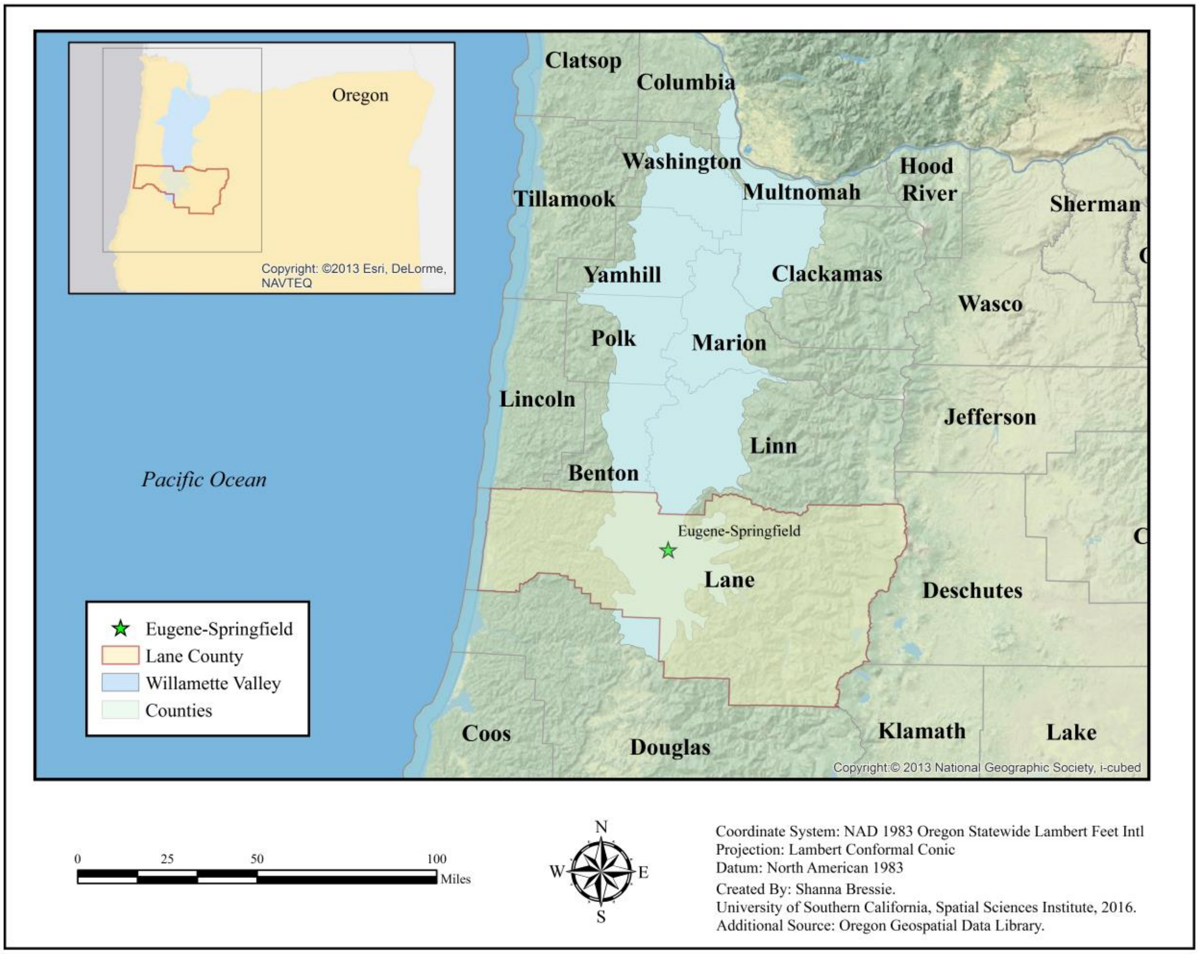

Figure 1 Lane County locator map

1.4.1. River and Road Networks

Early settlers and regional development relied upon the river system for natural resources and transportation. The Willamette River runs alongside I-5 and is the prominent natural feature on the valley floor which runs south to north before emptying into the Columbia River. Rail and roadways emerged alongside the banks of the Willamette River System in the 20^{th} century (Williams 2009). The river system has defined the region geographically for 35 million years and culturally for the past three centuries (Card and Lane County Historical Society 2008). Seven counties (Lincoln, Benton, Linn, Deschutes, Klamath, and Douglas) and the Pacific Ocean share the boundary with Lane County.

1.4.2. History of Eugene

Eugene Skinner, founder and visionary, foresaw the farming potential of the Willamette Valley. He built the first log cabin in the woods that served as a shelter for the settlers that followed him. The pioneer founder literally put Eugene on the map, opened the first post office and became its first postmaster. The topography of the valley as seen from a nearby butte, later named after him, reminded Skinner of a bird's nest. Pioneer settlers arrived slowly because the county was not easily accessible along early wagon routes, especially during flooding brought about by the winter rains (Card and Lane County Historical Society 2008).

In the middle of the 19th century, Calapooyah Native Americans burned the flatland because the land modification increased cultivation of camas and tarweed that were central to the diets at the time (Card and Lane County Historical Society 2008). Though crop focus has shifted in the 21st Century, agricultural production is still central to the state's economic viability. Grass, hazelnuts, Christmas trees, grapes, and hops now dominate the agricultural landscape.

1.4.3. The Population

Eugene, the largest urban center in the county, covers approximately 44 square miles. The Eugene Metropolitan Statistical Area (MSA) had a population of 160,561 in 2014 and accounted for 45% of the county total (U.S. Census Bureau 2015b). Springfield, the county's second most populated city, is situated on the eastern bank of the Willamette River and is approximately one-third of the size of Eugene in terms of both land area and population.

Florence and Oakridge flank the county on the far western and eastern sides, respectively. Each offers unique characteristics and challenges of near ocean and rural mountain living.

Smaller urban clusters like Florence with a population of 8,506 as of 2014 and Oakridge with 3,205 residents attract some tourism and rely on seasonal economies inherently linked to natural resource extraction and management (Hummel 2012). The remainder of the population is dispersed along waterways, railroad corridors, and roadways (Card and Lane County Historical Society 2008). The kernel density map reproduced in Figure 2 illustrates that the cities of Eugene and Springfield are the most densely populated area in the county.

1.5 Thesis Organization

The remaining four chapters are organized as follows. In Chapter Two, I review related studies, define relevant terminology, describe food environments, and review studies that employ GIS to analyze disparities in food access from early qualitative studies to current research. Chapter Three describes data sources, data collection, geoprocessing and data preparation and the network analysis. Chapter Four presents the results of the analysis and interprets the findings. The final chapter discusses the contribution of the findings and recommends some future food environment research needs.

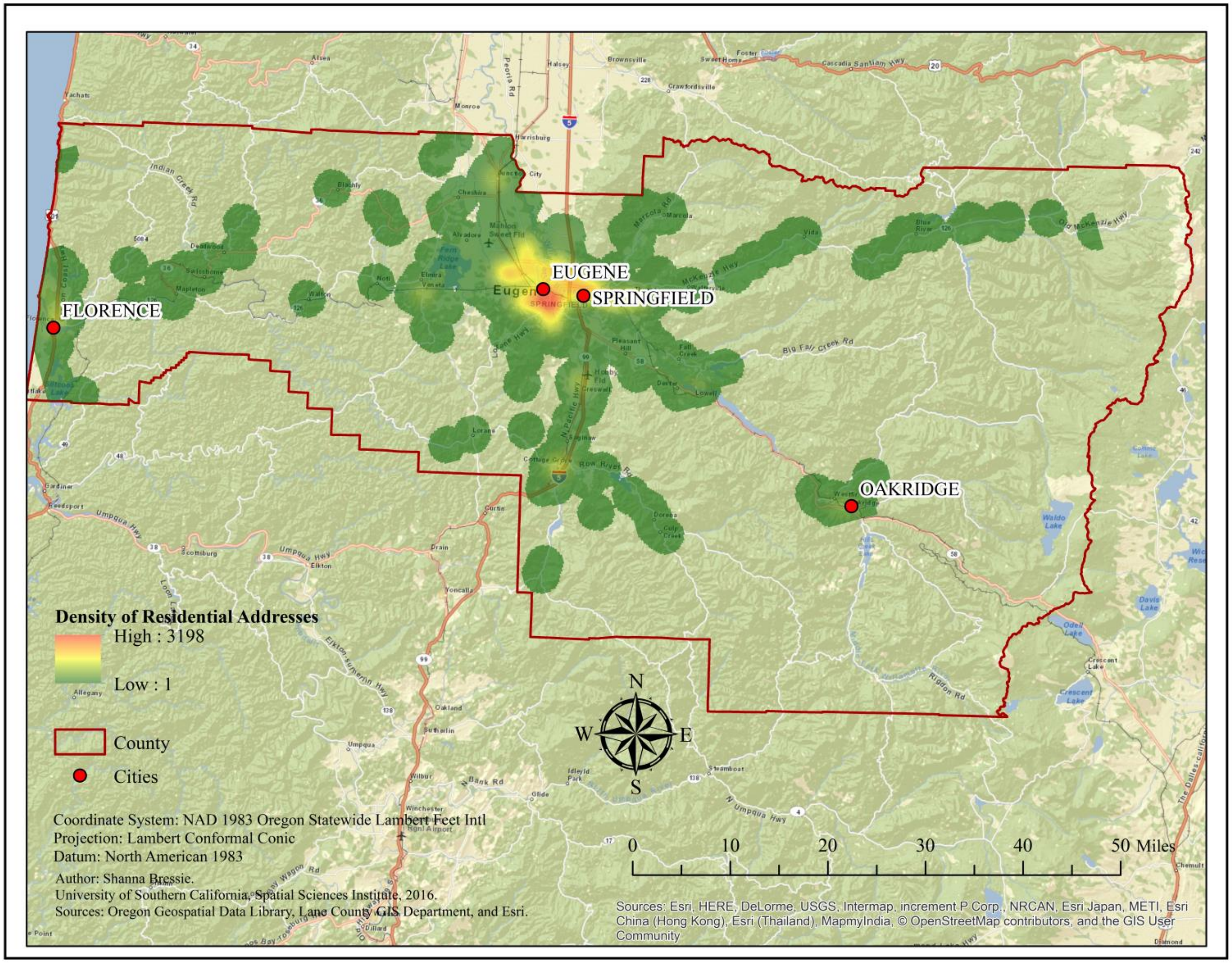

Figure 2 Kernel density map based on 5 year ACS estimates for the period 2009-2013

Chapter 2 Related Work

Supermarket accessibility is an important aspect of community health. Much of the literature focused on food store accessibility cited changing urban food environments. The evolution of food desert research linked lack of food access to social inequality and more recently public health studies concerning diet-related disease. Recent studies have shifted attention from the lack of supermarket access toward presence of other food store types that offer energy dense foods that are nutritionally insufficient for healthy dietary intakes.

The studies reviewed originated in the UK, the US, Canada, New Zealand, and Australia. Several authors suggested local interventions to address low supermarket access. Some food environment studies charted an increase in the levels of access to fast food restaurants and convenience stores. Advancements in spatial analysis tools and data collection allow researchers to more accurately model food environments at various scales and granularity. This chapter is divided into four sections: (1) Food environments; (2) food retailers: geolocation and type; (3) population distribution; and (4) connecting people to healthy foods.

2.1 Food Environments

Food environments are places where people purchase food (Glanz 2009, Morland 2015). Food environments provide a variety of food stores and restaurants where people purchase and consume food. It is well documented that proximity of food store types influences food choice and consumption (Alnasrallah 2012, Zenk et al. 2005). Supermarkets and grocery stores offer a complete selection of healthy foods like fresh fruits, vegetables, meats, dairy products and whole grains (Apparicio et al. 2007, Clarke et al. 2002, Donkin et al. 1999, Kowalski-Jones et al. 2009, Moore and Diez Roux 2005, Morland et al. 2002, Smoyer-Tomic et al. 2008, Sparks et al. 2011, Van Hoesen et al. 2013, Ver Ploeg et al. 2009). Recent studies show that fast food restaurants and convenience stores offer consumers less variety and unhealthier food options than larger supermarkets and grocery stores (Pearce et al. 2007, 2009, Shannon 2014). Researchers recently began testing food balance theory. They compared healthy and unhealthy food source ratios in the context of influence on diet and overall community health (Gallagher 2008, Larson et al. 2009, Sadler 2016).

The earliest research focused on identifying food deserts as areas where the lack of affordable food resulted in undernourishment of people in the area (Donkin et al. 1999, Clarke et al. 2002). Food deserts are geographical areas with low access to healthy food. The term "food desert" was first used in Scotland by residents living in a deprived neighborhood. Food in that Glasgow neighborhood was overpriced for low income individuals and thereby unavailable (Cummins and Macintyre 2002). Mooney (1990) found unhealthy foods were more prevalent and affordable in lower income neighborhoods, while fresh healthy food was scarce and expensive. It was concluded that food deserts were common features of cities in the UK during the mid-1990s (Cummins and Macintyre 2002). Retail practices shifted from small walkable grocery stores located in inner urban areas to super centers on the periphery. Superstores offered an automobile centric retail format and 80,000 square feet of floor space (Donkin et al. 1999). The same pattern followed in the US from 1960 to 1990 (Morland 2015, p. 274).

Suburbanization in the US reorganized the built environment and population dispersion patterns post World War II. Food stores followed people leaving inner cities. Anderson (1978) documented emigration in his book entitled *"The ghetto marketing life cycle: A case of underachievement"*. The "urban grocery gap" of the 1960s through the 1990s was evaluated by researchers at the University of Connecticut. They published a report that highlighted an urgent need for more efficient food distribution that was affordable in low-income neighborhoods within 21 US cities (Rabinowitz 2014, Morland 2015). The grocery gap in the US most commonly occurred in lower-income areas with higher minority compositions. Cheap land incentivized rapid retail development in suburbs (Morland 2015).

Researchers argued that grocery gaps are being filled by convenience stores and fast food restaurants, creating unhealthy food environments in low-income minority neighborhoods (Block et al. 2004, Pearce et al. 2007). Conversely, Moore and Diez Roux (2005) found better access to healthy foods provided by smaller stores in low-income, ethnic neighborhoods in New York, Baltimore, and Forsythe County, NC. Much of this research is focused on identifying whether or not proximity and food store variety contribute to obesity and other diet related health outcomes (Block et al. 2004, Thornton et al. 2009). Food environments with an abundance of fast food restaurants that serve energy dense food options are called “food swamps” (Morland 2015). Rose et al. (2009) argued that although food desert research provided a foundation to guide targeting federal food programs toward food deserts, food swamps may be more taxing to overall community health because more energy dense foods cause calorie over-consumption.

The questions Donkin et al. (1999) posed are still applicable to food access evaluations today: “(1) how do we define access? (2) how do we measure access? and (3) how do we improve access?” Researchers in Australia, New Zealand, Canada, the UK, and the US have answered with empirical evidence the study questions reviewed in this chapter.

2.1.1. GIS Accessibility

Geographical access refers to how easy it is for people to get to facilities and services (Apparicio et al. 2008). Caspi et al. (2012b) reviewed food environment case studies. Of the 38 studies reviewed 68% captured GIS measurements of relationships between residents and food store types. One year earlier, only one-third of the authors performed GIS analyses (Walker et al.

2010). Multiple dimensions of food environments cited by Charreire et al. (2010) in a third food access review included accessibility and availability as well as affordability, acceptability, and accommodation. At that time, store density calculations were most commonly calculated using buffer tools. Least common were studies employing kernel density analysis, a technique approximating intensity or estimating relative availability of healthy food in a continuous surface (Charreire et al. 2010, Sadler 2016).

The earliest food desert studies combined GIS for mapping results of statistical analysis calculated manually or in statistics software. Developments of GIS software, specifically transportation network tools and spatial statistics provide more accurate distance models for evaluating real-world conditions (Alnasrallah 2012, Morganstern 2015, D'Acosta 2015, Smith 2003). Sparks et al. (2011) noted the difficulty of comparing results across GIS-based food access studies due to lack of consensus in the use of terminology and research protocols among researchers.

2.1.2. Defining Measurements: Distance and Density

Accessibility varies based on the indicator modeled. How accessibility is measured has influenced study results. Distance type and spatial unit of aggregation are fundamental elements of GIS-based access analyses (Apparicio et al. 2007). Finer neighborhood granularities have resulted in less aggregation error in the distance measurements from dwellings to food stores (Caspi et al. 2012b, Eckert and Shetty 2011, McEntee and Agyeman 2010, Thornton et al. 2009, Van Hoesen et al. 2013). Several different types of access measurements exist: (1) Distance to the closest facility; (2) number of facilities or services within a given distance; (3) average distance to all services; (4) average distance to a given number of facilities; and (5) gravity modeling (Apparicio et al. 2008). Parameters for measures of access are: (1) definition of residential areas or the spatial unit; (2) aggregation of population (distribution); (3) a measure of access; and (4) distance or time for computing chosen access measures (Apparicio et al. 2007).

Proximity is a distance-based measure. There are conceptually and mathematically different types of measurements defined in GIS tools and varied approaches. Euclidean distance is the simplest straight line, as the crow flies measurement. Manhattan distance is an approximation based on right angles like city blocks. Travel networks may offer a more complex distance measurement, this could include roads, rail lines, subways, and rivers (Charreire et al. 2010, Morganstern 2015, O'Sullivan and Unwin 2010). Travel time is often the distance measure of concern most relevant to travel networks (Pearce et al. 2007). Networks distances do not account for factors like road construction or individual route preference (Alnasrallah 2012, O'Sullivan and Unwin 2010).

Apparicio et al. (2007) incorporated Euclidean distances into a food desert study in Montreal, Canada. They argued that gravity modeling was the most common GIS technique used to measure food access a decade ago. Sparks et al. (2011) modeled both Euclidean and network-based distances in food access models for Portland, Oregon. A national level study conducted in New Zealand is one of the few reviewed that incorporated travel times (Pearce et al. 2007). Pearce et al. (2009) evaluated whether access to certain types of outlets was associated with fruit and vegetable intake.

Five studies measured precise network distances from dwellings to food store types and then aggregated these measurements into larger census units. Among the five studies, no food deserts were found in all with one exception. Van Hoesen et al. (2013) included local farm stands and farmer's markets, which decreased mean travel distances and average maximum travel distances by 18.65 and 22.13%, respectively. Eckert and Shetty (2011) approached food deserts from a planning perspective. They compared access at one and two miles, and aggregated address locations into CBGs. Findings suggested no major food deserts in Toledo, OH. However, 28 block groups were identified at risk to develop access issues at one mile, and only one CBG was at risk at two miles. Caspi et al. (2012a) found that geographic access was not associated with low fruit and vegetable intake in the Greater Boston, MA Area. Residents of low-income housing survey responses indicated perception affected healthy food consumptions as they did have adequate access to a variety of healthy foods (Caspi et al. 2012a). Morganstern (2015) found higher income suburban residents had lower access in the Atlanta, GA MSA than those with lower incomes living in central areas of the city. In Vermont, McEntee and Agyeman (2010) aggregated finer resolution distance measurements to average distances within census tracts and defined > 10mile network distances as the threshold that indicated low access. The study refined Morton and Blanchard's (2007) conceptual framework for evaluating food access with higher measurement precision. Their findings indicated 12 census tract level food deserts in the state.

A density-based measurement inside of a buffer or service area, has also been adopted and used to estimate store variety and coverage. Buffering is the most common analysis technique to determine food store density (Charreire et al. 2010). Clarke et al. (2002) buffered 500 m zones around supermarkets, which represented five to seven minute walk times in Cardiff, Leeds, and Bradford in the UK. Circular buffers created around food stores were the earliest service area representations. Smith (2003) employed the same method at distances of 500 m and one mile in food access thesis research in Lane County, OR. Block et al. (2004) created shopping areas using buffered census tracts that accounted for shopping in adjacent tracts. Larsen and Gilliland (2008) employed 1 km buffers around supermarkets, representing 10 to 15 minute walk times. Smoyer-Tomic et al. (2008) generated neighborhood service area network buffers around the geometric center of census blocks in Edmonton, Canada. They compared densities of food store types at four different distance radii: 500, 800, 1,000, and 1,500 m. Two-thirds of Edmonton neighborhoods had at least one fast food restaurant within 500 m (Smoyer-Tomic et al. 2008).

2.1.3. Defining Boundaries

Census units have been frequently used to define neighborhood boundaries throughout the greater body of the literature. Rich datasets at various geographies offer researchers flexibility in scaling. National governments provide population enumerations with demographic and economic data in a hierarchy of geographic areas: National, state, county, census tract, block group, block, mesh blocks, postal codes, collection districts, and small area units. Large scale (i.e. small area) urban studies accounted for 61% of the articles reviewed whereas large area geographies at the national level accounted for 18% and small scale rural studies accounted for 21%.

Boundaries of local food environments are defined by the distribution of the population of interest and locations where people obtain food. The ways in which boundaries were defined in past studies affected findings. Food retailers are often situated in the centers of population concentration across the landscape. Local food environments in rural areas may include much larger land areas than local food environment boundaries in urban areas (Morland 2015).

A national level study in the US identified food deserts by county. They were characterized as rural with low population density, lower educational attainment, more elderly people and higher minority composition (Morton and Blanchard 2007). Ver Ploeg et al. (2009) estimated 1 km grids from CBG data compiled by the Socioeconomic Data and Applications

Center (SEDAC). Grids offered high resolutions that translated back to areal tract units easily and provided faster computation of national population data (Ver Ploeg et al. 2009). Findings from the national level study conducted by the USDA suggested that the northeastern region of the US has relatively high levels of access to food stores, whereas in the Great Plains the population is more dispersed across the landscape and food stores are sparse (Dutko et al. 2012, Ver Ploeg et al. 2009).

2.2 Food Retailers: Geolocation and Type

Supermarkets, grocery stores, restaurants, convenience stores, produce stands, bakeries, delicatessens, supercenters, and farmers' markets are examples of different types of food stores. Location addresses can be geocoded and located by planar coordinates on a map using GIS software. Investigators have collected food store information and location data from: (1) governments; (2) private companies that collect business information; and (3) direct measurement (Morland 2015, p.104).

Sharkey and Horel (2008) collaborated with a group of trained technicians who collected and ground-truthed food store location points with kinematic GPS units to measure a rural food environment in Brazos Valley, TX. Van Hoesen et al. (2013) located food stores in rural Vermont with data extracted from the national directory of food store authorization for the Supplemental Nutrition Assistance Program (SNAP). Zenk et al. (2005) studied Detroit's food access and poverty using supermarket location data from the Michigan Department of Agriculture. Several other investigators extracted food store types from Dun and Bradstreet's Business Database directly (Alviola et al. 2013, Kowalski-Jones et al. 2009, Powell et al. 2006). Morganstern (2015), D'Acosta (2015), and Caspi et al. (2012a), on the other hand, extracted Dun and Bradstreet data from Esri's Business Analyst Database.

2.2.1. Food Store Classification

Some authors adopted the North American Industry Classification System (NAICS) as a standard to categorize food retailers (Kelly et al. 2011). NAICS defines businesses based on industry and type of activity, e.g. retail department stores. For example, types of conventional or traditional food stores include supermarkets, grocery stores, specialty foods (butchers and bakeries). NAICS codes consist of six digits that identify sectors and subsectors (Morland 2015).

2.2.2. Relative Food Balance

The working assumption is that food environments offer both healthy and unhealthy options. Healthy and unhealthy food store access measures are indicators of each other based on spatial autocorrelation (Clary et al. 2015). Depending on the study area, the distance from a residence to the nearest supermarket may be three miles and the nearest fast food restaurant may be roughly the same distance (Gallagher 2008). Food balance scores allow for more comprehensive analysis on a continuous scale (Luan et al. 2015).

Luan et al. (2015) argued that relative healthy food access (RHFA) may provide more relevant metrics for food purchases than earlier absolute studies. Clary et al. (2015) concluded that RHFA may be more appropriate for investigating food access and diet associations in longitudinal health studies though, few studies have investigated how it performs across space and populations. RHFA is the ratio of healthy food outlets (supermarkets and grocery stores/supermarkets and grocery stores + convenience stores and fast food restaurants). RHFA reference metrics can be compared across urban, various suburban, as well as rural area studies (Gallagher 2008). Relative measurement avoids multi-collinearity in regression modeling caused by significant correlations between “healthy” and “unhealthy” foods stores (Luan et al. 2015).

2.3 Population Distribution

Population distribution across the landscape is an important consideration for land use planners and developers. It is by nature a spatial characteristic commonly expressed as density (Franco-Pata et al. 2012). GIS modeling tools provide a way to quantify population characteristics across space and map trends of relationships in food environments (Morland 2015). High resolution spatial data, pinpointing address points to dwellings where people occupy space support analyses which offer better precision and accuracy (Eckert and Shetty 2011, McEntee and Agyeman 2010, Owens et al. 2010, Van Hoesen et al. 2013).

2.3.1. Where People Live

Government census geographies are widely available and allow researchers flexibility to choose a scale that fits a particular study area. Enumerators compile census demographic data like age, gender, and race as well as economic data about income, occupation, and transportation (Donnelly 2013). Recently, many municipalities have created interdepartmental and public access to high precision housing and e911 address point datasets (Owens et al. 2010). This allows researchers an opportunity to reduce measurement error in developing models in built environments. This is particularly beneficial for more accurately mapping rural community health with larger census areas, lower population densities, and more dispersed populations (Owens et al. 2010, Sadler 2016).

Several researchers have created choropleth maps and overlays to represent food access and map the population across census units (Apparicio et al. 2007, 2008, Eckert and Shetty 2011, Larsen and Gilliland 2008, McEntee and Agyeman 2010, Sadler 2016, Van Hoesen et al. 2013). Luan et al. (2015) illustrated RHFA in Waterloo, Ontario using choropleth maps that represented DAs or dissemination areas. The assumption is that individuals are dispersed uniformly across units. This misrepresents real-world conditions because development patterns are not uniform across space. Furthermore, re-zoning, or aggregation changes either to larger or smaller units, impacts map patterns. This phenomenon is known as the modifiable areal unit problem (O'Sullivan and Unwin 2010).

2.3.2. US Census Areal Units Aggregation

The US Census enumerates the national population every 10 years. The top level is the country and the second level is the states and territories. States are then divided in counties, which are then divided into census tracts. Census tract contain between 1,000 and 8,000 people with the optimum size averaging 4,000. Census tract level aggregation with 2000 census data is common in the literature. A step smaller than census tracts are CBGs. CBGs are aggregated from the block units. Census blocks represent city blocks and most data is suppressed at this scale to protect individual identities (Langford et al. 2008, Morland 2015).

2.4 Connecting People to Healthy Foods

The goal of food access research is to guide policy makers to create healthy and equitable food environments. Researchers have suggested that such an outcome is possible by increasing people's opportunities for healthy balanced diets at the national, state, and community levels (Morland 2015, Opfer 2010, Treuhaft and Karpyn 2010, Van Hoesen et al. 2013). Some investigators found that location and type of food store as well as socio-economic factors correlate to consumer behavior and dietary intake (Morland et al. 2002, Rose and Richards 2004). Healthy food access reduces the risk of diet-related disease (Luan et al. 2015, Morland et al. 2002, Treuhaft and Karpyn 2010).

The main challenge faced by decision makers is inequality in food access at different scales (de Sherbinin et al. 2007, Van Hoesen et al. 2013). The complexity lies in striking a balance between economic free markets and land use development whilst increasing healthy food access, increasing availability of GIS and technology to optimize efficient food environment assessments, and creating development plans and policies that address community health at the appropriate scale (CDC 2010, Caspi et al. 2012a, Morland 2015, Opfer 2010, Sadler 2016).

Studies have produced mixed estimates of accessibility levels by race and poverty level. For example, Morland et al. (2002) compared neighborhood populations in Mississippi, North Carolina. Maryland, and Minnesota to supermarkets and found a 1:23,582 ratio in a predominantly African American neighborhood in contrast to a wealthy white neighborhood ratio of 1:3,816. Morganstern (2015) found better access in low-income high minority composition neighborhoods in central Atlanta, GA as did Sharkey and Horel (2008) in Brazos Valley, TX and Caspi et al. (2012a) in southeast Boston, MA.

Alviola et al. (2013) compared rural and urban CBGs in Arkansas. They concluded that Arkansans living in rural areas with more vacant houses experienced decreased access to healthy food and increased access to fast food restaurants. Morton and Blanchard (2007) asked whether access was a function of travel times or food costs. National studies showed varied interest in purchasing locally grown produce, though at the state level, studies showed increased interest in rural areas (Low et al. 2015).

Healthy food is more expensive than highly processed foods, and many view fresh fruits and vegetables as luxury items (Opfer 2010). Jetter and Cassady (2006) found that market basket price (MBP) was 17 to 19% more for healthy foods than a standard MBP. Rural Iowans paid 36% more for food with fewer large supermarkets dispersed across large areas (Morton et al. 2005). Oregonians in the rural town of Oakridge paid higher costs for less product variety and experienced the lowest level median household income of communities studied (Smith 2003).

Overall, food prices were lower in large supermarkets compared with small grocers and corner stores (Hendrickson et al. 2006). Therefore, access to large supermarkets and grocery stores increased low-income individual's opportunity to purchase and consume a well-balanced diet (Hendrickson et al. 2006, Morland et al. 2002, Opfer 2010, Powell et al. 2006, Sadler 2016).

Public buses increased consumer access in urban areas. Sadler (2016) and several others considered bus stop and routing proximity in urban area models (Alnasrallah 2012, Larsen and Gilliland 2008, Smith 2003). Powell et al. (2006) noted low-income rural residents paid higher food prices, lacked public transit, and how higher trip costs created barriers. Though mobility issues are partially addressed with public transit, urban models fail to factor in weight of carrying groceries varying distances from the store to the bus stop and then from the bus stop to the home. Some people may incur higher trip costs associated with taking a taxi on the return trip depending on the weight of the groceries and additional purchases of non-food products (Shaw 2006).

2.4.1. Spatial Scale Variation: The Story in Vermont

The spatial scale of measured food environments varied across the literature in accordance with research interests and study area sizes. Three studies investigated the state of food access in the state of Vermont at three different scales. Morton and Blanchard (2007) conducted a national level study that found all Vermont counties with adequate access to major chain supermarkets based on distance and population (US Census 2000) thresholds. Counties across the US with more than 50% of the county population living more than 10 miles from a supermarket were characterized as food deserts (Morton and Blanchard 2007).

Van Hoesen et al. (2013) measured the food environment Rutland County, VT with road network distance measurements calculated from address points to food stores including supermarkets, grocery stores, local farmer markets, and convenience stores. Investigators systematically created a base 10 composite index to account for the likelihood of finding an abundant variety of healthy foods. Supermarkets were assigned the highest value (1,000), grocery stores were assigned 100, and farmer's markets, co-ops, vegetable stands, and CSAs the lowest (10). Their findings for food access were consistent with Morton and Blanchard (2007), without consideration of food costs. Average travel distances were 6.91 miles and the maximum travel distance was 8.41 miles in rural areas of the county. Van Hoesen et al. (2013) illustrated that when smaller markets were excluded some rural residents travelled more than 10 miles to the nearest supermarket. They argued inclusion of smaller markets to better characterize access to high quality healthy foods in local rural food environments (Van Hoesen et al. 2013).

McEntee and Agyeman (2010) evaluated distance-based food access across census tracts in Vermont. Distances measured over the road network from residential address points to food stores were then aggregated to census tracts to find average travel distances within each tract. Food stores were defined as markets larger than 2,500 square feet. The distance threshold was greater than 10 miles, consistent with Morton and Blanchard (2007). Results of the analysis identified 12 food desert census tracts. The average distance to supermarkets within food desert census tracts was 13.15 miles compared to 4.14 miles statewide. Descriptive statistics for poverty and education were noted, but not used to define the model. The authors noted that refinements for the next modeling steps could include more information such as socio-economic statistics and demographics and price surveys (McEntee and Agyeman 2010).

2.4.2. Temporal Scale Variation: Ontario, Canada

Larsen and Gilliland (2008) conducted a historical analysis that compared temporal change of supermarket access in London, Ontario between 1961 and 2005. They found food retailers shifted from urban to suburban locations. Researchers estimated three measurements: (1) density; (2) variety; and (3) proximity. Street network data were compared and street patterns around supermarkets for 1961 and 2005 were unchanged. One kilometer network buffers around supermarkets were created over the street network to model walkable service areas. By counting the number of supermarkets in each service area, investigators determined store diversity and variety in each walkable service area. Block population weighted centroids that fell inside of the 1 km buffers were counted as having adequate walking access. Population counts were then aggregated into census tracts to evaluate socioeconomic neighborhood characteristics as Apparicio et al. (2007) demonstrated in the research evaluating Montreal's missing food deserts (Larsen and Gilliland 2008).

Larsen and Gilliland (2008) found supermarket access decreased from 1961 to 2005, while the population doubled. Central London had a strong central food access hub in 1961. The average ratio of census tract population with adequate access decreased from 45.2% in 1961 to 18.3% in 2005. The most distressed neighborhoods located in the central city travelled on average 66 m farther than the least distressed. Access did not improve in centrally located neighborhoods when researchers considered public transit. However, no significant correlation was found between low-income and access (Larsen and Gilliland 2008).

Researchers in Waterloo, Ontario evaluated food deserts and swamps using a spatio-temporal Bayesian approach from 2011 to 2014. Luan et al. (2015) modeled relative healthy food access (RHFA). Investigators built the model based on 4 km road network buffers from DA centroids. Food stores that fell outside of the study area, but inside of a buffer area were included in the model. The RHFA threshold that identified a DA as a food swamp was < 10%. Earlier studies had shown households have higher odds of healthier purchasing behavior in areas with 10% or more of healthy food stores (Luan et al. 2015).

Bayesian spatio-temporal models were analyzed to identify trends in RHFA and differentiate regional and local variations. Investigators identified strong spatial autocorrelation for small area RHFA using Moran's I, which they calculated using the WinBUGS software (Luan et al. 2015). Luan and colleagues extended the base model to test association between population density and RHFA, but this did not improve model fit significantly. They therefore ran simulations on the simpler model. Differential change trends were identified in the center and southeast edge of the study area over the four-year period (Luan et al. 2015). Researchers created a measure of estimated RHFAs, the probability of a food store being healthy based on RHFA calculations in adjacent areas. Estimated RHFA ratios were then used to identify four new areas with low RHFA, that given current trends, could emerge as new food swamps. This provided an efficient way to focus resources on local interventions. Results indicated food swamps were more prevalent that food deserts during the study period. The findings were consistent with similar urban studies conducted in Canada (Luan et al. 2015).

Given the background and insight provided by the varying perspectives summarized in this chapter, the next chapter explains the methodology and data sources that were used to explain contemporary food access across Lane County, OR.

Chapter 3 Methodology

The chapter opens with a description of the data that were used. The methodology is framed in four sections that expand upon project data; food store classification, measurement calculations, aggregation to areal units and statistical analysis. Esri's Network Analyst was used to calculate distance measurements over the road network. These systematic measurements were used to estimate the accessibility of food environments in Lane County, Oregon. The framework is an adaptation of high resolution data combined with mixed methods following works by McEntee and Agyeman (2010), Larsen and Gilliland (2008), Apparicio et al. (2007), and Morland et al. (2002). Figure 3 provides a simplified project workflow.

3.1 Data Descriptions

The Lane County GIS Department shared high resolution address point and street centerline datasets that made this research possible. The boundary files for the state and county as well as 2010 Census Block Group geographies, originally released by the US Census Bureau, were downloaded from the Oregon State Geospatial Data Library. Supermarket and other food store feature point datasets were downloaded from Esri's Business Analyst, sourced originally from Dun and Bradstreet, Infogroup USA. The US Census Bureau compiled socioeconomic and demographic estimates in the ACS 5-year tables (2009-2013). The census mails surveys out to residents in each region of the US The responses are obtained annually through a systematic population sample creating estimates representative of community populations of various sizes, regions, and timeframes (Donnelly 2013).

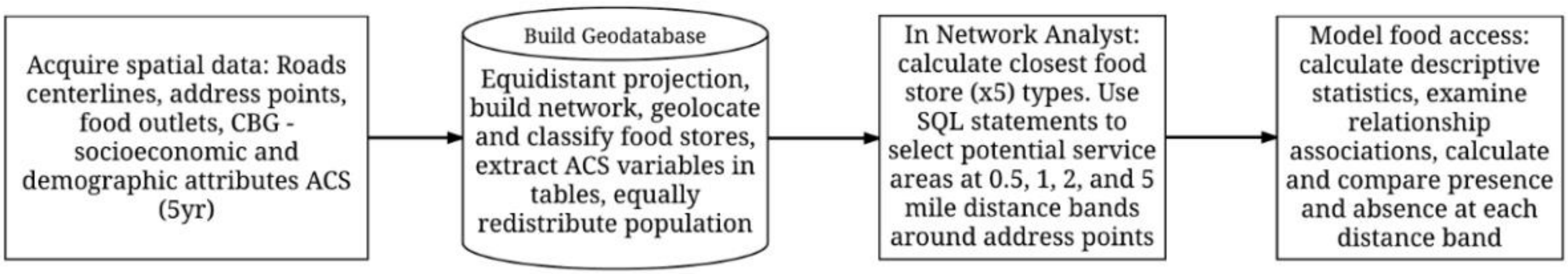

Figure 3 Project workflow

3.1.1. Reference Boundaries and Basemaps

Administrative boundary files for location and orientation maps including the state, counties, cities and towns, and the 2010 census block group file were acquired from the Oregon Geospatial Data Library. Boundary files were stored in the Lambert Conformal Conic Projected Coordinate System, Datum: North American Datum 1983 and Spheroid: Geodetic Reference System (GRS) 1980, and using the International Feet map units to map the study area and results. Basemaps used to reference the project maps were provided by Esri's Basemap map services.

3.1.2. Address Points

The analysis used very high resolution address points to estimate distances from resident's homes to food stores. Processing the address point features included joining the address point file to the parcel shapefile on the field '*maptaxlot*'. The property classification descriptions and zoning codes were used to extract residential points. The original point feature class contained 174,507 points, and 153,164 residential address points were used for the analysis reported in this thesis. The feature dataset was re-projected into the USA Contiguous Equidistant Conic Projection to facilitate more accurate distance measurements in Network Analyst. All initial proximity and service area measurements used this dataset as the point of origin for the subsequent analyses.

3.1.3. Street Network

An accurate high quality street centerline file was obtained from the county and quality checked against Esri's imagery basemap service. Using the new network dataset tool in ArcGIS 10.4, the street centerlines were converted to a connected network dataset. Based on the Network Analyst Extension, network tools were then used to create a Closest Facility Analysis Layer that calculated distances between address points and food stores.

3.1.4. Food Stores

Retail store address and location information were readily available in Esri's Business Analyst Extension. North American Industry Classification System codes were used to select the intended food retailer set by the NAICS attribute. The business attribute file is rich and details the company name, address, sales volumes, square foot codes for building footprints, and the number of employees. The initial extracted dataset, N=1,098, was validated and classified by retail format or size and type of store. Three main types of food stores were identified: (1) Supermarkets and grocers; (2) fast food restaurants; and (3) convenience stores (with and without gas). Supermarket and grocery stores were categorized as either large with a square food code (SQFT) = 'D' or small with a square foot code (SQFT) = 'B'. Table 1 records the original counts of store types in three broad categories as extracted from the Dun and Bradstreet database by associated NAICS codes.

Table 1 Numbers of broader categories of food store types prior to re-classification

Store Types	**Original Counts**
Supermarkets and Grocery Stores	115
All Restaurants	784
Convenience Stores	199
Totals	**1,098**

3.1.5. Non-spatial Data Sources

Non-spatial datasets were used to extract various attributes. NAICS codes were used to extract point features from the Business Analyst geodatabase, originally sourced from the Dun and Bradstreet business database. Table 2 summarizes NAICS food store categories and descriptions.

Table 2 NAICS codes

Type	NAICS Codes	Description	Examples
Supercenters	452990/45211101	Superstore, WarehouseClub	Walmart, Target, Costco
Supermarkets	44511003	Supermarkets, Grocery Stores	Safeway, Albertsons, Trader Joe's
Fast Food Restaurants	72251117/72251302	Fast food, Pizza delivery, Deli	McDonalds, KFC, Taco Bell, Subway, Delicatessens
Convenience Stores	447190/44512001	Convenience Stores, Truck stops	DariMart, AMPM, Cheveron

The ACS geodatabase tables were sourced from US Census Bureau TIGER/Line with Select Demographic and Economic Data (2015). The US Census Bureau produces ACS updates annually. It is a more cost effective replacement for the decennial census long-form (Donnelly 2013). Surveys are mailed to addresses in small and large geographies to estimate the population at 1-year, 3-year, and 5-year intervals. The individual attributes are represented by estimate counts and margins of error for each CBG in tables. The ACS data was preferred to the 2010 Census enumerations because they provided more current information for the study (Donnelly 2013).

3.1.6. Summary

The primary geospatial data were checked against imagery for quality and classified for modeling in Network Analyst. Food stores were validated using Google and phone calls by the author. This step ensured that the included food stores were in operation and selling foods. Table 3 summarizes the datasets used to model food access in this project.

Table 3 Data summary

Data Set	Content	Data Type	Processing	Source
Administrative	Boundaries	Polygons	Reproject (USA Equidistant Contiguous)	Oregon Spatial Data Library
Road Network (2015)	Street Centerlines	Lines	Build Network	Lane County GIS Department
Address Points	Dwellings	Points	Join to Parcels; Extract Residential Parcels	Lane County GIS Department
Food Stores	Location & Size Range	Points	Extract NAICS for Food Stores	Esri Business Analyst: Dun & Bradstreet
ACS 5-Year tables	Population Estimates	Tables	Join to Census Block Groups	US Census Bureau

3.2 Food Store Classification: Type and Size

Food retailers were classified by the kinds of foods available and store size. Supermarkets and grocery stores were grouped by size large or small. Since, supermarkets and grocery stores usually carry fruits and vegetables they are considered healthy food stores. Large and small supermarkets were delineated by square foot code (SQFT) = ‘D’ and ‘B’, respectively in database tables. For example, Walmart Supercenters are approximately 150,000 square feet and stock products from furniture and apparel to groceries. Walmart Neighborhood Markets, which are approximately 15,000 square feet, carry groceries and a small line of cleaning supplies. The two Walmart formats were categorized in separate datasets for the analysis.

Several stores were called to validate operations, food type availability, and sizes. Non-operational food outlets were eliminated. Most fast food formats and convenience stores ranged from 1,500 to 4,000 square feet, delineated by (SQFT) codes ‘A’ and ‘B’, respectively. They were considered unhealthy food stores for this analysis. However, a dataset of delicatessens and Subway Sandwich Shops were extracted to represent healthy fast food because they offer a variety of fresh meats, dairy, and vegetables. Several Subway meals are certified by the American Heart Association Heart-Check that guides health conscious dietary choices. Several store locations outside of the county boundary were included in the initial datasets, in case these represented the nearest store for residents living near the county boundary.

The initial supermarket and grocery store dataset included several smaller, (SQFT) = ‘A’, neighborhood and corner stores that were classified into the convenience store dataset based on size and limited product selection. Full service restaurants, bars and taverns, as well as lounges were removed from the original dataset. The store format criteria for inclusion in the fast food restaurant dataset was that locations have a drive through window, patrons must pay before eating, and table service is unavailable. The convenience and corner store dataset was refined by eliminating fuel only gas stations and included the smallest neighborhood stores originally coded (NAICS) grocery. Table 4 shows store type classification criteria and counts (N=539) following re-classification.

3.2.1. Supermarkets and Grocery Stores

Super Walmart was grouped with large supermarkets and the Walmart Neighborhood Market format was grouped with small supermarkets. Chains like Safeway have two formats as

Table 4 Numbers of food store types in each dataset following re-classification

Food Store Type	Classification Criteria	Dataset Counts
Large Supermarkets	Size = SQFT 'D' and fresh fruits, vegetables, whole grains, dairy, and meats	23
Small Grocery Stores	Size = SQFT 'B' and fresh fruits, vegetables, whole grains, dairy, and meats	46
Fast Food Restaurants	Pay counter, drive through present, no table service, processed foods	177
Healthy Fast Food Restaurants	Pay counter, drive through present, no table service, fresh whole foods	60
Convenience Stores	Size = SQFT 'A' and 'B' with gas and without, processed foods, few fruits and veggies	233
Totals		**539**

well, smaller stores are approximately 45,000 square feet. Large Safeways are approximately 60,000 square feet. The average size of Trader Joe's, that was included in the small supermarket set, is 8,000-12,000 square feet. Grocery Outlet, also a mid-sized supermarket, is about 11,000 square feet. However, the exception to smaller supermarkets are the independently owned stores in the area that average 4,000 square feet. Approximately one-third of all store types across the study area are independently owned. Table 5 highlights the number of independently owned stores in each category.

Table 5 Numbers of independently owned stores in all food store categories

Store Types (N)	Independent Ownership Counts	Percent
Large Supermarkets (23)	2	1.0
Small Grocery Stores (46)	23	14.0
Healthy Fast Food (60)	24	14.0
Fast Food Restaurants (177)	15	9.0
Convenience Stores (233)	106	62.0
Totals	**170**	**100.0**

3.2.2. Fast Food and Convenience Stores

Fast food retail formats are smaller and have more compact building footprints. They are more numerous throughout the county with several locations along major roads. Convenience stores had the highest frequency and were found on secondary streets and in more rural areas of the county. Several general stores or general merchandisers were reclassified from the small grocery store dataset to convenience stores or neighborhood stores if they were small and had fewer than 20 employees. There were two threshold exceptions, Travel Centers of America and AM/PM gas stations. These features were classified as convenience stores since these retail formats are aligned to the concept of convenience.

3.3 Food Environment Measurements

3.3.1. Equal Redistribution of the Total Population

The total population was equally distributed among address points present in each of the CBGs. This was done using geospatial processing tools in ArcGIS. The process incorporated five steps: (1) The total population attribute (B01003e1) was joined to CBGs using the 'geoid10' field in the table; (2) the CBGs and address points were then intersected to estimate the total population from the ACS data assigned to each address point; (3) the geoid10 attribute field was summarized to derive the number of address points within each CBG, the two tables were then joined and the feature set was exported to preserve the table for further calculations; (4) a new field with a float data type was added (POP_REDIST_CBG_TO_ADD) to store the equal redistribution of the total population; and (5) the SQL statement (POP_REDIST_CBG_TO _ADD) = [Average_B01003e1]/ [Count_geoid10] was executed to divide the newly created population estimate field (Average_B01003e1) by the number of address points in each CBG using the Field Calculator in ArcGIS. This provided for further precision in statistical analyses within food environments in Lane County, OR. Table 6 shows part of the address point table following the application of the process described above. Each row in Table 6 represents an address point and the number of rows for each CBG (geoid10) was determined by counting the number of address points in it (Count_geoid10).

Table 6 Part of an ArcGIS table for population redistribution from CBGs to address points

geoid10	Count_geoid10	Average_B01003e1	POP_REDIST_CBG_TO_ADD
410390001005	494	683	1.382591
410390001005	494	683	1.382591
410390001005	494	683	1.382591
410390001005	494	683	1.382591
410390001005	494	683	1.382591
410390001005	494	683	1.382591
410390001005	494	683	1.382591
410390001005	494	683	1.382591
410390001005	494	683	1.382591
410390001005	494	683	1.382591
410390001005	494	683	1.382591

3.3.2. Proximity

The distances were calculated from each residence to the nearest food store of each type. Network analyst calculated routes in the closest facility tool. The routes were exported from analysis layers joined together on Facility ID to add store information for each facility route layer. The routes were joined to the address points to compile distances to each store type for each residential unit in the study area. The routes to Super Target, Albertsons, and Safeway generated by Network Analyst are shown in Figure 4 in red for the Gateway and Cal Young areas, respectively.

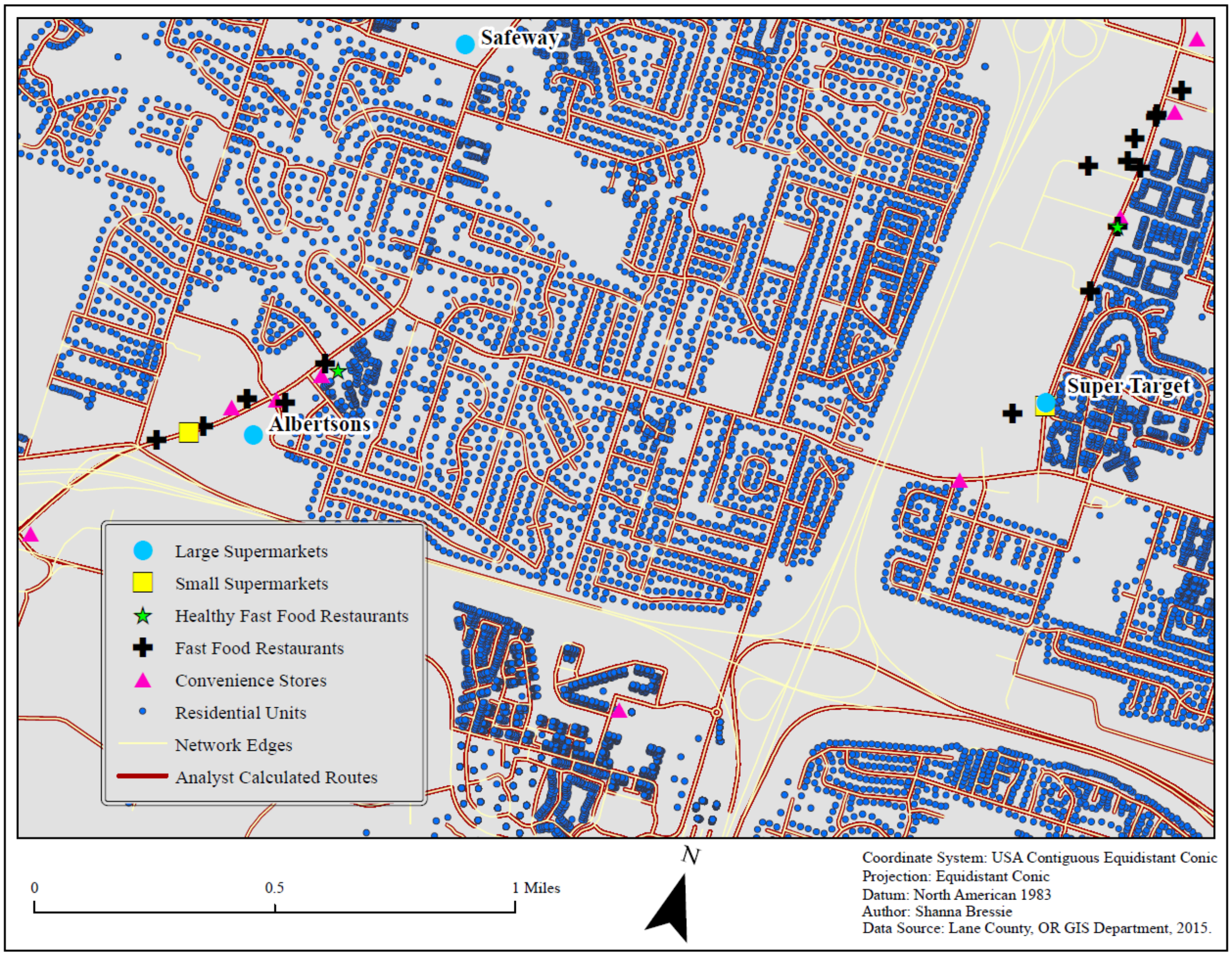

Figure 4 Closest routes to Super Target, Safeway, and Albertsons stores in the Gateway and Cal Young areas of Eugene, OR

3.3.3. Food Store Presence and Absence for Address Points at Four Distance Bands

The distances calculated for the address points during the proximity analysis were used in SQL selections to create the distance bands. Distance bands of 0.5, 1, 2, and 5 miles simulated service areas around the original address points set (n=153,164). SQL statements were used to determine whether or not at least one instance of each food store type fell into a given distance band for each address point. The process was recorded as a series of 1s and 0s into new attribute fields. The presence recordings for each store type were then tabulated into healthy and unhealthy attribute fields. Presence attributes for the 'both' and 'none' categories were derived from the healthy and unhealthy attribute fields using SQL selection statements.

For example, the following SQL statement 'CS_Dist_Miles <= 0.5' produced a set of address points where the nearest convenience stores are accessible at a distance of 0.5 miles or less. The new field for this set of address points was then calculated as a '1' using the field calculator. The attribute table selection tool 'switch selection' was then used to select the remainder of the points and the field calculator was used to calculate the remaining set as a '0' indicating this group of address points were beyond the 0.5 mile distance threshold. The 1s and 0s from the five food store type fields were then summarized in their respective categories as healthy or unhealthy food stores.

The SQL statements used to map food store presence are as follows: (1) at least one unhealthy and no healthy food stores [UNHF ≥1 AND HF =0]; (2) at least one healthy and no unhealthy food stores are present [HF ≥1 AND UNHF =0]; (3) at least one healthy and one unhealthy food stores are both present [UNHF ≥1 AND HF ≥1]; and (4) no food stores are present [UNHF =0 AND HF =0]. Layers were created for each address point set at each distance band. The results from this analysis were used to compare relative service areas for healthy and/or unhealthy food store presence and absence.

3.4 Census Block Group Neighborhood Statistics

The socioeconomic count data for ethnicity, housing, and poverty were extracted from the ACS 5-Year (2009-2013) database which contains 21 tables and 11,438 variables all together. Eleven variables were extracted from these tables and used to construct the following four variables: (1) Population density; (2) housing density; (3) minority composition; and (4) a deprivation index (Table 7) (Pearce et al. 2007). Land areas were calculated for each CBG (N=257) from the Census (2010) boundaries in order to calculate the population and housing density variables.

Table 7 Demographic and Socioeconomic variables used

ACS 2009-2013 5-Year Estimate Identification	Variables	Equations
B01001e1	Population Density	Total Population / Total Land Area in each CBG
B02001e2	Minority Composition	[Total Population - White Alone] / Total Population
B15002e3 (M), B15002e20 (F), B15003e18 (GED)	% Low Educational Attainment (Over 25 Years Old)	No Diploma + GED Only / Total Population Over 25 Years Old
B25001e1	Housing Unit Density	Total Housing Units / Total Land Area in each CBG
B19013e1	Median Household Income (Inflation Adjusted 2013)	Average No. of People per Household (2.3) * (11,490) Federal Poverty
B17017e2	% Households in Poverty	No. of Households in Poverty / Total No. of Housing Units
B25044e3, B25044e10	% Households Without Automobile Ownership	Owner + Renter Occupied / Total No. of Housing Units
B25002e3	% Housing Units Vacant	Vacant Housing Units / Total No. of Housing Units

3.4.1. Variable Construction

Population and housing unit densities were derived by dividing the totals by the total land area in each CBG unit. The minority composition variable was derived by adding all non-white ethnicity counts together and dividing by the total population. Race and ethnicity ratios were checked by working the calculations forward for all groups and then in reverse. The minority composition variable was then classified into quintiles and further simplified into three group values representing low, medium, and high minority composition in the process described in the next two pages. Variables were classified on ordinal scales to simplify comparisons.

A hybrid of Pearce et al.'s (2007) deprivation index was created in order to represent a single measure from five variables to indicate the level of poverty in each CBG: (1) median household income; (2) percentages of households below the federally designated poverty threshold; (3) percentages of households without a vehicle; (4) percentages of people over age 25 with low or no educational attainment; and (5) housing unit vacancy rates. The data were assigned quintile ranks instead of deciles. CBGs with a value of zero did not affect scoring totals. Variables were normalized by the population or housing totals, except for median household income. Household weighted densities were derived by multiplying the number of households per square mile by the housing unit weight, which is the ratio of housing units in each CBG divided by total housing units in the study area.

Household poverty rates, vehicle ownership rates, and housing vacancy rates were normalized by the number of housing units (e.g. % of housing units vacant = the number of vacant housing units / the total number of housing units). The education variable was derived from adding the population over age 25 with a high school diploma, the population over 25 with a general equivalency diploma, and the population over age 25 without either diploma which were then normalized by the total population over age 25.

Household poverty, private vehicle ownership, low educational attainment, median housing unit vacancy, and median household income were classified into quintiles using data ranges gathered from the descriptive statistics tool in ArcGIS tables. The variable ranges were divided into five equal groups and used to assign each CBG into ordinal ranks. Table 8 is an example of this procedure for the 'No Car' variable which was performed on each of the aforementioned variables. The data range was 0.0 to 0.5637581. The newly classified fields were added together in a composite of scores that were further simplified into low, medium, and high categories.

Table 8 Example of quintile ranking process using the 'No Car' variable

Households Without Automobiles Ranks	Minimum: % of Households Without Automobiles by CBG	Maximum: % of Households Without Automobiles by CBG
1	0	0.1127516
2	0.1127517	0.2255032
3	0.2255033	0.3382548
4	0.3382549	0.4510064
5	0.4510065	0.5637581

The ordinal scale ranges from 1 in CBGs with low deprivation to 5 in CBGs with high deprivation. Table 9 shows variable scores grouped into quintiles in an ArcGIS table that were further simplified to low (n=141), medium (n=80), and high (n=36). Low (1) and medium-low (2) ranks were compiled into the low deprivation rank (1). The medium CBG quintile grouping remained medium in the simplified ranking (2), while medium-high and high quintiles were grouped together to make up the 'high' grouping (3). The 'Index_Scoring' field (11) in the first row is the sum of scores for the fields 'Class_Pov' (2), 'Class_NoCar' (1), 'Class_LowEDU' (3), 'Class_Vacancy' (2), and 'Class_INC' (3). The median income class was ordered lowest to highest. The lowest income group ranked high, which was established as 2.3 (the estimated number of people per household in the study area) times Federal Poverty Level ($11,490).

The rows in Table 9 represent index values for each unique CBG. The sixth column (Table 9) sums the first five columns. The seventh column represents CBG quintile ranks.

Quintiles were classified as low (1), medium (2), or high (3) in the eighth column. The ninth column, minority composition ratios for each CBG, was classified into quintiles in the tenth column and the last column of Table 9 shows the minority composition index scores reclassified into low (1), medium (2), or high (3) ranks.

Table 9 Part of an ArcGIS table showing the additive index scoring and reclassification of five variables that were used to indicate the deprivation level for each CBG

Class_Pov	Class_NoCar	Class_LowEDU	Class_Vacancy	Class_INC	Index_Scoring	Index_CLASS	Index_LMH	Minority_Comp	MinComp_Quint	MinComp_LMH
2	1	3	2	3	11	3	2	0.417952	5	3
1	0	1	1	4	7	2	1	0.404799	5	3
1	1	3	0	3	8	2	1	0.388122	5	3
2	3	1	0	4	10	3	2	0.384437	5	3
1	1	3	1	4	10	3	2	0.368522	5	3
2	1	2	1	4	10	3	2	0.359821	5	3
1	1	3	3	4	12	3	2	0.358002	5	3
3	3	2	1	5	14	4	3	0.354975	5	3
1	1	1	2	3	8	2	1	0.348631	5	3
4	4	3	1	5	17	5	3	0.330373	4	3
2	2	2	1	4	11	3	2	0.327612	4	3
4	2	0	2	5	13	4	3	0.323626	4	3
2	2	4	0	4	12	3	2	0.320174	4	3
1	2	1	0	4	8	2	1	0.31579	4	3
4	3	1	1	5	14	4	3	0.310629	4	3

3.4.2. Statistical Analysis

The first type of analysis conducted evaluated food store distances over the road network by food store type. The second analysis compared minority and poverty compositions using the average aggregated distances as they were calculated from each address point to each food store by type into CBGs (N=257). Distance calculations from address points to the nearest food store for each store type were further classified into healthy or unhealthy food stores. The distance attribute fields for supermarkets and healthy fast food were summed into healthy fast food using SQL statements. The convenience stores and regular fast food restaurant distances were added together to get the average distances to unhealthy food stores at each address point. The third analysis evaluated presence or absences of recorded food store by category at 0.5, 1, 2 and 5 mile distance bands.

Chapter 4 Results

This chapter documents the results of the analysis of food environments in Lane County, OR. The analysis investigated residential accessibility to five different types of food stores. Associations with neighborhood deprivation and minority composition were explored. This chapter is comprised of four sections. The first describes the numbers and distribution of food store types. The second details results of the proximity calculations from address points to each store type. The third focuses on CBG distance aggregation to evaluate the connections between distance and minority composition and deprivation. The fourth investigates the distribution of presence and absence of healthy and unhealthy food stores in Lane County.

4.1 Number and Distribution of Food Stores by Type

The large supermarket dataset shows a cluster of locations in the center of the county that corresponds to Eugene-Springfield, the single major urban center of the study area. Periphery large supermarket locations are located in larger incorporated towns along the major roadways. Figure 5 shows the distributions of all five food store datasets across the study area. The distributions across the county are similar to each other. Cities and towns that host supermarkets also have a large number of fast food and convenience store options. According to O'Sullivan and Unwin (2010), this is the "first law of geography" and demonstrates Tobler's Law, "near things are more related than distant ones." Table 10 shows the number of stores in each dataset across the study area. Approximately 67% of the total number of stores in this study are shown in the inset map and are in or very near Eugene and Springfield, the largest urban area in the study area.

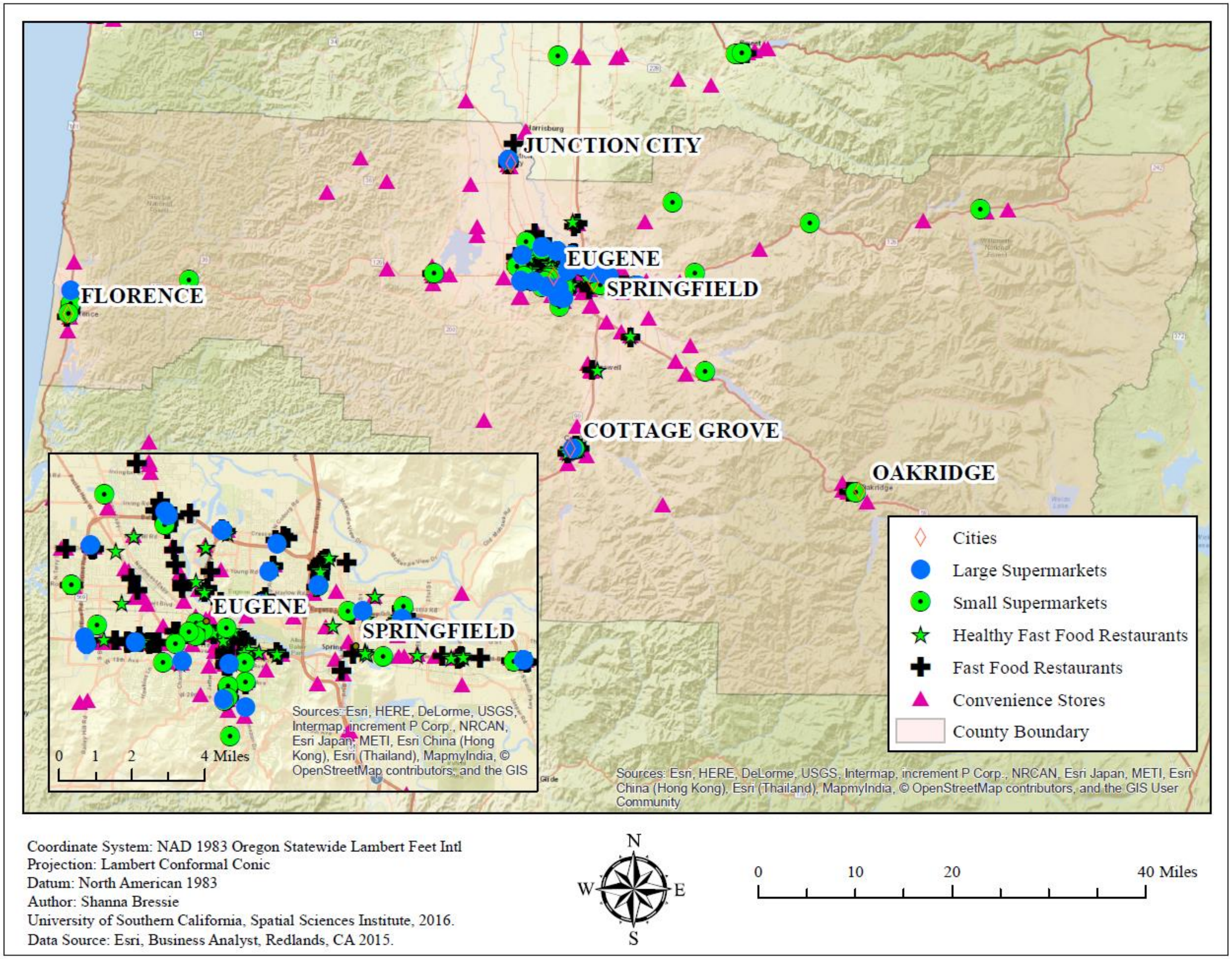

Figure 5 Distribution of store type datasets with an inset for the Eugene-Springfield urban area

Table 10 Number of store point features in each dataset by store type

Food Store Type	**Dataset Counts**
Large Supermarkets	23
Small Grocery Stores	46
Fast Food Restaurants	177
Healthy Fast Food Restaurants	60
Convenience Stores	233
Totals	**539**

Table 11 highlights frequencies for corporate chains present in all store type datasets. Approximately 34% of the food environment is represented by these chains across the study area. Walmart, Albertsons, and Safeway had stores represented in both the large and small supermarket datasets. These 15 chains represent 35% of all food stores.

Table 11 Frequency of large chains represented in the store type datasets

Major Chains	**Large Supermarket Counts**	**Small Grocery Store Counts**	**Healthy Fast Food Counts**	**Unhealthy Fast Food Counts**	**Convenience Store Counts**	**Total Counts**
Albertsons	5	2	0	0	0	7
Safeway	4	6	0	0	0	10
Fred Meyer	4	0	0	0	0	4
Grocery Outlet	0	4	0	0	0	4
WalMart	3	1	0	0	0	4
Ray's Food Place	0	5	0	0	0	5
Dari Mart	0	0	0	0	42	42
7-Eleven	0	0	0	0	14	14
Shell	0	0	0	0	9	9
Jacksons Food	0	0	0	0	7	7
McDonalds	0	0	0	21	0	21
Dairy Queen	0	0	0	11	0	11
Taco Bell	0	0	0	9	0	9
Taco Time	0	0	0	8	0	8
Subway	0	0	31	0	0	31
Totals	16	18	31	49	72	186

4.2 Distance Analysis: Proximity

Distances were measured over the road network from each address point (N=153,164) to the nearest store in each class or type. These distances were used as a foundation for grouping and aggregation into CBG units to compare distances to food stores for CBGs with varying minority composition and deprivation index scores. An index was built to characterize relative deprivation from housing unit vacancy rate, low education rate, vehicle ownership, household poverty rate, and median household income on a simple low, medium, or high ranked scale. Minority composition was classified in the same way for comparison purposes.

Less than 1% of the total population of 353,382 in Lane County travels ≥10 miles to all food store types. Overall, 47.9% of the population lives within one-half mile of the nearest food store. Approximately 9% of the population is less than one half mile from a large supermarket and 13% from the nearest small grocery store. Eight percent of residents live more than 10 miles from the nearest large supermarket. Only 2.5% of residents live more than 10 miles from a small grocery store. Better coverage for fast food restaurants and convenience stores provide 95% of the population stores of these types within 10 miles. Nearly one-third of the total population lives within a mile of the nearest large supermarket.

The average distance from residential address points to large supermarkets across the study area is 3.28 miles. The average distances traveled to a smaller grocery store or healthy fast food restaurant are 2.23 and 2.02 miles, respectively. The average distanced traveled countywide to the nearest fast food restaurant and convenience stores are 1.89 and 1.05 miles, respectively. The detail of these finer grained measurements were lost in the process of aggregation into CBGs in order to evaluate associations between travel distance and minority composition and poverty. Figures 6 through 10 highlight network distances to the nearest food store by type.

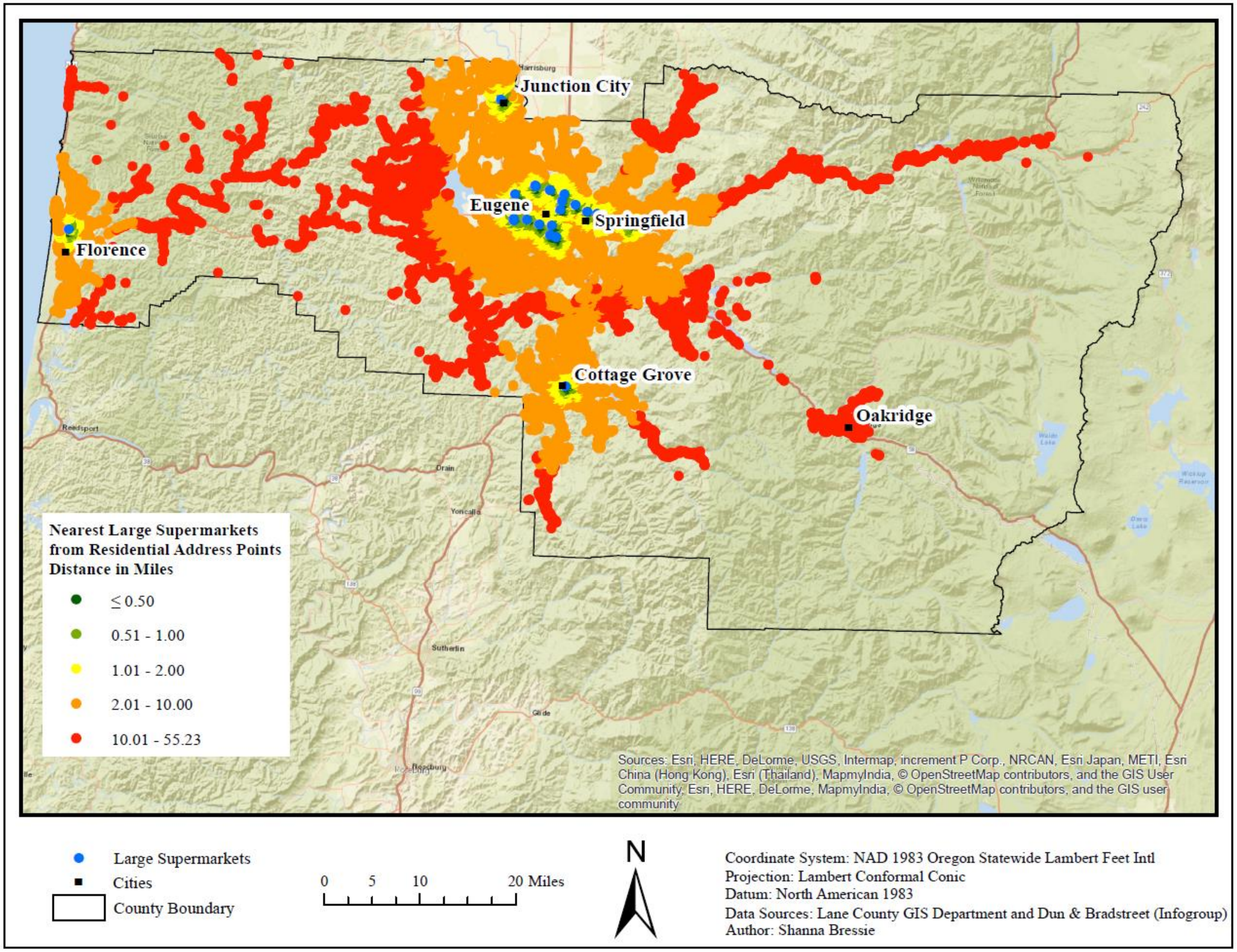

Figure 6 Network distance to nearest large supermarket from residential address points (N=23), where N is the store count

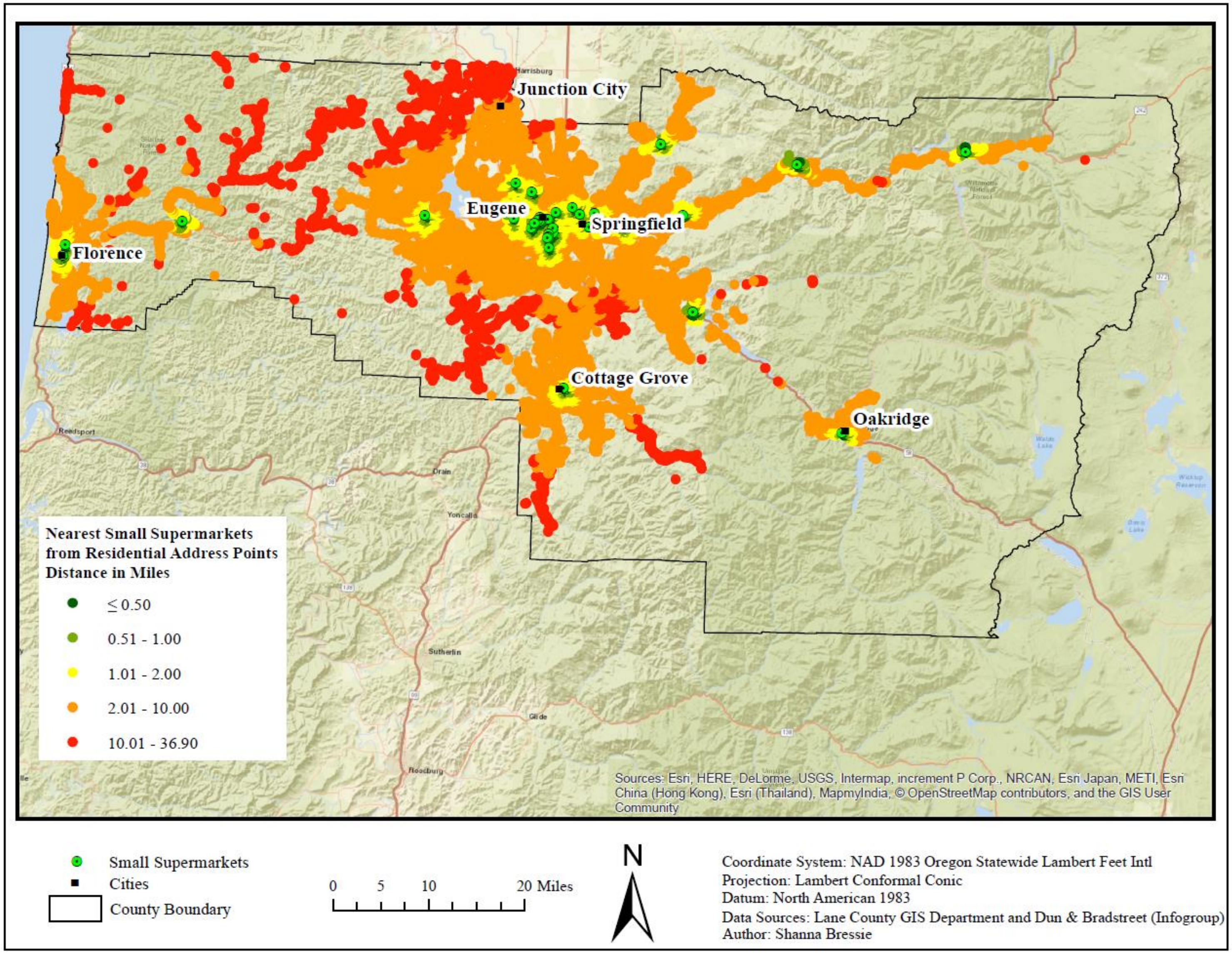

Figure 7 Network distance to nearest small grocery store from residential address points (N=46), where N is the store count

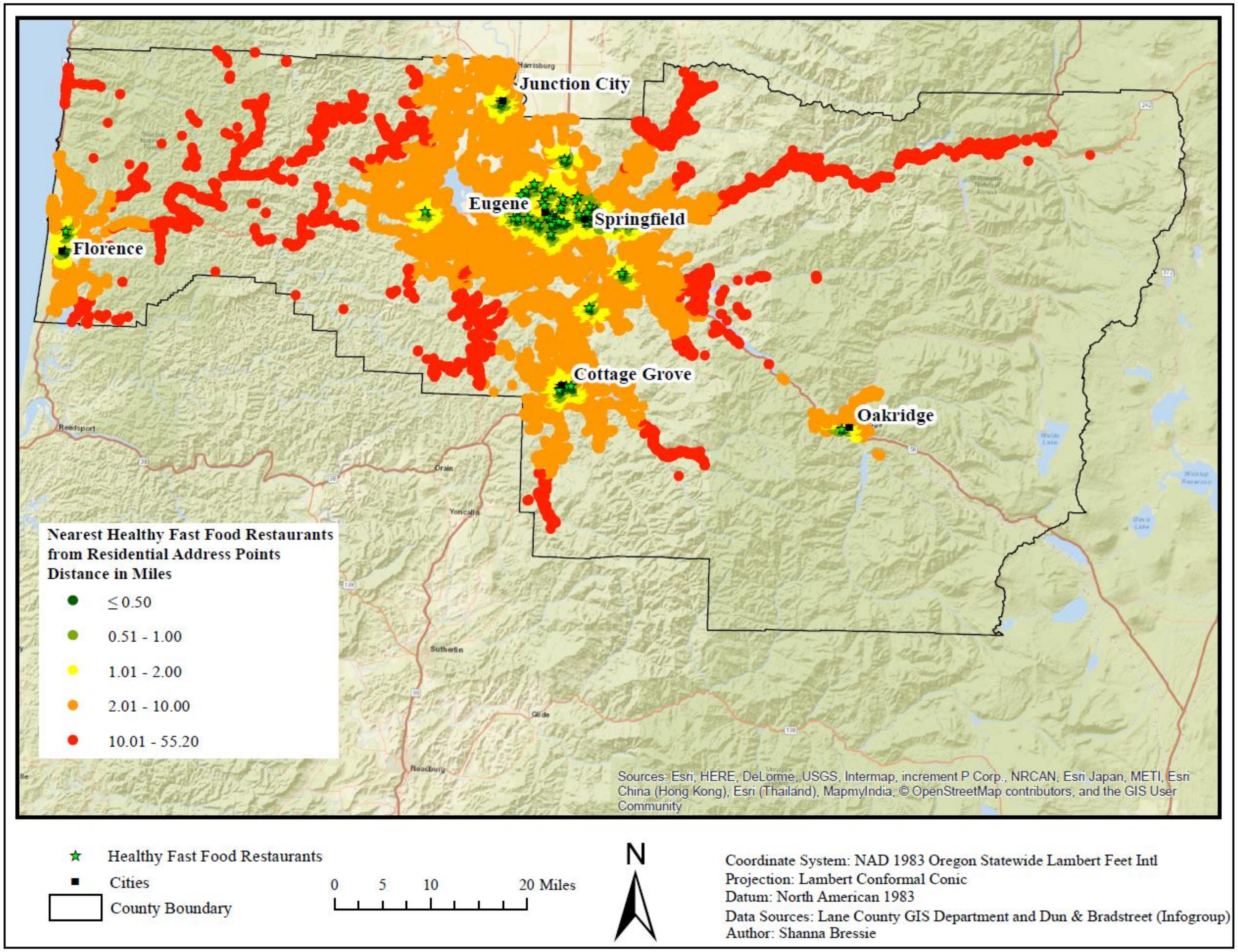

Figure 8 Network distance to nearest healthy fast food restaurant from residential address points (N=60), where N is the store count

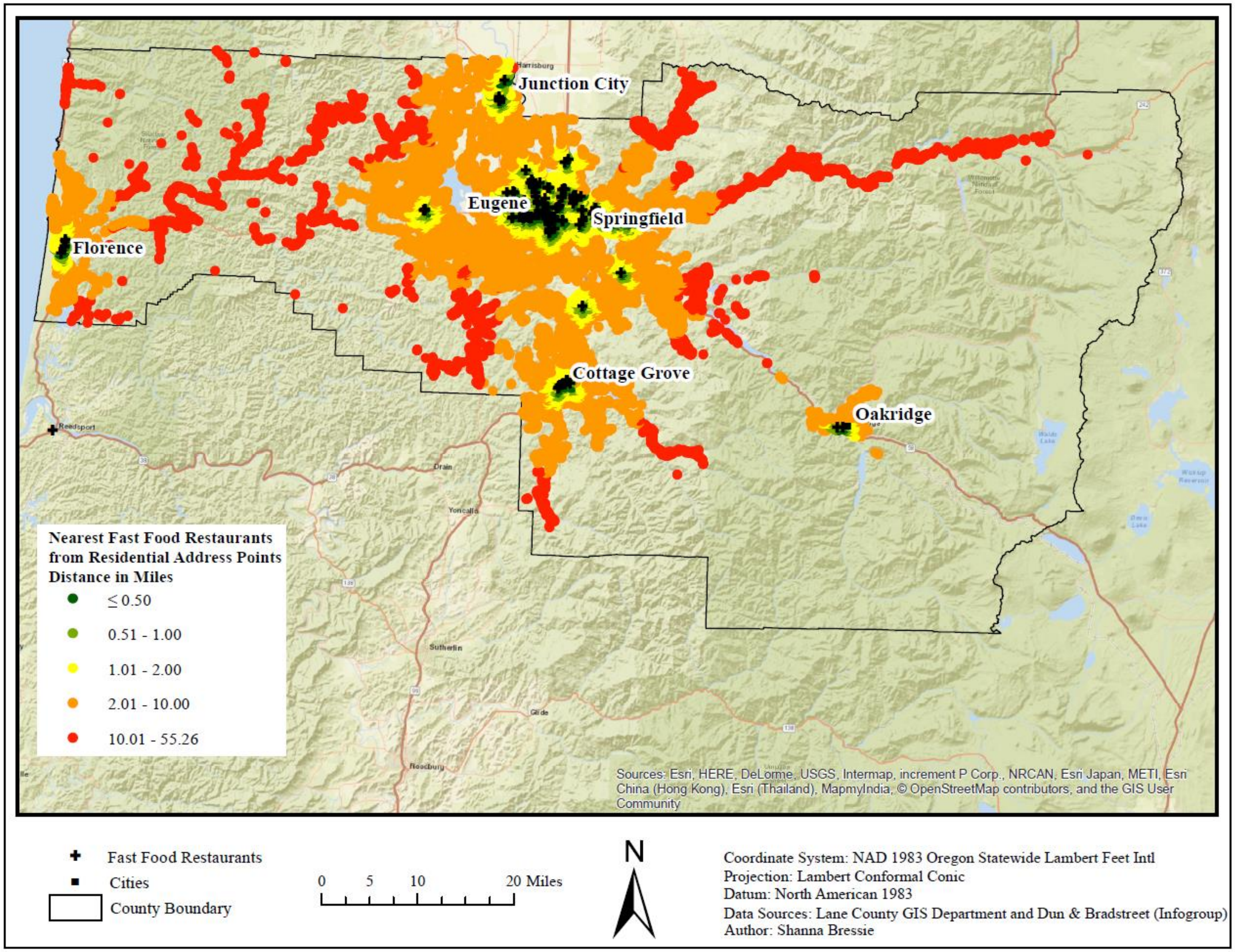

Figure 9 Network distance to nearest fast food restaurant from residential address points (N=177), where N is the store count

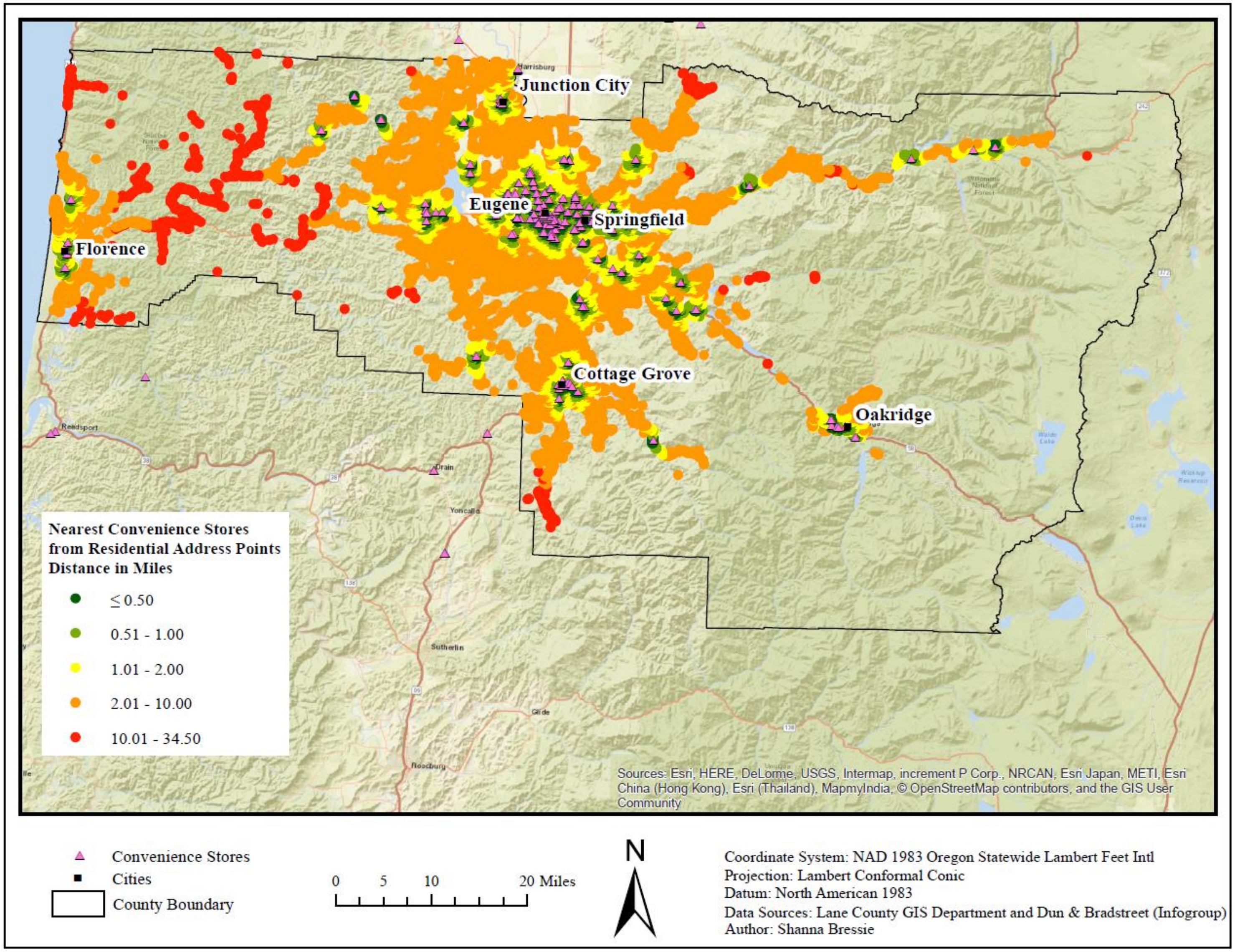

Figure 10 Network distance to nearest convenience store from residential address points (N=233), where N is the store count

Table 12 summarizes the population and household ratios in service areas for five store types using five distance bands and the average nearest distance to each store type within each distance band. The distance bands used the same distance class limits as Figures 6 through 10. The colors of the points from the previous maps correspond to the rows in Table 12 as follows: (1) ≤ 0.50 is dark green; (2) 0.51 to 1.00 is light green; (3) 1.01 to 2.00 is yellow; (4) 2.01 to 10.00 is orange; and (5) ≥ 10.01 is red.

The population was estimated at the specified distance ranges by gathering summary statistics from the newly created field in which the population in each CBG was equally distributed to each address point falling within its boundary. The household percentages were derived by gathering address point counts using summary statistics as well. Average distances of the address points for each store type within the ranges were gathered by using SQL queries to select the set of address points at each distance band after joining the table results from each store type following the distance analyses from address points to the closest store by store type. For example, an SQL query for selection of the set of address points that are ≥10 miles from the nearest large supermarket is: ‘CFS_LSM >= 10.01’. Summary statistics were then gathered from attribute fields to generate the summaries for address point distance ranges to each store type at each distance band.

The average distance from address points to large supermarkets for residents living farther than 10 miles from the nearest large supermarkets is 20.73 miles. The average distance to the nearest small grocery store, for residents traveling more than 10 miles to the nearest large market, is 5.55 miles. The same group travels an average of 11.19 miles to the nearest healthy fast food restaurant, 11.05 miles to the nearest fast food restaurant, and 3.97 miles to the nearest convenience store.

Approximately one third of all households are located within a mile of the nearest large supermarket and only 7.15% of households are farther than 10 miles away from the nearest large market. Nearly 38% of households are within the 1.01 to 2.00 mile distance band, whilst the remaining 22% of households are located between the 2.01 and 10.00 distance band for which the average travel distance to the nearest large supermarket is 4.79 miles.

Seventy-one percent of all households are within 2 miles of a large or small market. Approximately 80% and 83% of households are within 2 miles of the nearest healthy fast food and fast food restaurant, respectively. Only 10% of households are located beyond the 2 mile threshold of the nearest convenience store. The distance band 2.01 to 10.00 (i.e. orange dots) covers a large surface area (see Figures 6 through 10). However, the average distance from households to all five store types is only 4.37 miles and these households, on average, account for just 17.43% of all households. Convenience stores were the most accessible and large markets the least accessible at 3.88 and 7.79 miles, respectively (Table 12).

Table 12 summarizes the relationships for each type of food store at the distance bands shown by the point maps (Figures 6 through 10). For example, residents traveling ≥ 10.01 miles to the nearest small market travel nearly the same distance to the nearest large market, approximately 14 miles. Residents in the study area travel shorter distances to small grocers and convenience stores than fast food restaurants of either type and larger supermarkets. Small grocery store locations are more numerous (N=46) and more broadly dispersed across the study area than large markets. Convenience store locations are five times more numerous than small markets and also broadly dispersed. Though consumer preference and travel behavior are important factors, they were not considered this analysis. These factors may motivate residents to shop for food at locations that are not the nearest store to their homes.

Table 12 Populations served and mean distances from address points to five types of food stores

Distance Bands (Miles)	Population %	Household %	Large Supermarkets	Small Supermarkets	Healthy Fast Food Restaurants	Fast Food Restaurants	Convenience Stores
Large Supermarkets							
≤ 0.50	8.82	9.23	0.35	0.87	0.45	0.38	0.32
0.51 to 1.00	22.93	24.14	0.75	1.17	0.70	0.59	0.50
1.01 to 2.00	37.51	37.87	1.47	1.63	1.05	0.96	0.67
2.01 to 10.00	22.83	21.61	4.79	3.96	2.83	2.63	1.68
≥ 10.01	7.91	7.15	20.73	5.55	11.19	11.05	3.97
Small Supermarkets							
≤ 0.50	12.91	14.05	1.68	0.30	0.88	0.75	0.36
0.51 to 1.00	19.58	20.81	2.15	0.75	0.91	0.83	0.54
1.01 to 2.00	29.66	31.08	2.29	1.47	1.27	1.14	0.76
2.01 to 10.00	28.28	26.91	5.54	4.54	3.77	3.64	1.87
≥ 10.01	2.49	2.03	13.83	13.75	11.49	11.28	5.48
Healthy Fast Food Restaurants							
≤ 0.50	19.49	20.59	1.32	1.13	0.32	0.44	0.30
0.51 to 1.00	29.66	31.08	1.91	1.38	0.73	0.68	0.53
1.01 to 2.00	29.46	29.15	2.61	2.11	1.39	1.10	0.80
2.01 to 10.00	17.54	15.65	6.06	4.44	4.16	3.91	2.44
≥ 10.01	3.85	3.54	20.07	7.34	18.95	18.79	5.96
Fast Food Restaurants							
≤ 0.50	27.11	28.87	1.59	1.16	0.59	0.29	0.33
0.51 to 1.00	29.83	30.24	2.12	1.64	0.92	0.74	0.59
1.01 to 2.00	24.62	24.35	2.49	2.11	1.32	1.37	0.87
2.01 to 10.00	14.60	13.02	6.74	4.82	4.54	4.50	2.73
≥ 10.01	3.84	3.52	19.91	7.33	18.79	19.02	6.05
Convenience Stores							
≤ 0.50	41.03	42.63	2.15	1.38	0.93	0.80	0.28
0.51 to 1.00	32.12	31.98	2.61	1.88	1.38	1.24	0.71
1.01 to 2.00	14.82	14.63	3.37	2.64	2.45	2.28	1.35
2.01 to 10.00	11.21	9.96	8.76	5.77	6.76	6.76	3.88
≥ 10.01	0.82	0.80	20.65	9.72	18.82	19.19	15.04

4.2.1. Food Store Distribution

Accessibility to all food store types increases in areas with higher population densities. Most large supermarkets, for example, are located in Eugene-Springfield or along major roadways, the I-5 and 101 which are oriented north and south (Figure 11). Large markets make up only 4% of the local retail food environment. People living within two miles of the urban center have better access to supermarkets. People living in smaller towns must travel farther to large supermarkets. Smaller grocery stores fill the gap in terms of providing more options and coverage between large supermarkets and supercenters. Smaller grocery stores account for one-third of the number of stores classified as selling healthy food. The pattern for smaller markets is concentrated in the city center with several stores in smaller towns and along secondary routes on the periphery. Fast food options follow the same pattern as large markets with the greatest number concentrated in the urban core and along the two major north-south travel routes. Convenience stores make up 43% of the retail food environment. They are located in small towns and along secondary roads.

Healthy food stores, supermarkets and healthy fast food restaurants, account for 129 of the total number of stores (N=539). Overall, 23.9% of the food outlets across the study area provide healthy foods. This does not consider product quality, pricing, or purchasing behavior associated with healthy food. Figure 11 shows large supermarket chains, based on the residential address points. Seven corporate chains and one employee owned chain represent the retail food environment. Albertsons might serve as many as 48,787 households, Safeway might serve as many as 32,245, and Fred Myer might serve as many as 23,342 households based on this analysis. These three chains represent large supermarket locations that are the nearest market to 68% of households in the study area.

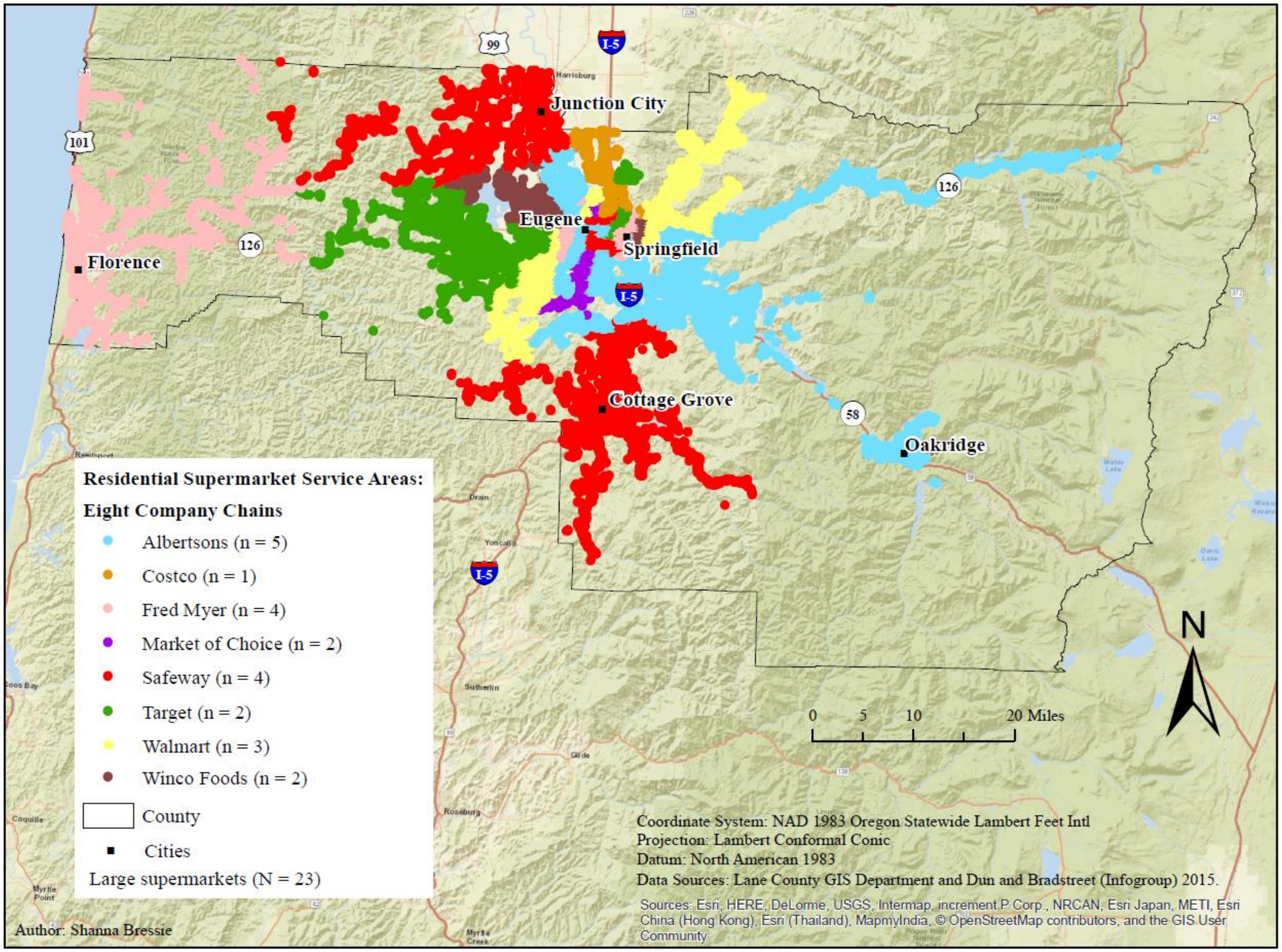

Figure 11 Delineation of service areas for large supermarkets by chain based on residential addresses and nearest store measurements, where n is the number of stores represented for each company and N is the total number of stores in the dataset

4.3 Address Points Aggregation to Areal Units

The distribution of address points across the study area coincide with street networks. In urban neighborhoods with more streets the address point dataset is denser than that of more rural neighborhoods with fewer streets. Dwelling units are the most abundant and dense within the city limits of Eugene. Smaller communities of various sizes are found throughout the periphery of the study area. Figure 12 records the number of residential address points on the yellow label in each grid cell. The grid provides a reference for housing point densities in grid cells that are 10 miles by 10 miles. The two cells that encompass most of Eugene-Springfield are the densest with 72% of address points falling within 200 square miles.

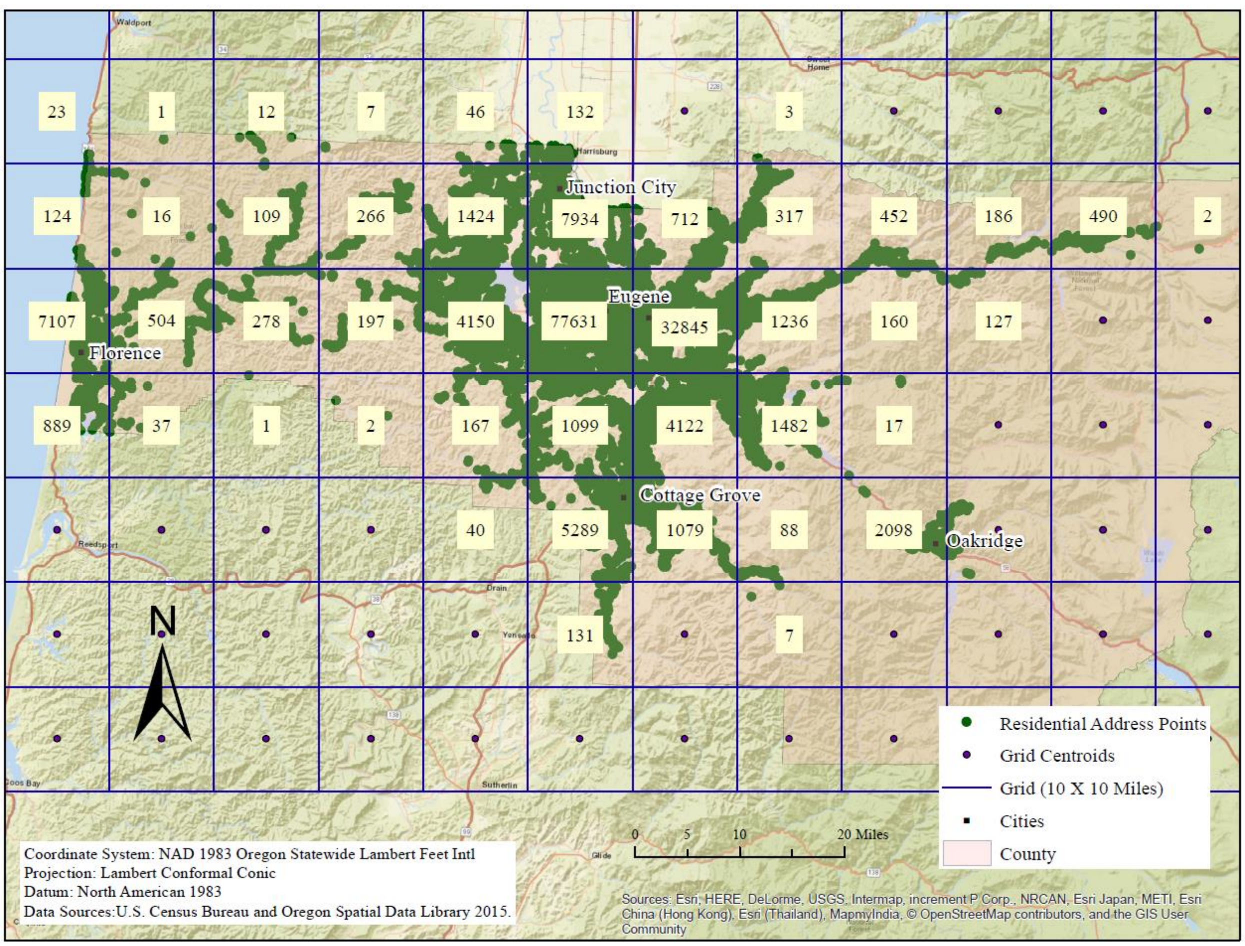

Figure 12 Residential address point data point densities in 10 by 10 mile grid cells

Average distance measurements from the 153,164 address points to large supermarkets was 3.28 miles prior to and 3.98 miles following aggregation to CBG units. The total number of CBGs in Lane County is 257. The statistics associated with the following figures were derived from selections of the CBG average distances and the summary of address points within the areal unit boundary. Ninety-three percent of the population is represented within ± 0.5 standard deviations of the mean distance of 3.98 miles. The standard deviation is 6.55 miles. The yellow colored areas in the center of the map show the best access to large supermarkets in the Willamette Valley and at the coast. Access decreased along the Coastal Range and in the foothills of the Cascades. Residents living in CBGs with distances displayed make up 7.4% of the overall population, derived from summary statistics on the selection by location set from the 'POP_REDIST_CBG_TO_ADD' attribute which was created in the process described in Section 3.3.1. CBGs where residents must travel more than 10 miles, on average, to the nearest large supermarket are shown in green shades in Figure 13.

Relative ease of access is shown along the major north-south travel routes in the region. The Pacific Coast Highway number 101 is the main connector for access to food stores along the coast near Florence. In the Willamette Valley, Highway 99 serves as the major connector for Junction City and west Eugene, while the I-5 is the major corridor for downtown Eugene-Springfield and Cottage Grove. The transportation network is denser near the main corridors and thereby provides the best access to food stores of all types. The address point set was very dense in areas where road networks support neighborhood traffic. In CBGs where average distances are more than 10 miles to the nearest food stores the address points were situated along county roads and secondary streets.

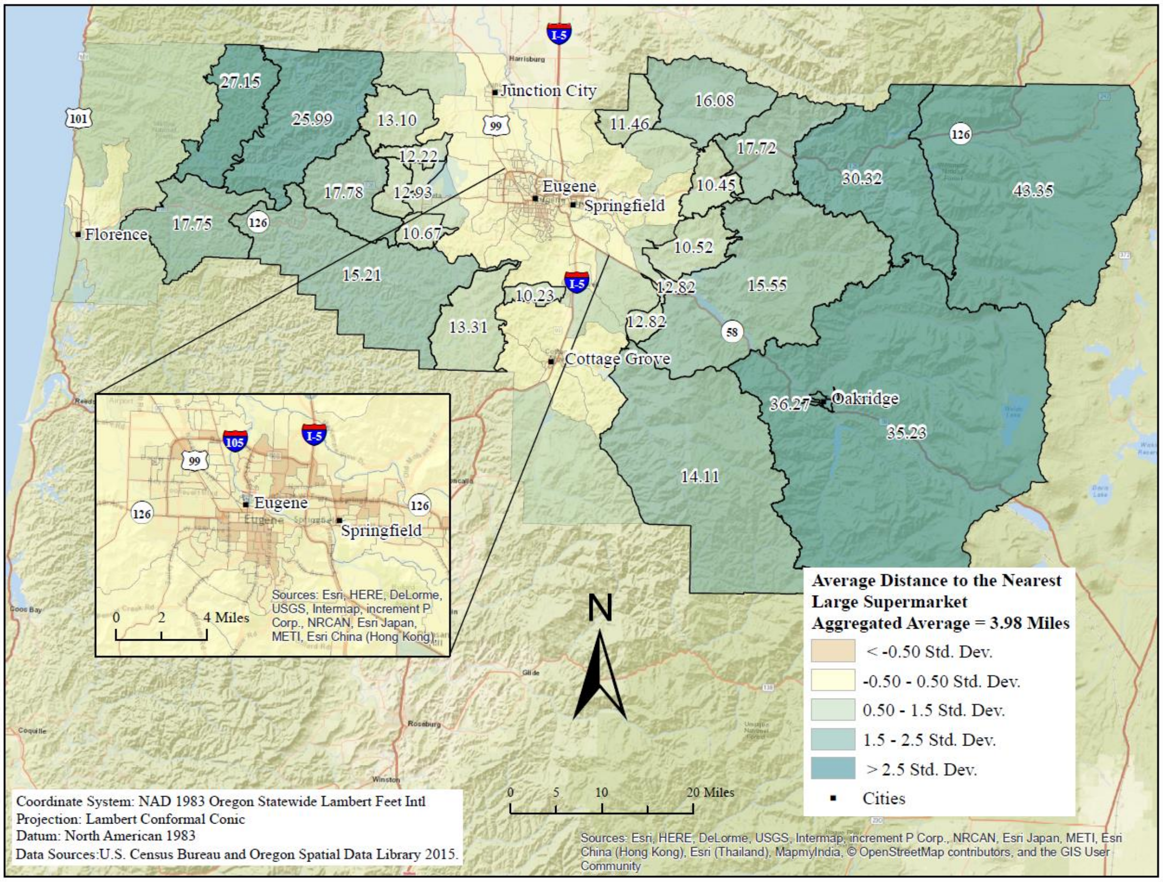

Figure 13 Distance to large supermarkets aggregated by CBG, displayed distances are > 10 miles traveled (n=27), n is the number of CBGs in the selection set

The pattern seen for travel distances to large supermarkets is similar to the overall pattern for all healthy food stores. However, the addition of small grocery stores and supermarkets as well as delicatessens and sub shops reduced the average distances one must travel to reach healthy foods. The smaller stores are five times as numerous and also more evenly dispersed across secondary roads. Distances to healthy food stores were aggregated to CBGs and distance calculations to large supermarkets, small supermarkets, and delicatessen datasets were averaged. Approximately 5% of the population lives in the 18 CBGs where travel distances to the nearest healthy food store are greater than 10 miles. Figure 14 illustrates the average distances traveled to the nearest healthy food store by residents in smaller communities outside of Eugene-

Springfield and the major transportation corridors. The average distance traveled to healthy food stores across the study area was 3.04 miles.

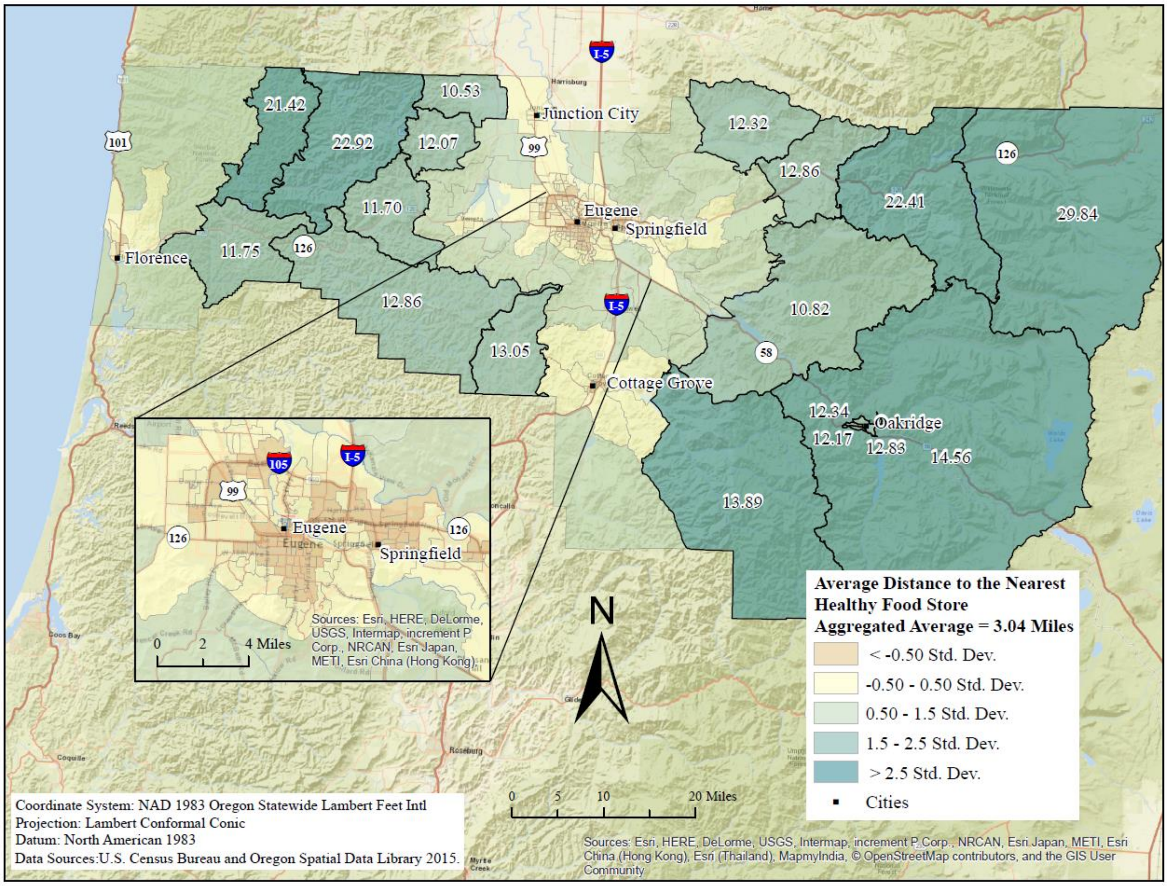

Figure 14 Average distances to the nearest healthy food stores aggregated by CBG, displayed distances are > 10 miles traveled (n= 18), n is the number of CBGs in the selection set

Convenience stores and fast food restaurants were classified as unhealthy food stores. The distance calculations from residential address points to unhealthy food stores were also aggregated and averaged. The results for the set selection of residents traveling farther than 10 miles to unhealthy food stores are shown in Figure 15. The map reveals that the abundance of convenience stores provide ready access to smaller communities. Only 1.8% of the population travels farther than 10 miles to reach the nearest unhealthy food store.

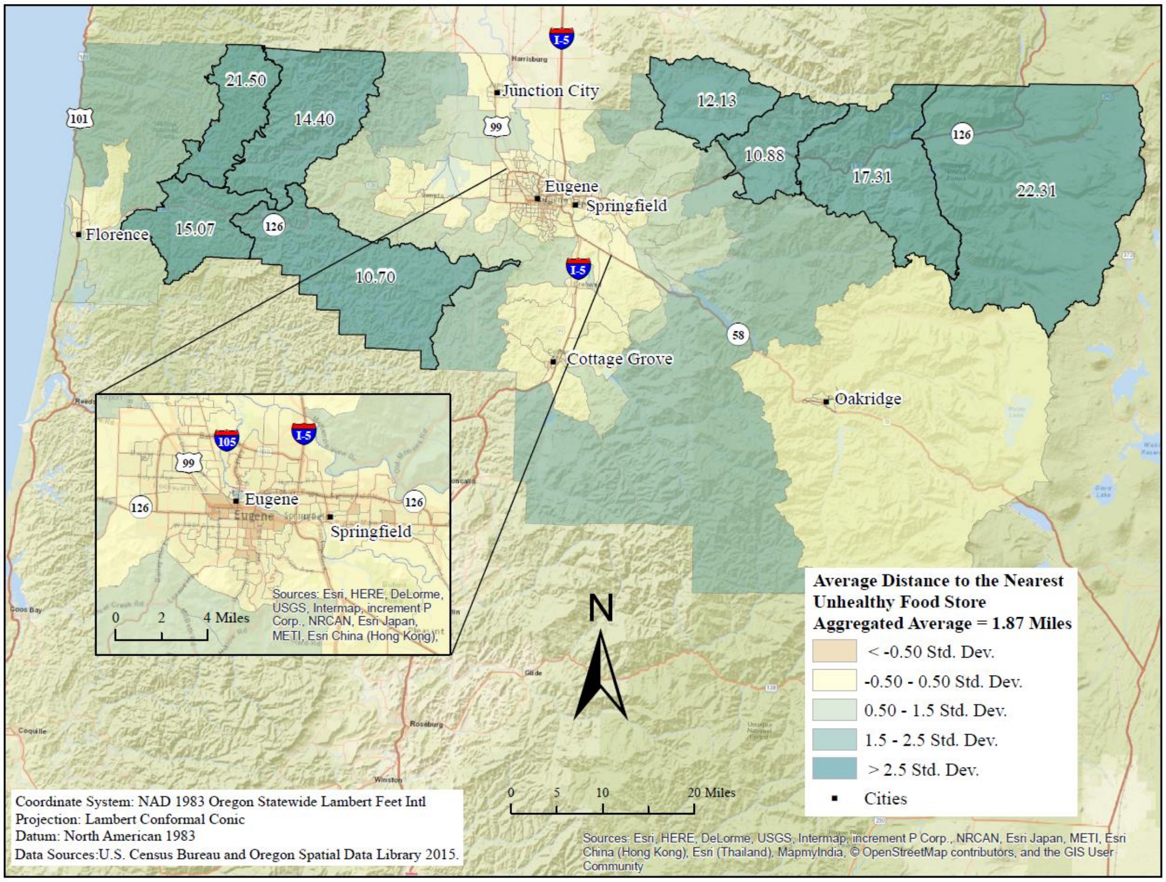

Figure 15 Distance to large supermarkets aggregated by CBG, displayed distances are > 10 miles traveled (n=8), n is the number of CBGs in the selection set

Overall, residents within Eugene-Springfield have better access to all food store types than residents living in smaller communities out in the county. Large food retailers are situated in the most densely populated areas of the county. Small supermarkets and locally owned grocery stores provide residents with an alternative to longer travel times. For example, the Oakridge community relies on Ray's Food Place for local grocery shopping. The alternative is a 70 mile round-trip to the nearest large supermarket, Albertsons in Springfield. Several small grocery stores are situated in communities with fewer residents than Oakridge. These stores increase food access for residents in suburban and rural neighborhoods.

4.3.1. CBG Minority Composition and Deprivation

Minority composition was classified into low, medium, and high groups using the following thresholds: (1) low = 0-16.9%; (2) medium=17-24.8%; and (3) high=25-42% (Figure 16). Average travel distances to the nearest large supermarket in the CBGs with low minority composition is the highest at 5.28 miles. Residents living in CBGs with medium and high minority compositions, travel 1.65 and 2.11 miles, respectively to large supermarkets.

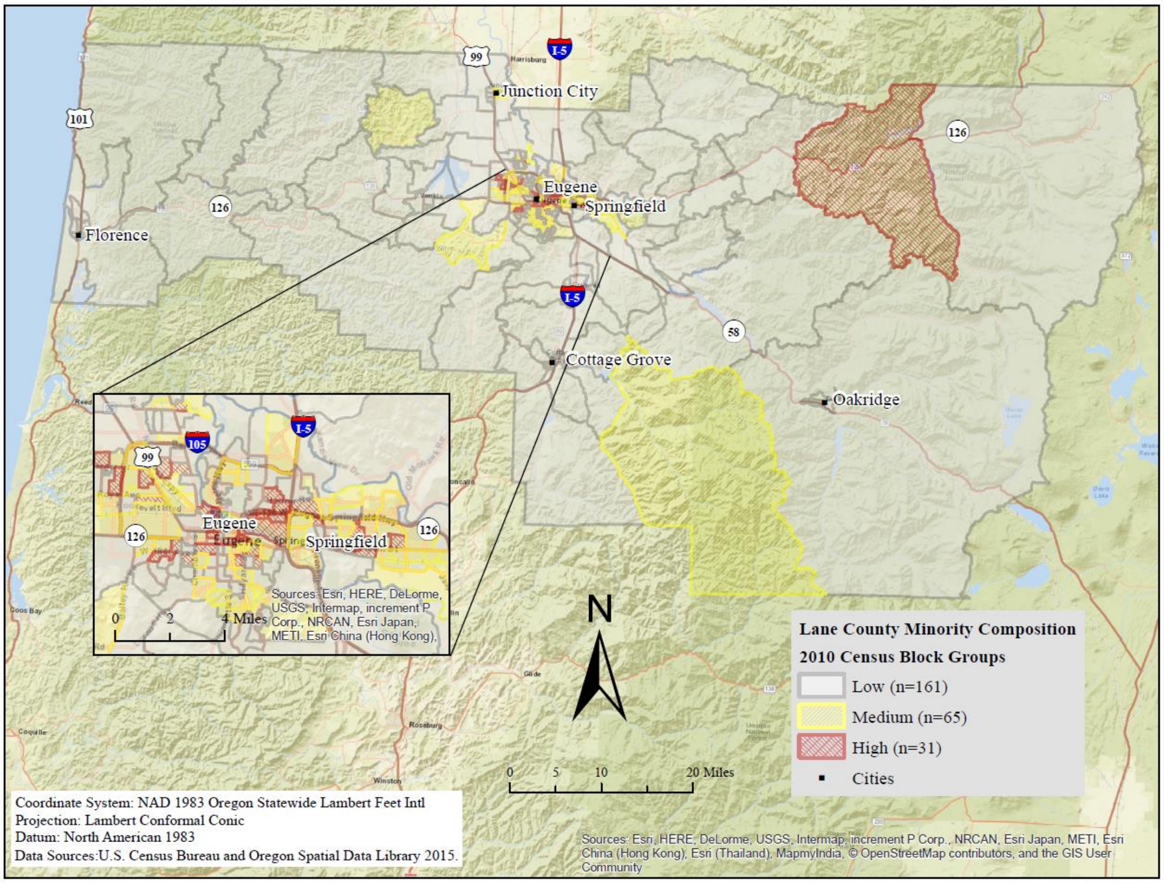

Figure 16 Minority composition in Lane County, OR by CBG, n is the number of CBGs in each category

The largest CBG with high minority composition east-north-east of Eugene-Springfield mapped in red cross-hatch covers 204 square miles and includes 0.03% of the total population. The average distance to the nearest large market following aggregation was 30.32 miles.

Residents living in CBGs with high relative minority composition, taken as a whole, travel less than half the average distances as residents in low minority composition CBGs. The results confirmed that the null hypothesis, that residents living within CBGs with high minority composition travel farther the than average distances traveled to large supermarkets by the total population, is rejected in favor of the alternative hypothesis. The alternative hypothesis is stated as the distance that residents travel from high minority composition CBGs is less than the average distance traveled by the total population from residential address points to large supermarkets. Minority composition was inversely associated with travel distances to large supermarkets. As minority composition increased the distances to large supermarkets decreased.

The deprivation index, which was built by classifying household poverty rates, percentage of households without vehicles, low education rates, housing vacancy rates, and median incomes into quintiles, and then low, medium, and high ranks, as seen in Figure 17. The low group's average travel distance to the nearest large supermarket is 3.89 miles. The medium and high groupings' travel distances are 4.08 and 4.10 miles, respectively. The residents in low deprivation CBGs travel two-tenths of a mile less on average to the nearest large supermarket than residents living in CBGs with medium and high deprivation ranks. The USDA threshold for rural residents in the US is 10 miles. The urban area threshold is ≤ 1 mile. Residents living beyond these threshold distances to the nearest grocery store live in areas of poor food access (Ver Ploeg et al. 2009). Some may consider these types of low access areas food deserts. The high deprivation group's average travel distance is only 4.10 miles. However, the residents in two high deprivation scored CBGs travel more than 35 miles on average from the mountainous areas to reach the nearest large market.

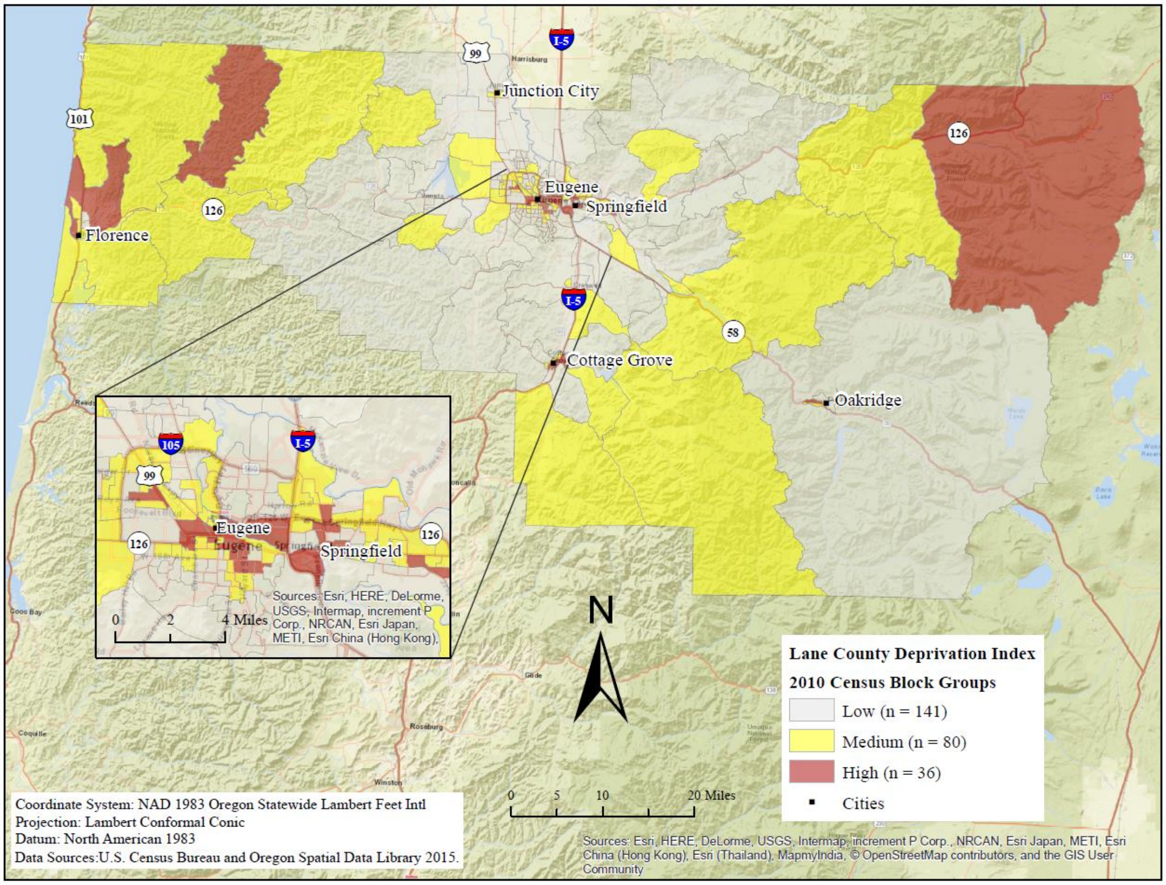

Figure 17 Deprivation index composite of socioeconomic variables in Lane County, OR, n is the number of CBGs in each category

Figure 18 is an overlay combination of the results of the minority compositions, deprivation index, and labeled CBGs where residents travel farther than the 10 mile threshold to the nearest large supermarket. Two CBGs beyond the threshold that ranked medium for deprivation and minority composition are shown with diagonal hatch over yellow. The average distance to a large market is 13.61 miles.

The single medium deprivation ranking and high ranked minority composition CBG beyond the 10 mile distance threshold is seen with a cross hatch over yellow in Figure 18. The distance to the nearest large market is 30.32 miles while the average distances to healthy and unhealthy food stores are 22.41 and 17.31 miles, respectively for this particular CBG. The three

CBGs with high deprivation scores (red) as well as the CBG with a high minority composition score and a medium deprivation (crosshatch and yellow) make up 1,586 households and <1% of the total population. Residents in these areas travel farther to food stores and may face economic disparities that create barriers to healthy food accessibility.

The smaller area shown in the inset in Figure 18 is the Oakridge Community. It is the largest in population of several smaller towns located in the foothills of the Cascade Range. Hummel (2012) suggested that the food security for the people in Oakridge relies on fishing, hunting, emergency food banks, and regular community hosted dinners to fill the grocery gap in an area characterized as medium to high deprivation. Residents in Oakridge travel >35 miles to the nearest large supermarket (Figure 18). However, households in this area are only 1.64 miles, on average, from the nearest small grocery store.

Residents in the mountain ranges that flank Eugene and Springfield may spend more time and resources on grocery trips. Travel distances to all five food store types are the greatest in the mountains and foothills. The public transportation system provides two trips per day to Florence and Oakridge to ease residents' ability to get to Eugene. Drive times may increase for travelers in rural areas because the roads are often narrow and curvy. Travel times may increase or become impossible during the winter due to snow and ice covered roads.

The CBGs that rank 'high' in both deprivation and minority composition are centrally located in Eugene-Springfield. The 7,165 households in these CBGs make up approximately 4% of the total population. Sixty-nine percent of these households, or approximately 4% of the total population, travel $\geq$ 0.5 mile to the nearest large supermarket while approximately 3% travel $\geq$1 mile to the nearest large market. Residents in these areas may experience lower food access.

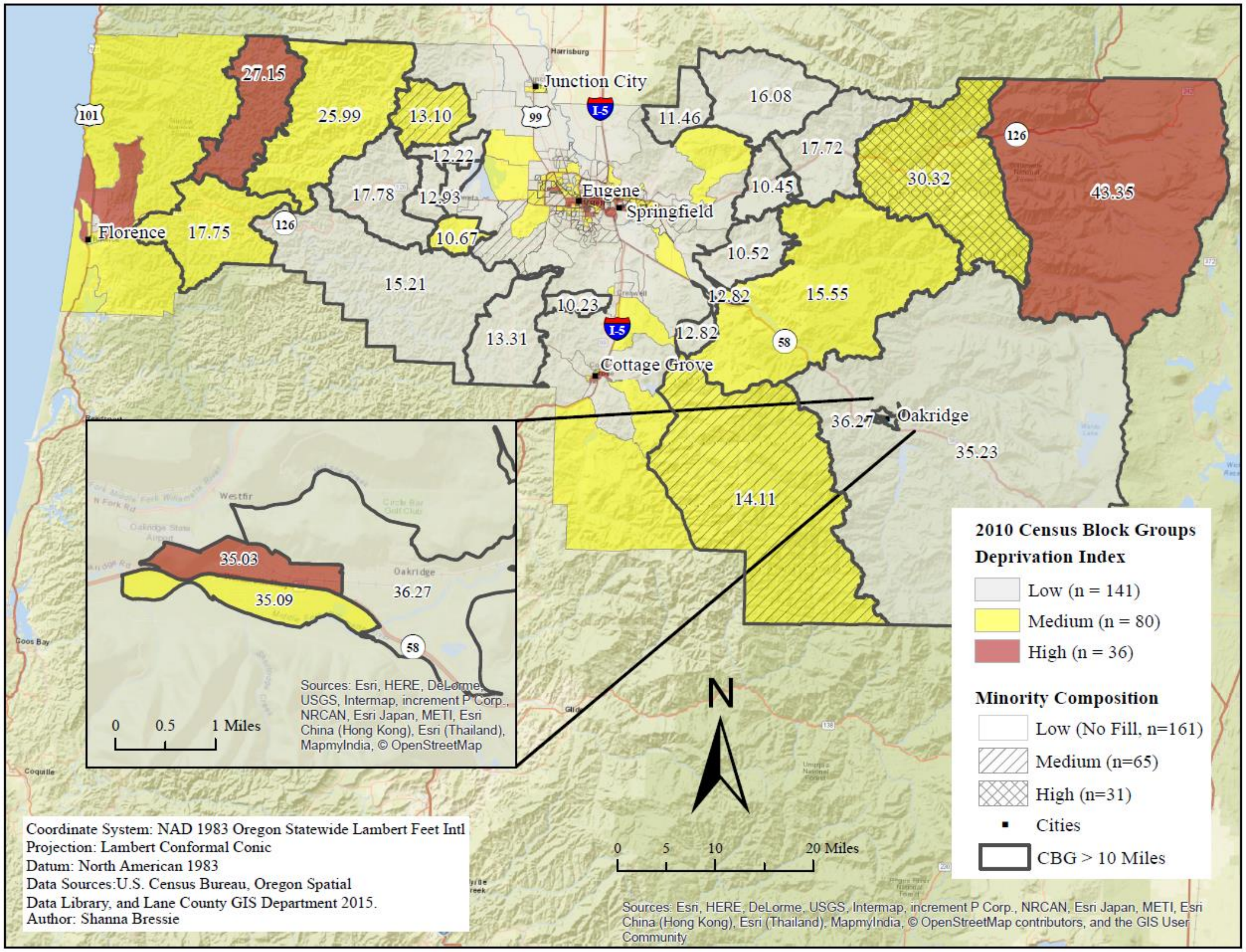

Figure 18 CBG (N=257) average distances to the nearest large market >10 miles, minority composition, and social deprivation, n is the number of CBGs in each category and N is the total number of CBGs

The most walkable area represented in Figure 19 is the CBG with an average distance of 0.51 miles. The CBGs with average distances of < 1 mile are more accessible in that they are within short walking or biking distance. Residents living in the two CBGs with average distances of 1.77 and 1.82 miles may experience travel challenges to access the nearest large supermarket. Private cars and public buses may be the easiest way for people living in these two CBGs to get across the major roadways between address points and large supermarkets nearby.

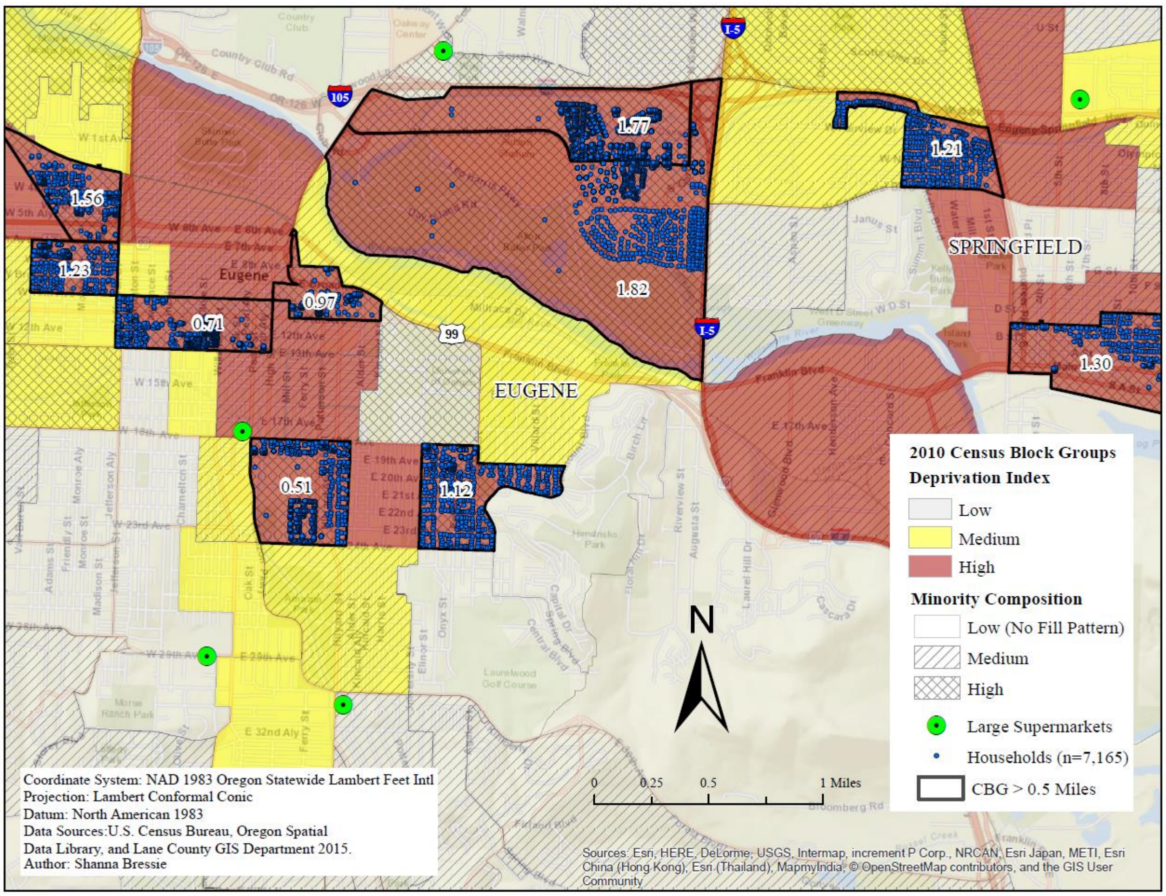

Figure 19 Urban area CBG average distances to the nearest large supermarket with high economic deprivation and minority composition index scores

4.3.2. Food Store Access

The travel distances and dispersion patterns for large markets and both types of fast food stores are similar. The dispersion pattern of small markets and convenience stores across the study area are similar to each other in that these market types are closer to residential addresses than large markets and fast food restaurants. People across the study area have better access to unhealthy fast food and convenience stores than grocery stores and healthy fast food restaurants because these store types are more abundant.

Several smaller grocery stores are located on the periphery of Eugene. The presence of small grocers provides food access to people between shopping trips to larger markets in the more rural areas in Lane County (Hummel 2012). They are dispersed more evenly across the study area than larger markets but are not as numerous as convenience stores. Smaller markets stock a variety of essentials like fresh produce, meats, dairy, grains, and household supplies. An owner of an independent small grocery store stated, “we carry a bit of everything to get people by until their bigger shopping trips” in a call with the author verifying that the location is currently operational. Residents in high deprivation CBGs travel shorter distances to shop there than in medium or low deprivation CBGs to small markets and convenience stores than other store types. Hummel (2012) surveyed residents in a small community east of Springfield to determine where food was obtained and reported that 70% of the respondents commuted to Springfield for staple items.

Smaller grocery stores in rural areas may be close and within the boundary of a CBG that is classified as high deprivation, but high prices may create a barrier for low-income residents and “would be” shoppers. A small grocery store owner in Blue River, nearly 40 miles east of Springfield, stated in an interview that the business is geared toward summer tourism and item pricing schemas reflected higher prices than larger supermarkets and small grocery stores nearer and in Springfield (Hummel 2012). Though distance may not be a barrier for residents in CBGs with high deprivation and easy access to small rural grocery stores, financial barriers may produce disparities for equal food access based on product affordability for consumers and seasonal operating costs for businesses.

Fast food restaurants in both categories are located on major roads and located in the same areas as large supermarkets. The pattern of dispersion across the study area and average distances to both types of fast food restaurants and supermarkets are more or less identical. Additionally, fast food locations outnumber large markets 10 to 1 with a few locations in small towns providing more opportunity and better access than is the case for large markets.

Convenience stores make up 43% of the retail food environment. Approximately one-half of all 257 CBGs in Lane County, OR currently contains at least one convenience store. The average distance from residential addresses to convenience stores is 1.7 miles. They are distributed similarly to smaller grocery stores across the study area as shown in Figures 7 and 10. However, convenience stores outnumber small grocers 5 to 1 and they are located within 2 miles of the residences of 88% of the total population (Table 12). Residents living in high minority composition and high deprivation CBGs travel distances of only 0.29 miles on average, as seen in the last row of Table 13 for the high deprivation and high minority grouping. Residents living in CBGs ranked as high minority composition classified as medium deprivation travel farther to all store types than residents in low or high deprivation CBGs.

Residents living in CBGs with low minority composition travel greater distances to all five food store types. Residents living in CBGs with high minority composition and medium deprivation travel average distances of 3.43 miles to large supermarkets and healthy fast food restaurants (Table 13). The same group travels 0.75 miles to convenience stores, 1.50 miles to small grocery stores, and 3.01 miles to fast food restaurants. The residents living in CBGs with

Table 13 CBG average distances from residential addresses to different types of food stores summarized by deprivation and minority composition groups

Food Store Type and Deprivation Index	Low Minority Composition	Medium Minority Composition	High Minority Composition
Supermarkets			
Low	4.71	1.51	1.07
Medium	5.54	2.10	3.43
High	8.80	1.02	1.22
Small Grocery Stores			
Low	3.24	1.74	1.14
Medium	3.30	2.34	1.50
High	2.10	0.79	0.74
Healthy Fast Food Restaurants			
Low	4.71	1.51	1.06
Medium	5.54	2.10	3.43
High	8.79	1.01	1.22
Fast Food Restaurants			
Low	2.63	1.26	0.63
Medium	3.39	1.46	3.01
High	5.85	0.39	0.68
Convenience Stores			
Low	1.52	0.87	0.53
Medium	1.91	0.74	0.75
High	2.14	0.33	0.29

medium minority composition and deprivation travel average distances of slightly over 2 miles to all healthy food store types and approximately 1 mile to both types of unhealthy food stores. All residents travel under 2 miles to the nearest convenience store with the exception of the grouping for low minority composition and high deprivation (2.14 miles). Residents in low minority composition and high deprivation CBGs travel 8.80 miles to the nearest large supermarket and 5.85 miles to the nearest fast food restaurant. This last group represents 4.4% of the total population.

4.4 Healthy and Unhealthy Food Store Presence for Address Point

This analysis recorded the presence or absence of healthy and unhealthy food stores within 0.5, 1, 2, and 5 mile distance bands. Several researchers argued in recent works that relative metrics are consistent with health outcomes due to a comprehensive framework that includes both types of food outlets. Decision making surrounding food purchases is impacted by the types and abundance of food stores directly available to people in their local food environments (Alnasrallah 2012, Luan et al. 2015, Morland 2015, Zenk 2015).

The percentages of households at each distance band that contain either healthy, unhealthy, or both types of food stores are: (1) 50% at 0.5 miles; (2) 79% at 1 mile; (3) 91% at 2 miles; and (4) 98% at 5 miles. The results for each distance band at each address point are color coded as follows: (1) red dots represent at least one unhealthy and no healthy food stores are present; (2) blue dots represent at least one healthy and no unhealthy food stores are present; (3) purple dots represent at least one unhealthy and one healthy food store are present; and (4) grey dots represent that both healthy and unhealthy food stores are not present. As the distance bands were expanded the frequencies and sizes of service areas defining conceptual food deserts and swamps changed.

The grey areas represent food deserts and these areas have no food stores present. The percentages of households with no food stores present (food deserts) within the given distances were 50%, 21%, 9%, and 2% for the 0.5, 1, 2, and 5 mile distances bands, respectively. The purple areas represent households with at least one healthy food store and one unhealthy food store within the given distance band. The blue areas are homes with access to healthy food stores only within the given distance band. The red areas in Figures 20 through 24 represent households that have access to unhealthy food stores only (food swamps) within the given distance band.

The Eugene-Springfield area has the largest representation of purple dots at all distance bands across the study area. The smaller cities like Florence and Oakridge have central clusters of purple dots adjacent to a cluster of blue dots. Clusters of red dots are found on either side of the central blue and purple clusters. Convenience stores and fast food restaurants are located along Highway 101 to the north and south of Florence's central business district. Convenience stores are located at both ends of Oakridge along Highway 58. The residents living in households in these areas have to travel farther to the nearest healthy food store.

Figures 20 and 21 show households with accessible food store types tightly clustered in urban areas and along major roads in small towns within the 0.5 and 1 mile distance bands, respectively. The red dot clusters along the I-5 Interstate and State Highways 126, 58, and 99 as well as secondary roads represent the location patterns of convenience stores. The grey dots cover a large surface area at the 0.5 mile distance band area that decreased as the distance bands were expanded. The inset maps of Eugene-Springfield show potential food desert and food swamp areas decreasing in surface area as distances were relaxed to include more food outlets.

Figures 22 and 23 show households within the 2 and 5 mile distance bands, respectively. The surface area of food deserts decreased and included < 10% of all households at the 2 and 5 mile distance bands. Areas with blue and purple dots clustered along major roadways in rural areas show the potential access to small grocery stores. The purple areas surrounded several of the blue and red dot clusters in urban areas and along the major roads. Red dot clusters that are potential food swamp areas impacted < 6% of all households across the study area.

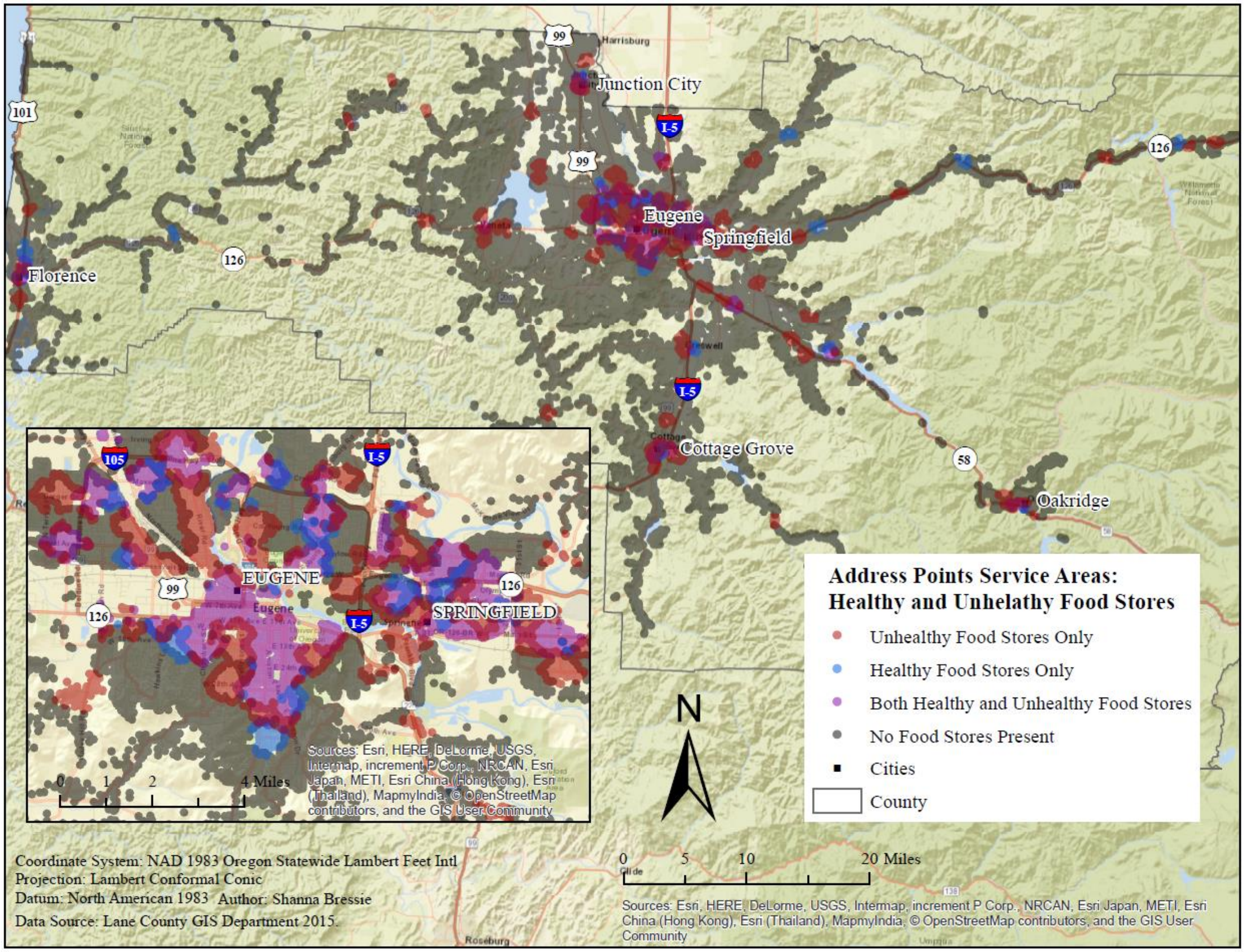

Figure 20 Half mile distance band for healthy and unhealthy food store presence calculated from address point proximity distances

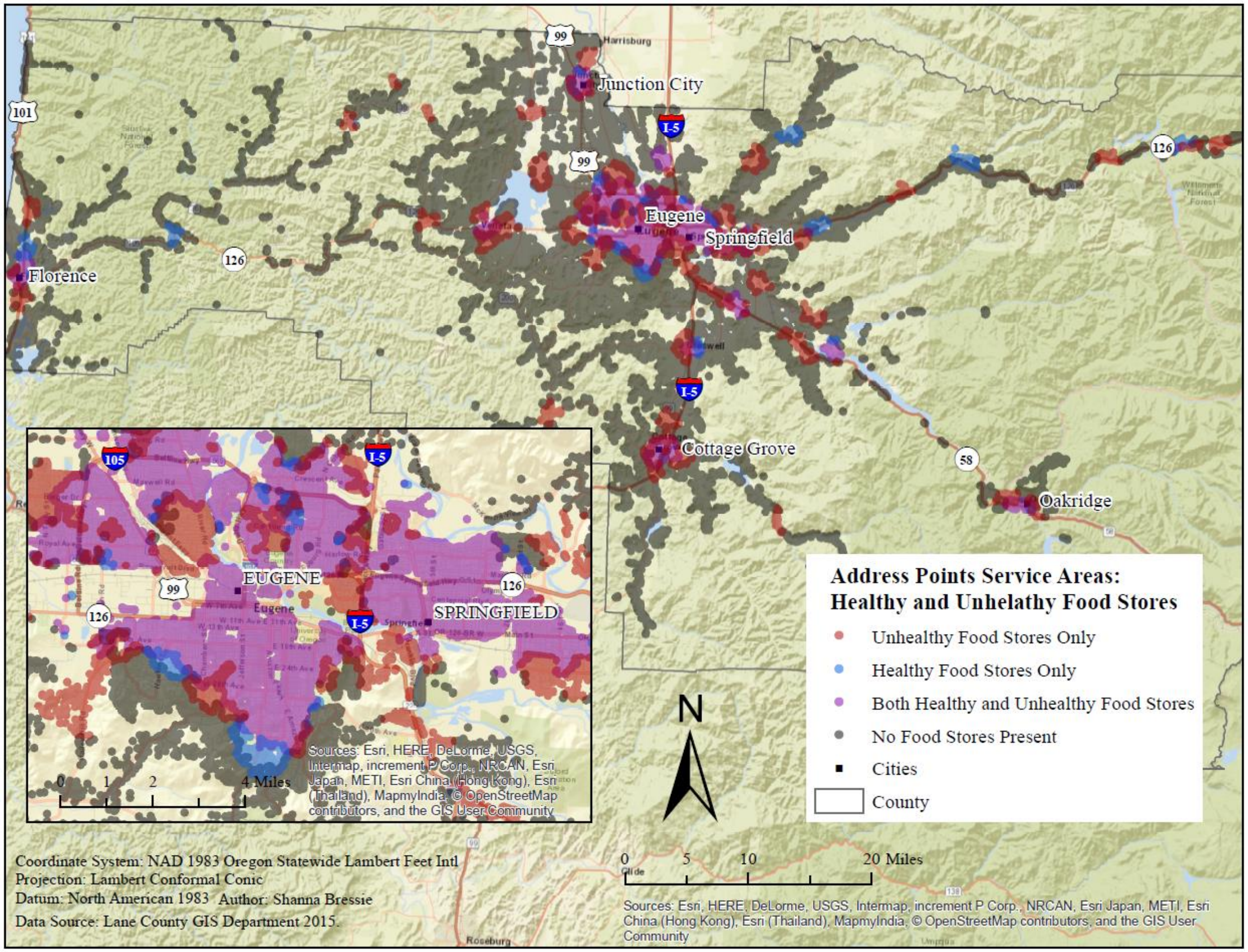

Figure 21 One mile distance band for healthy and unhealthy food store presence calculated from address point proximity distances

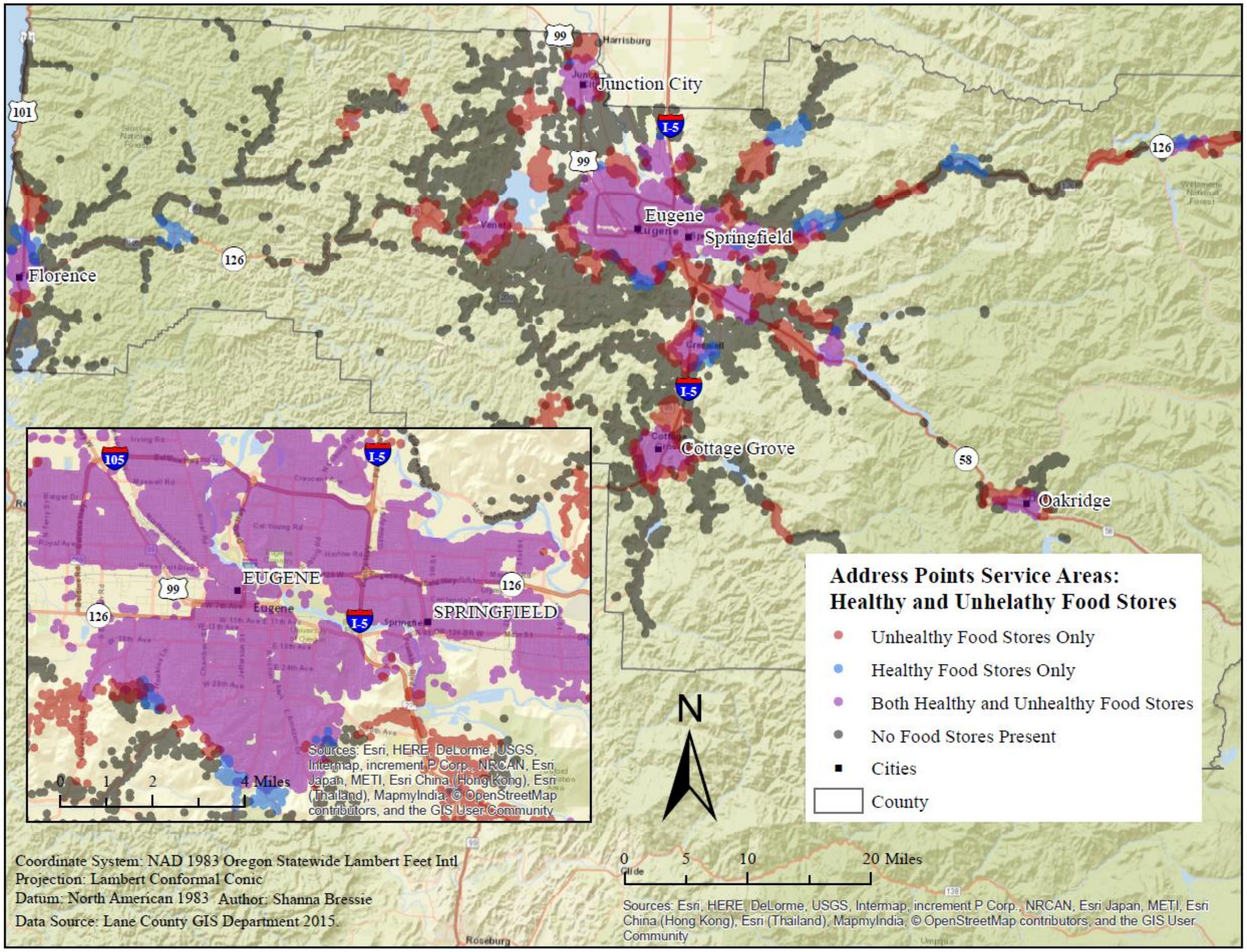

Figure 22 Two mile distance band for healthy and unhealthy food store presence calculated from address point proximity distances

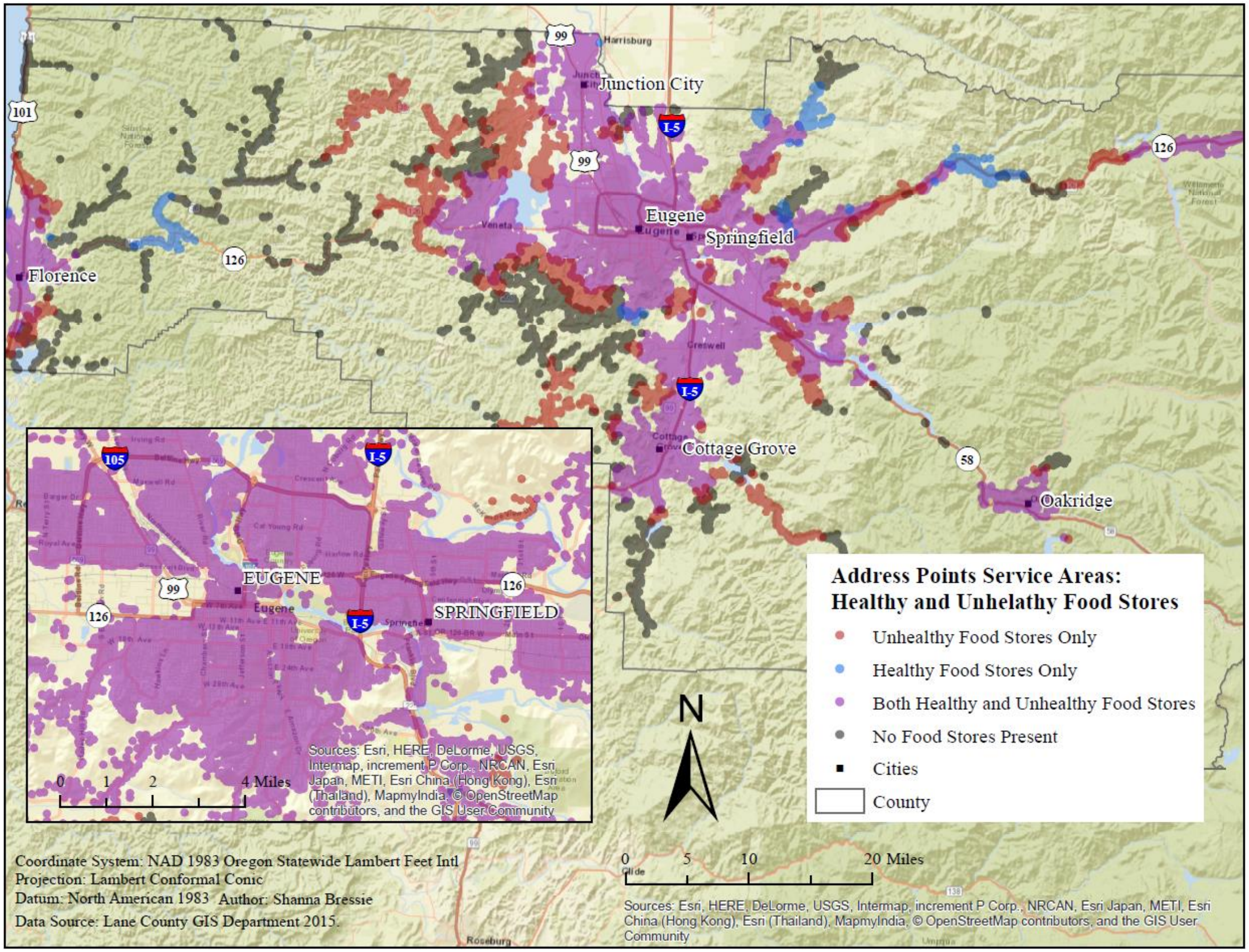

Figure 23 Five mile distance band for healthy and unhealthy food store presence calculated from address point proximity distances

Table 14 summarizes the number of households and population groupings for the previous series of maps. The unhealthy food stores only grouping encompasses about 20% of all households at the 0.5 and 1 mile distance bands. The percentage of households at the 1 mile distance band that represent food deserts and food swamps are approximately 19% and 21%, respectively. The healthy food stores only (i.e. blue clusters) represent under 4% of all households at all distance bands, decreasing to under 1% at the 5 mile distance band. The 'Both' grouping more than doubles from the 0.5 to 1 mile distance band and then increases to represent nearly 94% of households at the 5 mile distance band. The 'None' grouping that represents potential food deserts decreased in surface area (Figures 20 through 23) and also in the percentages of the households impacted from 50% to less than 3% from the 0.5 to 5 mile distance band.

These results were interpreted to mean that the number of people impacted by food desert and food swamp conditions changes depending upon how distance thresholds are defined as well as the types of stores included and the way in which they are categorized. Over 80% of residents in the study area live within 2 miles of at least one healthy and one unhealthy food outlet. At the same distance less than 15% of households were grouped into either food deserts or swamps.

Table 14 Summary of household and population estimates calculated for the distance bands examining healthy and unhealthy food store accessibility

Distance Bands	Total Population Estimates	Total Household Estimates	Population %	Household %
Half Mile				
None	184,218	76,871	52.13	50.18
Unhealthy food stores only	70,855	30,917	20.05	20.19
Healthy food stores only	10,613	4,834	3.00	3.16
Both	87,696	40,542	24.82	26.47
One Mile				
None	79,266	31,774	22.43	20.75
Unhealthy food stores only	70,645	28,957	19.99	18.90
Healthy food stores only	7,428	3,304	2.10	2.15
Both	196,043	89,129	55.48	58.20
Two Miles				
None	37,078	14,081	10.49	9.19
Unhealthy food stores only	22,006	8,466	6.23	5.53
Healthy food stores only	4,436	1,914	1.26	1.25
Both	289,862	128,703	82.03	84.03
Five Miles				
None	9,810	3,401	2.78	2.22
Unhealthy food stores only	12,646	4,756	3.58	3.11
Healthy food stores only	2,527	1,057	0.07	0.07
Both	328,399	143,950	92.93	93.98

Chapter 5 Summary and Discussion

5.1 Summary of Results

The primary analysis conducted for this study measured distances from residential address points to food stores over the street network. A second analysis was used to compare the aggregated average distances for census block groups to determine whether or not minority composition and deprivation influenced food store accessibility. A third measure of the food environment examined food store presence and absence to identify whether or not and if so, where food deserts or swamps existed within the study area at different distance bands. These analyses provide empirical evidence that most residents living in the study area have adequate access to healthy food and food store access increased in most areas as deprivation and minority composition increased.

The study confirmed that rural residents with reduced access to large chain food retailers travel farther or shop at smaller grocery stores that may provide less variety and/or higher prices for some products. The study results indicated that neighborhoods with higher deprivation and higher minority composition had better access to healthy food choices overall. Sharkey and Horel (2008) and Morganstern (2015) found the same type of relationships in Brazos Valley, TX and Atlanta, GA. Convenience stores were more common in all neighborhoods, followed by fast food restaurants, healthy fast food restaurants, small grocery stores, and large supermarkets.

The areas that may be considered problematic changed as distance thresholds defining these areas changed. Larger distance bands included more households and store types. The presence map at the 2 mile distance band was mashed up with the food stores classified by type and is shown in Figure 24.

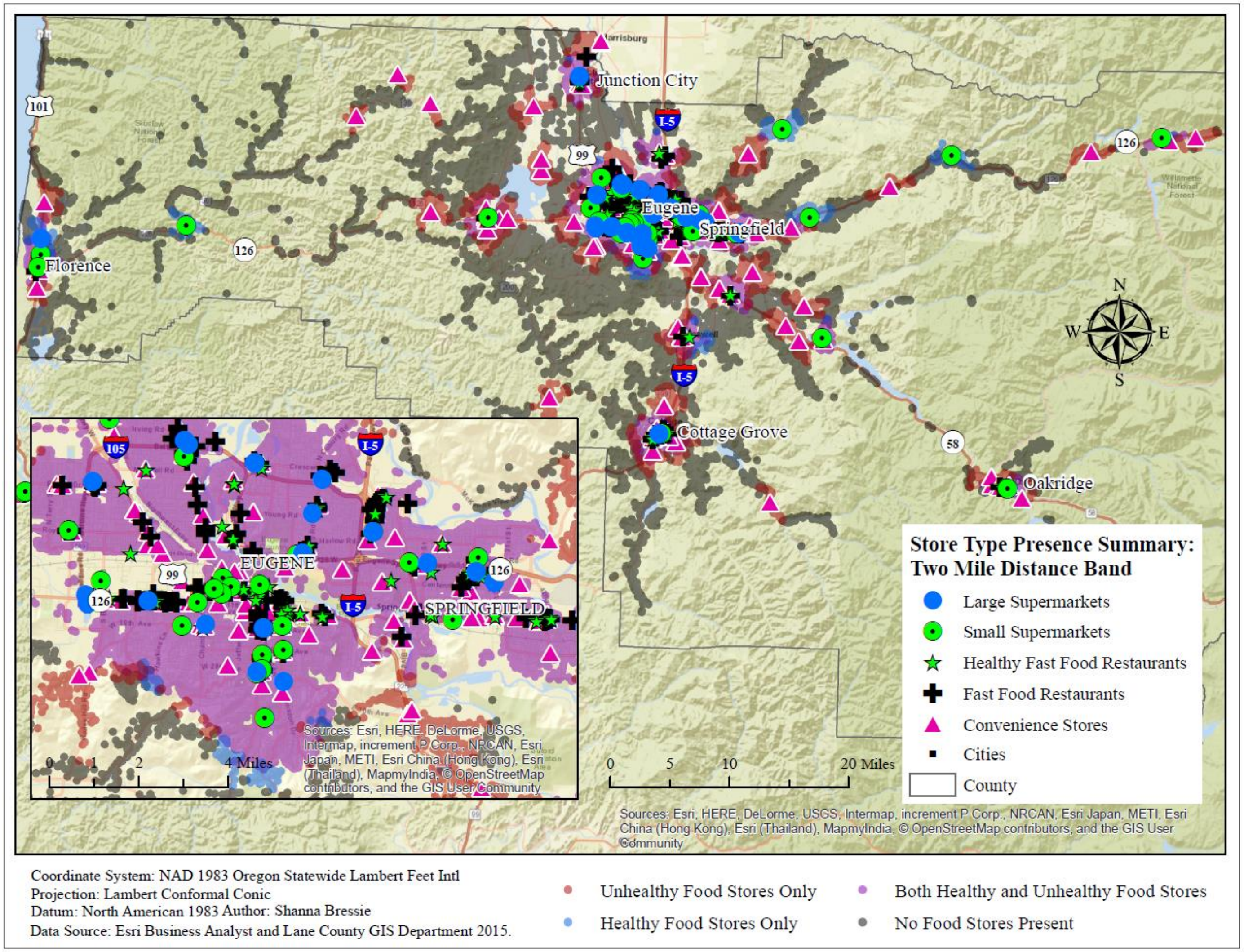

Figure 24 Summary of food store types mashed up with the results of the presence analysis at the two mile distance band

5.2 Significance of Findings

The primary finding of this work is that residents in living five CBGs that were classified as high deprivation experience reduced access to large supermarkets. Minority composition was classified as high in two of these CBGs that were located in the urban center. The CBGs with lower access to large markets represented less than 2% of households in Lane County, OR. Three of these CBGs were in located in different rural areas and two were adjacent to each other in the urban center. Each of the four communities have unique situations, based on their locations, for residents to consider while planning grocery trips.

The presence or absence of the healthy and unhealthy food stores across the study area varied depending upon the scale of measurement (i.e. the distance bands). Less than 10% of households were impacted by what may be considered food desert conditions at the two mile distance band. Two factors that are similar for most of the areas identified as potential food swamps were: the impacted households were located along major roadways and outside of the Eugene-Springfield urban center in suburban and rural areas.

5.3 Discussion

The parameters of what was measured for the study and how these concepts were defined and categorized set the tone for the research. It is important to emphasize that the models presented in these analyses measured only the retail-based food environment with a focus on large supermarkets and categorically defined healthy and unhealthy food stores. Residents may grocery shop locally through multiple channels like Saturday Market, tailgate markets, roadside stands, local farms (urban and rural), and grow food through a variety of community garden projects and dedicated legacy farmland preservation projects.

If these analyses included local fresh options as VanHoesen et al. (2013) did, both urban and rural distance measurements would change for the proximity analysis resulting in changes to aggregation and presence assessments as well. A growing number of smaller rural and urban farms in Lane County have expanded sales options to make it easier for residents to eat high quality locally produced fruits, vegetables, meats, and dairy. Several neighborhood stores stock local products as well as an increased number of farmer markets, tail gate markets, and road side stands. Expanded seasonal markets offer residents winter produce and options for sharing organic dairy and meats. The demand and supply of fresh locally produced food was noticeable in 2010 and has continued growing to the present (U.S. Department of Agriculture Economic Research Service 2016).

5.3.1. Research Goals

In terms of the research questions posed for this research, the findings seem to echo the findings in the literature reviewed, in that distance thresholds and scale impacted results. Eckert and Shetty (2011), Smith (2003), and Smoyer-Tomic et al. (2008) used multiple buffer distances to investigate food access, distance-based changes, and identify potential food deserts. The results of presence and absence modeling were used to determine whether or not food deserts exist in Lane County, OR for the period from 2015 to 2016. The proximity maps provide a better understanding of the distribution patterns of residents and food stores as well as distances that connect the two.

Fewer food deserts were reported in the results of McEntee and Agyeman (2010), Eckert and Shetty (2011), and VanHoesen et al. (2013) each of these works employed distance measurements from address points to food stores. The same is true for the social and economic comparisons. The results in this work were aligned with this group of researchers that found disadvantaged residents with better access to healthy food stores compared to wealthier segments of the population (Morganstern 2015, Sharkey and Horel 2008). Overall, Lane County's disadvantaged segments of the population have access to healthy foods.

Local food environments trek alongside the extant network systems within the built environment. Supply and demand, the mystical ouroboros, drive the economics of retail food sales and thus store locations. It seems as though retail trends in the 1980s and 1990s shifting toward car-centered suburban areas is morphing into a boomerang like movement that is coming at least halfway back to the urban cores to meet communities' needs. GIS tools provide a sophisticated approach to efficiently identify site and situation information that helps communities grow to meet the needs of society.

5.3.2. User Group Vision: Practical Applications

The two different types of maps reproduced in this work may serve different user groups. The proximity dot maps and service area maps could be used by a variety of organizations and small businesses to identify communities and pockets of underserved residents to launch locally scaled food interventions. These efforts could include adding a variety of healthy foods to existing convenience and small grocery stores and/or determining a site for future small retail food stores.

The thematic maps that relied on aggregated average distances and comparative economic and demographic statistics could potentially be used by local municipalities for similar purposes as stated above, in addition to providing tools to expand on the existing web map applications for tracking and maintenance purposes as they relate to health outcomes. The presence and absence dot maps would be useful to all aforementioned user groups as supporting evidence for neighborhood planning. This group of maps could also be used as a precursory step to further discussions on RHFA relative to achieving food balance in areas that may exhibit characteristics of food swamps (i.e. unhealthy food stores outnumber healthy food stores).

5.3.3. Opportunities

I see my work in these analyses as a stepping stone for food researchers, planners, citizen scientists, geographers, GISers, and more generally anyone with an interest in healthy eating. Ideally it will inspire unique solutions for community food access research using contemporary location aware datasets that connect people to healthy foods. The work could be reproduced and expanded to include several aspects of a multidimensional food environment research to deepen our understanding of consumer behavior and dietary decisions. An example from the results would be to examine whether or not passing fast food restaurants and convenience stores, coming into or leaving urban areas, affects consumers' diets. Another opportunity for this research would be to investigate store densities in potential food swamps in the study area to determine how many households are potentially impacted. Local food options could also be added as the potential sixth food store type. The scorecard produced from the USDA Economic Research Service Food Atlas (2016) tells us that Lane County does pretty well in the broader arena of food access, yet as a community member and resident food consumer, I know there is still plenty of work to be done.

5.3.4. Limitations

Computing power offered a special set of limitations in terms of the time and memory needed to run the Network Analyst Extension. Computations for solving the traveling salesman problem between the address points and food stores were quite slow. Loading the locations to run the network solver was a slow process. Solve times ran from 30 minutes up to days. Sometimes the computer ran out of memory altogether. Patience and perseverance provided the opportunity to become more familiar with the extension capabilities. Esri sets a high standard for modeling analysis capabilities and network solutions with Network Analyst.

The study did not utilize other dimensions from food and nutrition environment research such as accommodation, affordability, and acceptability. These non-spatial constructs may influence dietary decisions. Accommodation or store hours of operation is one of the least cited dimensions throughout the literature. Affordability was addressed through development of cost indices based on shelf audits (Cummins and Macintyre 2002, Donkin et al. 1999, Smith 2003). A few researchers integrated custom surveys called (FFQ) Food Frequency Questionnaires to assess diet quality. FFQs collected data about food group consumption based on frequency (Caspi et al. 2012a, Charreire et al. 2010). Surveys may provide insight to peoples' perceptions that shape grocery trip planning and dietary decisions.

This work focused on distance measurements from residential locations to food outlets only. People are constantly on the move and convenience may influence grocery shopping trips within several broader mixed trips to work, school, and recreation. Travel behavior is an important aspect to factor into the equation of food accessibility. For example, the results would look quite different if one changed the point of origin from residences to the workplace. Access to supermarkets along regular travel routes may influence grocery shopping trips as much as home-based accessibility.

5.4 Future Research

The future direction of this research would further investigate food environments through the lens of health outcomes. Using GIS to compare the proximity of the rates of diet related disease to the proximity analysis of healthy food store accessibility may provide insight to increases in community health. Identifying access levels to goods and services of varying demographics provides empirical results that may help to increase community health and also the health of individuals.

This study did not include smaller farm stands, seasonal farmers markets, food co-ops, community shared agriculture, and “you-pick” farms because of decreased hours of operation and seasonality constraints. These food sources fall into the healthy food category because producers focus on quality and freshness. Lane County, OR was considered a food hub in 2012 by the USDA ERS Food Access Research Atlas (2015) meaning that there are abundant farmers markets, food co-ops, and community agriculture projects in addition to the retail food environments explored in this thesis. The number of growers and food producers in Lane County increased annually from the early 2000s to the present (USDA ERS Food Access Research Atlas 2015). The number farmer’s markets around the county was 14 in 2015. This might add an interesting dimension to food environment metrics.

Food environments are complex. They are part of built environments, social environments, and economies. Food consumption and purchasing is influenced by complex factors like geography, psychology, culture, and other lifestyle influences. Utilizing GIS allows investigators to explore spatial processes and evaluate relationships of the components that make up the environments where people live, work, travel, and shop.

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