Service District Optimization

Usage of facility location methods and geographic information systems to analyze and optimize urban food retail distribution

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Abstract With the surge of obesity in the United States, improving urban food environments has gained in importance. Research on food deserts focuses mainly on assessing the food environment but lacks methods of generating good solutions for the placement of food stores. This work uses a maximum covering location problem in combination with census block group GIS data from the City of Philadelphia to find optimal locations for future food store openings. A socioeconomic index of vulnerability is computed to weigh regions based on their residents' sensitivity to food access limitations. The analysis found that supermarkets in Philadelphia are relatively unequally distributed and that there are many viable locations which could satisfy both the public interest of improving food access as well as the private interest of being profitable. Going forward, this joint approach of GIS data and operations research can be used to highlight locations for possible policy interventions in urban areas.

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1. Introduction

Over the past two decades, research in the field of health and nutrition has focused on defining and identifying urban food deserts through empirical research on individual shopping behavior and spatial mapping solutions using geographic information systems (GIS). However, the derivation of appropriate action plans that benefit public and private stakeholders is still a challenging task and specific to the study area. This lack of attention is significant because the misuse of incentives to shape the food environment can compound the disadvantages faced by the population in food deserts and waste taxpayer money and company resources. In order to address this problem, this study combines a GIS approach with a facility location model in order to identify food deserts and generate good solutions for possible facility placements in the city of Philadelphia, PA.

Over the last three decades, obesity in the United States has increased at an alarming rate. In 2009-2010, 35.7 percent of the US population were obese (Ogden et al., 2012), putting strain on the national health-care budget through costs associated with obesity and diet-related diseases. Studies have explored different environmental conditions that support regional health disparities and that these adverse health outcomes might be subject to socioeconomic factors such as income or ethnicity. Furthermore, studies on economic and geographic access to food find that poor populations in urban areas encounter food prices that are higher than middle-class families and that the development of the local food environment disadvantages people living in areas of high deprivation.
In his hierarchy of needs that shapes human motivation, Maslow (1943) describes physiological needs as the physical requirements for human survival. In comparison to water and housing, two goods that underlie strong regulations, the distribution mechanism of food is often neglected by local and federal governments and left to the private sector, leading to issues of inequal and inadequate food access. In the The Food, Conservation, and Energy Act of 2008, the United States government formally recognized the notion of "food deserts" and issued a large-scale study on the food desert problem (Ploeg et al., 2009), which provided a formal foundation for this study.
As a means of tackling this problem, empirical studies examined behavioral and economic aspects of food shopping by monitoring the local food environment and the buying patterns. Geographic access studies have undertaken several approaches with geographic information systems (GIS) to analyze the access to food on a spatial basis. These employed approaches help understand the problem and find problem areas, however, they lack the generation of distinct recommendations for policy interventions.

Public-private partnerships have been successfully applied to have an impact on the local food environment. In order for those to be effective, it is crucial to ensure incentive compatibility between public goals (such as welfare maximization and equality) and private sector imperatives (such as economic viability and long-term sustainability).
Modern facility location theory originally stems from private-sector applications based on profit maximization and has been amply employed in the optimization of the site selection processes. Especially in the retail environment, covering problems such as the one by ReVelle et al. (1970) provide means of maximizing revenue by maximizing population reach given constrained resources. The goal formulations of such problems can be fit to align with public and private interest. This study employs a combination of GIS and facility location models. Its aim is to unite easily accessible visual representation of a GIS with a quantitative approach. It helps overcoming market failures in the food sector by reducing demand information asymmetry through the identification of key locations of interest. Several urban areas in North America have been studied in regards to the existence of food deserts. Philadelphia has been cited as a city that lacks a significant amount of supermarkets and an adequate access to healthy and nutritious food and the relevant area of this study.

Throughout the course of this study, the following questions were examined:

1. Do food deserts in Philadelphia exist and if yes, where?
2. How can one take advantage of the possibilities offered by both a GIS and a mathematical optimization software?
3. How could a possible implementation of a facility location problem look like and how can it be solved?
4. What set of locations for possible facility sites are optimal from a public or private standpoint (neediness vs. profitability)?
5. Do identified locations satisfy the goals of both stakeholders?
6. Can this implementation be applied to different problem sets, such as other urban areas?

The thesis will be structured as follows: First, the background section will give a brief introduction on the definition of food deserts and its consequences. A review of the history and characteristics of urban food environments in the United States aims to provide an understanding of the interaction between food retail and the community. Following an introduction of the environment of this study - Philadelphia, PA in the United States - the importance of urban planning for tackling the problem of food deserts is depicted and recent undertakings in this area are presented. The section ends with a review of facility location problems that have been applied for retail site selection and might be applicable to this particular problem. The methodology section describes the means of collecting spatial data, the combination of vulnerability characteristics in a vulnerability index and lastly, the design, implementation and solution of the optimization problem. The results of the optimization are then presented in a map and table form and discussed on the grounds of feasibility, sensitivity, performance and incentive compatibility.

2. Background

2.1. Towards a definition of food deserts

The terminology *Food Desert* was reportedly first used by Scottish public sector housing residents in the early 1990s. It first appeared in a government publication in 1995 as part of a Nutrition Task Force of the Conservative UK Government (Cummins and Macintyre, 2002, pg. 1). Since then, it has been used differently by different researchers. The least common denominator of all definitions is the literal absence of retail food resource in a defined area. In light of obesity having reached "nationwide epidemic proportions" (Office Of The Surgeon General, 2001, pg. XIII), the local food environment becomes an increasingly pressing public health concern. A more advanced conceptual definition that incorporates nutritious value of different foods was given by the Department of Health (1996), decscribing food deserts as "areas of relative exclusion where people experience physical and economic barriers to accessing healthy food".
Studies have shown that people living in low-income and minority areas tend to have poor access to varied healthy food (Beaulac et al., 2009, pg. 4). Policy-makers and most studies therefore do not only consider access to food in general but focus on an unequal access to healthy and nutritious food. This is emphasized in the Food, Conservation, and Energy Act of 2008 (U.S. Government Printing Office, 2008, sec. 7527), also known as the 2008 Farm Bill, in which a food desert is defined as "an area in the United States with limited access to affordable and nutritious food, particularly such an area composed of predominantly lower income neighborhoods and communities".
From these definitions we can derive four important elements for the definition of a food desert (adapted from (Leete et al., 2012, pg. 205): (1) **Availability**: a definition of a sufficiently wide range of nutritious foods items; (2) **Affordability**: a definition where and at which price those food items can be attained; (3) **Access**: a measurement of geographic access and a threshold for determining low access; (4) **Vulnerability**:a threshold for determining which populations with low food access will lack the resources to access food from more distant retail outlets geographical access and social deprivation. These four factors will now be examined in detail.

2.1.1. Food availability

Defining a healthy diet

In order to examine whether the food environment imposes a constraint on a healthy and nutritious diet, one has to define what a healthy and nutritious diet consists of. While

total fat intake over the last 30 years has decreased, a trend towards a energy-dense diets has evolved and the intake of calories and carbohydrates has risen (Austin et al., 2011, pg. 839). This may be applicable to increasing portion sizes, marketing and pricing as well as changes in food production and higher rates of pre-processing and pre-packaging (Morland et al., 2006, pg. 334). (Swinburn et al., 2004, pg. 126) have shown that a diet filled with processed foods often leads to poorer health outcomes compared to a diet high in complex carbohydrates and fiber.
Whereas a pairwise comparison of similar foods can help attribute some foods as more nutritious than others, no one food can fulfill the recommendations for a healthy diet (Ploeg et al., 2009, pg. 2). Furthermore, nutritious food may come in various forms and packaging types. What is perceived as a healthy diet also varies between ethnic groups and might have differing acceptance rates among those (Donkin et al., 1999, pg. 556). Empirical researchers therefore use a more conceptual definition of insufficient food diversity: The lack of reasonable access to fresh fruits and vegetables and foods from all the major food groups required for a “modest but adequate diet” (Sparks et al., 2009, pg. 8).

Food sources

Food is sold in a wide range of retail outlets. Because of various forms of nutritious diets, research that studies the quality and availability uses food categories (e.g., fruits) or indicator items (e.g., ground beef, skim milk) to compare food variety between different types of these outlets (Glanz et al., 2007, pg. 283).
Grocery stores were found to have greater quality of those healthier food options compared to convenience stores and these differences may be large enough to have substantial effects on consumer purchasing and health (Glanz et al., 2007, pg. 287). In a cross-sectional study of 10,763 Atherosclerosis Risk in Communities participants, the presence of supermarkets was associated with a lower prevalence of obesity and overweight, and the presence of convenience stores was associated with a higher prevalence of obesity and overweight. A nationally representative sample of 2,400 stores accepting food stamps by Supplemental Nutrition Assistance Program (SNAP) showed that availability as well as variety of market basket items did not vary by poverty level for large grocery stores(Mantovani, 1997, pg. 98ff).
We can conclude that supermarkets and large grocery stores offer more variety and availability of food than other store types and can be used as proxies for food retailers that offer a variety of nutritious, affordable retail food (Ploeg et al., 2009, pg. 15).

2.1.2. Food affordability

A key concern for areas of limited *economic access* (see section 2.1.3) is not only whether a nutritious variety of food is available but whether it is affordable. Studies have examined food prices and have found that the types of stores that are available as well as individual shopping habits are key factors for the incurred costs of food.
Market-basket studies measure the price of a particular food or the relative price of a substitute or alternative good. Just like in variety and availability, studies have found that there are distinct differences between different types of food outlets. Firstly, Kaufman et al. (1997) point out that supermarket tend to have significantly lower prices than those of smaller foodstores (about ten percent on average) because they are able to capitalize on economies of scale and to withstand lower margins. Secondly, a study by Chung and Myers (1999) demonstrates that people in non-chain stores pay a premium to customers of chain stores. The net impact of chains on the price of a Thrifty food plan (TFP) market basket by the United States Department of Agriculture (USDA) was found to be as high as $15.94 (non-chain market price: $109.90).

These two food price factors put low-income neighbourhoods at a disadvantage. In these areas non-chain supermarkets and grocery stores are more prevalent than larger chain-supermarkets (Powell et al., 2007, pg. 189). The non-placement of large chain stores, where prices tend to be lower is a key factor contributing to higher grocery costs in poor areas. Kaufman et al. (1997) illustrates that low-income households tend to select more economical foods such as generic items or larger package sizes. In contrast, those people pay a premium to the average price of an identical market basket. They lack access to large-scale supermarkets that utilitze economies of scale to generate lower prices. In another study by Hendrickson et al. (2006), a significant number of foods in urban neighborhoods of Minnesota, USA were significantly more expensive than the TFP market price. One could argue that growing popularity of supercenters in suburban areas (see section 2.3.1) could have increased competitiveness in metropolitan statistical areas (MSA) that they are placed in. However, recent research provides evidence that this may not be the case and entry of supercenters does not have a significant effect on food prices within the MSA (Stiegert and Sharkey, 2007). The placement of supercenters in mostly suburban areas and only marginal procompetitive effects on the MSA food prices help explain the existing disparities in food prices among city limits.
It is apparent that policy motions to promote the placement of chain stores or supercenters could provide affordable food in communities that experience high food prices and vulnerability to food access.

2.1.3. Food access

Three barriers of access

After establishing a joint understanding of food options and prices, it should given consideration to measuring the way people access food. Following the topology of (McEntee and Agyeman, 2010, pg. 167), barriers of food access may be divided into three groups: informational, economic and geographical access . *Informational access* comprises the analysis of how and why certain types of food are consumed (knowledge of sources). Studies of *Economic access* examine the financial situation of consumers and the total cost incurred in the acquisition of food, such as food prices transportation costs.
The focus of this research is the measurement and optimization of *Geographic access*, which is defined in the following paragraph. However, it is important to notice that lack of food access is a multifaceted problem that has more dimensions than spatial and financial characteristics.

Defining and measuring geographic access

Geographic access specifies the physical accessibility of food and has a variety of representational frameworks for its attribution and measurement. It might be conceived as an attribute of either locations (place accessibility) or individuals personal accessibility (Kwan et al., 2003, pg. 130). In the example of grocery store placement, place or personal accessibility differentiates between a supply-driven (Does the outlet have access to a certain group of people?) or a demand-driven approach (Do individuals have access to sufficient food?). Hence, research employs individual-based measures and area-based measures of food access (Ploeg et al., 2009, pg. 11).
Individual-based measures examine access for individuals directly, regardless of their location. For example, an annual national representative food security survey by the USDA has found that 5.7 percent were experiencing access problems and more than half of them stated that insufficient money was the main reason for this (Ploeg et al., 2009, pg. 13). This gives an understanding of the general extent of the food desert problem and how many people are negatively affected on a national scale. It does not, however, help in

identifying who is affected and where policy interventions would be fruitful.
Area-based measures of access use aggregate spatial frameworks (e.g. block groups) to map geographic access as distance to the nearest retail outlet, such as a supermarket. Most commonly, the distance is measured in straight-line distance by the creation of circular buffers. The buffer size works as a proxy for an access range, representing a certain maximal distance to a store or a related time necessary to reach a store. Straight-line distance is not an exact measurement of distance or travel time because of unique road networks. Access-related studies such as (McEntee and Agyeman, 2010, pg. 170) have therefore made use of network measurement tools that calculate travel distances on a given road network. The majority of research however, has employed straight-line distance buffers because of its ease of use and representation.

Geographic access in urban and rural areas

Urban food access studies seek to identify areas outside of a walkability range. Common understandings of walkability ranges reach from a quarter mile up to one mile. Based on an average walking speed of 88m/minute for a male and 74m/minute for a female respectively (Donkin et al., 1999, pg. 558), these buffers represent a walking distance of five to six minutes (quarter mile) up until nineteen to twenty-two minutes (one mile). (Ploeg et al., 2009, pg. 17) employs a categorization of walkability, in which walkability is defined as 1) high (within $\frac{1}{2}$ mile); 2) medium ($\frac{1}{2}$ mile to one mile); and 3) low (more than a mile).
Access studies in rural areas require different access measures. Urban distance limit are not applicable here as most people live further from a food retailer and do heavily rely on an automobile for grocery shopping (McEntee and Agyeman, 2010, pg. 168). The focus lies on drivability more so than walkability. There have been several approaches towards rural access measurement, such as increasing the buffer to a drivability range of 10 miles or comparing potential spending from households to sales data from food stores. Rural areas are more error-prone to skewing of travel distances through metrics because the road network is usually less extensive than in urban areas. Additionally, zone-based aggregation of population in rural areas leads to much larger areas as in urban areas (e.g. census tracts). The geographic center may not accurately represent the population center (Sharkey and Horel, 2008, pg. 622). Hence, the more broken-down block groups are used to calculate population-weighted centers instead of geographic centers. Similarly, (McEntee and Agyeman, 2010, pg. 170) derive mean distances to supermarkets within an census tract using a network distance tool for residential units.
As this research is focusing on geographic access in the urban area of Philadelphia, a straight-line distance measure has been used. Appropriate access was defined as a maximum distance to the nearest store below $\frac{1}{2}$ mile, which is in line with the USDA definition of high walkability.

2.1.4. Characteristics of Vulnerability

After a variety of healthy and nutritious food has been defined and measures of geographic access has been established, it is of interest which subpopulations may experience particular challenges in accessing nutritious food sources from more distant retail outlets. Not all people experience access barriers in the same way. In order to relate geographic accessibility and access limitation vulnerability, different proxies for disadvantage have been used. These are based on the assumption that socioeconomically deprived residents are most likely to face transportation and time–cost barriers in seeking out more-distant shopping options (Leete et al., 2012, pg. 206). Examples are poverty rate, unemployment rate, percentage of residents with low levels of education, or presence of single-parent or immigrant households.

Measurement of disadvantage

To account for more than one characteristic and facilitate visual representation, existing socioeconomic indices are computed. Examples are "The Indices of Deprivation 2007" by the British Department for Communities and Local Government (made up of seven dimensions of deprivation: Income, Employment, Health and Disability, Education, Skills and Training, Barriers to Housing and Services, Living Environment, Crime) or the Carstairs Index (based on four census indicators: low social class, lack of car ownership, overcrowding and male unemployment) used by Clarke et al. (2002). On other occasions, a composite index of socioeconomic distress or deprivation was calculated with given socioeconomic data. Apparicio et al. (2007) computes a linear combination of five deprivation measures: 1) low-income population; 2) lone-parent families; 3) unemployment rate; 4) adults with low level schooling 4) recent immigrants. The exact same approach except for an omission of recent immigrants was used by Larsen and Gilliland (2008). Sharkey and Horel (2008) neglect recent immigrant and lone-parent family figures but include household crowding, public assistance, vehicle availability and telephone service. Unfortunately, there is little reasoning about why certain measures are included. The variety of deprivation indices shows that there is no "one right measure" for deprivation for this type of research, which shows the multitude of food desert definitions and compound effects of deprivation.

2.2. Consequences of food deserts

Obesity in the United States

Overweight and obesity in the United States have reached epidemic proportions. The United States have seen a dramatic increase in obesity (Body Mass Index greater than 30) from 1990 through 2010. According to the National Center for Health Statistics (Ogden et al., 2012), more than 35 percent of adults and almost 17 percent of youth in the U.S. were obese in 2009-2010. Both the prevention and treatment of overweight and obesity and their associated health problems are important public health goals.
Individuals who are obese have a 50 to 100 percent increased risk of premature death from all causes (most importantly type 2 diabetes and heart disease) compared to individuals with a BMI in the range of 20 to 25. An estimated 300,000 deaths a year may be attributable to obesity. In June of 2013, the American Medical Association announced a change in its recognition of obesity from a "major public health problem" to a "disease requiring a range of medical interventions for treatment and prevention" (American Medical Association, 2013).

Economic impact of obesity

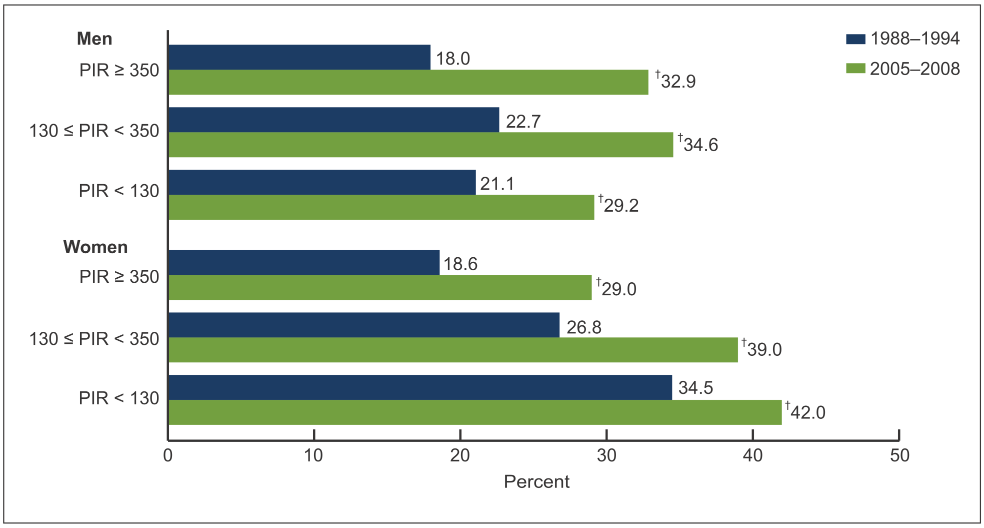
Rising rates of overweight and obesity pose an economic burden on both private payers and public authorities. Medical costs associated with obesity can be broken down to direct and indirect costs. Direct medical costs may include preventive, diagnostic, and treatment services related to obesity. Indirect costs relate to morbidity and mortality costs (Wolf and Colditz, 1998, pg. 98f). Finkelstein et al. (2009) state that the connection between rising rates of obesity and rising medical spending is undeniable. In the study, it is estimated that the medical costs of obesity through increased health care use and expenditure could amount to $147 billion per year by 2008 (up 87 percent from 1998). The per capita medical spending for obese people in 2006 was estimated to be 41.5 percent higher compared to normal weight people (a difference of $1,400).
Roughly half of those costs are borne by *Medicare* or *Medicaid*. These are public social insurance programs targeted at elderly people over 65 and people with low-income respectively. Elderly and low-income subpopulations also happen to be especially vulnerable to

food access barriers. The Patient Protection and Affordable Care Act by the U.S. government, effective in 2014, is aimed to improve the rights and benefits of obese people through equal access (Roddenberry and Fleming, 2013). Whereas adults with obesity will be protected from losing coverage due to pre-existing conditions (Manchikanti et al., 2011, pg. E55), it is still noteworthy that so-called "wellness benefits" dramatically expand the ability of companies to penalize employees for lifestyle issues, including being overweight or smoking. While the wellness benefits tend to be described as discriminatory towards poor and obese people (Roddenberry and Fleming, 2013), tackling the problem of obesity has clearly become a focus of recent US federal policy.

Health disparities

Obesity is a problem that affects some more than others. A National Health and Nutrition Examination Survey among adults aged twenty years and older between 2005 and 2008 has shown that there are relationships between socioeconomics, educational status and obesity prevalence (Ogden et al., 2010). The results differ by sex, race and ethnicity. Among men, the relationships seems to be less distinct. With the exception of non-Hispanic Black and Mexican-American men, who are more likely to be obese with rising income, obesity prevalence is generally similar among all income levels. Women, however, seem to be far more affected by socioeconomic status and educational attainment. Lower income of women is related to an increased likelihood of obesity, and obesity prevalence increases as education decreases.

A multi-level study surveyed 15,358 inhabitants of 327 zip code tabulation areas in Massachusetts, USA between 1998 and 2002 (Lopez, 2007). The presence of a supermarket was negatively associated with obesity risk. In a multiple regression model, having one supermarket in a zip code tabulation area decreased the risk of obesity by 10.7 percent. As median income (+$1000), population density (+1000 per square mile), and retail establishment density (+100 per square mile) increased, the risk of obesity declined by 0.8%, 2%, and 1.9%.



†Significant increase.
NOTE: PIR is poverty income ratio.

Figure 2.1.: Prevalence of obesity among adults aged 20 years and over, by poverty income ratio and sex: United States, 1988-1994 and 2005-2008 (Ogden et al., 2010)

These relationships between different factors of increased obesity prevalence are limited to only being observational. The current understanding of underlying complex causes of disparities are still very limited and do not allow a causal interpretation of the relationships.

It is apparent that obesity may be caused by many factors. In many cases though, weight gain can be backtracked to excess calorie consumption and inadequate physical activity. Dietary and physical activity choices are influenced by one's individual characteristics and interaction with the social and physical environment. Differential rates of available local physical fitness facilities and types of food stores by neighborhood characteristics are examples for factors of the physical environment that might help explain disparities in obesity prevalence. Population-based policies and programs that focus on environmental changes are most likely to be successful and crucial to promoting healthful eating as well as physical activity (Wang and Beydoun, 2007, pg. 24).
While the United States have traditionally relied on markets rather than social policies to distribute wealth (Swinburn, 2009, pg. 510), the federal government and many states are undertaking various policy initiatives to address the obesity crisis. For example, President Barack Obama has created a new White House Task Force on Childhood Obesity to create a new national obesity strategy and implement concrete measures and roles. By 2010, twenty states had introduced nutritional standards for school lunches, breakfasts and snacks that are stricter than USDA requirements, whereas only four states had introduced these standards by 2005 (Levi et al., 2011, pg. 43). First lady Michelle Obama has also started the "Let's Move!" initiative in 2010, an attempt to improve childhood obesity on a city-level. The initiative is aimed towards pooling the expertise and efforts of public officials, advocacy groups and the food industry (Levi et al., 2011, pg. 71f). This is just a small excerpt of the federal and state-level policies and programs that address the growing prevalence of obesity. A plurality of initiatives is necessary, because healthy choices can only be effectively supported if policies on every level cover all aspects of access - informational, economic and geographic.

Linkages between food access and a healthy diet

After delineating the consequences of obesity in the United States in its extent and showing distinctive disparities between socioeconomic, ethnic and geographic groups, the direct impact of food deserts on an unhealthy lifestyle needs to be assessed.
Dietary decisions are formed through individual characteristics and interdependencies with the physical and social environment (Ploeg et al., 2009, pg. 52). Food deserts describe areas where people with vulnerable individual characteristics are accumulated and experience a limitation of physical access to food. It should not come as a surprise that research shows linkages between food deserts and a less healthy dietary intake. In general, better access to a supermarket is associated with a healthier diet, while the opposite can be said about greater availability and lower prices of fast food items (Ploeg et al., 2009, pg. 52). Hendrickson et al. (2006) studied fruit and vegetable access in selected low-income food desert communities in Minnesota, USA. Focus group surveys showed that the lack of quality, affordable food for low-income residents in these four communities impedes their ability to choose food that helps maintaining a healthy lifestyle. A study of less affluent areas with a high share of African-American residents by Lewis et al. (2005) posted similar results. It also reported another common finding in food deserts, that restaurants and fast-food outlets in deprived areas heavily promote unhealthy food options to residents.
This shows that not only access limitations of healthy food alone is the main causes for the development of obesity but the substitution effects through savvily-advertised, low-priced fast food with a high energy density . A study of fast food marketing focusing on younger customers in 2010 found that only 12 of 3,039 possible kids' meal combinations meet nutrition criteria for preschoolers and that black children and teens see at least 50 percent more fast food advertising than white ones (Levi et al., 2011, pg. 62). A lack of options for nutritious food is intensified through early exposure to fast food in food deserts. Research of overweight schoolchildren in Pennsylvania, USA by Schafft et al. (2009) also finds a positive relationship between increased rates of child overweight and the percentage of the

district population residing in a food desert. A proposed "Healthy Food Financing Initiative" is geared towards bringing affordable healthy foods to under-served communities, particularly through building new retail food stores in these neighborhoods.
The US state of New York has also asked the USDA in 2011 to rule on a proposed ban of soda and sugar-sweetened beverages (SSB) for people using the Supplementary Nutrition Assistance Program (SNAP formerly known as the Food Stamp Program). On the contrary, fast food lobbying groups are campaigning for allowing SNAP recipients to buy food at fast food restaurants. This would incentivize a variety of new unhealthy food choices for a group that shows signs of vulnerability, such as individuals with disabilities, elderly, and homeless (Levi et al., 2011, pg. 58).

2.3. The urban food environment

Eating habits are shaped by the food environment that individuals are exposed to. This section describes what major changes the urban food environments in the United States have gone through over time and gives an explanation to the economic forces at work. Subsequently, the food retail situation in Philadelphia is depicted, followed by an overview of initiatives that show how change can be brought to urban food environments.

2.3.1. Historical development of the food retail environment

Over the last century, the retail environment in the U.S. has undergone several major changes that have formed the way people use and access food, with some of them being externally driven (e.g. by a geographic shift of demand) and others internally driven (e.g. by economies of scale). Mainly, the evolution of communities is the origin for changes in the retail environment. It is to be noted that the retail environment changes considerably lag behind influencing external factors, which could be attributed to a slow or conservative observe-and-adapt process of retailers to newly created demands.

Auto-mobility and suburban sprawl

The first and probably the most far-reaching change was the introduction of automobiles. Rising prevalence of auto-mobility in affluent households and highway construction made it easier for people to move more freely and cover greater distances. The establishment of a car-centered infrastructure however put poorer families that could not afford a car at a disadvantage - mobility is a luxury good and is unequally distributed (Larsen and Gilliland, 2008, pg. 2). The availability of motorized individual transportation opened up the possibility to escape the larger cities. Overpopulated centers of "walking cities" (Jackson, 1985, pg. 14) with increased levels of pollution and congestion were mostly perceived as unhealthy places. Suburbs offered domesticity, privacy, and isolation at relatively lower land costs (Ploeg et al., 2009, pg. 87). Antidromic to the urbanization, the move of affluent households to the suburbs fueled the urban sprawl of the cityscape. As more and more people of the customer base and workforce moved outside of the city centers, retailers and businesses followed suit and opened suburban establishments. Studies by Mieszkowski and Mills (1993) show the decreasing relevant of central cities: In 1950, 57 percent of metropolitan statistical area (MSA) residents in the and 70 percent of MSA jobs were located in central cities; in 1990, the percentages were about 37 and 45.

Economies of scale and Standardization

Another trend in food retail during the 20th century was the expulsion of independently-owned markets by chain stores, pioneered by The Great American Tea Company, the predecessor of A&P Inc. (Stiegert and Sharkey, 2007, pg. 295). The organization of

chains offered lower operating costs through standardization of marketing and sophisticated inventory systems. The pooling of demand and the cutting of middlemen ensured lower per-unit prices through stronger bargaining power with suppliers.
As a means of enabling economies of scale and catering to more demanding customer base, especially in the suburban areas with low land prices, average grocery stores began to grow larger in size. Through new outlet placement techniques, grocery stores were able to serve a larger number of customers. Full-line supermarkets (floor design > 5,000 square feet) that could offer a larger variety of goods in comparison to more specialized markets with less offering. As these smaller independent stores were superseded, the average number of stores per capita decreased (Larsen and Gilliland, 2008, pg. 2). Additionally, supermarkets started moving away from urban areas, which became especially apparent in the 1980s, when cities experienced a net loss of supermarkets even as, nationally, store openings exceeded closings, often referred to as "supermarket redlining" (Eisenhauer, 2001, pg. 127).
The two developments peaked in a trend towards fewer, bigger *supercenters* since the end of the 20th century. These outlets combine food retailing with general merchandising and pharmacy under one roof to cater to all routine shopping needs of their customers. Due to the "one-stop-shop" business model, supercenters rely almost exclusively on car access by their customers and require large parking facilities. Because of the large store size and coverage area, supercenters are mostly located in suburban or out-of-town locations that are well connected to major road networks.

Recent niche retail stores

Changes in the demographic and geographic environment of metropolitan areas and growing competition by supercenters have put traditional supermarkets in need of searching for new business models, of which two are most notable: Specialty stores and hard discount stores.

Specialty stores
As a response to no longer being able to compete for price-leadership with supercenters, certain stores have focused on a premium approach. It involves carrying specialty products, own premium store brands, an emphasis on organic products or local sourcing of food. Due to higher relative prices, premium products are primarily aimed at the more affluent population. Supermarkets that specialize on these premium products provide a niche of food retail that is capable of providing healthy and nutritious food. Whole Foods, one of the pioneers of the organic food movement, has recently targeted low-income neighborhoods in Detroit (Buss, 2013) and Chicago (Munshi, 2013). However, it remains to be seen whether a business model for upscale food retail in deprived areas can be sustainable and, more importantly, whether it will yield prices low enough to be affordable in areas of deprivation.

Hard discount stores
Another trend in food retail that goes the opposite direction of specialty stores are *hard discount stores* (e.g. Save-a-Lot or ALDI). Instead of providing a premium product offering above the price level of the competition, the stores employ a low-variety strategy to keep stock and lease costs down. This and the introduction of own-store-brands offer an affordable full-line grocery option, especially within low-income areas. There has also been a "channel blurring" effect among retailers traditionally carrying non-food items such as pharmacies and dollar stores (Ploeg et al., 2009, pg. 88), although they can not be expected to carry a full line of foods that comprise a healthy diet (Hillier et al., 2011, pg. 717).
Wholesale clubs offer discounts on a small variety of products that are either larger in size

or bulk. They require an annual membership fee (basic annual memberships costs in January 2014: $45 (Sam's Club); $50 (BJ's Wholesale Club); $55 (Costco)) and are often not included in food desert studies. This is firstly due to the industry not considering wholesale club stores as supermarkets and secondly due to only few of these stores accepting SNAP benefits. SNAP is an important means of food payment in vulnerable low-income neighborhoods (Ploeg et al., 2009, pg. 16). Hence, due to reasons stated above, discount stores were used as a means of providing adequate nutritious food in this study, while pharmacies, dollar stores and wholesale clubs were not.

2.3.2. Economic theory of retail facility location

The history of the food environment has shown significant changes in store types and especially store location that have led to the disparities in food access today. To improve the placement of food retail facilities, it is essential to understand the economic drivers and forces behind it. A framework by Bitler and Haider (2011) provides an economic analysis of relevant products (omitted here as it is covered in 2.1.1), demand- and supply-side factors of food access, the market environment and market failures leading to inefficient outcomes. The next part addresses causes of retail outlet agglomeration and discusses consequences of market failures on food access.

Demand-side issues

Basic determinants for consumer choice in an economic context are *income*, *price* and *personal preferences* (Bitler and Haider, 2011, pg. 156). In general, healthy food is assumed to be a normal good, meaning that demand increases with increasing income. Hence, high-income areas should see a higher prevalence of healthy food retail options than low-income areas. To cater to income discrepancies on the demand-side, government programs focus on increasing the spendable income through temporary assistance or supplemental income. Direct food assistance (e.g. SNAP) works similarly, it provides an increase in the income to be spent on food where necessary. Another approach is substituting food purchases through direct provision (e.g. Seniors Farmers Market Nutrition Program).
Regarding the price of food, it is important to note that indirect costs of food supply exist. The time cost of obtaining ingredients and preparing meals add up to the total price of unprepared food. One also has to account for disparities in consumer preferences. People with different ethnic and social backgrounds tend to demand different foods and diets. Heterogeneous preferences do affect the supply of food but might cloud the real issues. Additionally, customers are not perfectly rational concerning the health of food due to inadequate information about food choices (a lack of informational access) and behavioral factors (lack of self-control, time-inconsistent preferences, effects of habituation).

Supply-side issues

Supply of food retail is determined by the input costs to running an outlet. The fixed input costs include labor, land and equipment; transportation, stocking, inventory, and wholesale product costs are examples of variable input costs as they are sensitive to a change in quantity of outputs (Bitler and Haider, 2011, pg. 157). When considering serving urban food deserts, there is a controversy about land and labor costs: Generally, land prices in densely populated areas tend to be higher than in less densely populated areas. But as deprivation increases, land and labor costs decrease. However, the prevalence of food deserts shows that placement of large-scale retailers in those areas is rare. Research on the existence of food deserts from the supply-side is far from complex. One possible explanation for this anomaly could be stricter zoning requirements or higher security costs in poor areas. Another reason for high access disparity and certain areas being underserved are economic effects such as economies of scale, scope and agglomeration that support the clustering of food outlets and create areas of low and high food availability. Agglomeration is addressed in further detail later in this chapter.

The market

From an economic standpoint, the market is the place where supply-side and demand factors interact. Basic determinants for market interaction are market power, fixed costs and transportation, differentiation as well as endogenous fixed costs. In places where there is a shortage of firms serving a market (monopoly, duopoly or oligopoly), firms are able to exercise market power. Hence, consumers in underserved areas have little market power due to a deficit of competition. Market power is influenced by demand-side factors (such as transportation cost for consumers) as well as supply-side factors (such as fixed costs). As local market power is a determinant for price development, higher price levels could be sustained in food deserts where high market power and low store density is prevalent. Another theory states that the use of endogenous fixed costs to constrain or keep out competitors is a means of controlling market power, which could provide an explanation to the small number of large chains and a multitude of smaller stores (Bitler and Haider, 2011, pg. 159).

Another dimension of strategic decision making in the market is the level of product differentiation. Economic theory suggests that vendors selling indifferentiated products will enter a sequential price undercutting (Hotelling, 1929, pg. 43), hence companies that are not able to differentiate by location should differentiate by the range of products offered. The economic analysis shows that either supply-side factors or demand-side factors could lead to disparities across areas in location, type of store available and the products offered within stores. However, it is difficult to determine which factors affect location and the type of available products because they are interdependent and determined simultaneously (Ploeg et al., 2009, pg. 86).

Market failures

Food deserts constitute as an area where demand for certain products can not be satisfied shows signs of market inefficiencies. A deviation from an a perfectly competitive market (called a *market failure*) may lead to inefficient outcomes. Economists are concerned with causes of market failure and possible means of correction. If necessary, market inefficiencies may be grounds for policy interventions to restore or improve allocative efficiency. The problem with economic analysis in the public sector is that policymakers have to bear a trade-off between market efficiency and social equity; economic theory does not make a statement about how to weigh these factors.

To model appropriate public policy changes, it is important to note the reasons for market failure and ultimately understand the causes of inefficiencies. First, barriers to entry impede de novo entry of competitors, which is a valid regulatory mechanism to punish or limit the exercise of market power. In food retail, barriers to entry may include substantial fixed costs of operation in areas with a lack of competitors. Second, imperfect information among consumers as well as suppliers constitutes a market failure. A lack of informational access among consumers may yield a socially inefficient outcome, such as unhealthy eating habits resulting in rising health care costs. But also among retailers, imperfect information may lead to market inefficiency. This is closely related to the concept of bounded rationality proposed by Simon (1972). For example, inexact demand forecasts through incomplete consumer information may result in retail placements that are not efficient. Companies make use of learning effects for lack of a sufficient data or sophisticated analysis methods by adopting strategies from competitors.

One example is the placement technique of the fast food chains. Toivanen and Waterson

(2005) has found that the probability of opening a new fast food outlet in the UK between 1991 and 1995 increases with the stock of outlets belonging to a rival chain - the placement of a rival updates one's own market expectations in light of uncertain forecasts. A third example of market failures are externalities - situations, in which the consequences of actions are experienced by unrelated third parties. An unhealthy lifestyle may ensue health care costs that are only partly borne by the individual (Bitler and Haider, 2011, pg. 160), an issue that is magnified through the widespread introduction of public health care in the United States.

Outlet agglomeration

Store location is one of the most long-term and costly strategic decisions for food retailers. The (short-term) irreversible nature of location choice makes economic theory on facility location crucial for the placement of stores (Fox et al., 2007, pg. 3). A phenomenon that has been extensively studied and of utter importance for the formation of food deserts is *agglomeration*. Agglomeration is one of the reasons why most new grocery superstores, along with other 'big box' outlets, are found in expansive retail centers. These retail centers are almost always built in excess of a 500 meter walk of residential land uses (Larsen and Gilliland, 2008), constituting access barriers for people without access to individual transportation.

Agglomeration through proximity of stores to customers

Economic models of spatial competition seek to include the total costs incurred by customers as a function of actual product price and transportation costs. Hotelling first described the competitive effects in a market based on sheer proximity to customers (Hotelling, 1929). In models of spatial competition, being "closer" to the customer means experiencing a higher degree of price competition while catering to a larger customer base. The model has several limitations to actual facility location problems (such as inelastic demand, restriction of goods to one, constant economies of scale) but provides an simple analytic explanation why states of agglomeration are stable. Gravitational models offer another explanation to agglomeration as well as supermarket floor size growth by differentiating between outlets with different characteristics. Huffs measure of attractiveness is based on the notion that the larger a store, the farther a customer is willing to travel (Fox et al., 2007, pg. 6f).

Agglomeration through inter-store externalities

Other causes of agglomeration are externalities that arise between stores close to each other. One can differentiate between facilitated consumer search and multipurpose shopping opportunities (Fox et al., 2007, pg. 7).
Studies about *consumer search* have shown that consumers search for prices among products in outlets of the same type and visit different grocery stores in one trip, although evidence about the extent of aggressive price search shows mixed results at best (Urbany et al., 2000, pg. 244). Agglomeration of several similar store might increase attraction of retail centers for customers who exercise price search and and increase profits of all stores involved.
A second dimension of externalities are spillover effects between retail stores that are of a different type. Expectedly, evidence suggests that inter-type externalities are more beneficial than intra-type externalities because of less competitive pressure (Fox et al., 2007, pg. 8). Arentze et al. (2005) provide evidence that agglomerations of stores selling different goods experience agglomeration effects even beyond its effect of multipurpose shopping. Different store types add to the attraction of a retail location and draw both multi-purpose and single-purpose shopping trips, even if no purchases are made from these stores.

2.3.3. The importance of urban planning

The historical development century of food retail until the beginning of the 21st has rendered increasingly unequal food access. However, profound intervention in the food environment has often been and still is neglected by urban planning and government policy. The logic in policy was that food, in contrast to air and water, was not a public good, although it constitutes a basic human need (Eckert and Shetty, 2011, pg. 1218). Hence, the adequate supply of food was left to the private sector and balanced by market forces. From a welfare standpoint, this might provide evidence that the liberal approach towards food supply was flawed. Urban food system have a lower visibility than the main systems in urban planning such as transportation, housing, employment or the environment The reasons for lower visibility of food systems in urban areas are 1) the population takes food for granted; 2) food issues are perceived as an agricultural and therefore rural issue; 3) technology has geographically decoupled food production and food consumption and 4) policymakers in the United States follow a strict separation between urban and rural issues, which is why food programs tend to focus on the rural issues (Pothukuchi and Kaufman, 1999, pg. 213f).
Urban planning for effective and policy interventions could improve equity in food access and tackle the market failures that have arisen. It is apparent that a comprehensive solution must include several fields of planning and should cover all dimensions of access (Eckert and Shetty, 2011, pg. 1218). An optimization of geographic access for economic development planning alone, as covered in this research, can only be fully effective when combined with measures to improve economic and informational access as well.

2.3.4. The food environment in Philadelphia

With 29.1 percent self-reported obesity prevalence according to a national study by the Centers for Disease Control and Prevention (2013) in 2012, Pennsylvania shows a medium level of obesity on a national scale. However, among the states with the 20 highest adult obesity rates, Pennsylvania is the only one not located in the South or Midwest of the United States (Levi et al., 2011). Obesity rates of Pennsylvania also lie above the average and population-weighted average of neighboring states [1].
As the largest city of Pennsylvania, making up more than 12 percent of the total population, Philadelphia's health status has a considerable effect on those numbers. Philadelphia County shows the highest prevalence of adult obesity (35.1 percent) and diabetes (11.9 percent) and the second highest prevalence of heart disease (4.5 percent) among counties that contain the 10 largest U.S. cities (Gilewicz, 2011).
Philadelphia is commonly used as an example for a city that lacks general supermarket access. While Philadelphia does not stand out in characteristics of poverty status when compared to other large urban areas, the lack of access to healthy foods due to a shortage of supermarkets is remarkable (Giang et al., 2008, pg. 272). A national study of supermarket density in 20 metropolitan areas from the University of Connecticut Food Marketing Policy Center found that Philadelphia had the second lowest number of supermarkets per capita of any major city in the United States in 1990, second only to Boston (Cotterill and Franklin, 1995, pg. 15). According to (Duane Perry, 2001, pg. 2), the Greater Philadelphia region has 70 too few supermarkets in low-income neighborhoods.
In addition to a sheer lack in numbers, access to food in Philadelphia was found to be highly uneven. Instead of being dispersed throughout the metropolitan area in relation to the population, supermarket sales in Philadelphia were observed as concentrated in

[1] Obesity prevalence of neighboring states in 2012: New York 23.6 %, New Jersey 24.6 %, Maryland 27.6 %, Ohio 30.1 %, West Virginia 33.8 %: Mean: 26.8 %, population-weighted Mean: 27.8 %
Sources: Centers for Disease Control and Prevention (2013), United States Census Bureau (2013), Author's own calculation.

certain areas, indicating that many people lack geographic access and shoulder notable distances to buy food at supermarkets. Furthermore, low-income residents seem to be disproportionally affected by lack of geographic access. In the poorest parts of town there are fewer supermarkets (Weinberg, 2000, pg. 23). In Philadelphia, the disparity in supermarket density in the lowest-income neighborhoods compared to the highest-income neighborhoods was five times worse than the average of all 20 metropolitan areas. The number of supermarkets in the lowest-income neighborhoods was 38 percent less than in the highest-income neighborhoods, in contrast to 30 percent less on average (Cotterill and Franklin, 1995, pg. 57). Unsurprisingly, in a block-group-level study by Giang et al. (2008) low-income Philadelphia residents were more likely to incur deaths believed to be related to diet, such as deaths from heart disease, cancer, and diabetes.

2.3.5. Community initiatives to improve urban food access

Research has shown that Philadelphia's lack of supermarkets and an uneven distribution thereof puts low-income areas at a disadvantage and might negatively affect the health of communities. Across the country, there has been a vast array of public policy and private sector efforts to tackle this problem. The most far-reaching and relevant to this research topic are discussed in the following section.

Incentivizing urban super market establishment

Private sector efforts

An obvious solution to improving urban food access is the endorsement of new super market facilities in areas of need. According to (Cotterill and Franklin, 1995, pg. 9f) an explicit campaign by the First National Stores chain to re-enter urban city areas seems to have solved the grocery gap problem in Cleveland, Ohio. The two zip code groups with the highest quintiles of households on public assistance have a higher number of grocery stores per capita than the lower three groups. This could still be accounted to larger grocery stores serving suburban areas with higher car densities (Cotterill and Franklin, 1995, pg. 45). However, those two groups also have the highest square foor per capita than any other zip group (Cotterill and Franklin, 1995, pg. 14). This is a unique observation among the 21 metropolitan areas studied and shows that efforts towards urban grocery store relocation can have impact on the urban food landscape.

Public policy efforts

Public/private partnerships between local government and private sector organizations can be used to bring supermarkets into food deserts and provide access to a populaton that has been overlooked by the retail food industry.
Pothukuchi (2005) studied whether cities have addressed the lack of access to supermarkets through supermarket development initiatives in low-income, underserved neighborhoods. Only three cities (Dallas, Rochester and Chicago) were found to have succeeded through systematic and city-wide efforts to attract supermarkets in urban areas. These cities have leveraged public/private partnerships with supermarket business leaders to build and maintain infrastructure and necessary community facilities (Walker et al. (2010), pg. 882; Pothukuchi and Kaufman (1999)).
The city of Dallas negotiated the development of five sites in the city's Empowerment Zones with Fiesta Mart, a supermarket chain that caters to mixed-income and ethnic minority communities. In total, three supermarkets were built and the incentives that were offered attracted the settling of another supermarket chain, which, at the time of this study, had opened three additional stores.
Another partnership that has revived urban food retail was between the city of Rochester

and a local nonprofit citizens group (Partners Through Food). After a decline from 42 supermarkets within city limits in 1970 to five in 1995 (Pothukuchi, 2005, pg. 238), a major supermarket chain (Tops) committed to build four new stores and expand an existing one in exchange for public funding and a plan to improve areas of the newly built stores (Brunett and Pothukuchi, 2002).
The city of Chicago introduced the Chicago Retail program in 1994, which streamlined the process of retail development for potential developers. Apart from a range of financial incentives, it provided analyses of retail environments and guidance for facilitating approval, assembly and community involvement opportunities. The program helped one supermarket chain to stay competitive and open four new stores, among other new supermarkets.
The evidence suggests that collaboration between the public and the private sector can yield win-win situations because it combines welfare- and profit-maximizing principles. Unfortunately, it is rare to see city planners taking on a "proactive" role in developing the urban food retail environment because they tend to overstate its attraction towards businesses. On the contrary, the market conditions are perceived as poor and out of their locus of control by developers, tampering the design new development proposals (Pothukuchi, 2005, pg. 241f).
In 2004, the state of Pennsylvania took on this proactive role by introducing the nation's first statewide financing program for supermarket establishment. It provides financing for underserved communities where infrastructure costs and credit needs cannot be filled by conventional financial institutions alone. As a private/public partnership, it has attracted more than $190 million in private funding for supermarkets throughout the state. Pennsylvania appropriated $30 million to the program and the Reinvestment Fund, a Community Development Financial Institution (CDFI), leveraged the investment to create a $120 million initiative. As of June 2010, it has provided funding for 88 fresh food retail projects in 34 Pennsylvania counties, ranging from large, full-service urban-area supermarkets to small grocery stores in rural areas (The Reinvestment Fund, 2012).

Get Healthy Philly - a comprehensive Philadelphia health initiative

Get Healthy Philly is a comprehensive, equity-oriented approach to healthy eating and active living program that was started the Philadelphia Department of Public Health in 2004 and a fundamental component of *Philadelphia2035* (Bell et al., 2013, pg. 19). It is funded by the "Communities Putting Prevention to Work" Initiative from the Centers for Disease Control and Prevention (Kimberly, 2011). Its aim is the reduction and prevention of obesity and diet-related diseases through three specific objectives: 1) improving access to healthy and affordable food; 2) decrease the consumption of high-sugar drinks and junk foods and 3) establish spaces for physical activities in communities, such as walk- and bike-friendly neighborhoods. Food retail related programs of Get Healthy Philly include the Healthy Corner Store initiative, the addition of Farmers' Markets and the Philly Food Bucks Program, both of which are introduced in the following section.

Healthy Corner Store Initiative

In contrast to opening new supermarkets, Philadelphia has introduced the Healthy Corner Store Initiative in 2004 to improve the offering of corner stores in underserved communities. Instead of building a new facility, this strategy builds on the existing infrastructure to incentivize a healthier product offering. Corner stores in Philadelphia sell only a small selection of foods and its owners lack resources to advertise, stock and sell healthy food (Ploeg et al., 2009, pg. 99). Because they tend to be willing to make a transition to a healthy inventory (The Food Trust, 2012, pg. 3), the city provided corner stores in target neighborhoods with a phased framework to facilitate the process.
Each corner store in the network was required to add a minimum of four new products

with at least two healthy products in at least two food categories including: fruits and vegetables, low-fat dairy, lean meats and whole grains. As an incentive, stores in the network have received marketing materials and training. A subset of corner stores receives investments between $1,000 and $5,000 in form of equipment to stock and display fresh produce and healthy products, transforming the businesses into health-promoting food retail outlets (The Food Trust, 2012, pg. 6f). By December 2012, 640 corner stores within Philadelphia added at least four new required products; 200 qualified for one-on-one training and infrastructural investments as an "Enhanced Healthy Corner Store" (Open Data Philly, 2012).

Farmers' Markets

Recently, Farmers' Markets have seen growing popularity as components of urban revitalization. The number of Farmers' Markets throughout the United States has been growing steadily over the last decade, from 3,137 in 2002 to 7,864 in 2012 (United States Department of Health Agricultural Marketing Service, 2013). In Philadelphia the seasonal offering of local and fresh food was perceived as affordable (Get Healthy Philly, 2011, pg. 3), leading to a city-wide initiative to expand the Farmers' Market network and stimulate attraction among the low-income population. As part of a two-year $15 million grant through the U.S. Department of Health and Human Services', the city of Philadelphia has set a target of 10 new Farmers' Markets in addition to the roughly 40 stores in 2010. By January 2013, this goal has far been exceeded: 62 Farmers' Markets operate in Philadelphia (Open Data Philly, 2013). The funding also piloted the *Philly Food Bucks* coupon incentive program for SNAP participants at more than 25 Farmers' Market sites in Philadelphia. For each spending of $5 SNAP benefits, individuals receive a $2 dollar coupon that can only be redeemed for fresh fruits and vegetables. SNAP benefits at Farmers' Markets increased by 97 percent within one year after the introduction. Philly Food Bucks users have reported higher consumption of fruits and vegetables and show greater loyalty as compared to non-users (Get Healthy Philly, 2011, pg. 11f). Furthermore, an evaluation of Farmers' Market showed that the primary methods of customer transportation are walking or biking, suggesting that Farmers' Markets are mostly used by people from the direct vicinity of a Farmers' Market. Hence, the location of Farmers' Market in urban areas is even more crucial for its social and economic impact.

2.4. Facility location models and defining an optimization problem

As this research is concerned with the observation and optimization of food access through the search for appropriate locations of new facilities, the possible approaches from an operations research standpoints must be introduced and evaluated. ReVelle et al. (1970) classify location models into two broad classes of problems: continuous space and discrete network-based models. Location model development has focused on the latter of these two classes (Church, 2002, pg. 552). This section features a typology and existing formulations of discrete facility location problems. These are differentiated by geometric principles (the type of supply and demand objects and the type of measurement), objective function, constraints and solution techniques.

2.4.1. Geometric principles

The definition of a location model involves the decision of how a demand and how a facility is defined, based on what kind of spatial relationships between them exist. Even though demand is often continuously spread across an area, it is often aggregated as a single point. Geographic Information Systems (*GIS*) offer the opportunity of displaying

and storing a space of demand as spatial data. But most of the existing facility location models are based upon the assumption of point representation of demands. Facility sites can be defined as points, lines, or areas (Longley et al., 1999, pg. 296ff).
Miller (1996) has introduced a typology of location models based on the geometric representation of demand and the geometric representation of facilities. The drawback of different representations of demand is that they may provoke aggregation errors. Any spatial aggregation of dispersed demand propagates error to the value of the objective function and optimality of the results (Drezner and Hamacher, 2002, pg. 208). Miller states that the use of GIS allows for better representation of object features, such as facility size and shape, potentially to increase the relevance and flexibility of facility location models. Albeit, as the demand data in the case of food retail in an urban environment is polygon-based (e.g. in form of population per area respectively shape), the two manifest representations of demand are polygons or points of aggregation. While food outlets also cover a geographic space (the outlet's footprint), the discrepancy between the service area and the facility size is rather large, therefore a polygon representation may be neglected in favor of a point representation. Hence, the two types of location models most appropriate for further use in this study are point-point location problems and point-polygon location problems and are covered in the following section.

2.4.1.1. Point-polygon location problem

Point-polygon problems locate a set of facility points to serve a set of weighted polygons. They are based on the assumption that demand characteristics are almost evenly dispersed over a specific geographic area and can be represented as areal demands. The assumption that people living in close proximity or in a certain area (e.g. census tracts, planning districts) share similar characteristics is often a necessary trade-off between aggregation errors and the computational cost to obtain and implement individual data (Drezner and Hamacher, 2002, pg. 215). Furthermore, institutions that have the means to gather and publish individual information (such as the U.S. Census Bureau) often underlie strict privacy guidelines and use aggregation to sanitize personal data. Common usage for point-polygon location problems with demand data spatially aggregated as polygons is retail or service facility location (Miller, 1996, pg. 795).

2.4.1.2. Point-point location problem

A common simplifying assumption in location models is that both demand and facility sites are represented as a collection of discrete points ("site points to serve points"). The objective of a point-point location problem is locating a set of points in order to serve a subset of this collection of (weighted) demand points . The aggregation of client data in point form allows for easier solution techniques, as the complexity and the amount of information is reduced.
However, since most solution algorithms have been developed for such cases (Longley et al., 1999, pg. 297), a point-point based model is used more often than not, especially for applications such as retail or service facility location with disaggregate client data or aggregate client data represented by centroids (Miller, 1996, pg. 795).

2.4.2. Objective functions

Four basic models of deterministic discrete facility location problems are center problems, covering problems, median problems and warehouse location problems (Vahrenkamp and Mattfeld, 2007, pg. 144). Several abstractions are needed for modeling and solving these problems. First, the optimization needs to be based on a fixed network, meaning that user demands are represented as a finite set of discrete points that are fully or partly interconnected and that the potential locations are also a finite set of points. Second, a distance measure is required and the distances from demand points to potential facilities is known. Third, the set of demand nodes constitutes the potential locations for facilities, meaning that facilities may only be placed on points of demand (Toregas et al., 1971, pg. 1364).

2.4.2.1. Total or average distance problems

Median problems

A median problem involves locating a fixed number of facilities in such a manner that the average distance from any user to their closest facility is minimized. Classic median models are based upon the assumption that there are enough resources at each facility to handle whatever demand needs to be served. Thus, everyone is assumed to be served by their closest facility.

P-Median Extension: Warehouse location problem

The warehouse location problem, often referred to as *Simple Plant Location Problem* (SPLP) or *uncapacitated facility location problem* (UFL), is a particular version of a p-median problem that has been adapted for the distribution of consumption goods. Its goal is the cost-optimal placement of warehouses on nodes of a network in order to satisfy the consumer demands, while the nodes represent aggregated points of demand and possible locations for warehouses. The total costs incurred consists of two antidromic cost types: 1) variable transportation costs that increase with distance and weight of the demand points, and 2) fixed costs of opening a facility (Vahrenkamp and Mattfeld, 2007, pg. 165f). Because the opening of facilities is dependent on whether it yields a decrease in total costs, the number of facilities to be located is endogenous to the problem (ReVelle and Eiselt, 2005, pg. 8), in contrast to the fixed amount of facilities to be opened in a regular p-median problem.
In real life, companies encounter limits on what can be accomplished at each facility (e.g. the number of units that can be manufactured, the amount of demand that can be served or assigned, the volume of garbage that can be handled per day etc.). To account for this, warehouse location problem are commonly extended by warehouse (supplier) capacity constraints. The resulting problem is commonly referred to as a *capacitated plant location problem* (CPLP). These additional constraints destroy the binary property of service; all demand of a customer might not be satisfied from a single facility because supply is prone to running out. This complicates the allocation rule, making the capacitated plant location problem much more difficult to solve than the corresponding uncapacitated problem (ReVelle and Eiselt, 2005, pg. 8f), where just the assignment of demand point to the nearest facility normally does not underlie further constraints (Vahrenkamp and Mattfeld, 2007, pg. 164). The CPLP is strongly NP-hard (Farahani and Hekmatfar, 2009, pg. 180).

2.4.2.2. Maximum distance models

Center problems

A p-center problem seeks p ($1 <= p < n$) facility locations that minimize the maximum distance to the demand points, where the distance from one point to the facilities is the distance from the point to its nearest facility. The problem seeks to minimize the maximum distance from a site to any demand point, so to speak the worst case distance scenario, and is therefore often referred to as the *minimax facility location problem*. Rather than taking a given input coverage distance, this problem class determines a minimal coverage distance associated with the placement of p facilities(Owen and Daskin, 1998, pg. 429).

Covering problems

Minimizing average distance using a median problem can still leave individual demand points far from their closest facility, sometimes too far for ensuring the adequacy of the service (Longley et al., 1999, pg. 299). This issue is especially pressing for services that are perceived as “public”, as the amount of stakeholders involved is rather large and an equal, adequate service level is generally expected. Therefore, a different measure of location efficiency is needed (Owen and Daskin, 1998, pg. 427). For example, in food retail, average distance to healthy and nutritious food does not capture the extent of inequalities in access. Covering models use a different measure of service. They involve locating facilities in order to cover all or most demand within some desired service distance or response time standard (often referred to as the *maximum service distance*). The idea is that the more users who are relatively close to a facility, the better the service. One key issue of covering models is the definition of coverage.
An acceptable upper limit for the service distance should best represents a point of indifference between costs of travel and individual demand for a product. This is especially important when considering a basic assumption of “binary coverage” in almost all covering models up to date: demand points are covered completely if located within the critical distance of the facility and not covered at all outside of the critical distance (although there have been approaches to account for “partial coverage” in relation to distance from a facility such as Karasakal and Karasakal (2004)). In this application, the service distance of a food retail outlet should resemble a barrier after which it is no longer practicable to bear the periodic travel to and from the outlet based on a means of transportation.

Maximal covering location and location set covering problems

The *maximal covering location problem* (MCLP) and the *location set location problem* (LSCP) form the basis of a large class of location models.
The location set covering models determine the cost-minimal spatial arrangement of facilities needed to cover all demand nodes. If costs are identical for all possible facility locations, then an equivalent goal formulation would be minimizing the total number of facilities necessary to meet all demand. The solution will provide the locations as well as the number of facilities that offer the required service (Toregas et al., 1971, pg. 1363f).
The definition of the location set covering model implies a guaranteed coverage, as every demand point must be within the maximal service distance to a facility. In planning situations there may exist a budget constraint, setting an upper limit on the number of facilities. The maximal covering location problem assumes that there is an abundance of demand and there may not be enough facilities to cover all demand nodes. Subsequently, the goal of the MCLP is locating a fixed number of facilities in a manner that coverage is maximized (Drezner and Hamacher, 2002, pg. 86ff).
Median models can address many different types of application, which may explain the wide array of extensions that have been added over time. However, in light of limited limited food access being defined on a binary basis (located within a certain range to a food retail store), covering problems offer a direct representation of geographic access. The maximum covering location problem is used to determine what levels of coverage can be provided given a specific levels of investment, which might be one of the first questions asked in the stages of retail coverage modeling. To lay the foundation for this research, the following paragraph addresses the solving process of large covering problems through exact and heuristic methods.

2.4.3. Computational strategies

2.4.3.1. Problem formulation

To formulate the covering problems, the following notation will be used:

Sets

I set of demand points
J set of potential facility sites
S maximum coverage distance

Parameters

i = index of demand node ($i \in I$),
j = index of potential facility sites ($j \in J$),
p = number of facilities to be located,
a_i = demand at demand point i,
d_{ij} = distance between demand i and facility site j,

$$x_{ij} = \begin{cases} 1, & \text{if demand at } i \text{ is covered by a facility at } j \Rightarrow d_{ij} < S. \\ 0, & \text{otherwise.} \end{cases}$$

$$y_i = \begin{cases} 1, & \text{if demand at } i \text{ is covered.} \\ 0, & \text{otherwise.} \end{cases}$$

$$o_j = \begin{cases} 1, & \text{if facility is opened at } j. \\ 0, & \text{otherwise.} \end{cases}$$

Maximum covering location problem (MCLP)

The MCLP can be formulated as the following ((Church and ReVelle, 1974, pg. 103ff), (Longley et al., 1999, pg. 299ff)):

$$\begin{array}{lrcll} \max & \sum_{i \in I} a_i y_i & & & \\ \text{s.t.} & \sum_j x_{ij} + (1 - y_i) & \geq & 1 & \forall i \in I \\ & \sum_j o_j & = & p & \\ & o_j & = & (0,1) & \forall j \in J \\ & x_{ij} & = & (0,1) & \forall i \in I, j \in J \\ & y_i & = & (0,1) & \forall i \in I \end{array}$$

Location set covering problem (LSCP)

The problem formulation for an LSCP is analogous to the MCLP:

$$\begin{array}{lrcll} \min & \sum_{j \in J} o_j & & & \\ \text{s.t.} & \sum_j x_{ij} + (1 - y_i) & \geq & 1 & \forall i \in I \\ & o_j & = & (0,1) & \forall j \in J \\ & x_{ij} & = & (0,1) & \forall i \in I, j \in J \\ & y_i & = & (0,1) & \forall i \in I \end{array}$$

2.4.3.2. Solution techniques

Single-site location search problems usually are solved by enumerating all possibilities. Even with a large amount of possible sites, scoring sites and select the highest scoring site is not very computationally burdensome. Through interaction between newly placed facilities, multiple-site location search is a more complex task (Longley et al., 1999, pg. 297ff). Except for the rare cases in which, all coverage can be provided by one facility in the LSCP or, only one facility is to be opened in the MCLP, both models must be solved as multiple-site location search problems.

Links between p-median and covering problems

(Church and ReVelle, 2010, pg. 409ff) noted that there are theoretical links between the p-Median and covering problems. The MCLP as well as the LSCP can both be defined as a special class of general p-median problem by transforming the real distances of a p-median problem into binary values representing coverage or no coverage:

$$d'_{ij} = \begin{cases} 0, & \text{if } d_{ij} \leq S. \\ 1, & \text{if } d_{ij} > S. \end{cases} \tag{2.1}$$

A value of one indicates that a demand at node i can not be covered by a facility at node j and vice versa because the distance exceeds the maximum service distance. Therefore, in addition to being able to solve the MCLP using the LP approach or the heuristics developed by (Church and ReVelle, 1974, pg. 105), any covering problem structured in a p-median format may be solved with approaches for a p-median problem.

Lagrangian Relaxation

There are two prevalent solution techniques for the p-median problem: Lagrangian Relaxation with limited branch and bound and heuristics. Special purpose Lagrangian Relaxation with branch and bound has been used to identify an exact optimum or a solution within a known percentage of optimality. A Lagrangian Relaxation with subgradient optimization has been employed to solve problems of up to 800-900 nodes (Beasley, 1993) but can be quite sensitive to parameter changes(Longley et al., 1999, pg. 300f).
Maximal covering (Longley et al., 1999, pg. 300) and set covering (ReVelle and Eiselt, 2005, pg. 9) problems are non-deterministic polynomial (NP)-hard. This means that specific instances of this problem might not be solvable through branch and bound within a reasonable amount of processing time. Since covering problems can be represented by thousands of nodes, it is virtually impossible to consider solving problems of these proportions optimally. This is where heuristics offer techniques that provide a solution which is not guaranteed to be optimal in mostly a much shorter amount of computing time.

Heuristics

Because of the high degree of interoperability between the generic p-median problem and other location problems, it is not surprising that several types of heuristic for the problem have been developed.
One of the first heuristic methods for the p-median problem is a location–allocation heuristic by Maranzana (1964). The method "approaches the p-median by finding successive single vertex medians of p subsets of destination vertices each associated with one source, and then adjusting the subsets before repeating the process" (Teitz and Bart, 1968, pg. 957f). In other words, it partitions the customers by facility and then finds centers of gravity within each partition. If any facility location changes, the re-partitioning of customers and the search for new optimal locations are iterated until no further improvement in the solution can be found (Farahani and Hekmatfar, 2009, pg. 497).
Another one of the older but more common heuristics for the p-median problem is the vertex substitution technique of Teitz and Bart (1968). The procedure starts with a pattern of p facilities. At each step of the heuristic, a candidate site is selected and tested to see if a substitution with other already sited facilities is possible. If any such substitution yields an improvement in the target function, a substitution is made. The heuristic was one of the first to work with a 1-opt search space, for the number of items being simultaneously

exchanged (ReVelle and Eiselt, 2005, pg. 8). Until now, it has received the widest recognition and is recognized as fairly robust at finding good, if not optimal, solutions. The main drawback of the vertex substitution technique is that its performance is restrained by the potential existence of a multitude of many local optima resulting from different starting solutions (Church and Sorensen, 1994, pg. 12). However, assuming there is a unique location with the best improvement in the iterations of the Greedy algorithm, the resulting solutions are unique and deterministic.

In their proceedings on the MCLP, Church and ReVelle (1974) posted two solution techniques, Greedy Adding Algorithm (GA) and Greedy Adding with Substitution Algorithm. In a performance analysis of a 55-node network by (Church and ReVelle, 2010, pg. 412), both heuristics usually provided good solutions to a given MCLP and the GAS algorithm outperforming both the Maranzana and the GA algorithm. The solutions were optimal between 30 percent for the GA and 50 percent of the time for the GAS algorithm. The better performance of the GAS algorithm can be led back to the "piggybacking" approach of the GAS algorithm by initiating a second solution technique with the final results from the first (GA). Essentially, the GA algorithm is a method of finding a starting solution for the vertex substitution procedure of Teitz and Bart used subsequently in the GAS algorithm. The only difference between GAS and Teitz and Bart is that GAS iteratively develops solution, whereas the algorithm Teitz and Bart relies on an initial start from the user (Church and ReVelle, 2010, pg. 411).

Following Maranzana (1964) and Teitz and Bart (1968), a number of other heuristic techniques have evolved (including genetic algorithm simulated annealing, TABU search, GRASP, and hybrids like Global- Regional Interchange Approach). Church and Sorensen (1994) described these techniques in detail and compared them in robustness as well as applicability in problem sets arising from geographic information systems. The algorithm of Teitz and Bart was favored due to its speed, robustness and ease of integration and should provide a good solution for the application in this study.

3. Methodology

The goal of this study was to assess the city-wide geographic access to supermarkets of Philadelphia and design a general facility location problem to identify possible new locations of supermarkets that bring a maximal improvement in supermarket accessibility, especially in areas that could be classified as food deserts. This analysis could help policy makers to not only become aware of deserted areas but provide resources for future business initiatives to effectively incentivize urban supermarket placements.

3.1. Form and acquisition of necessary data

To identify areas that lack supermarkets, a spatial representation of food access was created by mapping the locations of supermarkets and farmers markets combined with characteristics of increased vulnerability to food deserts. An initial series of maps was generated using the open source geographic information system software QGIS 2.0.1 (formerly Quantum GIS). Food demand was aggregated in geometric centroids (points of gravity)of Census Block Groups, the smallest geographical unit for which the Census Bureau publishes sample data. The distances between the demand points and existing supermarkets were extracted using QGIS functionalities. Available socioeconomic data was used to determine a measure of vulnerability. Finally, a covering location problem was defined and a Greedy Adding and a Greedy Adding & Substitution heuristic was programmed to solve the problem. The robustness of the heuristics was tested in a sensitivity analysis and the solutions were mapped and analyzed to propose feasible locations for urban supermarket openings.

3.1.1. Study area

This study focuses on the city of Philadelphia, which is the only consolidated city-county of Pennsylvania and has a population of 1,526,006 as of the 2010 Census. The city encompasses an area of 141.6 square miles (367 square kilometers) and is divided into 384 Census tracts and 1336 Census block groups. In comparison to the national average, Philadelphia shows signs of high relative deprivation [1]. Additionally, Philadelphia has the highest prevalence of obesity among the largest ten cities in the United States (Get Healthy Philly, 2013, pg. 4) and is home to a large black and Hispanic population[2], two ethnic groups that

[1] 26.2% of the population ranks below poverty level, a percentage twice as large as in the state of Pennsylvania (13.1%) (United States Census Bureau, 2014b)

[2] Black or African American alone, 2012: Philadelphia 44.3%, Pennsylvania 11.4%
Hispanic or Latino, 2012: Philadelphia 13.0%, Pennsylvania 6.1%(United States Census Bureau, 2014b)

have shown above-average obesity rates among lower-income levels (Ogden et al., 2010). Because of the combination of poverty and obesity in an urban area, access to food is an important social concern for public policy.

3.1.2. Spatial data

Mapping data of the city boundaries and statistical subdivisions of interest (block group level and census tract level) were drawn from 2010 Census TIGER/Line[3] Shapefiles provided by the United States Census Bureau (United States Census Bureau, 2010a). The Shapefile is a vector data format for the use in GIS which describes vector features such as points, lines and polygons and the attributes describing these features. The shapefiles provided describes outlines of the statistical subdivisions (Block groups in this case) and includes attributes about size (land/water area), population, location and various socioeconomic sample data.

3.1.3. Demand point aggregation

As a means of minimizing complexity for the solution of the problem, the subdivisions were discreticized. Because aggregation error increases with the subdivision size, the smallest subdivisions for which demographic data was available - block groups - were aggregated as geographic centroids, representing population-weighted points of demand in the optimization problem later on.

3.1.4. Socioeconomic data

The use of the shapefiles by the Census Bureau however, is restricted to mapping purposes as they do not include demographic data. This type of data was only offered in form of pre-joined Shapefiles with Geodatabases, which are not directly compatible with QGIS. Therefore it had to be resorted to the proprietary commercial GIS software ArcGIS 10.2 for an export of the demographic data to Comma-Separated-Value tables. The tables could then be re-joined with the subdivisions in QGIS using unique identifiers. Population data was taken from the 2010 Census, whereas the 2007-2011 American Community Survey 5-year estimates Summary File (United States Census Bureau, 2014a) served as a data set for other socioeconomic data. The most finely granulated representation of demographic data available are the block group level data sets, due to smallest subdivision size and therefore the smallest aggregation error.

3.1.5. Retail outlets

Farmers' Markets and supermarkets were used as existing facilities that can serve as sources for healthy food. Farmers' Market locations are made accessible by the City of Philadelphia on (Open Data Philly, 2013) as Shapefiles. Supermarket locations were identified by online location listings of chain stores serving the Philadelphia area and Google Maps. Food outlets had to have a full-line grocery offering, including a produce and fresh meat section, in order to be considered (e.g. Walmart supercenters were considered whereas Walmart Discount Stores were not because they lack fresh produce). This is also the reason why, although available on Open Data Philly (2012), Healthy Corner Store locations were not considered. Even though the initiative has been highly successful (see section 2.3.5), the very small selection of fresh produce rules out Healthy Corner Stores from full-line grocery stores. Hence, they were not considered an option for ensuring an adequate and full supply

[3] "TIGER = Topologically Integrated Geographic Encoding and Referencing.
TIGER products are spatial extracts from the Census Bureau's MAF/TIGER database, containing features such as roads, railroads, rivers, as well as legal and statistical geographic areas." (United States Census Bureau, 2010b)

of healthy food in the course of this study. After the addresses of eligible supermarkets were obtained, the WGS 84 (GPS) coordinates of the supermarkets were queried using a Google Geocode API XML request in an Excel VBA macro and joined with the Census layers in QGIS. In addition to 62 listed Farmers' Markets, 81 supermarkets within the city limits could be identified. The complete list of supermarkets can be found in the Appendix section A.

3.2. Underlying assumptions

3.2.1. Definition of coverage and access

Two different types of optimization about food access were made for the facility location problem. The first type models a supply pattern during the "farmers' market low season" with only supermarkets providing adequate access, whereas the second type represents a situation where farmers' markets can provide adequate access as well, but within a smaller range.

1. Supermarkets and supercenters can provide adequate healthy food access within an area of 1/2 mile (2640 feet).
2. Supermarkets and supercenters can provide adequate healthy food access to an area of 1/2 mile (2640 feet) and Farmers' Markets can provide adequate healthy food access to an area of 1/4 mile (1320 feet).

The service areas are in line with the service areas use in an access study by the (Get Healthy Philly, 2013, pg. 5). It should be noted that supermarket and farmers' market access was measured using the straight-line distance metric. The distances between each demand point and food retail stores was calculated using the QGIS Distance Matrix function.

3.3. Vulnerability Index

3.3.1. Variable selection

Socioeconomic variables can represent how communities are composed and the social conditions that prevail. To give a measure of how vulnerable some subdivisions are from a statistical standpoint, this index was based on composite deprivation indices that have been used in geographic access studies by Apparicio et al. (2007) and Larsen and Gilliland (2008) and are described in 2.1.4. Figures of recent immigration, however, could not be obtained from the Census Bureau and are not included in this study. To specially account for lack of physical mobility, two economic variables were added, vehicle access and share of elderly people. This measure included seven variables, computed from the 2007-2011 American Community Survey 5-year estimates: Three poverty, one employment, one education and two mobility variables (see the detailed variable description in3.1 and its descriptive statistics in 3.2).

3.3.2. Data reduction

The individual vulnerability of a subdivision to a geographic access barrier was measured using a composite Vulnerability Index, whose inputs are comparable to the ones used in indices by Apparicio et al. (2007), Larsen and Gilliland (2008). These studies compute a linear combination of five social indices. However, it is apparent deprivation variables can be strongly interdependent, skewing the composite index by over-representing certain causal links. Our data set showed significant correlations between all variable pairs except

Table 3.1.: Socioeconomic variables of neighborhood vulnerability

Domain	Variable	Description
Poverty	Low-Income population	Share of households with income of last 12 months below poverty level
	Public assistance	Share of households on public assistance
	Lone-parent families	Share of Lone-Parent-families of in relation to all households
Employment	Unemployment	Unemployment rate of labor force
Education	Low-level education	Share of population 25 years and over with with no no more than grade 8 education
Mobility	Elderly population	Share of population 65 years and older
	No vehicle access	Share of housing units with no vehicle access

Table 3.2.: Descriptive statistics of vulnerability variables in block groups of Philadelphia

		Low-Income population [%]	Public assistance [%]	Lone-parent families [%]	Unemployment [%]	Low-level education [%]	Elderly population [%]	No vehicle access [%]
Mean		25.09	8.64	27.98	14.57	5.49	12.48	34.62
Std. Deviation		17.49	9.52	17.29	11.36	6.52	8.75	21.06
Skewness		.81	1.45	.37	1.05	1.89	1.49	.28
Kurtosis		.29	2.18	-.47	1.07	4.68	3.84	-.81
Minimum		.00	.00	.00	.00	.00	.00	.00
Maximum		91.18	60.00	87.04	66.24	48.26	63.96	100.00
Percentiles	25	10.97	.00	14.25	6.20	.00	6.36	17.16
	50	22.13	5.75	26.32	12.21	3.42	10.89	33.48
	75	35.17	12.95	40.13	20.69	8.11	16.86	50.84

the one involving elderly population (see 3.3), which is unsurprising but stresses the importance of reducing linear combinations.
To merge the data and reduce the number of linear combinations in an overall index of neighborhood vulnerability, a factor extraction through a Principal Component Analysis (PCA) was constructed in IBM SPSS Statistics Version 21 following the method of Laerd Statistics (2014). The PCA procedure has also been used for similar composite deprivation indices such as the one computed by (Sharkey and Horel, 2008, pg. 622).
It is apparent that the share of elderly population is negatively correlated with variables that generally characterize socioeconomic deprivation. It should be included in the measure of vulnerability because it corresponds to a individual mobility dimension of vulnerability that is, in contrast to car accessibility, independent to the economic circumstances. Due to the negative correlations, including the elderly population variable in the PCA results in a negative component loading - a higher share of elderly people would lead to a lower vulnerability index. To avoid this misrepresentation of the elderly population, only the "deprivation-related" variables (excluding the elderly population share) underwent a PCA and combined with the elderly population later on (see 3.3.3).

Before conducting a factor analysis, the variables were tested on multicollinearity using a Kaiser-Meyer-Ohlin (KMO) measure of Sampling Adequacy (MSA). This test resulted in a KMO value of .793, ranking between a "middling" value of 0.70 and a "meritous" value of 0.80. The Bartlett's Test of Sphericity tests the null hypothesis of uncorrelation among the variables and showed a significance level of 0.00, a value that justifies the rejection of

Table 3.3.: Pearson correlations of vulnerability variables in block groups of Philadelphia

	Low-Income population [%]	Public assistance [%]	Lone-parent families [%]	Unemploy-ment [%]	Low-level education [%]	Elderly population [%]	No vehicle access [%]
Low-Income population [%]	1						
Public assistance [%]	.526**	1					
Lone-parent families [%]	.433**	.477**	1				
Unemployment [%]	.415**	.367**	.401**	1			
Low-level education [%]	.298**	.273**	.256**	.128**	1		
Elderly population [%]	-.237**	-.187**	-.267**	-.141**	-.043	1	
No vehicle access [%]	.631**	.386**	.300**	.295**	.208**	-.040	1

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

the hypothesis. The values indicate the appropriateness of the data for a PCA and do not compel the continuance of the factor analysis (Vyas and Kumaranayake, 2006, pg. 15f).
The eigenvalue-one criterion (Kaiser's criterion) was used in order to decide which components to retain. Any component with an eigenvalue less than 1.00 is accounting for a greater amount of variance than ha been contributed by one variable. Hence, an effective reduction of variables can be effectively achieved by just retaining components with eigenvalues greater than 1.
Kaiser's criterion revealed one factor with an eigenvalues of 2.858. The corresponding scree plot in 3.1 shows that the smooth decrease of eigenvalues appears to level off after the first two components, however, too little variables have been used to make a proper statement with a scree plot. The one component retained and explains 47.626 percent of the total Variance. The internal consistency of the measure following the rule of George and Mallery (2003) with a Crohnbach's Alpha of $\alpha = 0.753$ value is acceptable.

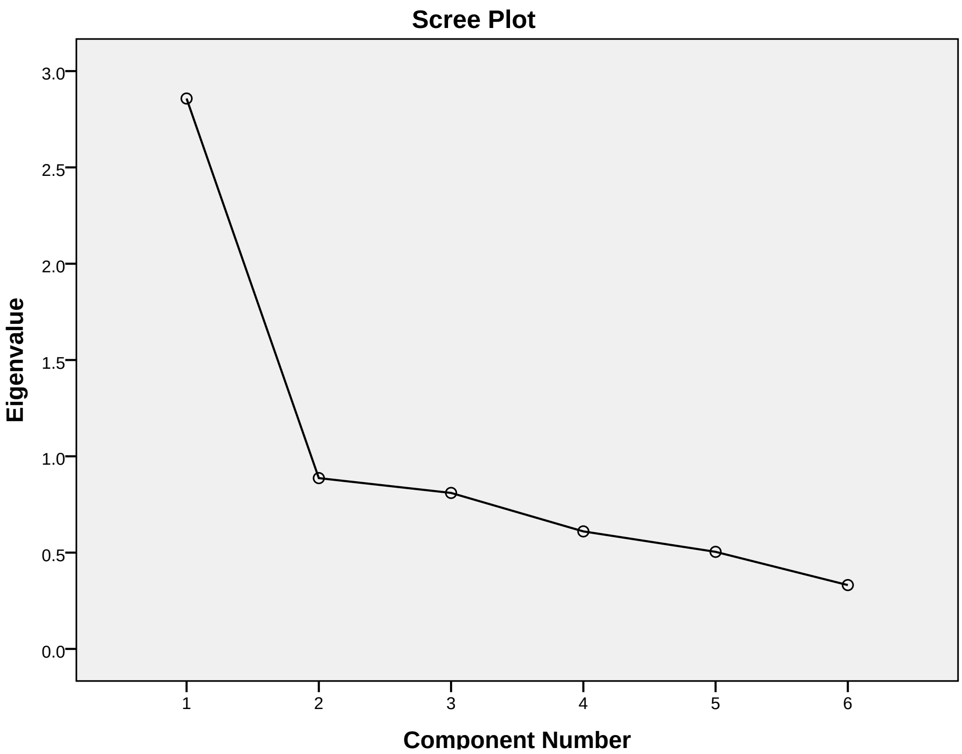


Figure 3.1.: Scree plot from eigenvalues of factors

The resulting component loadings using are shown in the component matrix in 3.4. Because only one component is retained, the solution has not been rotated. The factor loadings represent both the weighting of variables for each factor but also the correlation between the variables and the factor.

Table 3.4.: Principal Factor Analysis component matrix

	Component
	1
Low-Income population [%]	.831
Public assistance [%]	.754
No vehicle access [%]	.704
Lone-parent families [%]	.701
Unemployment [%]	.630
Low-level education [%]	.463

Extraction Method: Principal Component Analysis

3.3.3. Constructing the Index

The resulting factor from the Principal Component Analysis was then normalized so that it ranges between zero and one, representing a Deprivation index I_D (Vyas and Kumaranayake, 2006, pg. 19).

$$I_D = \frac{f_1 - f_{1,min}}{f_{1,max} - f_{1,min}} \tag{3.1}$$

To get to the final Vulnerability Index the elderly population share needs to be included. For weighting purposes, the assumption that being aged over 65 poses a similar vulnerability to access barriers than not having access to a vehicle in the household was necessary. Hence, the contribution of both variables to the composite Vulnerability Index should be equal. Solving the equation for the weighting leaves us with a weighting of the elderly share w_e of 14.71 percent. [4]
Hence, the Vulnerability Index I_V for each block group is combined from the Deprivation Index I_D and the normalized[5] elderly population share I_e in the following way:

$$I_V = (1 - w_e) * I_D + w_e * I_e = (1 - .1471) * I_D + .1471 * I_e \tag{3.2}$$

3.4. Input and Output parameters

Inputs

The inputs for the optimization program are drawn directly from the spatial data using QGIS. Given the nature of covering problems, the following matrices are inputs to the optimization model:

- Number of facilities to be opened (p) - this only applies to the MCLP
- Population vector: provides populations per block group

[4]The no-vehicle-access-share had a loading for the deprivation index of .704. The sum of all loadings is (.831 + .754 + .704 + .701 + .630 + .463) = 4.083, therefore the contribution to the deprivation index is $\frac{.704}{4.083} = 17.24\%$. Solving for the contribution of the elderly population share to the composite Vulnerability Index (under the assumption stated above) results in $x = frac.7044.083 * (1 - x) \Leftrightarrow x = \frac{.704}{4.787} \approx 14.71\%$

[5]The normalization of the elderly population share is done analogous to the Deprivation index: $I_e = \frac{S_e - S_{e,min}}{S_{e,max} - S_{e,min}}$

- Vulnerability Index vector: provides Vulnerability scores per block group
- Inter-block-group-centroid-distance matrix: necessary for determining distances between demand points and possible new supermarkets
- Block group to facility distance matrices
- Maximum service distances for supermarkets and Farmers' Markets: the distance relates to the coverage area per facility type

The number of facilities to be opened as well as the service distances are the only parameters that are not exogenous and could be chosen arbitrarily. As mentioned in 2.1.3, this study used service distances of $\frac{1}{2}$ mile (2640 feet) for supermarkets and $\frac{1}{4}$ mile (1320 feet) for Farmers' Markets. The initial amount of facilities to be placed was ten but adapted based on the iterative coverage results later on. Both parameters were adjusted in a sensitivity analysis to test the robustness of the algorithm.

Outputs

As MATLAB operates on matrices, a comma-separated output file is a matrix with the different pieces of information saved in columns. The matrix is converted to a comma-separated-value (CSV) file, whose naming scheme makes it possible to differentiate between the following parameters: 1) MCLP or SCLP; 2) Vulnerability-weighting of population; 3) Type of initial stores included; 3) buffer size; 4) Heuristic (GA or GAS); and, 5) type of placed facilities. The resulting output file includes the following information:

- Iteration in which facility was placed as an integer values from one to p
- Location of facility as an integer ID of block group centroid
- Sum of newly covered population per facility
- Sum of newly covered weighted population per facility
- Sum of newly covered demand nodes per facility
- Average distance of demand nodes to facilities
- Improvement of average distance per iteration

The sum of newly covered (weighted) population represents the MCLP objective function, whereas the newly covered (weighted) population values are the basis for the selection function in each iteration of the Greedy-Adding algorithm. The newly covered demand nodes are the basis for the Greedy-Adding selection function in each iteration to solve the SCLP. Hence, using a Greedy-Adding algorithm, the values of new coverage per iteration (both in the MCLP and SCLP) is a concave function as new facilities will either have an equal or lower amount of new coverage. Solving the MCLP with a GA heuristic for a certain value of p therefore also reveals the GA solutions for all MCLP with a smaller value of p.
Adding a substitution heuristic in each iteration takes away the concavity of the new coverage, meaning that the first $p - k, 1 <= k < p$ opened facilities of a MCLP solved with a GAS heuristic do not necessarily represent the solutions of the $p - k$ MCLP. Whereas the GAS heuristic guarantees a globally better or at least equal objective value, it increases computational complexity per iteration through the piggybacking of another heuristic. It also needs to be recomputed for different values of p in case there are additional substitutions in between the p_{new} and p_{old}.

3.5. Implementation of the algorithm

The following section describes the how the different steps in creating necessary input variables, solving the actual problem and presenting the output were implemented. The algorithm programmed to solve the MCLP for the food retail application was implemented in four steps:

1. Computation of initial coverage and construction of input variables
2. Subsequent Greedy-Adding of facilities
3. Substitution of facilities
4. Output of results

3.5.1. Computation of initial coverage

The main difference in this algorithm to the GAS prototype from Church and ReVelle (1974) are already existing facilities which are able to cover a certain amount of nodes. So after a creation of initial variables in MATLAB, the imported locations of existing facilities had to be imported and the present level of coverage had to be computed. This was done by transforming the facility-to-block-group-centroids distance matrix to an adjacency matrix. A logical comparison of all distances to the corresponding maximal service distance results in values of one if the block group lies within the maximal service distance to a facility and zero if not. By summing these binary variables of supply, a vector of the amount of facilities supplying each demand node was extracted. This vector can then be further transformed to a vector of supply by checking whether each block group is covered by zero (no coverage) or at least one facility (coverage). The vector can now be used as a vector of initial coverage to not include already covered nodes in the heuristic.

3.5.2. Greedy-Adding Heuristic

The Greedy-Adding algorithm is a well-established heuristic which solution procedure is described in detail by (Daskin, 2013, pg. 146ff). The implementation of the Greedy Adding heuristic in MATLAB draws heavily from the Pseudo-Code provided by (Vahrenkamp and Mattfeld, 2007, pg. 160), with a differing initialization phase, as described in the section above. In each of the p iterations, the possible additional coverage provided from a facility at each demand node is calculated. The location with the maximum new coverage (of population, weighted population or demand nodes, respectively) is selected for a facility placement at that location. The ID and improvement is stored and the entries of newly covered nodes in the coverage vector are adjusted.

3.5.3. Substitution Heuristic

In each of the p iterations (or an unknown number of iterations in the SCLP), the Substitution heuristic works downstream the Greedy-Adding heuristic to improve the coverage to a 1-optimal solution (Church and ReVelle, 1974, pg. 106). For all already opened facilities, the heuristic calculates the effect of a swap of that facility to a "free" site on the objective total coverage function. If an improvement through such a replacement is possible, the opened facility is closed, all "unique" coverage (nodes that are only covered by that one facility alone) is eliminated from the coverage vector. Subsequently, a new facility is opened at the identified location with newly covered demand nodes. Because further opportunities for improvement might arise through the swap, all opened facilities have to be examined on possible substitutions again, which explains the greatly larger computation time with an additional Substitution heuristic. The Substitution heuristic was implemented using a while-loop which uses a counter that resets each time a substitution is made and terminates if all locations have been checked for substitutions without finding a possible improvement.

3.5.4. Output of results

Both the GAS and GA algorithm create a comma-separated-value output file that includes the values mentioned in 3.4. Because frequent changes of the solution during runtime of the GAS algorithm (which can be attributed to the nature of the Substitution heuristic), the output matrix only includes the bare minimum of information during the iterations (iteration number, facility ID and new coverage) and is filled with the other values at the very end. In order to estimate how much of an effect the heuristic would have on the objective function of a SCLP or a p-Median problem, the development of the average distance (p-Median) and the amount of newly covered demand nodes is also included. Both unweighted and weighted values of new population coverage help analyze the influence of a Vulnerability weighting on the objective value of the unweighted problem and vice versa. For improved error backtracking, several other output matrices were created in MATLAB but exported in the solution table. This included substitution iterations including information such as the swaps made and the possible improvement for each facility. However, these are not necessary pieces of information when considering the final solution of the algorithm and meant for development uses only.

4. Results

4.1. Status quo: Limited access and deprivation in Philadelphia

4.1.1. Mapping population distribution and retail outlets

The map population density and food retail locations (see Figure 4.1) reveals that the most densely populated areas in Philadelphia are located in and south of the Center City district. Two areas that also show relatively high density levels are the University city district west of Schuylkill River and the Upper North area. The predominantly suburban areas of Northeast and Northwest Philadelphia are among the least populated areas, considering that large parts of the Southernmost part of Philadelphia and the Riverfront are non-residential areas. Especially in South Philadeplhia and northeast of the City Center, an agglomeration of supermarkets is apparent.

The Star Map in (see Figure 4.2) gives a visual representation of the straight-line distances from each Block Group centroid to a supermarket. Although the distances to the nearest supermarket seem to increase the further from the city center, the stars from supermarket in the city center still reveal that many block group centroids are still out of walking distance (distances greater than $\frac{1}{2}$ mile, colored red) from a supermarket. Furthermore, assuming each customer visits the closest supermarket, there are several supermarkets that seem to be serving an abnormally large amount of customers, such as two facilities west and south of the City Center District. One could presume that the area is undersaturated with food retail opportunities or the supermarket is oversaturated and might be working at or above capacity limit.

4.1.2. Mapping low access and vulnerability characteristics

After analyzing the concentration of people living in Philadelphia and the food retail environment, it is of importance to examine if there are areas that show signs of high vulnerability and low access. Figure 4.3 represents the Block Group level Vulnerability Index values and the coverage areas of the existing supermarkets. Generally, vulnerability seems to be higher in the core areas that are heavily populated and decreases with the distance from the city core. An exception is the City Center district, which shows the highest levels of population but low vulnerability.
Four areas can be made out that show relatively high Vulnerability scores. First, Kensington/Upper North (located northeast of the City Center District) shows the highest levels

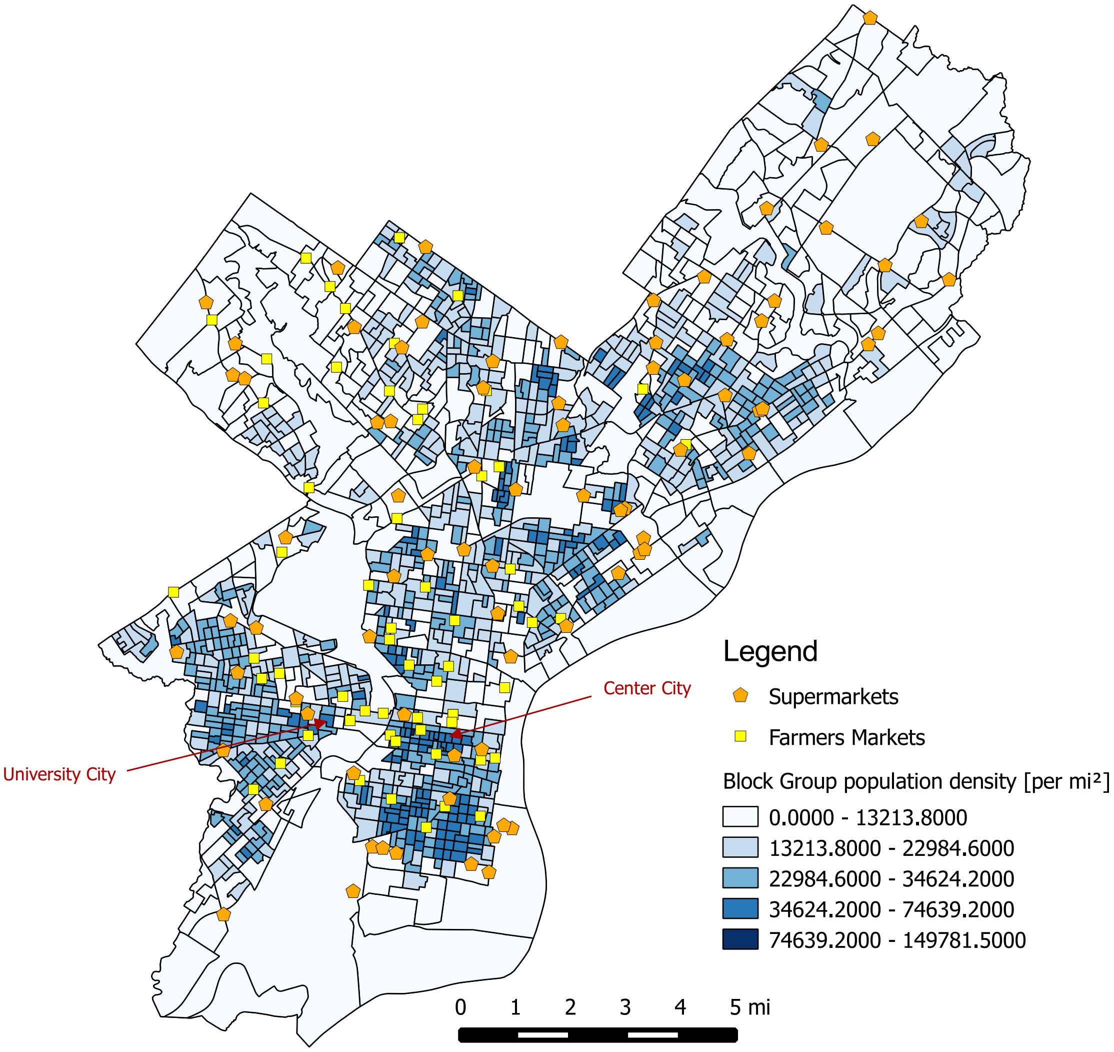


Figure 4.1.: Population density and food retail locations in Philadelphia

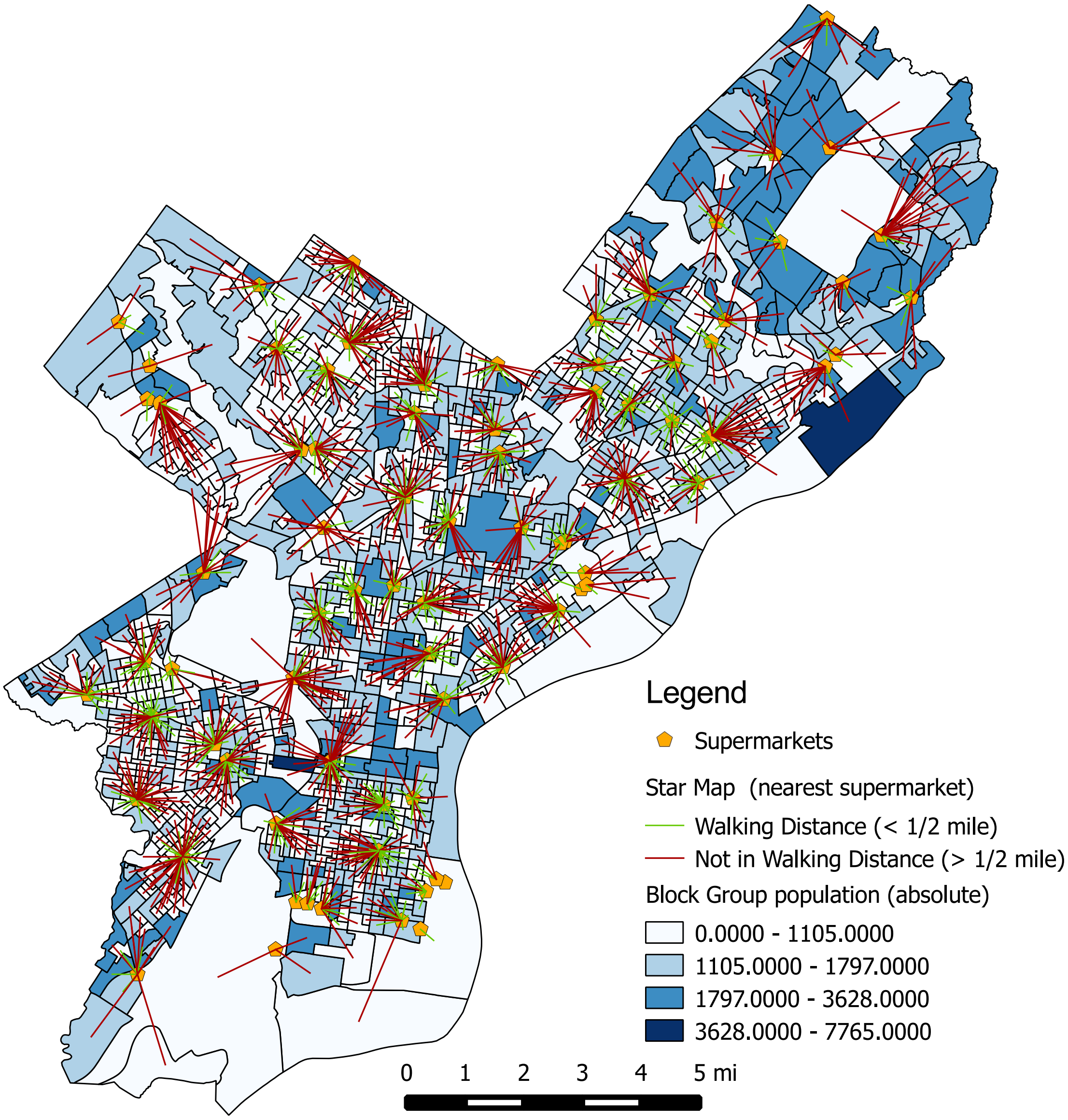


Figure 4.2.: Star Map of nearest supermarket per Block Group centroid

of vulnerability at a relatively high population density and many block groups without walking accessibility to a supermarket. Areas that share similar characteristics are the surrounding areas of University City, the western part of South Philadelphia as well as Lower North Philadelphia (bordering the City Center to the Northwest).
Figure 4.4 depicts the combination of several Vulnerability characteristics to show areas that are vulnerable to access limitations on several dimensions. Again, the four areas mentioned above stand out as potential food deserts. Although socioeconomic deprivation is negatively correlated with the share of elders, there are several areas north of the City Center District and west of University City that show signs of deprivation and a relatively large concentration of seniors. The combination both characteristics might justify the inclusion of the elderly people share in the Vulnerability Index.
It should be noted that in contrast to the Vulnerability Index, the characteristics were defined on a relative basis (attributes in highest Block Group quartile). This means that this visual measure represents relative but not absolute vulnerability and does not allow for comparisons among different study areas.

4.2. Results of algorithms

Before the optimization, the 81 supermarkets with a maximum service distance of $\frac{1}{2}$ mile were able to cover a total of 605 demand points (about 45 percent of the demand points) and a population of 700,606 (46 percent of the total population). The average population that each supermarket provides coverage for is 8,649. This number can provide a rough estimate for the minimum covered population necessary for a new feasible supermarket to operate, as this is a measure of the uncontested market within walking distance of the facility.

4.2.1. MCLP: Supermarket location

Unweighted population

After running the GAS algorithm for the MCLP of supermarket location ($\frac{1}{2}$ mile supermarket service distance and existing supermarket locations considered) with different values of p, it became apparent that the Substitution heuristic was not able to find a swap yielding in an improvement until the 46th iteration. Therefore, the results of the Greedy-Adding and the Greedy Adding with Substitution are identical every value of $p <= 45$. But already after 34 opened facilities, the newly covered population falls below the average population coverage of 8,649. This would mean that facilities added after 33 iterations might have a below-average spatial market (except for iterations with substitutions, but that would decrease the coverage of a previously opened facility so that the total covered population per iteration would still fall below the average).
The GA/GAS solution for the 40-MCLP of supermarket location can be found in the Appendix (see B.3). The development of the newly covered population is depicted in Figure 4.5. There is a visible break in coverage after 14 facilities (coverage roughly 2,000 people less). The top 14 facility locations were added to the existing supermarkets in Philadelphia and plotted in Figure 4.6.

Vulnerability-weighted population

The Vulnerability Index as a weighting influenced the algorithm procedure so that Substitutions were made earlier on (at the 21st iteration). This means that the iteration counts to the 40-wMCLP (vulnerability-weighted MCLP) in Table B.4 no longer match the “ranks” of contribution to the objective function. Decreasing p to a value of 20 and examining the development of the new coverage per iteration, a break is visible after nine iterations

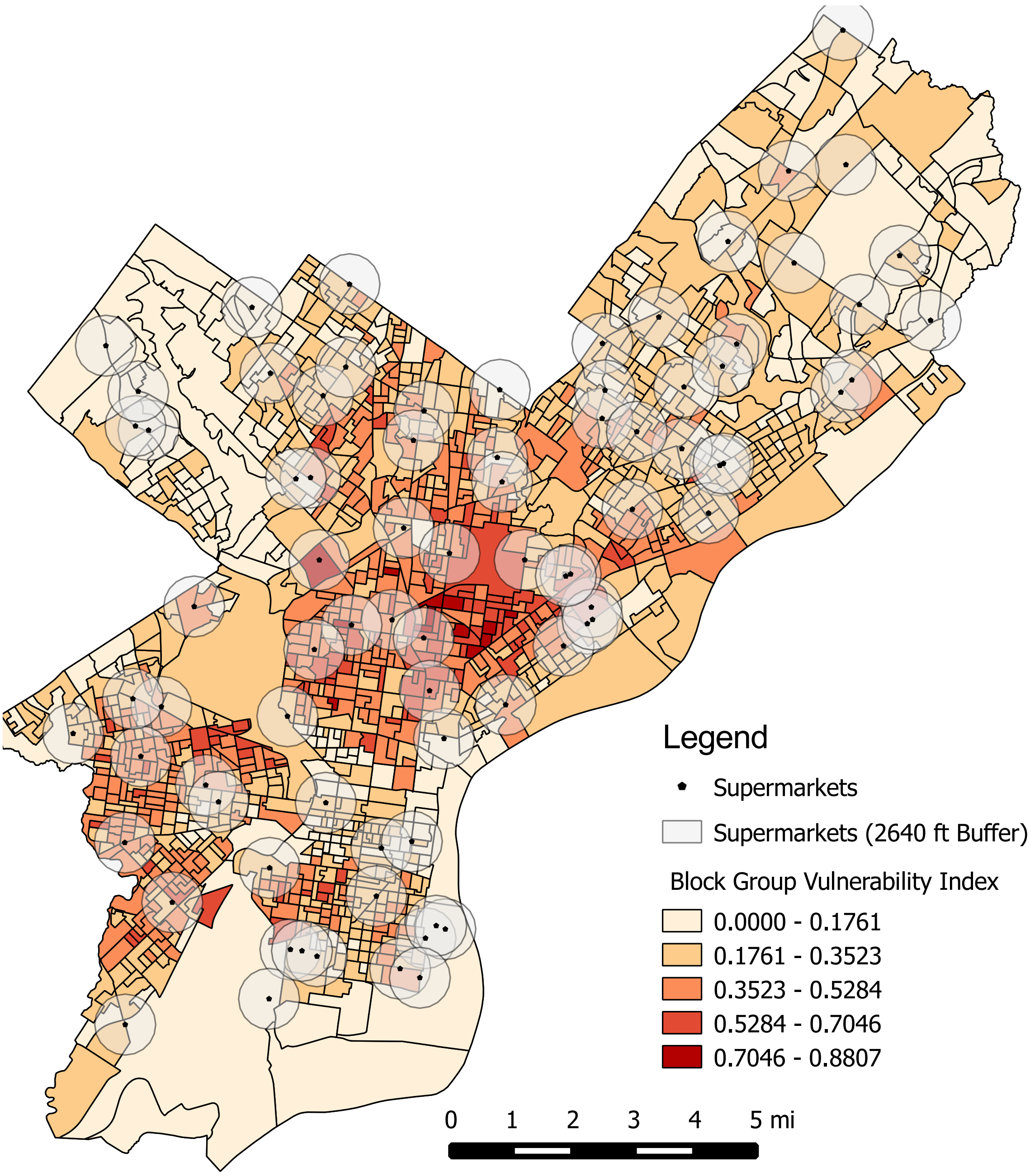


Figure 4.3.: Map of Block Group level Vulnerability and supermarket coverage areas

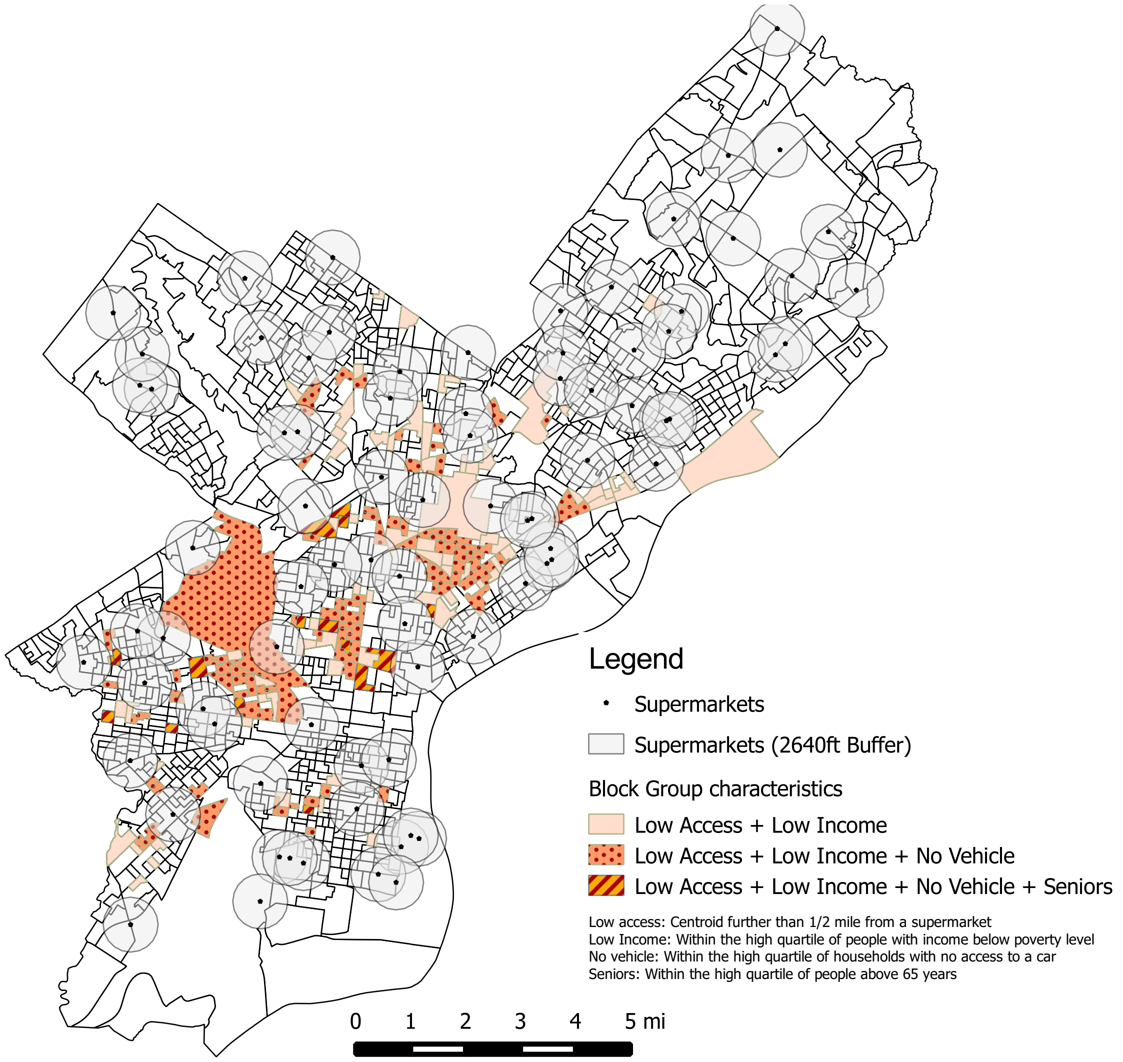


Figure 4.4.: Map of Combinations of Vulnerability characteristics

(see Figure 4.7). To improve comparability, a map of both the 14 optimal locations from unweighted and vulnerability-weighted optimization shows the effect of the weighting on the spatial placement (Figure 4.8).

4.2.2. MCLP: Farmers' Market location

The first model assumes that outside of the Farmers' Market season supermarkets do not face competition in the market of fresh produce and meat. Therefore, it models the out-of-season food retail environment. The second model is based on the fact that Farmers' Markets have to compete with supermarkets for customers during Farmers' Market season and a public authority should not promote Farmers' Markets that are in direct competition with a full-line supermarket. In this model, additional Farmers' Markets optimal locations are computed based on the existing supermarkets and Farmers' Markets. The Farmers' Markets' service distance was set to $\frac{1}{4}$ mile, whereas the supermarkets' larger product offering appeal is represented in a $\frac{1}{2}$ mile service distance that has also been used above.
When not taking the existing supermarkets into account, the 62 existing Farmers' Markets cover a total population of 201,533 people. Again, the average coverage per facility of 3,250 is used as an indicator of when the addition of new facilities becomes not economically viable.
The GAS algorithm does not substitute facilities up until a p of 80, meaning that the

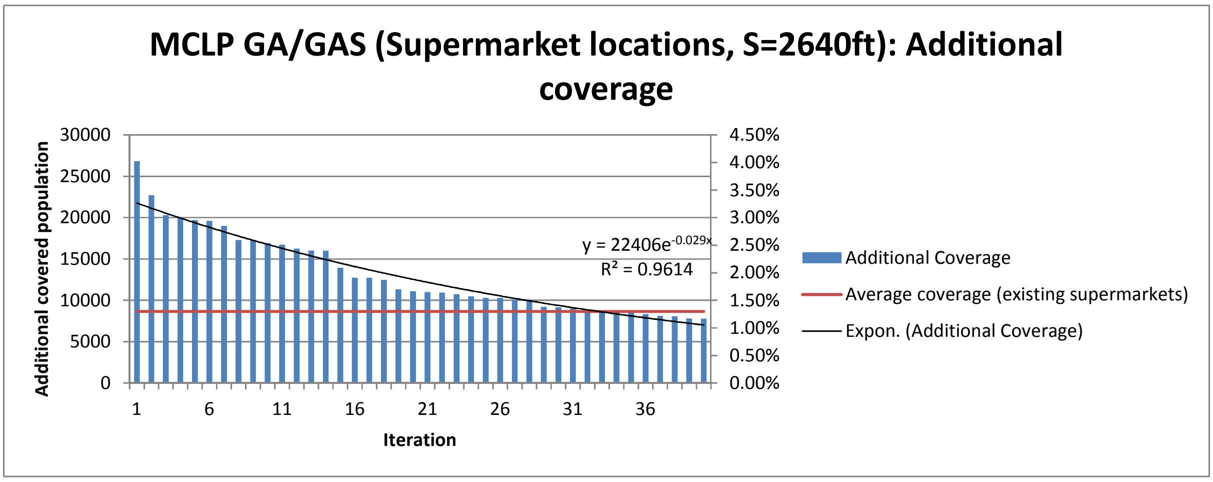


Figure 4.5.: 40-MCLP of supermarket placement coverage graph

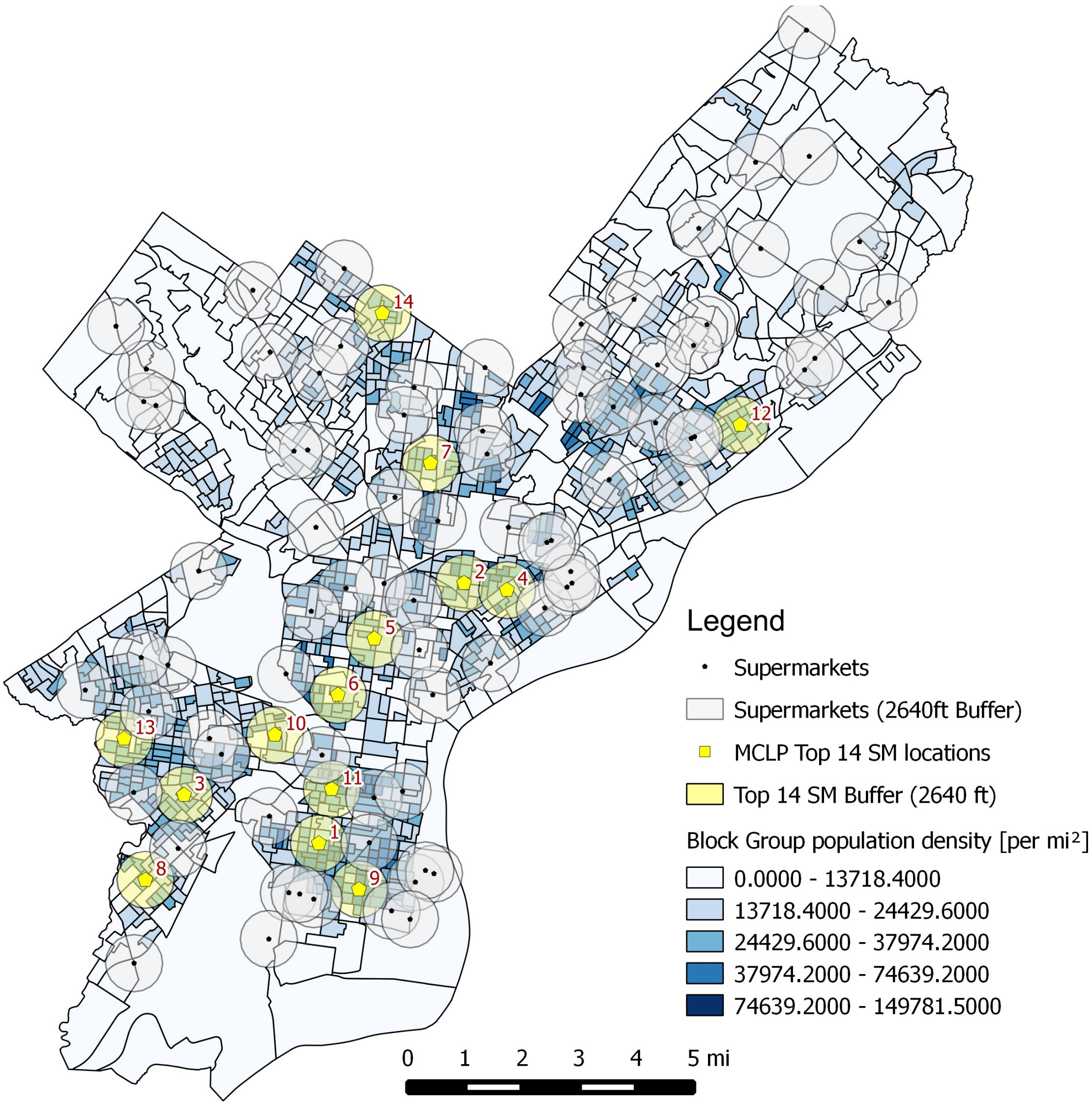


Figure 4.6.: Map of optimal 14 MCLP locations (placement: Supermarkets, p=40, initial coverage: supermarkets (S=$\frac{1}{2}$ mile)

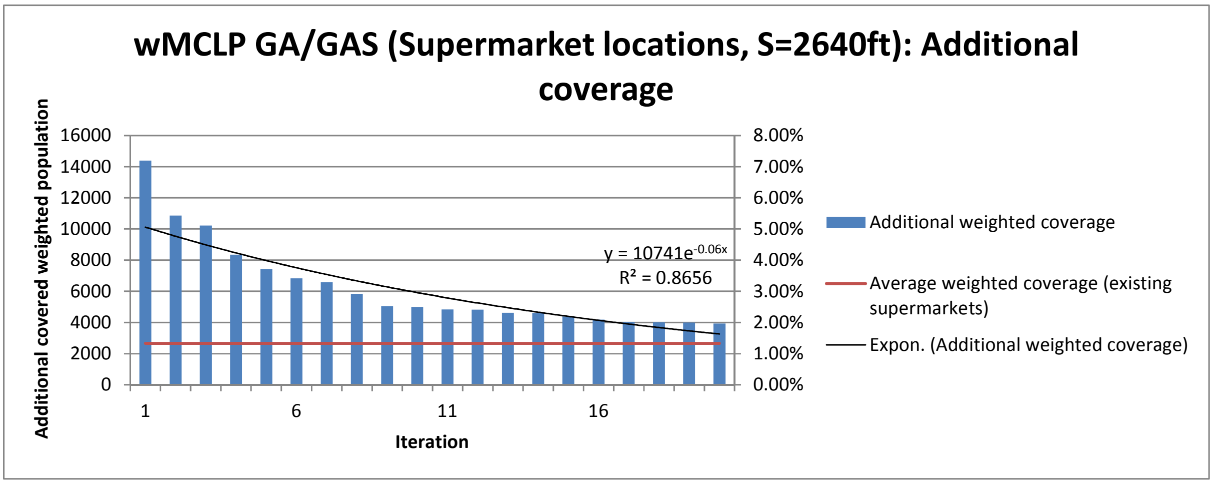


Figure 4.7.: 20-wMCLP of supermarket placement coverage graph

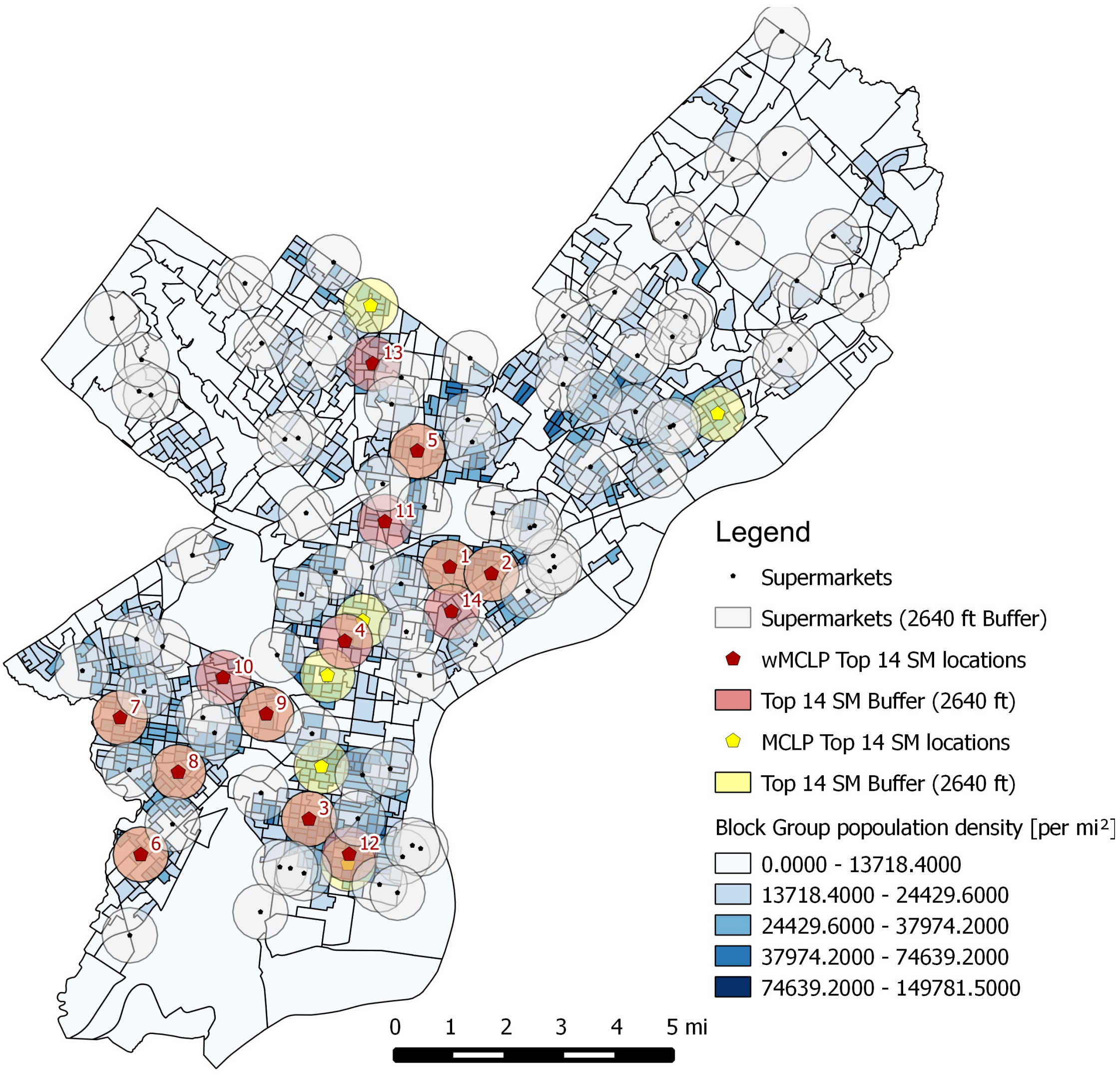


Figure 4.8.: Map of optimal 14 wMCLP locations in comparison to MCLP locations (placement: Supermarkets, p=40, initial coverage: supermarkets (S=$\frac{1}{2}$ mile)

resulting list of facilities is ranked by contribution to the objective function and that the objective value of the GA heuristic solution is identical to value of the GAS heuristic solution. The coverage graph in Figure 4.9 reveals that openings of 67 Farmers' Markets would yield above-average coverage. That is surprising, considering that the coverage of existing Farmers' Markets was calculated based on a no competition from supermarkets, while the new located Farmers' Markets' coverage only consists of areas that are left uncovered by existing Farmers' Markets as well as supermarkets. Reasons for this anomaly could include the inefficient placement of existing Farmers' Markets, a too small buffer in correspondence to too large subdivisions (Block Groups) or the aggregation of several Farmers' Markets in the city center, leading to overlapping areas of coverage. A map of the above-mentioned 67 Farmers' Markets is another sign for the amount of demand for food that is not satisfied in high-density areas, as new facility proposals concentrate on areas with high relative density (see Figure 4.10).

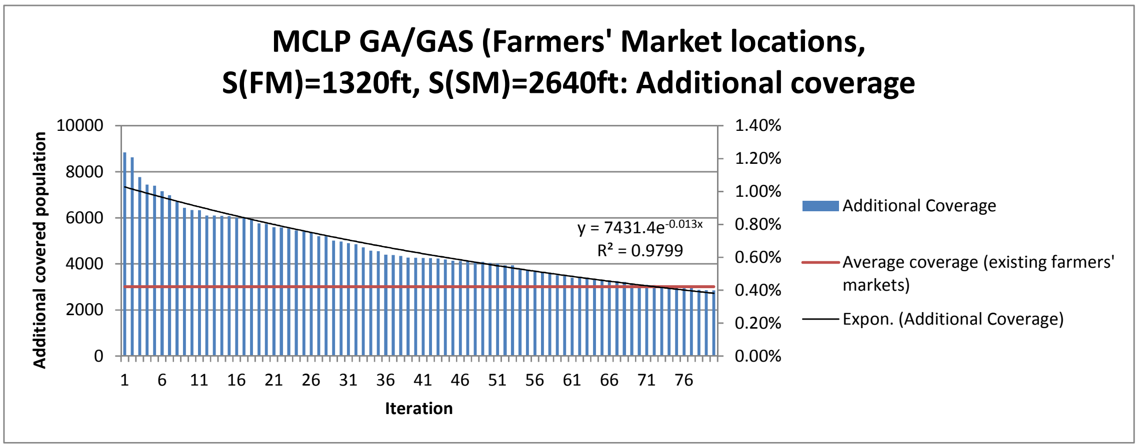


Figure 4.9.: 80-MCLP of farmers' market placement coverage graph

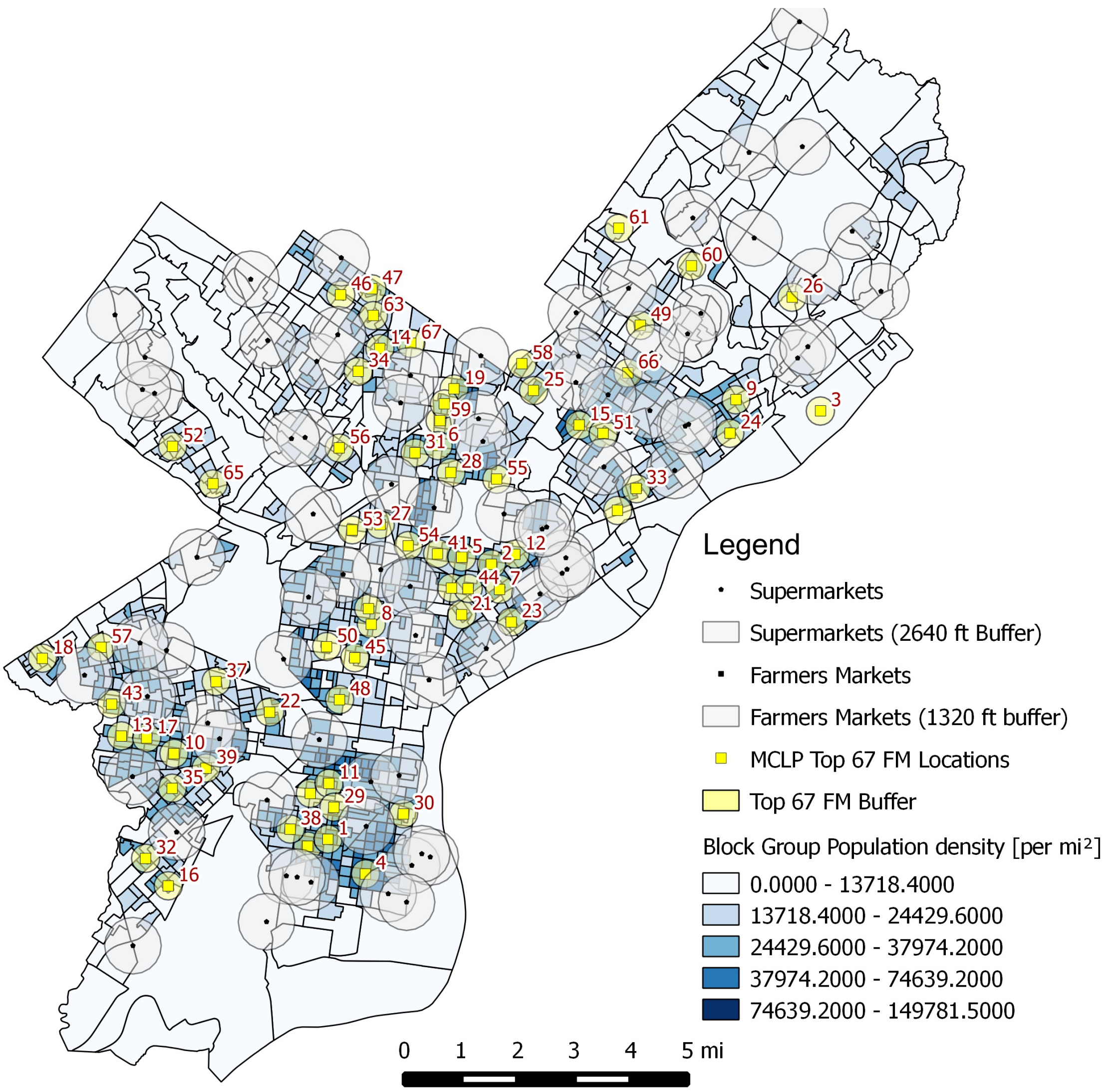


Figure 4.10.: Map of optimal 67 MCLP locations (placement: Farmers' markets, p=80, initial coverage: supermarkets (S=$\frac{1}{2}$ mile), Farmers' Markets (S=$\frac{1}{4}$ mile)

4.3. Performance and sensitivity analysis

Performance

The Substition heuristic was implemented on top of the Greedy-Adding heuristic in order to find better solutions for the location problems at hand than a normal Greedy-Adding algorithm would find. Both algorithms were written parametric, such that they allowed for quick change of input parameters. The trade-off is a higher computation time for the Substitution heuristic, as the amount of pairwise combinations of locations to be checked increases with the iterations (set by the value of p). The values of p (possible facility openings) that were relevant for this application were fairly small, because certain feasibility constraints for new store openings were applied (such as above-average new coverage).
The algorithms were run in MATLAB R2013b on a 2.0 GHz Intel Core 2 Duo laptop with 3GB of memory running Windows 7 (64 Bit) with service pack 1. Tables 4.1 and 4.2 depict several runs of both algorithms. In the MCLP, the first swap of locations was only done in the 46^{th} iteration. Hence, only for values higher than 46 would the GAS yield an improvement but overall takes much longer computing time (e.g. increasing the value of p by the factor five from 20 to 100 lead to a computing time increase by the factor of five for the GA heuristic and a computing time increase by the factor of 31 for the GAS heuristic.
For the performance test of the SCLP algorithm, the buffer sizes were varied. This had two effects: First, the amount of necessary facilities increases because of the smaller coverage area and second, the amount nodes to be covered increases as well. Higher values of p result in more opportunities for Substitutions, so the GAS solutions need a smaller amount of facilities to cover the whole demand point set (2.2 percent and 4.7 percent respectively). However, the general computing time of the GAS algorithm is higher and furthermore increases more strongly with decreasing buffer size. A maximal service distance of $\frac{1}{2}$, technically inducing the problem of trying to cover all demand points by placing supermarkets, takes a computing time of over five minutes. Cutting the service distance in half took more than ten times the computing time.
In theory, the GAS algorithm yields better objective function values in exchange for more computing time. For this application, the improvement through substitution did not matter for the values of p that were constrained by the minimum coverage constraints. Hence, the GAS heuristic could only be used as an affirmation of the good solution provided by the Greedy-Adding algorithm.

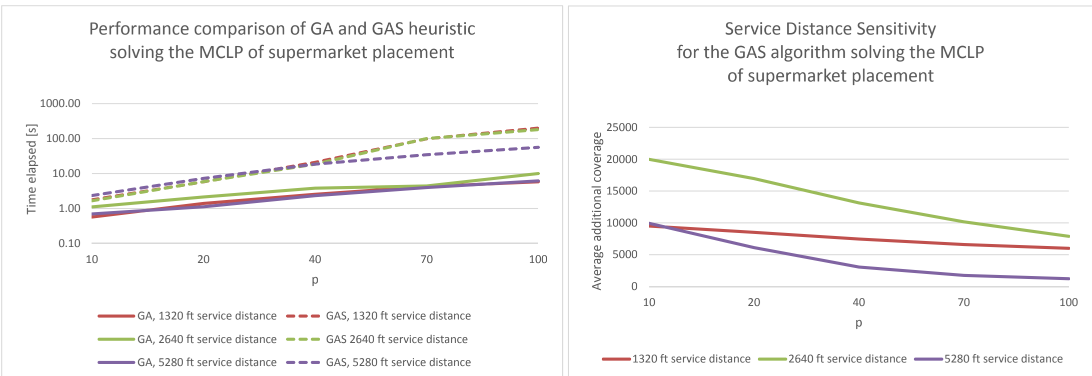


Figure 4.11.: Performance comparison of GA and GAS heuristic for a supermarket MCLP and Sensitivity of the GAS algorithm towards maximum service distance

Sensitivity towards service distance and facility placements

Along with the performance, the algorithms for solving the supermarket placement MCLP and SCLP were tested on its robustness in a sensitivity analysis. The varied parameters

included the maximum service distance (buffer sizes of $\frac{1}{4}$ mile, $\frac{1}{2}$ mile and one mile - 1320, 2640 and 5280 feet, respectively) and the amount of facilities placed p.
The analysis revealed that the fit of the algorithm is dependent on the maximum service distance employed. First, the average additional coverage is decreasing with the number of facilities placed, which is in line with the expectation of a greedy heuristic. The decay of average coverage in relation to p increases with the maximum service distance.
A potential explanation for this observation is the quadratically increasing coverage area when varying the service distance. Smaller buffers lead to more uncovered subdivisions and more gaps to be filled by new facilities. For a $\frac{1}{4}$-mile service distance, the average additional coverage per facility exceeds the average coverage of existing facilities in all cases (even in the case of $p = 100$), which could be attributed to the level of aggregation: Because in contrast to the possible locations for new facilities, the existing facilities are not located directly on the block group centroids, hence, the level coverage is prone to coverage gaps resulting from a small service distance. Additionally, some block groups are heavily populated (larger population than the average existing coverage), which even puts one-block-group-covering facilities on an above-average population coverage. The one-mile service distance could be assumed as exceedingly large, as new facilities employing this distance are only barely competitive, whereas the quarter-mile service distance could be assumed as too small for the level of aggregation in the given data.

Table 4.1.: Performance and Sensitivities of algorithms for a MCLPs

MCLP				**GA algorithm**			**GAS algorithm**		
Buffer size [ft]	Nodes	avg. existing coverage	p	New coverage	average	Time elapsed [s]	New coverage	average	Time elapsed [s]
1320	1172	2368	10	94991	9499	0.57	94991	9499	1.77
1320	1172	2368	20	170149	8507	1.40	170149	8507	5.81
1320	1172	2368	40	297139	7428	2.55	298441	7461	20.92
1320	1172	2368	70	460348	6576	4.24	461650	6595	98.59
1320	1172	2368	100	598479	5985	5.81	600305	6003	199.41
2640	745	8649	10	199783	19978	1.11	199783	19978	1.66
2640	745	8649	20	339083	16954	2.14	339083	16954	5.86
2640	745	8649	40	525278	13132	3.82	525278	13132	18.57
2640	745	8649	70	698272	9975	4.42	711176	10160	100.30
2640	745	8649	100	780316	7803	10.01	788645	7886	180.91
5280	93	17330	10	99290	9929	0.70	99290	9929	2.35
5280	93	17330	20	122268	6113	1.12	122268	6113	7.27
5280	93	17330	40	122311	3058	2.33	122311	3058	18.58
5280	93	17330	70	122311	1747	3.98	122311	1747	34.54
5280	93	17330	100	122311	1223	6.18	122311	1223	56.22

Table 4.2.: Performance and Sensitivities of algorithms for SCLPs

SCLP		**GA algorithm**		**GAS algorithm**	
Buffer size [ft]	Nodes	Facilities	Time elapsed [s]	Facilities	Time elapsed [s]
1320	1172	514	31.07	503	3815.75
2640	745	148	5.16	141	309.86
5280	93	23	0.64	23	7.07

5. Evaluation

5.1. Discussion

Inadequacy of city-wide food access

The results of this study reveal that, in 2014 the inner-city supermarket coverage in Philadelphia in most cases is still inadequate. Taking supermarkets and supercenters that offer a full range of nutritious food into account, with 2866.9 feet the average distance from representational block group centroids to a supermarket is still above the widely used walkability distance of $\frac{1}{2}$ mile (2640 feet). 46.9 percent of the population does not fall within walkability range to a supermarket, and within the block groups in the highest quantile of the Vulnerability Index (measuring vulnerability towards food access limitations), roughly 55.5 percent of the population is confronted with limited access to supermarkets.

Deprivation and food access

On first glance, no systematic link can be drawn between deprivation and low food access. The data reveals that the level of vulnerability towards food access barriers (consisting of characteristics of deprivation and the share of elderly population) shows a weak negative Pearson correlation ($\varrho = -0.278$) to the distance to a supermarket offering a full range of nutritious food. Higher vulnerability shows a Pearson correlation to population density ($\varrho = +0.203$). The goodness of the fit is poor in both cases ($R = 0.078$ and 0.042, respectively), however. But taking the visual representations on the generated maps into account, this shows that subpopulations with elevated levels of vulnerability seem to concentrate in the old core area of Philadelphia.
Walkable supermarket access across the city limits is limited to a minority of the examined population. In total, 54.1 percent of the population (825,400 of 1.52 million) are not serviced by a supermarket in walkability range. The share for the areas with the highest levels of vulnerability is larger; 55.5 percent of the population living in the highest quantile vulnerability block groups face non-walkable distances to supermarkets.
The average distance from the highest quantile vulnerability block groups to supermarkets was found to be smaller than the average of all block groups, but only by a small margin (2866 vs. 2967 feet). This means however, that on average, the most vulnerable block groups (that also tend to have relatively low levels of car ownership) do not offer walkable supermarket access.
Although no systematical discrimination of vulnerable areas could be detected, two major clusters (Lower North/Northeast Philadelphia and the surrounding areas of University

City) of low access and high vulnerability were found. Considering the existence of coherent areas that are not only susceptible to access barriers but also densely populated, firstly, deprivation is a factor of food deserts that should be incorporated and secondly, public policy incentives for the private market might prove efficient in these singled-out areas.
The share of elderly population has mostly been neglected in vulnerability, as mostly vulnerability was measured in socioeconomic deprivation. Areas with a large elderly population however tend to be less deprived and in our case, the share of elderly people showed a strong negative correlation with socioeconomic deprivation. Figure 4.4 indicates that Philadelphia is scattered with block groups that show a combination of deprivation characteristics and a high share of elderly people. The amount of high-risk areas with another factor of vulnerability provides a means of justification for the inclusion of disadvantages in food access through elevated shares of elderly population.

Marginal utility of new supermarket placement

The marginal utility from new supermarket openings at the locations found with the algorithm from both the supply- as well as the demand-side can be measured in the marginal coverage per store opening. The marginal coverage per facility decreases monotonously for a large range of p. In general, marginal coverage showed a pattern of exponential decay. The first 40 supermarket locations exhibit an exponential decay of $\lambda = 0.29$, whereas the first 40 farmers' markets exhibited a decay of $\lambda = 0.13$. This means that the marginal coverage per facility with a smaller service distance (farmers' market: $\frac{1}{4}$ mile) decreases by a smaller margin than the marginal coverage per facility with a larger service distance (supermarket: $\frac{1}{2}$ mile). Hence, this indicates that a possible point of saturation for the opening of larger, further-servicing stores is reached earlier. Additionally, the existing food environment seems to not feature a multitude of equally large coverage gaps in which new supermarkets could garner a large new customer base. This is relatively speaking though, it should be noted that the absolute numbers of marginal coverage for these stores are still above average for more than 30 facilities. However, the placement of farmers' markets should provide coverage for areas where new supermarkets are not economically viable. Due to this insensitivity of farmers' markets to new store openings and its weakly decreasing marginal utility could lead a recommendation of city-wide initiatives stores offering an extensive choice of healthy and nutritious foods but with a smaller service area. Although Healthy Corner Stores were not considered in this study because of the restricted fresh produce offering, this result indicates that Corner Stores are a quick way of improving the food retail situation partially by providing a small share of nutritious food retail in city core areas. However, the relatively higher prices are a burden for equal food access. Poor people are more price-sensitive and tend to shoulder longer distances to food retail for these reasons. The existence of (Healthy) Corner Stores might hint at well-serviced areas through short shopping distances whereas in reality the majority of the population incurs much longer routes for food shopping. Corner Stores might also embrace people to make more short-term and impulsive, thus less rational purchases.
The marginal vulnerability-weighted populations from the corresponding vulnerability-weighted MCLP for supermarket openings showed an exponential decay of $\lambda = 0.42$. The stronger decreasing marginal utility based on the weighted population compared to the unweighted MCLP could be partially explained due to the variance in the distribution of (relative) vulnerability index values. On the other hand, this might also provide evidence that vulnerable subpopulations are concentrated in a small amount of certain densely populated areas; the "right" placement of a small amount of stores is very effective in tackling the problem of limited food access in these areas.

Unifying equality and profitability

Because the weighted population is only an absolute abstract measure of population and vulnerability of the people, the goal value is less meaningful in an economic, supply-side context. In order for local government to support the placement of new food retail facilities in food deserts of high vulnerability and low access, the profitability of proposed locations needs to be assessed. This comparison of the newly covered vulnerability-weighted population and the total covered weighted population allows for identifying the feasibility of a possible project. Table number 5.1 shows both measurement for the optimal locations of the weighted 20-MCLP of supermarket placement. The results show that the public quest for equal food access is not necessarily antagonistic to the private sector constraints through profitability and a large enough market area. In fact, each of the optimal vulnerability-weighted locations combines the goal of welfare optimization with above-average exclusive customer coverage resulting from a placement. Although effects from lower income levels in socially deprived areas have to be taken into account, the competitive advantage from opening a larger store with relatively low prices in areas with high price elasticity might even outweigh the income effect.

Table 5.1.: Economic Feasibility of supermarket placement: vulnerability-weighted and unweighted coverage from weighted 20-MCLP solution

Iteration	ID	Weighted coverage improvement	Relative to average weighted coverage [%]	Unweighted coverage improvement	Relative to average unweighted coverage [%]
1	120	14381	540.3%	22722	262.7%
2	538	10871	408.5%	20042	231.7%
3	508	10220	384.0%	26842	310.3%
4	239	8347.1	313.6%	18962	219.2%
5	193	7443.6	279.7%	19016	219.9%
6	867	6825.3	256.4%	17314	200.2%
7	1098	6583.9	247.4%	16026	185.3%
8	973	5839.7	219.4%	20305	234.8%
9	1199	5045.6	189.6%	16938	195.8%
10	1176	5005.5	188.1%	10746	124.2%
11	76	4837.5	181.8%	10468	121.0%
12	693	4831.7	181.5%	16928	195.7%
13	172	4622.8	173.7%	12464	144.1%
14	338	4614.7	173.4%	10310	119.2%
15	1250	4393.9	165.1%	16610	192.0%
16	457	4188	157.4%	13501	156.1%
17	834	4026.1	151.3%	16248	187.8%
18	139	4011.4	150.7%	9570	110.6%
19	27	4000	150.3%	15996	184.9%
20	102	3928.5	147.6%	10800	124.9%

5.2. Limitations and Recommendations

A distributed use of facility location problem solution among different areas sometimes proves to be problematic. The results are subject to type and quality of inputs, which might differ due to regional differences in market environment, such as supply and demand factors, level of competition or prevalent public policy. However, many cities in the United

States face similar problems of food access and deprivation as Philadelphia. A transfer of this solution approach might bring substantial informational benefit to public and private efforts tackling urban food deserts. As there is no general consensus about the adequacy of certain service levels for food retail and types of demand aggregation, the applicability of this model stems from a strong set of (objective) assumptions. Further enhancement of this parametric problem and an increased level of automation should provide a foundation for extended use in different urban areas plagued to identify and, more importantly, help in managing efforts and funding.

5.2.1. Level of demand aggregation

The discretization of demand was driven by limitations in computing power, a lack of sophisticated solution algorithms and poor interoperability between QGIS' spatial and MATLAB's matrix data structures. It is to be noted that this procedure produces aggregation errors, mainly stemming from two sources.
Firstly, the population and socioeconomic data on a level of spatial subdivisions assumes an evenly distributed population among the area. This is rather unproblematic in areas that are homogenously populated, such as city centers with a high population density, leading to relatively small subdivisions. As block groups are supposed to contain between 600 and 3,000 people (United States Census Bureau, 2013), areas that are not populated enough to make up a block group on their own might be merged. Thus, this leads to an averaging of population density and socioeconomic characteristics and a lossy representation of the communities' characteristics. However, the most populous block group not only strongly exceeds the the target populations with 7,765 inhabitants but also is the 15$^{\text{th}}$ largest block group (GEOID 421019891001). The break-up of this block group would inherently improve population as well as size parity among block groups. This provides evidence that the Census subdivisions leave much room for improvement. An explanation for this anomaly might be historical consistency among Census surveys for comparability reasons. The usage of block level data could reduce aggregation error in exchange for increased computation time. The drawback of this is that on on block level, only population data is available while socioeconomic data is omitted in the data sets provided by the US Census Bureau.
Secondly, the discretization itself is another source of aggregation errors. While the covering problems optimize point-based coverage or, in case of the SCLP, guarantee it, the area represented by the centroids may not be fully covered, which is problematic as heavily populated parts of block groups might be assumed as covered while they truly aren't. The reduction in subdivision size as a means of reducing spacing between utilized points should decrease the possibility of coverage gaps while again increasing the problem size and computational complexity beyond the capabilities of available algorithms or heuristics (Murray et al., 2008, pg. 342). However, employing population-weighted centroids could improve the representational qualities of demand points.
Lastly, the aggregation of demand point also has an effect on the feasibility of the proposed store openings. As in the algorithm employed here, every demand point is a possible location for a facility, meaning that new openings should optimally take place in the centroids of the corresponding block groups. Obviously, the feasibility of this undertaking can not be guaranteed due to zoning laws, housing structures, parks or recreational areas or prices of land.

5.2.2. Definition of coverage

Types of retail facilities and store data

Due to limited means of data acquisition and time, the considered facility types were narrowed down to supermarket-plus-sized facilities and Farmers' Markets. The binary

definition of coverage required by the MCLP and SCLP models forces strong assumptions to be made among store types, and in fact might misrepresent actual shopping behaviors. Further research in this field is necessary and could involve a median problem that focuses on optimizing coverage as a linear combination of food availability scores provided by facilities in reach, with different scores per type and size of facility such as in (Get Healthy Philly, 2011, pg. 5) and a decay of service level relating to the distance.
Because of the data collection methods employed (such as using an "advertisement-biased" source like Google Maps or a public list on Wikipedia) and a lack of local presence or knowledge, the exhaustiveness of the supermarket set can neither be guaranteed nor measured. Professional collections of food retail obtainable from ACNielsen's TradeDimensions Retail Database employed by Duane Perry (2001) should provide a more complete set of existing facilities and further data of interest, allowing for more detailed classification of different stores by size or sale.

Distance Functions

The use of straight-line distances is prone to measurement errors. While the straight-line distance should provide good estimates of travel times in street-dense areas like the city of Philadelphia, the transfer of this algorithm to another environment should be evaluated carefully. Especially for areas with heterogeneous street patterns and natural barriers such as rivers or lakes, a network distance measurement based on the actual transportation infrastructure should yield better results. Lopez (2007) employs a different accessibility and safety measure by calculating an "Intersection density" value from the 2000 Census street shape files. Furthermore, Google Maps could provide accurate travel times by different means of travel (foot, bike, public transportation, car) and can be accessed by XML or JSON requests Google Developers (2014). Another possible extension is a measure of public infrastructure accessibility per demand point, such as amount of walkable bus stops or LRT stations. Additionally, the measurement of distances from residences food stores does not take into account that food shopping may be integrated into regular daytime trips, such as the commute to work or child care locations (Sparks et al., 2009, pg. 26).

5.2.3. Adequateness of vulnerability measure

The vast array of Deprivation Indices described in section 2.1.4 shows that measurements of socioeconomic status are based on an objective choice of input characteristics and mostly relative to the environment. Hence, the calculated Vulnerability Index can only represent a fraction of the characteristics related to nutritious limitations following geographical access barriers. Extensions might include obesity-related data (obesity rates could not be obtained on block group level) or public transit accessibility measures mentioned above. It is also relative to the population of Philadelphia, hence, the values are not comparable to calculations for other cities and the distribution might be skewed by outliers.

5.2.4. Implementation and software interoperability

A tedious component of the study was the exchange of raw data and results between the geographic representation in QGIS and the optimization in MATLAB. Both programs offer interfaces for importing comma separated value files (CSV) that can be converted to matrices (MATLAB) or joined with layers (QGIS). A block group ID was used for referencing purposes so that distance matrices and optimization output files were compatible. Thanks to a table join of block group centroids and the output tables, this also allowed for examining proposed facility openings in QGIS for output variable values.
The manual import and export of data put a constraint on the time associated with each optimization run and hence, the amount of runs executed. Further research could utilize

the QGIS' Python interface (QGIS Development Team, 2014) to offer a turn-key solution of objective values and a visual representation of the results in map form. It provides the necessary commands for loading layers, geometric operations (such as the creation of distance buffers), and map rendering. Thus, a better connectivity of a GIS system and a numerical computing environment could be achieved.

Another approach that might allow for more sophisticated problem definitions is the use of a dedicated optimization software package such as IBM ILOG CPLEX. Murray et al. (2008) combined CPLEX and ArcView for a service coverage modeling problem, however, the data exchange between the GIS and CPLEX was still done manually with text files. The advantage of a dedicated optimization software in contrast to more general mathematical programming software is the array of integrated solution techniques for common optimization problems. This shifts the workload from programming a solution algorithm towards defining more elaborate problem sets while still remaining flexible about the actual means of solving the problem. Further research would benefit from easier problem definition and visual representation through the combination of two fairly specialized programs.

6. Conclusion

Food is a basic need, whose means of distribution has recently become a more and more pressing public concern. The allocation of food distribution responsibilities to the private sector has formed a market structure that focuses on demand patterns and segmentation through demographic characteristics instead of population distress through limited food access.

Especially in North America, rising rates of obesity and cardiovascular diseases not only threaten general healthiness but more importantly strain national health care budgets. Observed disparities in diet-related health issues among different ethnic subpopulations or levels of individual socioeconomic deprivation have raised the question as to what the causes and driving forces for these disparities are. Individuals' food choices are shaped by the food environment that they are surrounded by. Hence, "food deserts" as area that exhibit geographic limitations in adequate food access and whose population is especially vulnerable to these limitations has garnered scientific attention.

With empirical studies indicating that the food environment in urban areas of high deprivation hampers the people's upkeep of a healthy and nutritious diet due to issues of affordability and limited access, the systematic identification of such areas constitutes a cornerstone of efforts to tackle the food desert problem. There have been several approaches in identifying food deserts, the majority employing a geographic information system (GIS) for the spatial analysis of food retail facilities and socioeconomic characteristic of urban geographic subdivisions. However, the multi-dimensional definitions of adequate food access and socioeconomic deprivation have led to a multitude of different city-based approaches that account for local specifics and thus, are not directly transferable to other study areas.

This study introduces a joint approach to not only identifying food deserts but generating good solutions for possible policy interventions - in this case in the city of Philadelphia, PA. The first step consisted of an analysis of typical socioeconomic characteristics of food deserts and combinations of these characteristics that pose a high risk of food access barriers. In the second step, a maximal covering optimization problem was defined and solved, based on maximizing the newly covered population or minimizing the population with low access to food retail facilities, respectively. A novelty of this study is the merging of a (visual and quantitative) analysis of the status quo with a constrained optimization algorithm to generate solutions for future policy implementations meant to shape the urban food environment.

Firstly, the map-based analysis of the existing food environment revealed that supermarket access in Philadelphia is unequally distributed. Two distinct problem areas could be

identified (Lower North/Northeast Philadelphia and the surroundings of University City) which share common characteristics of food deserts and should receive urgent attention by the local government for food access interventions. Secondly, the application of a vulnerability-weighted maximum covering location problem exposed that there are a multitude of viable options for the placement of new food retail facilities. Considering the aim of satisfying both the public as well as private-sector interests, almost all of the proposed welfare-optimal locations should offer yield above-average market reach. Another point of interest is that stores with a smaller coverage area are less sensitive to the amount of new openings at locations that are considered “good”. For the city of Philadelphia, one could derive two recommendations for food retail policies from this: The placement of large stores such as full-line supermarkets in food deserts should undergo individual assessments in order to maximize the population reach and the contribution to the additional welfare generated. On the other hand, the placement of smaller stores contributing to the service level of the food environment (such as farmers' markets, fruit and vegetable stores or ethnic specialty stores) should be more liberal and far-reaching in order to take advantage of the smaller decay in marginal utility.
Food access varies greatly from city to city, let alone from country to country. This examination of food access should readily be applicable to other cities in the United States, considering the employed spatial data is standardized and publicly accessible. However, current and future food desert research stresses the interconnectedness of a plurality of possible food sources, especially in an urban setting. Additionally , the sensitivity analysis showed the vulnerability to a under- or overestimation of assumed service distances as proxies for the ease of geographic access. A combination of further empirical studies of consumer behavior over time (especially pertaining to deprivation and type of food retail facility) and more sophisticated optimization problems that assess and optimize level of service for consumers is needed to increase understanding of food deserts and to provide better solutions for appropriate policy.

Bibliography

American Medical Association (2013). AMA Adopts New Policies on Second Day of Voting at Annual Meeting. URL: `http://www.ama-assn.org/ama/pub/news/news/2013/2013-06-18-new-ama-policies-annual-meeting.page` (accessed January 12, 2014).

Apparicio, P., M.-S. Cloutier, and R. Shearmur (2007, January). The case of Montréal's missing food deserts: evaluation of accessibility to food supermarkets. *International Journal of Health Geographics 6*, 1–13.

Arentze, T., H. Oppewal, and H. Timmermans (2005). A multipurpose shopping trip model to assess retail agglomeration effects. *Journal of Marketing Research 42*(1), 109–115.

Austin, G. L., L. G. Ogden, and J. O. Hill (2011). Trends in carbohydrate, fat, and protein intakes and association with energy intake in normal-weight, overweight, and obese individuals: 1971-2006. *The American Journal of Clinical Nutrition 93*, 836–843.

Beasley, J. (1993). Lagrangean heuristics for location problems. *European Journal of Operational Research 65*, 383–399.

Beaulac, J., E. Kristjansson, and S. Cummins (2009). A systematic review of food deserts, 1966-2007. *Preventing Chronic Disease 6*, A105.

Bell, J., G. Mora, E. Hagan, V. Rubin, and A. Karpyn (2013). Access to Healthy Food and Why It Matters: A Review of the Research. Technical report, The Food Trust, Philadelphia.

Bitler, M. and S. J. Haider (2011, December). An economic view of food deserts in the united states. *Journal of Policy Analysis and Management 30*(1), 153–176.

Brunett, D. and K. Pothukuchi (2002). Supermarket Access in Low-Income Communities. Technical report, Prevention Institute for the Center for Health Improvement, Oakland, CA.

Buss, D. (2013). Whole Foods Opens In Detroit, But Don't Get Maudlin Over It. URL: `http://www.forbes.com/sites/dalebuss/2013/06/05/whole-foods-opens-in-detroit-but-dont-get-maudlin-over-it/` (accessed January 20, 2014).

Centers for Disease Control and Prevention (2013). BRFSS 2012 Survey Data and Documentation. URL: `http://www.cdc.gov/brfss/annual_data/annual_2012.html` (accessed January 26, 2014).

Chung, C. and S. L. Myers (1999). Do the Poor Pay More for Food? An Analysis of Grocery Store Availability and Food Price Disparities. *Journal of Consumer Affairs 33*, 276–296.

Church, R. and C. ReVelle (1974, January). The maximal covering location problem. *Papers in Regional Science 32*(1), 101–118.

Church, R. L. (2002). Geographical information systems and location science. *Computers & Operations Research 29*(6), 541–562.

Church, R. L. and C. S. ReVelle (2010, September). Theoretical and Computational Links between the p-Median, Location Set-covering, and the Maximal Covering Location Problem. *Geographical Analysis 8*(4), 406–415.

Church, R. L. and P. Sorensen (1994). Integrating Normative Location Models into GIS: Problems and Prospects with the p-median Model. Technical Report 94-5. Technical report, NCGIA, Santa Barbara.

Clarke, G., H. Eyre, and C. Guy (2002). Deriving indicators of access to food retail provision in British cities: studies of Cardiff, Leeds and Bradford. *Urban Studies 39*(11), 2041–2060.

Cotterill, R. W. and A. W. Franklin (1995). The urban grocery store gap. Technical report, University of Connecticut, Department of Agricultural and Resource Economics, Charles J. Zwick Center for Food and Resource Policy, Storrs, CT.

Cummins, S. and S. Macintyre (2002). "Food deserts"–evidence and assumption in health policy making. *BMJ 325*, 436–438.

Daskin, M. S. (2013, September). *Network and Discrete Location: Models, Algorithms, and Applications* (Second Edi ed.). Hoboken, New Jersey: John Wiley & Sons, Inc.

Department of Health (1996). Low income, food, nutrition and health: strategies for improvement. A Report from the Low Income Project Team to the Nutrition Task Force. Technical report, Department of Health, London.

Donkin, A. J., E. A. Dowler, S. J. Stevenson, and S. A. Turner (1999, January). Mapping access to food at a local level. *British Food Journal 101*(7), 554–564.

Drezner, Z. and H. W. Hamacher (2002). *Facility location: applications and theory.* Berlin; Heidelberg; New York: Springer.

Duane Perry (2001). The Need for More Supermarkets in Philadelphia. Technical report, The Food Trust, Philadelphia.

Eckert, J. and S. Shetty (2011, October). Food systems, planning and quantifying access: Using GIS to plan for food retail. *Applied Geography 31*(4), 1216–1223.

Eisenhauer, E. (2001, February). In poor health: Supermarket redlining and urban nutrition. *GeoJournal 53*(2), 125–133.

Farahani, R. and M. Hekmatfar (2009). *Facility location: concepts, models, algorithms and case studies.* Berlin Heidelberg: Springer-Verlag.

FindTheData (2014). SNAP Retailers | Food Stamp Locations. URL: `http://snap-retailers.findthedata.org` (accessed February 17, 2014).

Finkelstein, E., J. Trogdon, J. Cohen, and W. Dietz (2009). Annual medical spending attributable to obesity: payer-and service-specific estimates. *Health Affairs 28*(5), 822–831.

Fox, E., S. Postrel, and A. McLaughlin (2007). The impact of retail location on retailer revenues: An Empirical investigation. Technical report, Southern Methodist University, Dallas, TX.

George, D. and P. Mallery (2003). *SPSS for Windows step by step: A simple guide and reference. 11.0 update* (4th editio ed.), Volume 11.0 updat. Boston: Pearson Education, Inc.

Get Healthy Philly (2011). Farmers' Market and Philly Food Bucks 2010 Report. Technical report, Philadelphia Department of Public Health, Philadelphia, PA.

Get Healthy Philly (2013). Walkable Access to Healthy Food in Philadelphia, 2010-2012. Technical report, Philadelphia Department of Public Health, Philadelphia, PA.

Giang, T., A. Karpyn, H. B. Laurison, A. Hillier, and R. D. Perry (2008). Closing the grocery gap in underserved communities: the creation of the Pennsylvania Fresh Food Financing Initiative. *Journal of Public Health Management Practice 14*(3), 272–279.

Gilewicz, N. (2011). Zoning. URL: `http://www.nextgreatcity.com/taxonomy/term/14` (accessed January 26, 2014).

Glanz, K., J. F. Sallis, B. E. Saelens, and L. D. Frank (2007). Nutrition Environment Measures Survey in stores (NEMS-S): development and evaluation. *American Journal of Preventive Medicine 32*, 282–289.

Google Developers (2014). The Google Directions API - Google Maps API Web Services. URL: `https://developers.google.com/maps/documentation/directions` (accessed February 27, 2014).

Hendrickson, D., C. Smith, and N. Eikenberry (2006). Fruit and vegetable access in four low-income food deserts communities in Minnesota. *Agriculture and Human Values 23*, 371–383.

Hillier, A., C. C. Cannuscio, A. Karpyn, J. McLaughlin, M. Chilton, and K. Glanz (2011). How Far Do Low-Income Parents Travel to Shop for Food? Empirical Evidence from Two Urban Neighborhoods. *Urban Geography 32*, 712–729.

Hotelling, H. (1929). Stability in competition. *The Economic Journal 39*, 41–57.

Jackson, K. (1985). *Crabgrass frontier: The suburbanization of the United States.* New York: Oxford University Press.

Karasakal, O. and E. K. Karasakal (2004). A maximal covering location model in the presence of partial coverage. *Computers & Operations Research 31*(9), 1515–1526.

Kaufman, P. R., J. M. MacDonald, S. M. Lutz, and D. M. Smallwood (1997). Do the Poor Pay More for Food? Item Selection and Price Differences Affect Low-Income Household Food Costs. Technical report, Food and Rural Economics Division, Economic Research Service, U.S. Department of Agriculture.

Kimberly, L. (2011). Get Healthy Philly: Policy Change to Promote Healthy Eating, Active Living, and Tobacco Control. *Population Health Matters (Formerly Health Policy Newsletter) 24*(1), 1.

Kwan, M.-P., A. T. Murray, M. E. O'Kelly, and M. Tiefelsdorf (2003, May). Recent advances in accessibility research: Representation, methodology and applications. *Journal of Geographical Systems 5*(1), 129–138.

Laerd Statistics (2014). How to perform a principal components analysis (PCA) in SPSS. URL: `https://statistics.laerd.com/spss-tutorials/principal-components-analysis-pca-using-spss-statistics.php` (accessed February 10, 2014).

Larsen, K. and J. Gilliland (2008). Mapping the evolution of 'food deserts' in a Canadian city: supermarket accessibility in London, Ontario, 1961-2005. *International Journal of Health Geographics 7*, 16.

Leete, L., N. Bania, and A. Sparks-Ibanga (2012). Congruence and Coverage: Alternative Approaches to Identifying Urban Food Deserts and Food Hinterlands. *Journal of Planning Education and Research 32*, 204–218.

Levi, J., L. M. Segal, R. S. Laurent, and D. Kohn (2011). F as in Fat : How obesity threatens America's future. Technical report, Trust for America's Health, Washington, DC.

Lewis, L. B., D. C. Sloane, L. M. Nascimento, A. L. Diamant, J. J. Guinyard, A. K. Yancey, and G. Flynn (2005). African Americans' access to healthy food options in South Los Angeles restaurants. *American Journal of Public Health 95*, 668–673.

Longley, P. A., M. F. Goodchild, D. J. Maguire, and D. W. Rhind (1999). *Geographical information systems: principles, techniques, applications and management* (2nd unabri ed.). New York: John Wiley & Sons, Inc.

Lopez, R. P. (2007). Neighborhood risk factors for obesity. *Obesity 15*, 2111–2119.

Manchikanti, L., D. L. Caraway, A. T. Parr, B. Fellows, and J. a. Hirsch (2011). Patient Protection and Affordable Care Act of 2010: reforming the health care reform for the new decade. *Pain Physician 14*, E35–67.

Mantovani, R. E. (1997). Authorized Food Retailer Characteristics Study: Technical Report IV : Authorized Food Retailers' Characteristics and Access Study. Technical report, U.S. Dept. of Agriculture, Food and Consumer Service, Office of Analysis and Evaluation, Alexandria, VA.

Maranzana, F. (1964). On the location of supply points to minimize transport costs. *OR 15*(3), 261–270.

Maslow, A. H. (1943). A theory of human motivation. *Psychological Review 50*(4), 370–396.

McEntee, J. and J. Agyeman (2010, January). Towards the development of a GIS method for identifying rural food deserts: Geographic access in Vermont, USA. *Applied Geography 30*(1), 165–176.

Mieszkowski, P. and E. Mills (1993). The causes of metropolitan suburbanization. *The Journal of Economic Perspectives 7*(3), 135–147.

Miller, H. J. (1996). GIS and geometric representation in facility location problems. *Geographical Information Systems 10*(7), 791–816.

Morland, K., A. V. Diez Roux, and S. Wing (2006). Supermarkets, Other Food Stores, and Obesity. *American Journal of Preventive Medicine 30*(4), 333–339.

Munshi, N. (2013). Whole Foods targets low-income market in Chicago's mean streets. URL: `http://www.ft.com/intl/cms/s/0/1c3375e6-1b36-11e3-b781-00144feab7de.html` (accessed January 20, 2014).

Murray, A. T., M. E. O. Kelly, and R. L. Church (2008). Regional service coverage modeling. *Computers & Operations Research 35*, 339–355.

Office Of The Surgeon General (2001). The Surgeon General's Call to Action To Prevent and Decrease Overweight and Obesity: Overweight in Children and Adolescents. *Health San Francisco 2007*, 1–39.

Ogden, C. L., M. D. Carroll, B. K. Kit, and K. M. Flegal (2012). Prevalence of obesity in the United States, 2009-2010. Technical report, National Center for Health Statistics, Hyattsville, MD.

Ogden, C. L., M. M. Lamb, M. D. Carroll, and K. M. Flegal (2010). Obesity and socioeconomic status in adults: United States, 2005-2008. Technical report, National Center for Health Statistics, Hyattsville, MD.

Open Data Philly (2012). Healthy Corner Store Locations. URL: `http://www.opendataphilly.org/opendata/resource/216/healthy-corner-store-locations/` (accessed January 28, 2014).

Open Data Philly (2013). Farmers Markets Locations. URL: `http://www.opendataphilly.org/opendata/resource/217/farmers-markets-locations/` (accessed January 28, 2014).

Owen, S. H. and M. S. Daskin (1998, December). Strategic facility location: A review. *European Journal of Operational Research 111* (3), 423–447.

Ploeg, M. V., V. Breneman, T. Farrigan, K. Hamrick, D. Hopkins, P. Kaufman, B.-h. Lin, M. Nord, T. Smith, R. Williams, K. Kinnison, C. Olander, A. Singh, E. Tuckermanty, R. Krantz-kent, C. Polen, H. Mcgowan, and S. Kim (2009). Access to Affordable and Nutritious Food : Measuring and Understanding Food Deserts and Their Consequences Report to Congress. Technical Report June, United States Department of Agriculture.

Pothukuchi, K. (2005, August). Attracting Supermarkets to Inner-City Neighborhoods: Economic Development Outside the Box. *Economic Development Quarterly 19* (3), 232–244.

Pothukuchi, K. and J. Kaufman (1999). Placing the food system on the urban agenda: The role of municipal institutions in food systems planning. *Agriculture and Human Values 16*, 213–224.

Powell, L. M., S. Slater, D. Mirtcheva, Y. Bao, and F. J. Chaloupka (2007). Food store availability and neighborhood characteristics in the United States. *Preventive Medicine 44*, 189–195.

QGIS Development Team (2014). PyQGIS Developer Cookbook. URL: `http://www.qgis.org/en/docs/pyqgis_developer_cookbook/intro.html` (accessed February 28, 2014).

ReVelle, C. and H. Eiselt (2005). Location analysis: A synthesis and survey. *European Journal of Operational Research 165*, 1–19.

ReVelle, C., D. Marks, and J. C. Liebman (1970, July). An Analysis of Private and Public Sector Location Models. *Management Science 16* (11), 692–707.

Roddenberry, D. and J. Fleming (2013). Do Obamacare wellness incentives penalize the poor and overweight? URL: `http://ebn.benefitnews.com/blog/ebviews/do-obamacare-wellness-incentives-penalize-the-poor-and-overweight-2738050-1.html` (accessed January 12, 2014).

Schafft, K. a., E. B. Jensen, and C. C. Hinrichs (2009). Food Deserts and Overweight Schoolchildren: Evidence from Pennsylvania. *Rural Sociology 74*, 153–177.

Sharkey, J. R. and S. Horel (2008). Neighborhood socioeconomic deprivation and minority composition are associated with better potential spatial access to the ground-truthed food environment in a large rural area. *The Journal of Nutrition 138*, 620–627.

Simon, H. (1972). Theories of Bounded Rationality. In C. B. McGuire and R. Radner (Eds.), *Decision and Organization*, pp. 161–176. Amsterdam: North-Holland Publishing Company.

Sparks, A., N. Bania, and L. Leete (2009). Finding Food Deserts: Methodology and Measurement of Food Access in Portland , Oregon. In *National Poverty Center/USDA Economic Research Service research conference "Understanding the Economic Concepts and Characteristics of Food Access"*, Washington, DC, pp. 54. University of Oregon.

Stiegert, K. W. and T. Sharkey (2007, January). Food pricing, competition, and the emerging supercenter format. *Agribusiness 23*(3), 295–312.

Swinburn, B. A. (2009, April). Commentary: Closing the disparity gaps in obesity. *International Journal of Epidemiology 38*(2), 509–11.

Swinburn, B. A., I. Caterson, J. C. Seidell, and W. P. T. James (2004). Diet, nutrition and the prevention of excess weight gain and obesity. *Public Health nutrition 7*, 123–146.

Teitz, M. B. and P. Bart (1968). Heuristic Methods for Estimating the Generalized Vertex Median of a Weighted Graph. *Operations Research 16*, 955–961.

The Food Trust (2012). Philadelphia's Healthy Corner Store Initiative 2010-2012. Technical report, The Food Trust, Philadelphia.

The Reinvestment Fund (2012). Searching for Markets: The Geography of Inequitable Access to Healthy & Affordable Food in the United States. Technical report, CDFI Fund, Philadelphia, PA.

Toivanen, O. and M. Waterson (2005). Market Structure and Entry: Where's the Beef? *RAND Journal of Economics 36*(3), 680–699.

Toregas, C., R. Swain, C. ReVelle, and L. Bergman (1971, October). The Location of Emergency Service Facilities. *Operations Research 19*(6), 1363–1373.

United States Census Bureau (2010a). TIGER Products. URL: `http://www.census.gov/geo/maps-data/data/tiger.html` (accessed February 8, 2014).

United States Census Bureau (2010b). TIGER/Line® with Demographic Data. URL: `http://www.census.gov/geo/maps-data/data/tiger-data.html` (accessed February 8, 2014).

United States Census Bureau (2013). Population Estimates. URL: `http://www.census.gov/popest/data/state/totals/2013/index.html` (accessed January 26, 2014).

United States Census Bureau (2014a). American Community Survey Summary File. URL: `http://www.census.gov/acs/www/data_documentation/summary_file/` (accessed February 10, 2014).

United States Census Bureau (2014b). Philadelphia County QuickFacts from the US Census Bureau. URL: `http://quickfacts.census.gov/qfd/states/42/42101.html` (accessed February 8, 2014).

United States Department of Agriculture (2014). SNAP Retailer Locator | Food and Nutrition Service. URL: `http://www.fns.usda.gov/snap/retailerlocator` (accessed February 17, 2014).

United States Department of Health Agricultural Marketing Service (2013). Farmers Market Growth. URL: `http://www.ams.usda.gov/AMSv1.0/ams.fetchTemplateData.do?template=TemplateS&navID=WholesaleandFarmersMarkets&leftNav=WholesaleandFarmersMarkets&page=WFMFarmersMarketGrowth&description=Farmers%20Market%20Growth&acct=frmrdirmkt` (accessed January 28, 2014).

Urbany, J. E., P. R. Dickson, and A. G. Sawyer (2000). Insights into cross- and within-store price search: retailer estimates vs. consumer self-reports. *Journal of Retailing 76*(2), 243–258.

U.S. Government Printing Office (2008). Food, Conservation, and Energy Act of 2008. URL: http://www.gpo.gov/fdsys/pkg/PLAW-110publ234/pdf/PLAW-110publ234.pdf (accessed December 27, 2013).

Vahrenkamp, R. and D. Mattfeld (2007). *Logistiknetzwerke: Modelle für Standortwahl und Tourenplanung* (1. Auflage ed.). Wiesbaden: Springer Gabler.

Vyas, S. and L. Kumaranayake (2006, November). Constructing socio-economic status indices: how to use principal components analysis. *Health Policy and Planning 21*(6), 459–68.

Walker, R. E., C. R. Keane, and J. G. Burke (2010). Disparities and access to healthy food in the United States: A review of food deserts literature. *Health & Place 16*, 876–884.

Wang, Y. and M. A. Beydoun (2007). The obesity epidemic in the United States–gender, age, socioeconomic, racial/ethnic, and geographic characteristics: a systematic review and meta-regression analysis. *Epidemiologic Reviews 29*, 6–28.

Weinberg, Z. (2000). No place to shop: food access lacking in the inner city. *Race, Poverty & the Environment 7*(2), 22–24.

Wikipedia Contributors (2014). List of supermarket chains in the United States. URL: http://en.wikipedia.org/w/index.php?title=List_of_supermarket_chains_in_the_United_States&oldid=594929611 (accessed February 17, 2014).

Wolf, A. M. and G. A. Colditz (1998). Current estimates of the economic cost of obesity in the United States. *Obesity Research 6*, 97–106.

Appendix

A. List of considered supermarkets

Table A.1.: List of considered supermarket chains in Philadelphia

Store	Locations [1]	SNAP [2]
GIANT	1	Yes
Trader Joe's	1	Yes
ShopRite	14	Yes
Pathmark	9	Yes
Super Fresh	5	Yes
Food Basics	2	Yes
Acme	10	Yes
Walmart Supercenter	2	Yes
ALDI	4	Yes
Bottom Dollar Food	7	Yes
Shop n Bag	3	Yes
Thriftway	3	Yes
Supreme Food Market	1	Yes
Save-A-Lot	13	Yes
Cousins Supermarket	2	Yes
	$\sum$ **81**	

Sources

- Chains: Google Maps, Wikipedia Contributors (2014)
- Store locations: Store locators of correspondent retailer websites
- SNAP: FindTheData (2014), United States Department of Agriculture (2014)

B. MCLP results

Table A.2.: List of considered supermarkets in Philadelphia

ID	X	Y	NAME	ADDRESS	SNAP	ZIP
1	-75.0264552	40.0791841	GIANT	2550 Grant Ave, 19114	Yes	19114
2	-75.1761220	39.9542770	Trader Joe's	2121 Market St, 19103	Yes	19103
3	-75.0937467	39.9949708	ShopRite	3745 Aramingo Avenue	Yes	19137
4	-75.1641307	40.0773099	ShopRite	2385 Cheltenham Avenue	Yes	19150
5	-75.1200327	40.0351153	ShopRite	101 E. Olney Avenue	Yes	19120
6	-75.2535227	39.9724547	ShopRite	6710 Haverford Avenue	Yes	19151
7	-75.2399895	39.9029486	ShopRite	2946 Island Avenue	Yes	19153
8	-75.0513320	40.0316280	ShopRite	6725 Frankford Avenue	Yes	19135
9	-74.9848140	40.0645440	ShopRite	9910 Frankford Avenue	Yes	19114
10	-75.1883675	39.9196722	ShopRite	24th St at Oregon Ave	Yes	19145
11	-75.0872612	40.0436409	ShopRite	6301 Oxford Avenue	Yes	19111
12	-75.2260450	39.9782212	ShopRite	1575 N 52nd Street	Yes	19131
13	-75.0094850	40.1021610	ShopRite	11000 Roosevelt Blvd.	Yes	19116
14	-75.2275630	40.0440210	ShopRite	6901 Ridge Avenue	Yes	19128
15	-75.1465950	39.9214073	ShopRite	29 Snyder Avenue	Yes	19148
16	-75.1759520	40.0119930	ShopRite	Fox St at Roberts Ave.	Yes	19129
17	-75.1940453	39.9391875	Pathmark	3021 Grays Ferry Ave.	Yes	19146
18	-75.1547092	39.9143351	Pathmark	330 Oregon Ave.	Yes	19148
19	-75.1540189	39.9972711	Pathmark	2900 North Broad St.	Yes	19132
20	-75.1013173	39.9898654	Pathmark	3399 Aramingo Ave.	Yes	19134
21	-75.2150200	40.0018130	Pathmark	4160 Monument Ave.	Yes	19131
22	-75.1779090	40.0316380	Pathmark	176-82 West Chelten Ave	Yes	19144
23	-75.1944800	40.0724870	Pathmark	7700 Crittenden St.	Yes	19118
24	-75.0864740	40.0614769	Pathmark	840 Cottman Ave.	Yes	19111
25	-75.0616622	40.0505382	Pathmark	2101-41 Cottman Ave	Yes	19149
26	-75.0132206	40.0481391	Pathmark	8700 Frankford Ave.	Yes	19136
27	-75.0097148	40.0509782	Food Basics	8920 Frankford Ave	Yes	19136
28	-75.0091308	40.1341236	Food Basics	15501 Bustleton Ave	Yes	19116
29	-75.1593730	39.9431040	Super Fresh	1001 South St	Yes	19147
30	-75.1499340	39.9444880	Super Fresh	309 S Fifth St.	Yes	19106
31	-75.1390650	39.9686990	Super Fresh	180 West Girard Avenue	Yes	19123
32	-75.1403901	39.9234256	Super Fresh	1851 South Columbus Boulevard	Yes	19148
33	-75.2315647	40.0450892	Super Fresh	7162 Ridge Ave	Yes	19128
34	-75.1613800	39.9317359	Acme	1400 East Passyunk Avenue	Yes	19147
35	-75.1802329	39.9178652	Acme	1901 Johnston Street	Yes	19145
36	-75.2304038	40.0532987	Acme	5927-59 Ridge Avenue	Yes	19128
37	-75.1894020	40.0567270	Acme	7010 Germantown Avenue	Yes	19119
38	-75.0629150	40.0358760	Acme	6601 Roosevelt Blvd	Yes	19149
39	-75.2400011	40.0643746	Acme	8600 Ridge Avenue	Yes	19128
40	-75.0861146	40.0503161	Acme	6640 Oxford Avenue	Yes	19111
41	-75.0449660	40.0603520	Acme	8200 Roosevelt Blvd	Yes	19152
42	-74.9937500	40.0801580	Acme	3200-09 Red Lion Road	Yes	19114
43	-75.0272786	40.1010882	Acme	920 Red Lion Road	Yes	19115
44	-75.1431726	39.9243039	Walmart Supercenter	1675 S Christopher Columbus Bl	Yes	19148
45	-75.0923540	39.9988830	Walmart Supercenter	2200 Wheatsheaf Ln	Yes	19137
46	-75.1487007	39.9120596	ALDI	2603 S. Front Street	Yes	19148
47	-75.2130154	39.9593055	ALDI	4421 Market St.	Yes	19104
48	-75.1124952	40.0105759	ALDI	4104 G. Street	Yes	19124
49	-75.0066768	40.0688217	ALDI	3320 Grant Avenue	Yes	19114
50	-75.1422270	40.0466660	Bottom Dollar Food	6119 N Broad St	Yes	19141
51	-75.0466760	40.0847760	Bottom Dollar Food	9303 Krewstown Road	Yes	19115
52	-75.1457820	40.0397682	Bottom Dollar Food	7627 Lindbergh Blvd.	Yes	19153
53	-75.0495920	40.0551850	Bottom Dollar Food	7900 Roosevelt Blvd	Yes	19152
54	-75.0984430	40.0068830	Bottom Dollar Food	3975 Castor Avenue	Yes	19124
55	-75.1871991	39.9751004	Bottom Dollar Food	3101 West Girard Avenue	Yes	19130
56	-75.1733040	40.0510040	Bottom Dollar Food	6301 Chew Ave.	Yes	19138
57	-75.1495960	40.0189970	Shop n Bag	4424 North Broad Street	Yes	19140
58	-75.0687944	40.0673073	Shop n Bag	7938 Dungan Road	Yes	19111
59	-75.0552739	40.0203813	Shop n Bag	6499 Sackett Street	Yes	19135
60	-75.0787779	40.0218504	Thriftway	5147 Frankford Ave	Yes	19124
61	-75.1665820	39.9963229	Thriftway	2101 W Lehigh Ave	Yes	19132
62	-75.1197180	39.9762952	Thriftway	2497 Aramingo Avenue	Yes	19125
63	-75.2092340	39.9552229	Supreme Food Market	4301 Walnut Street	Yes	19104
64	-75.1660331	40.0576520	Save-A-Lot	1300 Washington Ave	Yes	19145
65	-75.1824430	40.0314480	Save-A-Lot	5834 Pulaski Ave	Yes	19144
66	-75.1953934	39.9080850	Save-A-Lot	2132 E Lehigh Ave	Yes	19125
67	-75.1848119	39.9192630	Save-A-Lot	2201 W Oregon Ave	Yes	19145
68	-75.1782972	39.9907760	Save-A-Lot	2801 W Dauphin St	Yes	19132
69	-75.0766840	40.0402329	Save-A-Lot	6422 Castor Ave	Yes	19149
70	-75.0920920	39.9959408	Save-A-Lot	3801-03 Aramingo Ave	Yes	19137
71	-75.2385229	39.9461913	Save-A-Lot	5740 Baltimore Ave	Yes	19143
72	-75.2328090	39.9665700	Save-A-Lot	5601 Vine St	Yes	19139
73	-75.2244090	39.9316760	Save-A-Lot	5800 Woodland Ave	Yes	19143
74	-75.0999400	40.0064380	Save-A-Lot	3901-29 M Street	Yes	19124
75	-75.1187770	40.0292780	Save-A-Lot	5201 Rising Sun Ave	Yes	19120
76	-75.2347780	39.9802990	Save-A-Lot	5610 Lancaster Ave	Yes	19125
77	-75.1444137	39.9927606	Save-A-Lot	701 West Lehigh	Yes	19133
78	-75.1186445	40.0511816	Save-A-Lot	101 West Cheltenham Ave	Yes	19012
79	-75.0501880	40.0320630	Save-A-Lot	6801 Frankford	Yes	19135
80	-75.1430777	39.9801746	Cousin's Supermarket	1900 North 5th St	Yes	19122
81	-75.1356815	40.0126873	Cousin's Supermarket	4037 North 5th St	Yes	19140

Table B.3.: MCLP solution - placement: Supermarkets, p=40, initial coverage: supermarkets (S=$\frac{1}{2}$ mile)

Iteration	Index	ID	Additional Coverage	Covered nodes	Nearest supermarket [ft]	Improvement
1	508	508	26842	28	2923.8	43.256
2	120	120	22722	18	2875.5	51.543
3	973	973	20305	22	2840.7	34.836
4	538	538	20042	16	2817.6	23.078
5	253	253	19716	14	2785.7	53.015
6	158	158	19620	18	2744.6	21.727
7	193	193	19016	17	2720.3	25.187
8	867	867	17314	15	2682.8	26.661
9	691	691	17268	14	2662.6	35.614
10	1199	1199	16938	14	2636.1	17.533
11	324	324	16731	17	2611.3	26.548
12	834	834	16248	15	2565.2	24.835
13	1098	1098	16026	17	2542.6	46.128
14	27	27	15996	17	2505.2	22.65
15	660	660	13939	13	2484.2	33.278
16	460	460	12744	10	2465	20.677
17	893	893	12743	15	2398.8	11.874
18	172	172	12464	15	2376.1	14.112
19	1067	1067	11329	10	2358.3	47.661
20	106	106	11080	9	2346.3	17.808
21	59	59	10991	5	2328.1	12.065
22	378	378	10955	7	2315	18.151
23	1176	1176	10746	12	2291.3	12.713
24	76	76	10468	10	2276.6	19.539
25	338	338	10310	10	2262.3	21.642
26	1072	1072	10300	9	2249.4	23.703
27	1316	1316	10098	6	2201.1	43.92
28	364	364	10091	10	2179.2	21.723
29	1127	1127	9219	10	2162.1	17.142
30	240	240	9144	10	2146.3	13.577
31	987	987	8999	10	2128.8	17.605
32	1184	1184	8849	7	2119.6	9.181
33	1225	1225	8770	9	2103.4	9.7139
34	540	540	8574	8	2094.2	10.535
35	1313	1313	8548	4	2083.7	14.139
36	46	46	8344	6	2072.8	14.625
37	264	264	8141	6	2065.9	15.752
38	1078	1078	8084	7	2046.7	7.8967
39	920	920	7799	7	2038.5	19.196
40	762	762	7765	1	2034.5	8.1638

Table B.4.: weighted MCLP solution - placement: Supermarkets, p=40, initial coverage: supermarkets (S=$\frac{1}{2}$ mile)

Iteration	Index	ID	Coverage	Newly covered nodes	Nearest supermarket [ft]	improvement	Weighted coverage
1	120	120	22722	18	2918.8	48.309	14381
2	538	538	20042	16	2895.7	23.077	10871
3	508	508	26842	28	2852.5	43.256	10220
4	1261	1261	17741	17	2807.7	44.757	7340.8
5	193	193	19016	17	2783.4	24.329	7443.6
6	868	868	15438	14	2747.8	35.612	6195.8
7	1098	1098	16026	17	2725.1	22.7	6583.9
8	1026	1026	18802	21	2690.7	34.337	5721.4
9	1199	1199	16938	14	2664.2	26.548	5045.6
10	1176	1176	10746	12	2640.5	23.702	5005.5
11	796	796	9326	9	2627.6	12.921	4816.6
12	693	693	16928	13	2608.1	19.49	4831.7
13	172	172	12464	15	2581.1	27.012	4622.8
14	338	338	10310	10	2566.8	14.261	4614.7
15	155	155	14497	11	2542	24.8	3810.2
16	457	457	13501	13	2521.2	20.831	4188
17	834	834	16248	15	2475.2	46.003	4026.1
18	139	139	9570	10	2453.6	21.58	4011.4
19	27	27	15996	17	2420.5	33.065	4000
20	102	102	10800	9	2408.2	12.264	3928.5
21	253	253	15777	12	2391.6	16.605	6377
22	460	460	12744	10	2372.4	19.231	3747.1
23	1126	1126	11138	12	2353.3	19.093	4138.3
24	1067	1067	11329	10	2335.5	17.809	3716.5
25	324	324	16731	17	2310.7	24.836	3252.1
26	263	263	7284	6	2301.3	9.3904	3224.2
27	805	805	9166	9	2288.1	13.203	3819.1
28	540	540	8574	8	2278.9	9.2232	2625.7
29	1274	1274	7123	7	2268.2	10.672	2542.6
30	1134	1134	8235	9	2253.4	14.788	3407.3
31	893	893	12743	15	2187.3	66.131	2086.1
32	1252	1252	5938	7	2176.2	11.115	2499.4
33	865	865	9455	8	2162.6	13.6	2975.7
34	59	59	10991	5	2144.4	18.151	1953.4
35	355	355	5866	4	2138.2	6.1627	1939.2
36	987	987	8999	10	2120.7	17.531	1851.5
37	1225	1225	8770	9	2104.5	16.188	1806.5
38	1086	1086	7209	4	2094.9	9.6508	1778.8
39	130	130	8252	4	2087.1	7.8033	2042.6
40	180	180	4913	5	2079.1	7.919	1733.1

Table B.5.: MCLP solution - placement: Farmers' Markets, p=80, initial coverage: supermarkets (S=$\frac{1}{2}$ mile) and Farmers' Markets (S=$\frac{1}{4}$ mile

Iteration	ID	Coverage	Newly covered nodes	Nearest supermarket [ft]	improvement	Weighted coverage
1	504	8839	9	5590.5	9.2862	3480.5
2	533	8629	7	5465	125.56	5061.8
3	762	7765	1	4708.7	756.28	1235
4	700	7446	5	4686.2	22.469	2148.3
5	723	7389	5	4671.3	14.916	4047.2
6	381	7160	5	4617.4	53.933	2546.1
7	534	6984	6	4591	26.401	3627.4
8	253	6697	4	4583	7.9718	2684
9	905	6439	7	4291.3	291.68	1413.7
10	1043	6340	6	4250.2	41.089	1774
11	942	6326	6	4244.1	6.1655	1035.5
12	141	6105	4	4214.3	29.791	3304.8
13	60	6098	5	4155.6	58.64	2552.3
14	295	6085	7	4114.8	40.843	2013.2
15	568	6076	6	4097.9	16.91	1937.2
16	863	6008	5	4007.6	90.244	1910.9
17	1100	5993	7	3998	9.5945	2399.8
18	1265	5945	4	3974.9	23.129	1164.3
19	103	5756	4	3919	55.88	1977
20	78	5730	5	3912.5	6.506	4005.7
21	338	5590	4	3907.7	4.8005	2086.6
22	1310	5583	5	3902.1	5.5937	1631.9
23	617	5528	5	3884.6	17.514	1393.4
24	828	5448	5	3854.8	29.77	1395.3
25	463	5412	3	3824.5	30.302	1725
26	1156	5373	3	3378.5	446	1137.7
27	803	5202	5	3351.7	26.829	2380.6
28	262	5192	4	3334.3	17.374	2449.1
29	1016	5010	6	3327.8	6.5469	1820.5
30	413	4966	5	3321.4	6.4436	1307.1
31	189	4904	6	3310.9	10.428	1841.7
32	868	4854	5	3294.5	16.461	2371.1
33	360	4715	5	3248.1	46.387	1728.1
34	1138	4578	6	3234.8	13.247	1884.7
35	965	4550	5	3226.4	8.456	1664.5
36	139	4405	4	3203.2	23.201	1762.4
37	1281	4382	4	3186.9	16.228	2158.5
38	516	4341	4	3182.3	4.6085	1780.9
39	1036	4277	4	3178.6	3.754	783.1
40	397	4268	5	3174.2	4.3552	1343.4
41	683	4257	3	3166.9	7.2803	2647.2
42	351	4243	5	3158.6	8.3025	1905.4
43	1262	4238	5	3131.4	27.279	1754.7
44	528	4196	4	3128.2	3.1227	2931.1
45	170	4136	4	3123.4	4.8413	1644.1
46	1232	4122	5	3103.6	19.799	877
47	1289	4112	3	3101	2.5562	1007.4
48	671	4102	3	3098.6	2.4061	680.29
49	921	4086	3	2876.5	222.14	684.41
50	169	4043	4	2872	4.537	2212.9
51	749	4017	4	2856.6	15.317	926.49
52	899	3944	5	2839.8	16.89	639.28
53	805	3937	5	2830.5	9.2758	1571.4
54	74	3745	3	2822.3	8.2219	2169.6
55	271	3745	3	2796.5	25.752	1357.5
56	226	3708	3	2787.9	8.6465	1373
57	23	3631	3	2761.3	26.607	1020.9
58	459	3624	3	2750.8	10.421	836.24
59	108	3504	3	2745.8	5.0777	1507.4
60	997	3472	3	2636.9	108.9	752.46
61	565	3399	2	2594.9	41.93	669.55
62	597	3380	2	2586.9	8.0591	847.98
63	1299	3358	4	2583.9	2.9246	802.46
64	110	3306	3	2580.8	3.1622	1134
65	883	3294	4	2572.2	8.5868	482.42
66	646	3275	3	2527.5	44.671	693.81
67	36	3253	4	2515.2	12.323	853.84
68	840	3214	2	2500.5	14.682	859.83
69	604	3104	2	2301.7	198.8	467.49
70	894	3093	4	2295.9	5.8203	444.01
71	909	3091	3	2284.8	11.13	445.97
72	85	3080	3	2266	18.803	516.19
73	1178	3061	4	2261.5	4.4196	1339.3
74	90	3047	3	2249.6	11.96	649.64
75	447	3022	3	2233.1	16.49	745.79
76	497	2957	2	2229.5	3.5759	1235.1
77	588	2946	3	2208.1	21.469	771.91
78	50	2873	2	2162	46.022	297.97
79	490	2852	1	2036.9	125.14	351.11
80	1236	2847	1	2012.3	24.544	502.15