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A Geographical Analysis of Food Access in the Greater Hartford Area of Connecticut

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Abstract

Food access is an important measurement in food deserts and food insecurity research, yet it is one, which has not been defined or employed systematically in urban settings. To some authors *access* refers to physical distance to grocery stores, or simply the number of stores, while to others it characterizes factors such as price and quality of food sold. This ambiguity leads to contrasting delineation of food deserts, which has ramifications on estimating its effects on vulnerable populations and subsequent food policies.

The main goal of this dissertation is to formulate a taxonomic index of access, which summarizes a set of multidimensional factors - *accessibility*, *availability*, *affordability*, *acceptability*, and *accommodation*. This index is an extension of Penchansky and Thomas' theoretical model of access and its relation to consumer satisfaction. The secondary objectives are to i) design and build a user-friendly toolbox in a popular GIS software package (ESRI's ArcGIS) to calculate travel time by public transit time between points of interest using Google Direction API; ii) assess the vulnerability of food insecurity among low-income and ethnic minorities in the events of supermarket redlining； and iii) using survey data assess the role and needs of local grocery stores to be an alternative source of nutritious foods in place of large chain supermarkets. These objectives were tested and analyzed in the study area including the City of Hartford as well as the Greater Hartford Area of Connecticut including 29 towns. The data came from disparate

sources of secondary data and a comprehensive survey of 99 grocery stores on the availability, price, and quality of items in a typical food basket.

Comparing with suburban towns in Connecticut, city of Hartford had lowest scores of the comprehensive 5A-Indicator and 61% of block-groups were identified as food deserts. This is in contrast with USDA's delineation of 33% of block-groups as food deserts. If we disaggregate the 5 dimensions, one of the major findings is the significant variability of the average availability, acceptability and accommodation, with Hartford faring much worse than that of other the towns. Compared with the large chain supermarkets located in the suburban towns, local small and medium sized grocery stores in Hartford offered lower prices of food items but these stores lacked in terms of other dimensions of access such as the acceptable quality of food and internal cleanliness and organization, and accommodative factors such as well-lit parking lot and convenient hours of operation.

There is no study to our knowledge to date, which has applied such a robust model of access to identify and understand the implications of low access to nutritious and affordable food on neighborhoods and communities experiencing food insecurity. We hope this study can help influence recommendations for the Hartford Advisory Commission on Food Policy and promote action from other city agencies to improve food availability, quality, and stores' internal/external appearances in Hartford.

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Chapter 1: Introduction

The concept of the term *food access* is multidimensional. Even when the Food and Agriculture Organization of the United Nations (FAO) defines it as *"access by individuals to adequate resources for acquiring appropriate foods for a nutritious diet"* (FAO, 2006), there is quite a lot of variation among organizations and researchers on how access to food is defined. There are even more differences on how access is *conceptualized* and *measured*. It is also critical to understand *who* (socio-economic status) is accessing and from *where* (geographical area). For example, people living in low income neighborhoods face greater barriers in accessing nutritious food not only in terms of number of stores available but also distance to stores and prices than people living in affluent neighborhoods (Andreyeva, Blumenthal, Schwartz, Long, & Brownell, 2008; Ball, Timperio, & Crawford, 2009; Chung & Myers, 1999; Larsen & Gilliland, 2008; L. V. Moore & Roux, 2006; K. Morland, Wing, Roux, & Poole, 2002; Powell, Slater, Mirtcheva, Bao, & Chaloupka, 2007).

Literature identifies socio-economic disadvantaged neighborhoods, typically located in urban areas, with limited or inadequate physical or economic access to healthy and affordable food as *food deserts* (Apparicio, Cloutier, & Shearmur, 2007; Larsen & Gilliland, 2008; Smoyer-Tomic, Spence, & Amrhein, 2006; Whelan, Wrigley, Warm, & Cannings, 2002; Wrigley, Warm, & Margetts, 2003). Often, people living in food deserts experience *food insecurity*, which describes a condition where people have limited access to sufficient, safe, and nutritious food to meet their daily needs for healthy living (Hamelin, Beaudry, & Habicht, 2002; Lopez, Martin, Tchumtchoua, & Drake, 2005; Olson, 1999). The health implications of living in food deserts, experiencing food insecurity, or a combination of both disproportionately affects populations with lower

socioeconomic status, ethnic minority status, elderly, and people with existing negative health outcomes (K. Morland et al., 2002; Raja, Ma, & Yadav, 2008; Zenk et al., 2005). Zenk et al. (2005) found that even within low-income neighborhoods, residents living in areas with higher proportion of African-American population had to travel on an average 1 to 1.25 miles more to the nearest supermarket than neighborhoods with predominantly white population. White neighborhoods, on the other hand, had almost 4 times more supermarkets compared to neighborhoods with significantly higher black population (K. Morland et al., 2002). In terms of prices of food, the majority of research showed that the poor had to pay more for healthy food (Chung & Myers, 1999; Hendrickson, Smith, & Eikenberry, 2006; Jetter & Cassady, 2006; K. Morland et al., 2002). In a case study conducted in the Twin Cities Metropolitan Area of Minnesota, Chung and Myers pointed out that big chain supermarkets had much lower price but were not likely to locate in poor areas (Chung & Myers, 1999). Non-chains and small stores were more likely to be located in impoverished areas, where typically choices for fresh food were limited but with an abundant variety of high-calorie packaged foods at higher prices (Chung & Myers, 1999).

It is therefore important to systematically define and measure food access and to understand its effects on communities with different socioeconomic status. The primary goal of this dissertation is to propose and test the validity of a robust taxonomic definition of access, one that disaggregates the broad and ambiguous concept into a set of dimensions that can be given specific definitions and for which operational measures can be developed. The secondary goals to achieve the primary goal focus on extending the current techniques to measure geographic access, identify neighborhoods and measure vulnerabilities related to food insecurity in communities if supermarket redlining happens, and finally evaluate the role of local grocery stores as an alternative source of nutritious and affordable food in place of large supermarkets.

1.1 Techniques to Measure Geographic Access

In recent accessibility studies, the traditional Euclidean distance measure (Azar, Ferreira, & Wiggins, 1994; Nyerges, 1995) has been replaced with more plausible measures such as the travel distance (Aultman-Hall, Roorda, & Baetz, 1997; Liu & Zhu, 2004; Widener, Metcalf, & Bar-Yam, 2011; Wu & Murray, 2005) or travel time (Gent & Symonds, 2005; Hillman & Pool, 1997; Lei & Church, 2010; Liu & Zhu, 2004; O'Sullivan, Morrison, & Shearer, 2000; Widener & Shannon, 2014). Travel distance, although an improvement over Euclidean distance, lacks to incorporate impedances such as speed limit (Liu & Zhu, 2004; van Eck & De Jong, 1999) or time of the day (Arentze, Borgers, & Timmermans, 1994; Kim & Kwan, 2003; Leggat, Kerker, Nonas, & Marcus, 2012; O'Sullivan et al., 2000; Polzin, Pendyala, & Navari, 2002). Travel time, on the other hand, is an accurate measure of access and travel time by different modes of transportation (e.g. public transit) is even more realistic for urban settings. Recent studies have employed transit time but using external data (Farber, Morang, & Widener, 2014; McGlone, 2013; O'Sullivan et al., 2000; Tallis, 2014; Widener, Farber, Neutens, & Horner, 2015; Widener, Metcalf, & Bar-Yam, 2013) and combining multiple GIS functions (de Jong & van Eck, 1996; Farber et al., 2014; Geertman & Ritsema Van Eck, 1995; Hillman & Pool, 1997; Liu & Zhu, 2004; McGlone, 2013; Peng, 1997; Polzin et al., 2002; Tallis, 2014; Widener et al., 2015), perhaps not so user-friendly for a Geographic Information System (GIS) beginner. This is an impedance for researchers to use more travel time in their studies. Recently, few researchers and web developers, including some geographers, began to use Mapping Application Programming Interfaces (APIs) to create Internet applications (Miller 2006, Chow 2008, Gibin et al. 2008, Roth and Ross 2009, Bugs et al. 2010, Kobayashi et al. 2010), however, more easy to use tools are required. In this dissertation, a user-friendly toolbox in a popular GIS software package (ESRI's ArcGIS) was designed and built to

calculate travel time by public transit between two locations (here between block-group centroids and grocery store) using Google Direction API.

1.2 Implications of Low Access to Food: Supermarket Redlining

Supermarket redlining is a term used to describe a phenomenon when major chain supermarkets are disinclined to locate their stores in inner cities or low-income neighborhoods and usually relocate existing stores to the suburbs (Eisenhauer 2001). If a neighborhood's supermarket closes with limited chances of a new one opening, what remains are vacant buildings and demoralized residents. Supermarkets also tend to drive smaller grocery stores out of business when they move in; so, when they relocate or close down, residents face difficulties in accessing healthy and affordable food—thus widening the *grocery gap*, increasing *food insecurity*, and perhaps creating a *food desert.*

In the United States, isolated incidents of supermarket closures or possible supermarket redlining incidents began in 1960s and since then the trend had been on the rise (IFDP, 1997). For example, in Boston, Massachusetts, 34 out of 50 big chain supermarkets have closed since 1970s. In Los Angeles county in California, the number of supermarkets decreased from 1068 in 1970 to 694 in 1990 (Turque, 1992). Safeway, a well-known supermarket chain, closed more than 600 stores in the country from 1978 to 1984 (Eisenhauer, 2001). Many of these stores were the primary or only source of affordable, safe, and acceptable quality of meat and produce in their neighborhoods. In Hartford, 11 out 13 chain supermarkets (almost 85% of the stores) left the city between 1968 to 1984 (Kane, 1984). Such incidents are still happening today (Eisenhauer, 2001; Raja et al., 2008; Russell & Heidkamp, 2011).

There is no study to our knowledge, particularly from an empirical approach, that focuses on potential *spatial supermarket redlining* as an early indicator of risk for food deserts and food insecurity. In this dissertation, using the travel time by both public transit and cars, low or difficult access to grocery stores among low-income and minority communities were measured. Implications of such unequal access to food on vulnerable communities were analyzed using the concept of supermarket redlining and theory of place-of-food vulnerability model modified from Cutter's research (Cutter 1996, Cutter, Mitchell, and Scott 2000, Cutter, Boruff, and Shirley 2003).

1.3 Multidimensional Assessment of Local Grocery Stores

Researchers use different techniques to measure food access. Some research focused on the accessibility to the number of food stores, or ratio of grocery store to all stores per unit area in a neighborhood (Block & Kouba, 2006; Cummins & Macintyre, 2002; L. Moore & Diez Roux, 2006; K Morland, Wing S, & AV., 2002b) or the minimum distance to the nearest food stores (Zenk SN, Schulz AJ, & Hollis-Neely T et al., 2005). These improvements in measuring food access and understanding its effects on vulnerable population are still perhaps one-dimensional, that is focusing more on the relationship between location of households and food stores. Researchers in healthcare (Aday and Andersen 1974, Salkever 1976, Penchansky and Thomas 1981, Dutton 1986, Frenk and White 1992, Margolis et al. 1995, Gulliford et al. 2002, Haddad and Mohindra 2002, Peters et al. 2008, Levesque, Harris, and Russell 2013, Shengelia, Murray, and Adams 2003, Gibson et al. 2014) argue that access is rather a multidimensional concept. For example, some studies used affordability of receiving care (Guagliardo 2004, Wang and Luo 2005) or variety of healthcare services provided at the facilities (Guagliardo 2004) as a measure of access.

Based on that, we can see how classifying urban areas with low geographic access (i.e. only distance) to few large supermarkets as food deserts may overlook the availability of healthy

foods at affordable prices in local grocery stores, which are common in inner cities. Many residents of Hartford, Connecticut, which is considered a food desert on the basis of United States Department of Agriculture's definition and criteria for food deserts, buy most of their food from local grocers. However, some small supermarkets may not stock fresh produce or a variety of food items for the ethnically diverse population of Hartford. The prices of food items in these stores may also vary significantly. If these small supermarkets have higher prices and a limited variety, will the residents consider these stores as an alternative for large chain supermarkets? If not, then these local supermarkets are not an alternative source for healthy foods and therefore will further increase food insecurity. So, what's actually inside the local grocery stores? This is an important question and there is no study to our knowledge that have measured these aspects either from either a seller or a buyer's perspectives.

For this dissertation, survey data were collected on price, quality, and variety of available food items, and external and internal appearances of the large to small sized grocery stores in Hartford and adjacent towns. This data was then used to measure other factors or dimensions of access (availability, affordability, acceptability, and accommodation) that might improve the grocery shopping experiences of people in large to small local stores, which were not chain supermarkets.

1.4 Comprehensive Food Access Model

In terms of methodology, there was no clear agreement on what measures were absolutely necessary in identifying food deserts. Initially researchers focused on the number of food stores, ratio of stores per unit area in a neighborhood (Cummins and Macintyre 2002, Morland et al. 2002, Moore and Roux 2006, Block and Kouba 2006), or the minimum distance to the nearest food stores (Zenk et al. 2005). Researchers who argued that food deserts did not have clear boundaries began

using GIS, remote sensing, and complex modeling techniques to delineate food deserts (Hallett and McDermott 2011, Sparks, Bania, and Leete 2011, Sadler, Gilliland, and Arku 2011). Some had also used mixed methods to measure accessibility to food stores (Hallett and McDermott 2011).

Penchansky and Thomas (1981) described a robust taxonomy of access to healthcare facilities including dimensions such as *availability, accessibility, accommodation, affordability, and acceptability.* This concept has been further adapted by several other researchers from public health, social work, and economics (Gulliford et al. 2002, Peters et al. 2008, Levesque, Harris, and Russell 2013, Gibson et al. 2014). Gulliford et al. (2002) pointed out that access in terms of utilization is dependent on the affordability, physical accessibility, and acceptability of service and not mere adequacy of supply. In another study, Penchansky's dimensions were conceptualized to 1) approachability, 2) acceptability, 3) availability and accommodation, 4) affordability and 5) appropriateness (Levesque, Harris, and Russell (2013). While the concepts of acceptability (ability to seek), availability and accommodation (ability to reach), and affordability (ability to pay) was similar to Penchansky's, approachability and appropriateness were defined as ability to perceive and ability to engage respectively.

There is no study to our knowledge to date, which has applied Penchansky and Thomas's (1981) robust framework to understand access to grocery stores by combining 5 dimensions: *availability, acceptability, affordability, accommodation and accessibility*. Based on this framework, in this dissertation, a comprehensive food access index of the "5A-Indicator' was calculated to delineate food deserts in the City of Hartford. Each of the five dimensions were defined and measured separately with appropriate sets of variables. For testing and validation, the results were compared to the USDA's methodology of defining food deserts.

1.5 Organization of the dissertation

The dissertation is organized as follows. Chapter 2 describes the design of a new toolbox – Transit Time Calculator (TTC), in a popular GIS software package (ESRI's ArcGIS) to collect transit time data under different transportation modes such as car and public transportation by using Google Direction API. A case study and users' responses from an online feasibility survey show its utility and effectiveness for calculating transit accessibility. Chapter 3 introduces the concept of spatial supermarket redlining – a vulnerability concept applied to the issues of unequal access to healthy food. With a case study, this chapter attempts to map and understand the effects of potential spatial supermarket redlining on food access in urban disadvantaged neighborhoods of Hartford, Connecticut. Chapter 4 and 5 expand upon the robust meaning of food access, its relation to food desert and food insecurity, and finally its effect on vulnerable populations. The data for chapters 4 and 5 is from a food access assessment survey of local stores in the Greater Hartford region, particularly designed for this dissertation. Using this data, in Chapter 4, four dimensions of assessments were calculated: *Availability* (standard and non-seasonal 38 food items), *Affordability* (average price of a market basket of food), *Acceptability* (quality of fresh produce; internal appearance including lighting, cleanliness, and organization; external appearance including lighting, parking, median household income, and crime rates of the store's neighborhood), and *Accommodation* (operation hours, open cash counters, and overall satisfaction of shopping). Chapter 5 then combines the 5th dimension, *Accessibility* (travel time by transit) with the other four dimensions from the previous chapter to develop the taxonomic model of food access or the "5A-Indicator". This indicator of access is robust, goes beyond just distance to stores, and disaggregates the broad and ambiguous concept into a set of dimensions. As a test of validity,

the 5A-Indicator was used to identify the most critical areas with low access to food in the City of Hartford and compared to the USDA's well accepted methodology of delineating food deserts.

Chapter 2: An application of the Google Direction API and Geographic Information System to measure transit-based travel time

2.1 Introduction

Geographic accessibility or distance between locations has been widely used in transportation, land-use planning, urban design, housing, health care utilization, marketing, and food desert research. In its simplest form, geographic accessibility is defined as the "*ease with which activities at one place may be reached from another via a particular travel mode*" (Liu and Zhu 2004)(p. 105). From a measurement perspective, accessibility is the relationship between the location of destinations such as stores, hospitals, parks, and workplaces, and the location of people, taking into account transportation mode, travel time, distance, and associated impedances (Penchansky and Thomas 1981, Farber, Morang and Widener 2014, Litman 2015). While a plethora of approaches exist to measure geographic accessibility, there is relatively little research on accessibility using public transit as the travel mode and even less research on measuring travel time. This is perhaps due to lack of availability of transit data, easy to use tools to calculate travel time, and more sophisticated analyses required due to the complexity of the trips that can be undertaken by transit (Gulliford et al. 2002, Mavoa et al. 2012).

Yet, measuring geographic accessibility by public transit is becoming increasingly critical in understanding equity and disparity of access among different groups of population for two reasons. First, if the spatial distribution of the destinations (say supermarkets) remains unchanged, car drivers will have higher levels of access to supermarkets compared with a segment of the population who do not have access to a car and are entirely dependent on public transit for travel (Martin, Jordan and Roderick 2008). Such relative inequity of access to supermarkets or any other

amenities for public-transit dependent populations - typically low-income, marginalized, and elderly populations - will need more attention to incorporate public transit as an important travel mode in accessibility research. A second reason for the importance of measuring geographic accessibility by transit is its inherently dynamic nature. Among several parameters, travel time by public transit will at least vary by the day of the week, diurnal variation on a given day, or traffic congestion. Therefore, static and/or spatial measures of accessibility will provide overly generalized estimates that may not suitably represent the actual scenario of access for different population groups. Despite the recent evidences of incorporating public transit in accessibility research (O'Sullivan, Morrison and Shearer 2000, Lei and Church 2010, Mavoa et al. 2012, Farber et al. 2014, Tallis 2014), calculating travel time by transit is not straightforward and sometimes needs additional transportation data or very advanced Geographic Information Systems (ArcGIS) functions involving programing skills (Polzin, Pendyala and Navari 2002, Liu and Zhu 2004, McGlone 2013, Tallis 2014, Farber et al. 2014, Widener et al. 2015).

This research addresses this shortcoming with four specific objectives. First, build a toolbox (*'Transit Time Calculator'*) in a popular GIS software package (ArcGIS 2014) using the Application Programming Interface provided by Google Maps (API 2015). This user-friendly toolbox will help users with no programing background to calculate historical or real travel time by different modes of transportation (car and public transit). Second, test and evaluate the proposed toolbox by a user survey. Third, based on travel time, identify neighborhoods of low access to supermarkets in Hartford, Connecticut, a city with high percentage of households with no or limited access to cars. Fourth, validate the identification of low access areas by comparing the results with the United States Department of Agriculture's methodology of identifying food deserts (USDA 2015). The paper is organized as follows. Section 2.1.1 provides a short review of the prior

and current research on measuring geographic accessibility between locations; Section 2.2 describes the study area (2.2.1), data (2.2.2), methodology (2.2.3); Section 2.3 explains the results with further discussions and limitations mentioned in Section 2.4.

2.1.1 Measuring geographic accessibility

We review the existing approaches of measuring geographic accessibility into two broad categories of spatial (travel distance) and spatiotemporal (travel distance and travel time) approaches for both car and public transit. We further divide these categories by popular data models and methods used in a GIS such as the object-based vector model (Euclidean travel distance) and the field-based raster model (travel cost distance) (Sander et al. 2010). The vector data model can also be extended to incorporate network or graph features and is referred to as a network data model (Table 2.1.1).

Table 2.1.1: Spatial and spatiotemporal approaches to measure geographic accessibility

	Euclidean distance	Mode	Raster based	Network based
Spatial	Shannon, Skinner, and Bashshur (1973), Truelove (1993), Azar, Ferreira, and Wiggins (1994), Love and Lindquist (1995), Nyerges (1995), Truelove (2000), Jones et al. (2010)	Car	Couclelis (1992), Van Bemmelen et al. (1993)	Couclelis (1992), Van Bemmelen et al. (1993), Handy and Niemeier (1997), Bamford et al. (1998), Talen and Anselin (1998), Cervero, Rood, and Appleyard (1999), Fortney et al. (1999), Witten, Exeter, and Field (2003), Liu and Zhu (2004), Zenk et al. (2005), Goodchild, Yuan, and Cova (2007), Apparicio, Cloutier, and Shearmur (2007), Jones et al. (2010)
		Public Transit	NA	Witten, Exeter, and Field (2003), Liu and Zhu (2004)
Space-Time	NA	Car	Messina et al. (2006)	O'Sullivan, Morrison, and Shearer (2000), Liu and Zhu (2004), Burns and Inglis (2007a), Yigitcanlar et al. (2007), Lei and Church (2010), Delamater et al. (2012), Owen and Levinson (2013), Tallis (2014)
		Public Transit	NA	O'Sullivan, Morrison, and Shearer (2000), Liu and Zhu (2004), Huang and Wei (2002), Polzin, Pendyala, and Navari (2002), Burns and Inglis (2007b), Yigitcanlar et al. (2007), Lei and Church (2010), Mavoa et al. (2012), Owen and Levinson (2013), Farber, Morang, and Widener (2014), Tallis (2014)

A straight-line, ‘as the crow flies’, or the Euclidean distance is the most widely used technique of measuring geographic accessibility, to the point that few studies specifically mention the type of distance used because it is generally understood as Euclidean distance (Shannon, Skinner and Bashshur 1973, Truelove 1993, Azar, Ferreira and Wiggins 1994, Love and Lindquist 1995, Nyerges 1995, Truelove 2000, Jones et al. 2010). The chief advantage of Euclidean distance is that it is easy to calculate and conceptually straightforward. Its use in accessibility research is however questionable, because people usually travel along road or sidewalk network and thus may not perceive distances as straight lines. From the measurement perspective, Euclidean distance is

simplistic and does not incorporate transportation structures (density of road network, road type), travel time (speed limit, traffic congestion at a particular time), and modality (private car or public transit).

With the advancement of computational power, availability of data, storage capacity, and GIS tools, more detailed representations of geographic accessibility have emerged. Vector-based road-network distance calculates 'travel distance' and is a significant improvement over straight-line distance. This measure may correspond more accurately to human perceptions of geographic or spatial accessibility because it calculates the estimated road distance between two locations by a car (Couclelis 1992, Van Bemmelen et al. 1993, Handy and Niemeier 1997, Bamford et al. 1998, Talen and Anselin 1998, Cervero, Rood and Appleyard 1999, Fortney et al. 1999, Witten, Exeter and Field 2003, Liu and Zhu 2004, Zenk et al. 2005, Goodchild, Yuan and Cova 2007, Apparicio, Cloutier and Shearmur 2007, Jones et al. 2010) and public transit (Witten et al. 2003, Liu and Zhu 2004, Hadas and Ranjitkar 2012, Hadas 2013). In areas with nearly ubiquitous sidewalks, network distance can also estimate the walking distance (Sander et al. 2010). Even though measurement of network distances are made more realistic by adding features such as spatial impedances (e.g. road types or one-way streets and modality: walking versus cycling versus driving), it lacks to incorporate temporal impedances such as speed limits (van Eck and De Jong 1999, Liu and Zhu 2004), diurnal variation of travel time due to traffic congestion, or variation of travel time between week or weekend days (Arentze, Borgers and Timmermans 1994, O'Sullivan et al. 2000, Polzin et al. 2002, Kim and Kwan 2003, Leggat et al. 2012, Mavoa et al. 2012, Farber et al. 2014). It is important to incorporate these temporal features in measuring geographic accessibility by public transit due to its dependence on frequency, schedules, and transfers.

Travel time, instead, is a much more accurate measure of accessibility and calculating time by different modes of transportation such as car or public transit is even more realistic to understand the equity of access among different groups of population. Despite the growing evidences of representing geographic accessibility by car travel time (O'Sullivan et al. 2000, Liu and Zhu 2004, Burns and Inglis 2007b, Yigitcanlar et al. 2007, Lei and Church 2010, Delamater et al. 2012, Owen and Levinson 2013, Tallis 2014), there is relatively little research on calculating travel time using public transit (O'Sullivan et al. 2000, Huang and Wei 2002, Polzin et al. 2002, Liu and Zhu 2004, Currie 2004, Burns and Inglis 2007a, Yigitcanlar et al. 2007, Lei and Church 2010, Curtis and Scheurer 2010, Currie 2010, Mavoa et al. 2012, Owen and Levinson 2013, Farber et al. 2014, Tallis 2014). For example, recent studies have measured transit time using an additional General Transit Feed Specification (GTFS) dataset (O'Sullivan et al. 2000, Widener, Metcalf and Bar-Yam 2013b, McGlone 2013, Farber et al. 2014, Tallis 2014, Widener et al. 2015) and/or combining multiple GIS functions (Polzin et al. 2002, Liu and Zhu 2004, McGlone 2013, Hadas 2013, Tallis 2014, Farber et al. 2014, Widener et al. 2015), which perhaps are not user-friendly techniques for a GIS beginner. As an alternative, recently, an increasing number of researchers and web developers, including geographers and non-geographers have begun to use existing Mapping APIs provided by Google, Yahoo, MapQuest, to calculate travel distances and time for various purposes such as cartographic visualization, event animation, urban planning and guidance to referral hospitals in different Internet GIS Applications (Miller 2006, Chow 2008, Gibin et al. 2008, Roth and Ross 2009, Bugs et al. 2010, Kobayashi et al. 2010, Curtis and Scheurer 2010). However, to our knowledge, there has been no prior effort on combining Google Direction API and GIS to design a customized ArcGIS toolbox to calculate historical or real travel time for

different modes of transportation. The users of the proposed toolbox will not be required to have a programming background or need to use additional detailed transit data.

2.2 Method

2.2.1 Study Area

Our study area is the city of Hartford, Connecticut (CT), which has a diverse population. The population is primarily urban with approximately 125,000 people in 2014 (ESRI 2014), of which 45.6% are Hispanics, followed by non-Hispanic blacks (35.2%) and non-Hispanic whites (13.9%) (ESRI 2014). The poverty rate is 32.9%, almost twice the poverty rate of United States (Martin et al. 2012, United-States-Census-Bureau 2013b). Similar is the comparison of unemployment rates between Hartford (14.8%) and United States (7%) (Connecticut Department of Labor 2013; US-Bureau of Labor Statistics 2014). The median household income in 2013 was estimated at $27,417, which was less than half of both the median household incomes for the Hartford County and for the nation (United-States-Census-Bureau 2013a, 2012). In 2013, the crime rate per 1,000 residents was 52.27 including 11.96 violent crimes and 40.31 property crimes, which made Hartford one of high-crime cities in the Unites States (NeighorhoodScout 2015).

The residents of Hartford also experience health disparities. In 2013, approximately 48% of children in Hartford lived below the poverty line, which is almost 3.5 times higher than that of nation's child poverty rate of 14.3% (Zhang and Ghosh 2015). A study found that the prevalence of childhood obesity among preschool children in Hartford was more than twice as high as Centers for Disease Control and Prevention's (CDC) age and gender adjusted body mass index guidelines (University-of-Connecticut's-Center-for-Public-Health-and-Health-Policy 2012). Due to lack of

access to nutritionally balanced foods in some neighborhoods, both the children and the adults of Hartford are at increased risk of diet-related negative health outcomes.

In terms of public transportation and connectivity, Hartford has over 30 local and 12 express bus routes. Many local routes operate 7 days a week and express services operate on weekdays only (TTCransit 2015). A large number of residents in Hartford avail by public transit, which is an inexpensive transportation option for their daily commute. The NeighorhoodScout (2015)'s research shows that more than 33% of households in the neighborhoods of downtown Hartford do not own a car. In Figure 2.2.1, out of 97 block-groups in Hartford, 57 block-groups (63.33%) have 10% or more households with no access to a vehicle (Census 2013). Residents living in these neighborhoods will likely depend on public transit for their daily activities and commute.

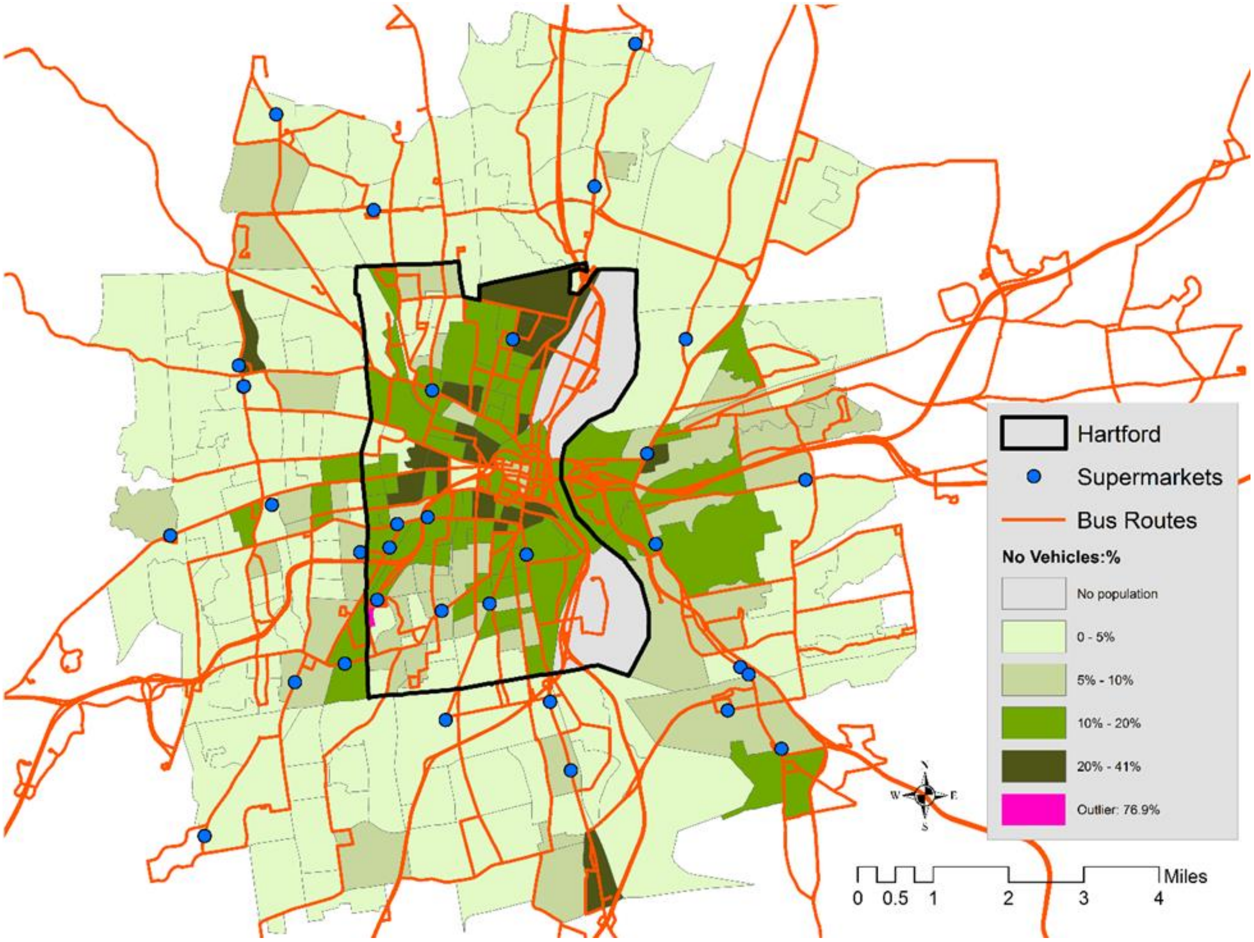

Figure 2.2.1: Percentage of population with no access to vehicles and location of large supermarkets

2.2.2 Data

The data was grouped into the following five categories.

(1) Location of 33 large supermarkets (employee count greater than 15 persons, e.g. Stop and Shop) in Hartford and a 3-miles buffer around the city were obtained from ESRI's Business Analysis 2014 dataset and the Connecticut Department of Energy & Environmental Protection (DEEP) (Figure 1.2.1). A buffer was used because it was likely that the residents of Hartford would

sometimes shop outside their town limits. Also, a buffer minimizes errors from edge effects in the subsequent spatial analysis (Haefner et al. 1991, Lawson, Biggeri and Dreassi 1999, Laurance 2000, Zhang and Ghosh 2015).

(2) ESRI’ Business Analysis datasets provided the GIS shapefiles of Connecticut’s roads. Other boundary shapefiles such as the state, town, and the US census block-group were obtained from the Map and Geographic Information Center at University of Connecticut (MAGIC 2013).

(3) The socioeconomic data such as poverty rate and the vehicle availability were obtained from US Census Bureau’s American Community Survey (ACS) at the block-group level (Census 2013).

(4) Travel time by public-transit and by car from the population centroids of the block-groups to the large supermarkets were calculated by using the proposed Transit Time Calculator (TTC) - a Google Direction API application that will be described in the following sections.

(5) Data obtained from a pilot survey (see Appendix A) to test the usability of TTC. This is a web-based survey, distributed to all the graduate students (n=50) enrolled in any one of the online or in-class GIS courses provided by the Department of Geography at the University of Connecticut in Fall 2015. The survey was conducted from September 1st to October 1st in 2015.

2.2.3 Method

2.2.3.1 Transit Time Calculator

Transit Time Calculator or TTC is a toolbox that we built for use with ESRI’s ArcGIS 10.3 or above, a popular and widely used GIS software package (ArcGIS 2014). The tool calculates

travel time by two modes of transportation (car and public transit) between origin and destination points using Google Maps services. We used Google Directions API, a free service provided by Google Maps, to build this toolbox. To call the API functions, the toolbox uses python requests library. This library provides the http capabilities, which can then send calculation requests to the API as well as receive calculated travel-time between two users provided locations. Each request must include a unique identifier or an API key, which is similar to the concept of a username and a password. These unique identifiers enable the API developer's console to tie requests to specific projects in order to monitor traffic (i.e. number of requests), enforce quotas (limits on the requests), and handle billing (if number of requests are more than the free limit). The instructions to generate a unique identifier can be found in the URL: https://developers.google.com/api-client-library/python/guide/aaa_apikeys. Similar to other existing toolboxes in the ArcGIS interface, TTC is also written in Python programming language. This way the tool uses the existing arcpy libraries of ArcGIS with no additional installations.

The TTC toolbox has 13 parameters including required and optional fields (Figure 2.2.3). The parameter description is as follows.

- *Input Feature Class (required):* To begin, a user will choose a point shapefile. Each row in the shape file will have the X and Y coordinates of the origin and the destination locations.
- *API Key (required):* A user will input their Google Direction API Key.
- *Offset and Span (required):* The free API service has a limit of 2500 requests per day. As per the documentation of Google Directions API, one travel-time calculation between two locations by public transit is counted as four requests. To circumvent this limitation, we included the offset parameter, which allows a user to choose a particular row to start

calculating travel time. Span allows user to specify how many rows to calculate at one time. These parameters combined allow users to run this tool multiple times over several days if the shapefile with origin-destination locations has more than the daily usage limit of requests.

- *ID Field (required):* It is recommended to use FID, which starts from 0. If Offset is 0, and Span is 50, it calculates rows from FID = 0 to FID = 49.
- *Origin Longitude Field, Origin Latitude Field, Destination Longitude Field, and Destination Latitude Field (required):* The input feature class is arranged in a way that each row has the latitude and longitude values of origin and destination points, which are the inputs values for these four parameters.
- *Travel Mode (required):* This input will ask a user to select a mode of transportation: automobile or public transit. The public transit time includes the average walking time from origin to the transit station, waiting time at the station, actual transit time (on the bus/train), and average walking time from the station to the final destination.
- *Output Field Name (required):* A new field name to store the travel time calculations.
- *Date, Time (optional, for transit only):* These input fields would let the user to select a specific date (in the format of "02/20/2015") and time (in the format of "09:00") for calculating travel time by public transit. For driving, this tool will only calculate the travel time from the current time of tool execution. Therefore, a user can conduct travel time by public transit retrospectively but not for cars.

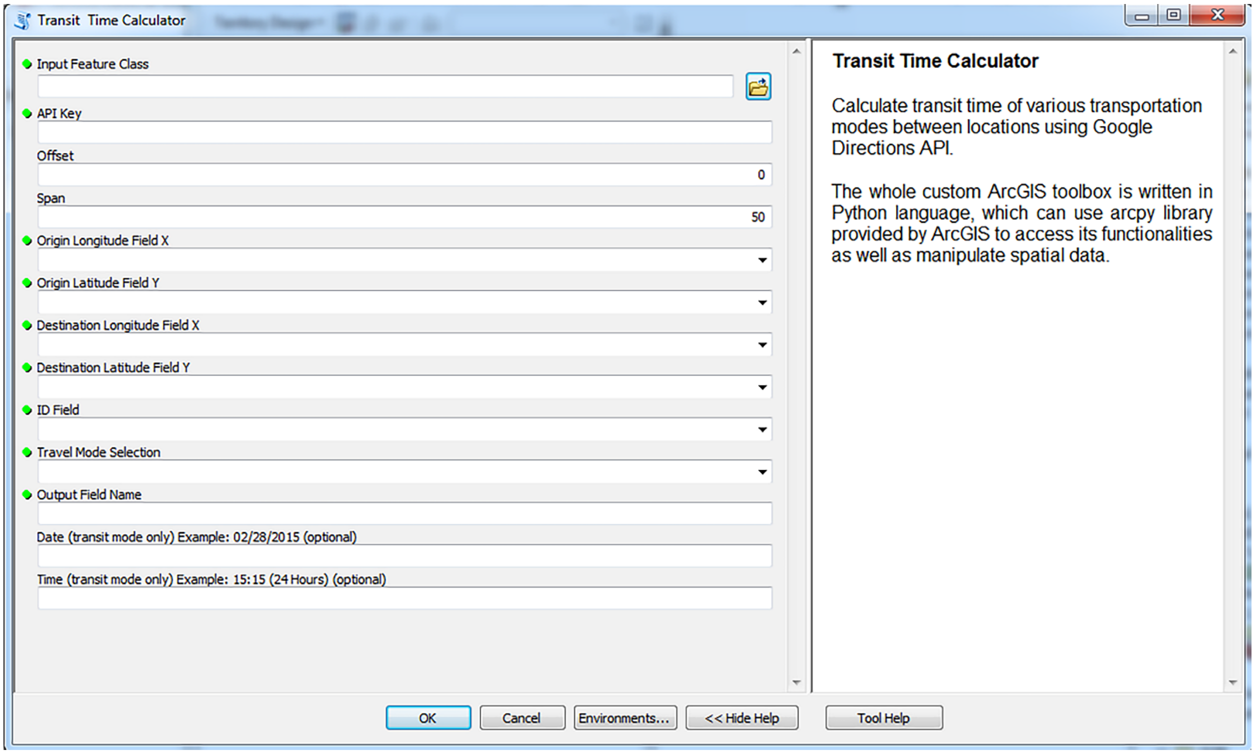

Figure 2.2.3: Transit Time Calculator Interface in ESRI's ArcGIS 10.3

2.2.3.2 User Survey

To understand the applicability and feasibility of TTC, a pilot online survey was distributed to all the graduate students (n=50) who had enrolled in any one of the online or in-class GIS courses provided by the Department of Geography at the University of Connecticut in Fall 2015. The survey was conducted from September 1st to October 1st 2015. We conducted the online survey through SurveyMonkey (SurveyMonkey 2015) and distributed the toolbox, sample data, and the instructions to all the participants. The link to the online survey is here https://www.surveymonkey.com/s/ZKNB9VG. The offline version of the survey is provided as Appendix A.

2.2.3.3. Application of Transit Time Calculator (TTC)

To further demonstrate the features and application of TTC, comprehensive travel time to the closest large supermarket from each block-group centroid in the study area was calculated. Food desert literature show evidences that it is likely we do not always buy groceries from the nearest store, however, the primary objective here is to demonstrate the application of TTC in calculating travel time and not the nuances of food desert parameters and hence we chose the closest supermarket. The comprehensive travel time is defined as follows:

$$Comprehensive\ Travel\ Time = NV \times PT + (1 - NV) \times CT \text{ .... (Formula 1)}$$

NV: Percentage of households without vehicles in a given block-group;

PT: Public transit time calculated by TTC;

CT: Car travel time calculated by TTC.

By using the variable, percentage of households without vehicles (NV), this equation combines travel time by both car and public transit for a given block-group. This provides a comprehensive and more realistic way to describe access to supermarkets because in a given block-group there will be households with both with and without access to cars. The value of the percentage of household without vehicles (NV) ranges from 0 to 1. If the value for a block-group is close to 1, it indicates that the block-group has very high proportion of households with no access to personal vehicles and is mostly dependent on public transit for transportation. On the contrary, if the value is close to 0, households of the block-group have access to vehicles and are not entirely dependent on public transit. We chose four representative times-points for our calculation: Wednesday at 10 am and 5 pm and Saturday at 10 am and 5 pm. The selected times-

points reflect weekday, weekend, and rush hour commute times. Statistical functions such as Pearson's correlations and t-tests were conducted to compare the calculated travel time for the four time-points and by two travel modes, car and public transit.

In order to identify spatial patterns of low-access (longer) and high-access (shorter) travel time areas, the results were represented on choropleth maps. Finally, the critical areas (low-income and low-access, LILA) identified by the comprehensive travel time were compared to the low-income and low-access (LILA) areas identified by the Euclidean (USDA methodology) and network distances to the closest supermarkets.

2.3 Results

2.3.1 Pilot survey

Out of 50 graduate students invited to complete the online survey, 37 (74%) of them completed the survey and provided their feedback. Approximately 30% of response rate from web-based surveys is typical (Shih and Fan 2008, Nulty 2008) and 15-20 participants in a pilot survey is considered adequate for providing preliminary results for a follow-up larger study (Hertzog 2008, Leon, Davis and Kraemer 2011). The survey result showed that 21.6% of the users had used ArcGIS or any other GIS software package for more than five years and 27% have used it between one to five years. Over 75.7% of the participants were satisfied (satisfied and very satisfied categories combined) with this toolbox and 70.3% of users would likely (likely and very likely categories combined) recommend this to a friend or a colleague.

The most frequent words used by the participants to describe the toolbox were: accessible (51%), creative (46%), fast (35%), and meaningful (30%). Twenty-four percent of the respondents

also mentioned it was well organized and 21% mentioned it was fresh, friendly, straight forward, helpful, useful, efficient, and easy to use. Among the open-ended questions on the survey, most participants responded that prior to this tool, they did not use any other functions to calculate travel time in a GIS environment. However, one student had used python programming language and three students used Google Maps before to accomplish similar calculations. Eighty percent of the participants provided positive feedback emphasizing on its simplicity of combining Google API and GIS functions with no programming steps, self-explanatory tool parameters, and usefulness. Several improvements were also suggested, such as 33% recommended that the format of the calculated travel time could be changed to minute-seconds style and to reduce the number of the required parameters from the tool interface.

2.3.2 Application of Transit Time Calculator

Out of the 33 large supermarkets located in the study area, only 9 (27%) are located in the city of Hartford: in the west, southwest, and south central neighborhoods (Figure 1.2.1). Prior research suggested that these neighborhoods have lower percentage of low-income families compared to the families living in the Downtown North, northern, and northwestern neighborhoods of the city (HartfordFoodSystem 2006, Martin et al. 2014, Jacobson 2014, Zhang and Ghosh 2015).

The TTC computed time to travel from population-based block-group centroids to the closest large supermarkets by both car and public transit for four time periods. Statistical results from the Pearson’s Correlation showed high correlation between the travel times for same time of the day but different days of the week i.e. 10 am on Wednesday and Saturday (r2 = 0.998, mean = 15.4 minutes). Similar were the results for 5 pm on Wednesday and Saturday, indicating that there

were no differences between weekday and weekend travel time at 10 am or 5 pm. Such high correlation can be explained by several plausible reasons, such as, no changes in bus frequency, routes, or schedules at 10 am (or 5 pm) every day of the week. However, on any given day (e.g. Wednesday or Saturday), the travel time results were statistically different between 10 am and 5 pm (mean = 15.4 minutes at 10 am, and mean = 15.1 minutes at 5 pm) indicating a modest diurnal variation of travel time due to traffic volume between morning and evening hours.

On the contrary, if driving by a car, Wednesday and Saturday had different traffic volumes between a weekday and a weekend, which led to different travel times (mean of 10.9 minutes on Wed 10 am and mean of 11.02 minutes on Sat. 5 pm). However, on any given day (Wednesday or Saturday), 10am and 5pm had no significant differences in travelling time. Based on these results, we have chosen the following representative travel times for further analysis: 1) Wednesday 10am by public transit, 2) Saturday 5pm by public transit, 3) Wednesday 10 am by car, and 4) Saturday 5 pm by car (Figure 2.3.2.1).

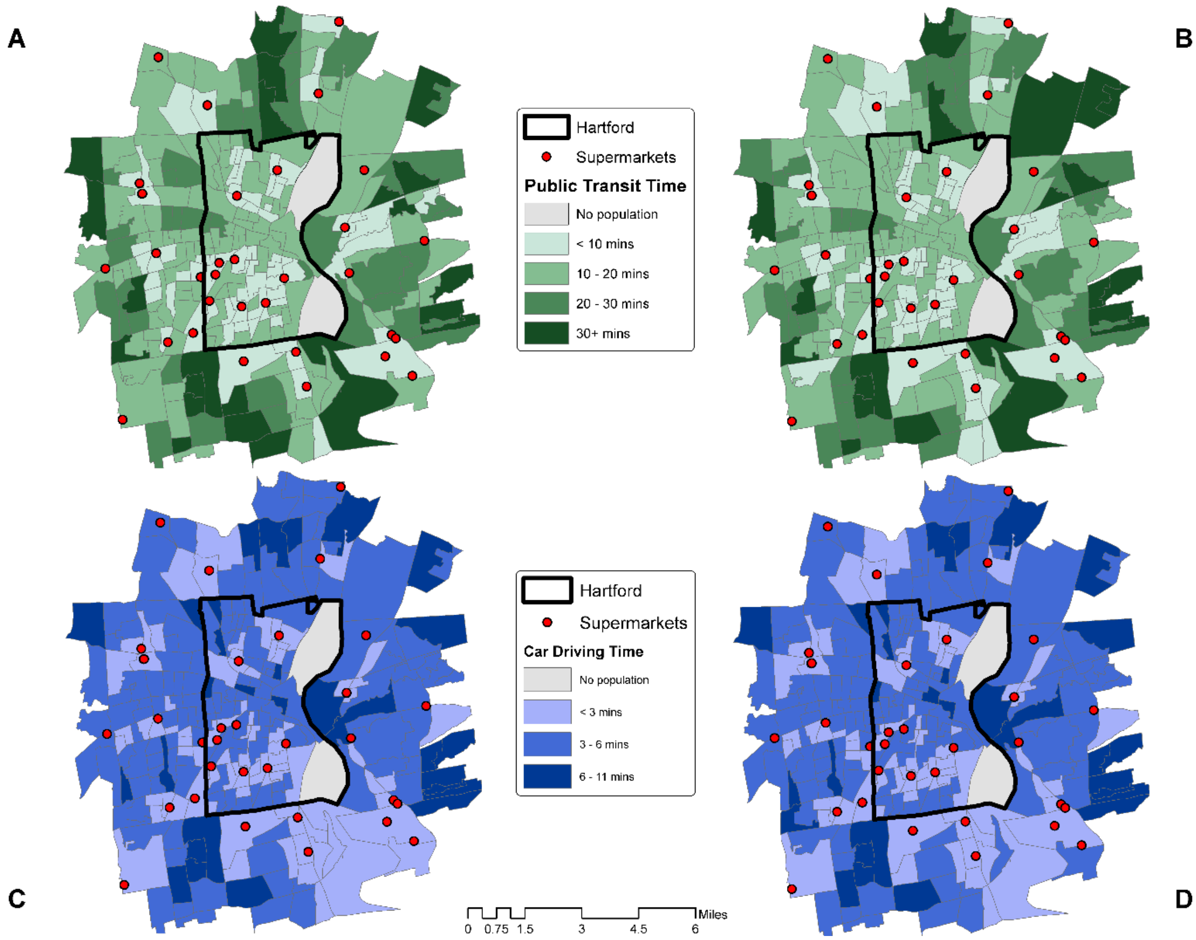

Figure 2.3.2.1: Transit Time (A: Wednesday 10 am by public transit; B: Saturday 5 pm by public transit; C: Wednesday 10 am by car; D: Saturday 5 pm by car)

The travel time by car ranged from 0.3 to 11 minutes for the study area. The figures 2.3.2.1C and 2.3.2.1D show that from 20% of the block-groups, it takes on average 6 – 11 minutes by car to travel to the nearest supermarket from their centroids. These block-groups are located in Hartford. However in the city, 36% of the population do not have access to a car, especially for residents living in the northern neighborhoods, where 20%-76% of the population do not have to vehicles (ESRI 2011). Therefore, conceiving accessibility solely by car is not likely to adequately represent the population who have no vehicle availability and therefore need consideration the

most. The figures 2.3.2.1A and 2.3.2.1B thus show the travel time by public transit, in which block-groups in deepest shade represent longer travel time (over 30 minutes) from the population centroids to the nearest supermarket. Interestingly, all the 22 block-groups in this category are located outside the city, indicating that public transportation is mainly focused in the city and that there is less connectivity between city and the suburbs. Within Hartford, the travel time from 46.4% of the block-groups is between 10-20 minutes and 47.4% below 10 minutes. Based on these results, although one could possibly conclude that accessibility to the supermarkets by both car and public transit is relatively higher in Hartford (with more low-income residents) than the suburban areas (with more affluent residents) but perhaps this is incomplete and does not reflect the real scenario. The affluent residents of the suburbs are less likely to depend on public transport for their groceries and low-income residents of the city with no access to vehicles are dependent on public transportation. To address this disparity of access and measurement challenge, we suggested a more realistic scenario or perhaps a better measure, i.e., comprehensive accessibility, which combines the travel time by both car and public transit (See section 2.2.3.3 and Figure 2.3.2.2).

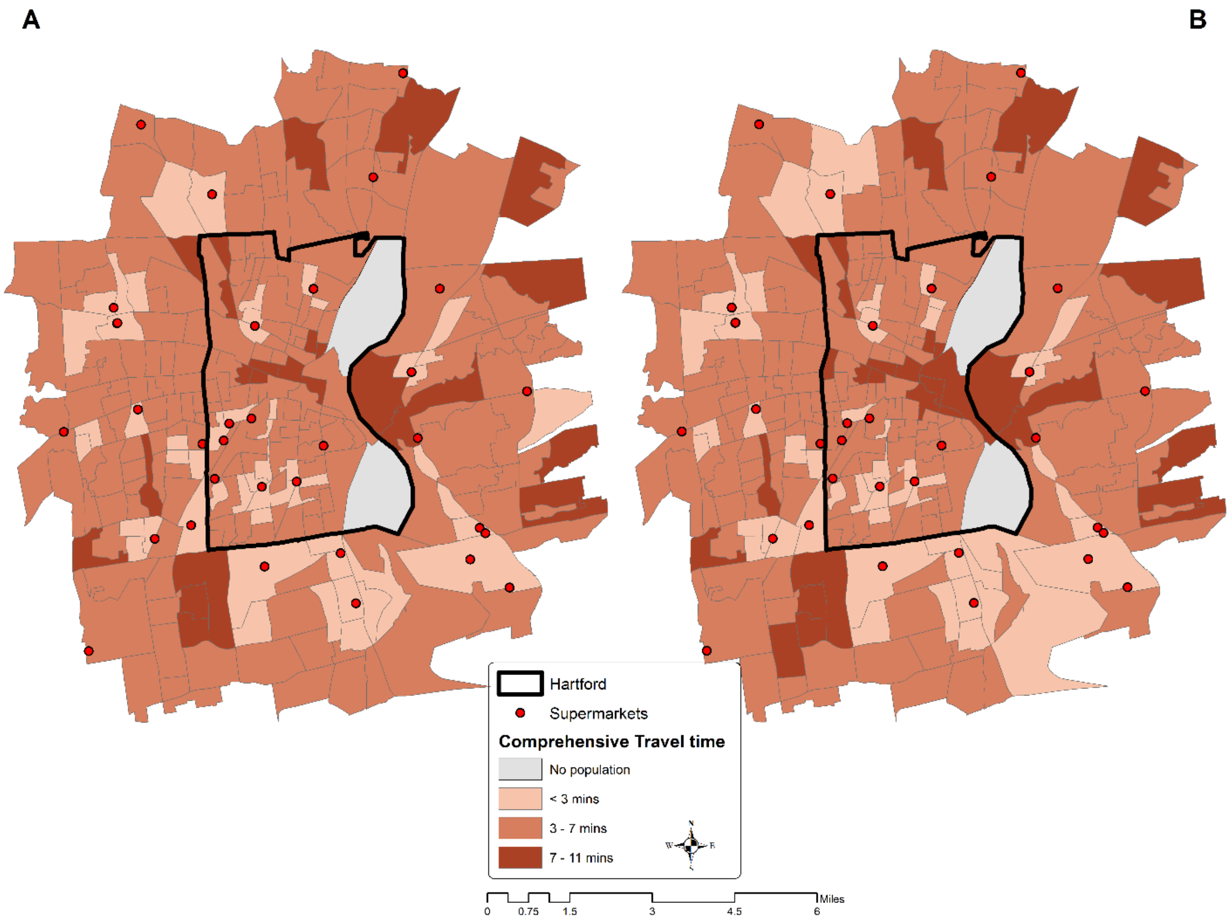

Figure 2.3.2.2: Comprehensive Travel time (A: Wednesday 10 am; B: Saturday 5 pm)

The Figure 2.3.2.2 shows the comprehensive travel time (TTCransit) to the closest large supermarket from each block-group centroid in the study area on Wednesday 10am and Saturday 5 pm. The cross-tabulation between number of block-groups at different travel time periods (< 3 minutes, 3 – 7 minutes, 7 -11 minutes) and two study scales (Hartford vs. 3-mile buffer around Hartford) is shown in Table 2.3.2.1. The statistical comparison results show majority of the block-groups (68% - 70.1%) are in the 3 – 7 minutes' travel time to their closest supermarket at the both 10 am and 5 pm. This trend is similar for both Hartford and its 3-mile buffer. Within Hartford, however, there are more block-groups with longer travel time (7 – 11 minutes) on Saturday 5 pm

(11 block-groups) than that on Wednesday 10 am (8 block-groups). These block-groups are located in the low-income and high diversity neighborhoods of northwest, downtown, downtown north (DoNo), and East Hartford (Figure 2.3.2.2). Similarly, outside Hartford, there are 23 block-groups with longer travel time (7 – 11 minutes) on Wednesday 10 am, while 27 on Saturday 5 pm.

Table 2.3.2.1: Cross-tabulation of Comprehensive Travel Time and study area

Day and Time			< 3 mins	3 - 7 mins	7 - 11 mins	Total
Hartford	Wed 10am	No. of BGs	19	68	8	95
		Percentage	19.6%	70.1%	8.2%	97.9%
	Sat 5pm	No. of BGs	18	66	11	95
		Percentage	18.6%	68.0%	11.3%	97.9%
Hartford 3-mile buffer	Wed. 10 am	No. of BGs	55	183	23	261
		Percentage	20.9%	69.6%	8.7%	99.2%
	Sat. 5pm	No. of BGs	55	179	27	261
		Percentage	20.9%	68.1%	10.3%	99.2%

Note: 2 out of 97 (2.1%) block-groups in Hartford do not have any population
2 out of 263 (0.8%) block-groups in Hartford 3-mile buffer do not have any population

2.3.2.1. Identifying low-income and low-access areas

The United States Department of Agriculture (USDA) designates a census tract a food desert by two criteria: 1) Low-income (LI): poverty rate of 20 percent or greater and 2) Low-access (LA): at least 500 people or one-third of the population reside more than a mile (10 miles in rural areas and 1.0 - 0.5 miles in metropolitan areas) from a large grocery store (USDA). Based on USDA's methodology of food deserts, which is well accepted in the food desert literature, we identified the low-income and low-access (LILA) block-groups in our study area by Euclidean and network distances to the closest supermarket from the population-based block-group centroids

(Figure 2.3.2.3). Here the criteria are: LI - poverty rate of 20 percent or greater and LA - 0.5 miles' distance.

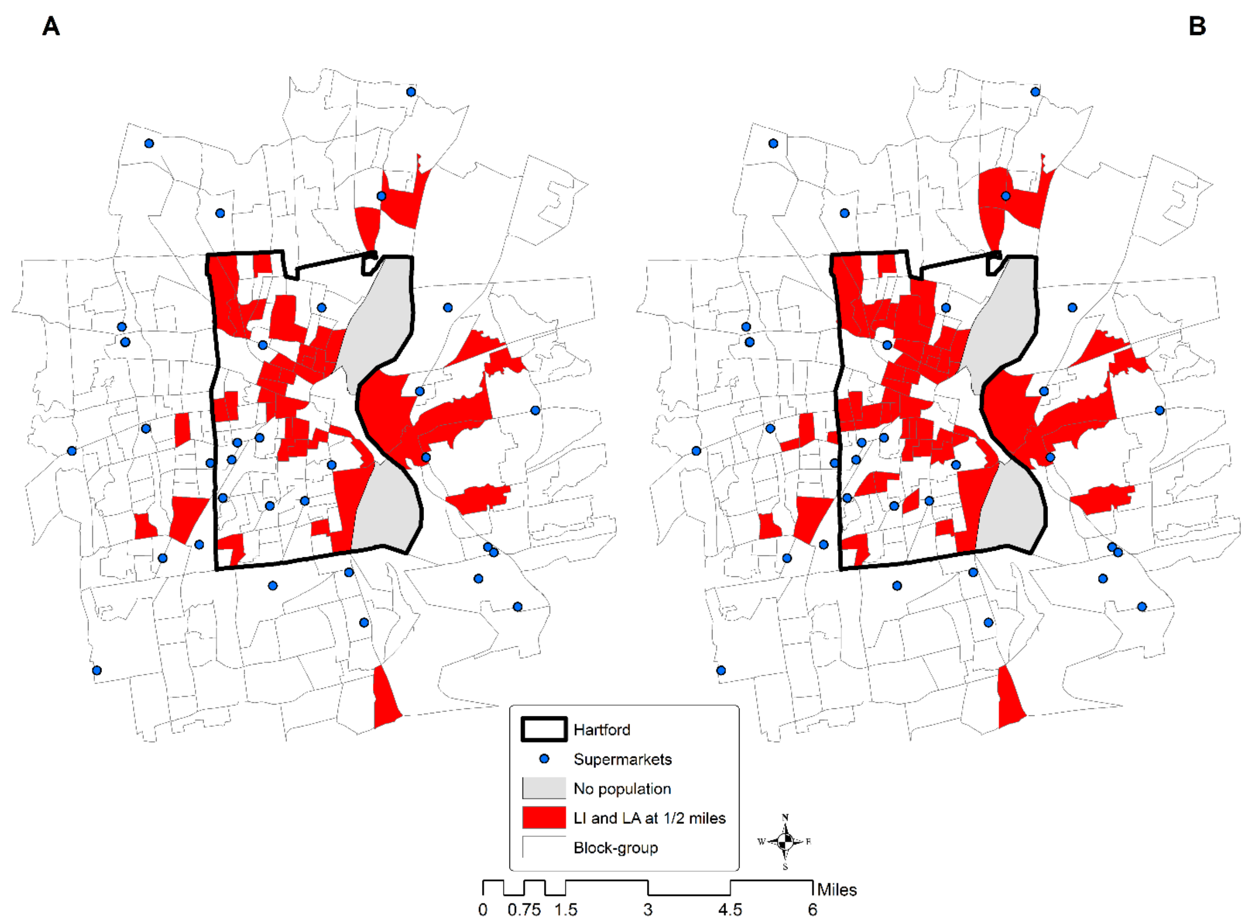

Figure 2.3.2.3: LI (Low Income) and LA (Low Access) at ½ miles (A: Euclidean B: Network)

We then compared the results with the comprehensive travel time on Wednesday 10 am and Saturday 5 pm using the same LI criteria and 6 -7 minutes as the LA threshold (Figure 2.3.2.4 and Figure 2.3.2.5). By reviewing the frequency tables and the histograms (not shown here) of the comprehensive time, we noticed that 6 – 7 minutes' travel time is the threshold where the tail of the distribution starts to form. Also, due to lack of prior literature on using travel time to identify

food deserts and this being the first attempt to do so, we used both 6 and 7 minutes as the time thresholds to define LA in our study area.

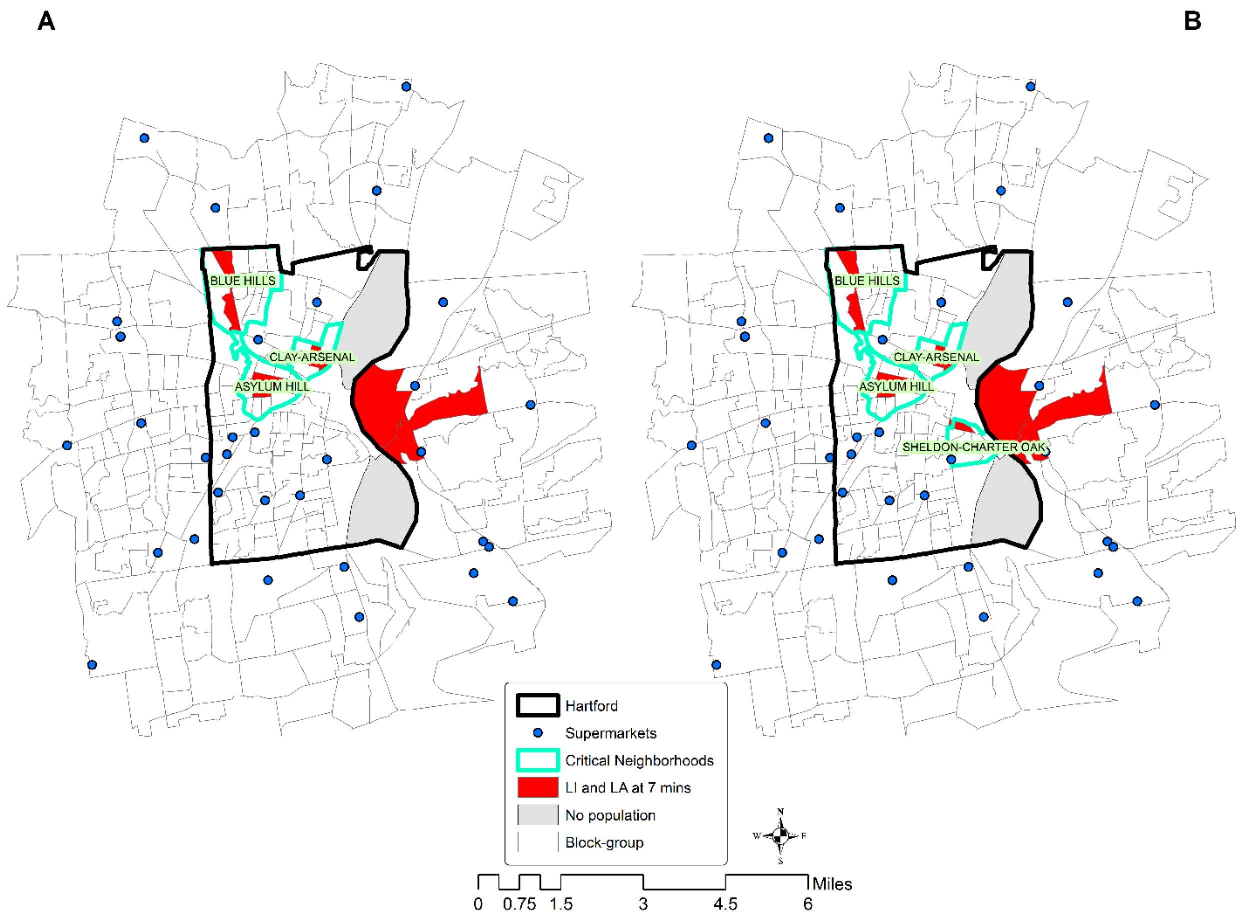

Figure 2.3.2.4: Low Income (LI) and Comprehensive Travel Time (LA) of 7 minutes (A: Wed. 10am; B: Sat. 5pm)

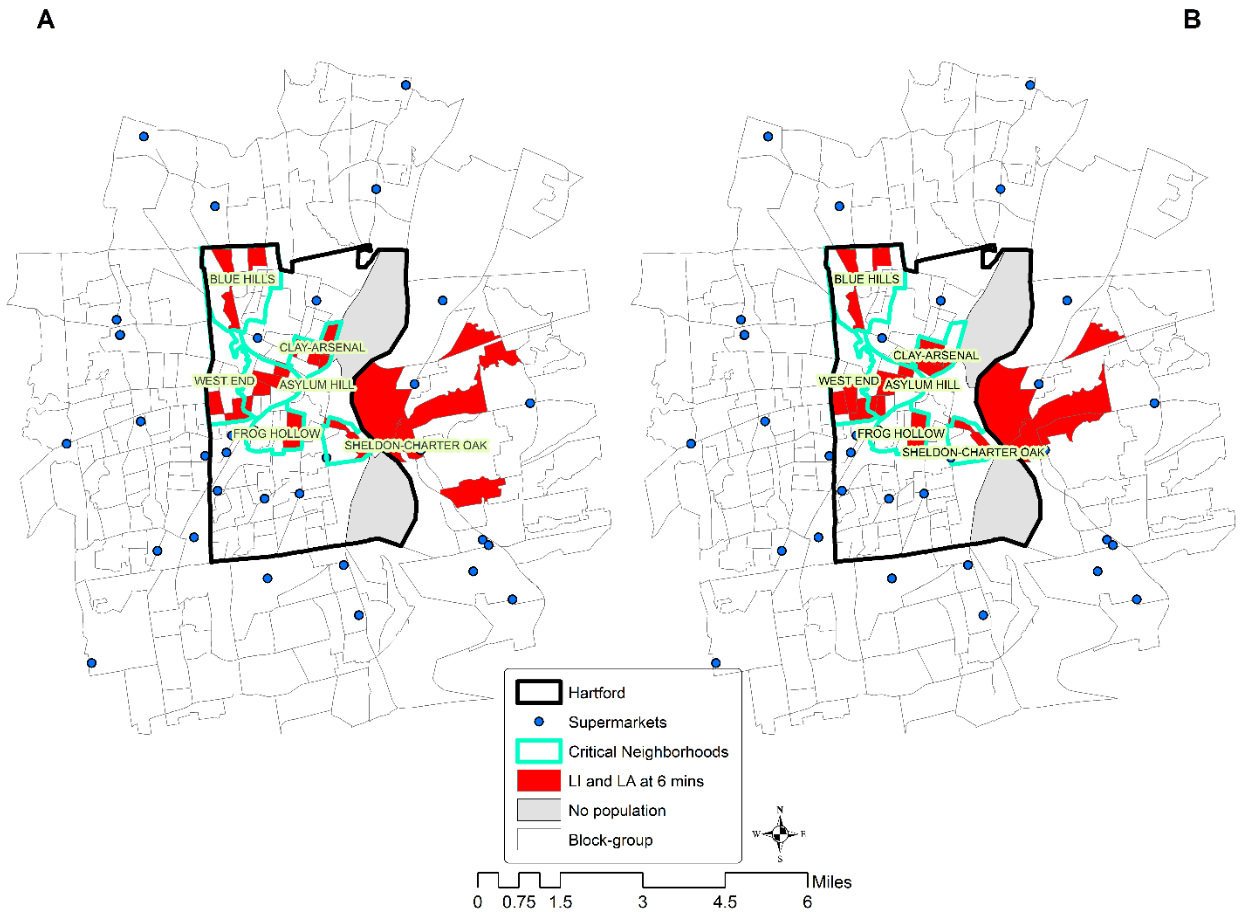

Figure 2.3.2.5: Low Income (LI) and Comprehensive Travel Time (LA) of 6 minutes (A: Wed. 10am; B: Sat. 5pm)

The comparison of LILA bock-groups is further tabulated in Table 2.3.2.2. Thirty three percent of block-groups in Hartford and 16.7% of block-groups in the suburbs has been identified as LILA by using the Euclidean method (Figure 2.3.2.3A). While using Network distances, the percentage of LILA changed to 45.4% and 22.4% in Hartford and the suburbs respectively (Figure 2.3.2.3B and Table 2.3.2.2). For the TTC, the distribution of the block-groups identified as LILA varied by time of the day (10 am or 5 pm) and by time thresholds (6 or 7 minutes) (Table 2.3.2.2). Within Hartford the minimum number of block-groups identified as LILA was 5 (5.2%) by the 7-

minutes threshold on Wednesday at 10 am. The maximum was 17 block-groups (17.5%) identified by the 6-minutes threshold on Saturday at 5 pm. Table 1.3.2.3 further summarizes the distribution of the LILA block-groups by the 17 neighborhoods of Hartford. Neighborhoods of Clay-Arsenal and Asylum Hill have the highest number and percentage (20 – 40%) of LILA by different time cut-offs (6 and 7 minutes). Blue Hills has approximately 11.8% - 20%, followed by Sheldon Charter Oak (11.8% - 16.7%), West End (13.3%- 17.6%), and Frog Hollow (11.8% - 13.3%) (Figures 2.3.2.4 and 2.3.2.5). These are the same neighborhoods with higher percentage of households with limited access to vehicles, low-income, high racial and ethnic diversity, and with no large supermarkets within 1-2 miles (Martin et al. 2014, Zhang and Ghosh 2015).

Table 2.3.2.2: Comparison of Low-Income and Low-Access (LILA) areas by Euclidean, Road-Network, and Comprehensive Travel Time

<table>
<tr><th colspan="3">LILA Area</th><th>Within Hartford</th><th>Within 3-mile buffer</th></tr>
<tr><td colspan="3">Total No. of BGs</td><td>97</td><td>263</td></tr>
<tr><td colspan="2" rowspan="2">Euclidean</td><td>No. of BGs</td><td>32</td><td>44</td></tr>
<tr><td>Percentage</td><td>33.0%</td><td>16.7%</td></tr>
<tr><td colspan="2" rowspan="2">Network</td><td>No. of BGs</td><td>44</td><td>59</td></tr>
<tr><td>Percentage</td><td>45.4%</td><td>22.4%</td></tr>
<tr><td rowspan="4">Transit Time
7 mins</td><td rowspan="2">Wed. 10 am</td><td>No. of BGs</td><td>5</td><td>7</td></tr>
<tr><td>Percentage</td><td>5.2%</td><td>2.7%</td></tr>
<tr><td rowspan="2">Sat. 5 pm</td><td>No. of BGs</td><td>6</td><td>8</td></tr>
<tr><td>Percentage</td><td>6.2%</td><td>3.0%</td></tr>
<tr><td rowspan="4">Transit Time
6 mins</td><td rowspan="2">Wed. 10 am</td><td>No. of BGs</td><td>15</td><td>20</td></tr>
<tr><td>Percentage</td><td>15.5%</td><td>7.6%</td></tr>
<tr><td rowspan="2">Sat. 5 pm</td><td>No. of BGs</td><td>17</td><td>21</td></tr>
<tr><td>Percentage</td><td>17.5%</td><td>7.98%</td></tr>
</table>

Table 2.3.2.3: Low-access areas to large supermarkets in neighborhoods of Hartford, Connecticut

Neighborhood	6 minutes				7 minutes			
	Wed. 10 am		Sat. 5 pm		Wed. 10 am		Sat. 5 pm	
	No. of BGs	Percentage	No. of BGs	Percentage	No. of BGs	Percentage	No. of BGs	Percentage
Blue Hills	2	13.3%	2	11.8%	1	20.0%	1	16.7%
North Meadows	0	0%	0	0%	0	0%	0	0%
West End	2	13.3%	3	17.6%	0	0%	0	0%
Upper Albany	0	0%	0	0%	0	0%	0	0%
Clay-Arsenal	4	26.7%	4	23.5%	2	40.0%	2	33.3%
Asylum Hill	3	20.0%	4	23.5%	2	40.0%	2	33.3%
Downtown	0	0%	0	0%	0	0%	0	0%
Frog Hollow	2	13.3%	2	11.8%	0	0%	0	0%
Parkville	0	0%	0	0.0%	0	0%	0	0%
Sheldon Charter Oak	2	13.3%	2	11.8%	0	0%	1	16.7%
South Green	0	0%	0	0%	0	0%	0	0%
Behind the Rocks	0	0%	0	0%	0	0%	0	0%
South Meadows	0	0%	0	0%	0	0%	0	0%
Barry Square	0	0%	0	0%	0	0%	0	0%
South End	0	0%	0	0%	0	0%	0	0%
South West	0	0%	0	0%	0	0%	0	0%
Northeast	0	0%	0	0%	0	0%	0	0%
Total	15	100%	17	100%	5	100%	6	100%

2.4 Discussion and Limitations

We highlight the major contributions of our study here. First, we built a user-friendly free toolbox (Transit-Time Calculator, TTC) for ArcGIS 10.3 and above, which can calculate travel time by various modes of transportation for users with no programing background. The toolbox with example data and detailed instructions can be downloaded from this url: http://www.dghosh.net/transit-time-calculator-toolbox/ in comparison with other studies (McGlone 2013, Farber et al. 2014, Tallis 2014) using external data sources such as the General Transit Feed Specification (GTFS), TTC do not need any additional traffic related dataset to

calculate travel time. Google Direction API is using GTFS data (As of August 20, 2015, Google lists approximately 5900 agencies around the world for Google Transit coverage), besides that, some of the transit information is derived from sources other than GTFS. On the other hand, Google Direction API can provide us a lot more accurate travel time results incorporating traffic conditions, road works, waiting time for the public transit etc. based on a broader dataset (including the GTFS data). This toolbox - TTC helps us to send calculation requests to Google as well as receive and save the calculated travel-time to the attribute table of the shapefile within few seconds. Comparing with another toolbox – Add GTFS, provided by Esri, TTC does not need installation, network extension, or preparation of GTFS/street or sidewalks feature class to build the network dataset. TTC can fast, and efficiently acquire the travel time between two locations by different transportation modes (driving and public transit) rather can the public transit only. Add GTFS can provide more applications based on Network Analysis to perform transit/pedestrian accessibility analysis such as the closest facilities, OD matrix, and showing the transit routes. Add GTFS is more flexible for different researchers on various topics but requires more preparation works and a complete network dataset. While TTC is more useful for researchers or other basic GIS users who wish to compute mode-specific travel times as one of the variables in their studies. Through a pilot survey we also tested and evaluated the toolbox. Users' responses showed that the toolbox was "user friendly", "accessible", "creative", "fast", and "meaningful". Second, TTC also has the potential of calculating travel time at any time of the day, incorporating additional time due to traffic and public transit frequency. This is critical for studies on accessibility, tracking, and surveillance to accurately and realistically measure public transit time. Thus, we argue that the Transit Time Calculator has the potential to become a flexible and a useful tool in transit analysis, essential for the wellbeing of non-car households.

Third, we use 0.5 miles to identify low access (LA) for two reasons: 1) based on USDA's methodology of food deserts, which is well accepted in the food desert literature, low-access (LA) is define as 0.5 miles in urban area irrespective of walking or driving. 2) It is possible to walk 0.5 miles as for such a distance walking is quicker. However, we also need to consider the trip back home with heavy grocery bags, the safety of walking (due to the high crime rate in Hartford), time of walking etc. Since these parameters are so subjective and to keep the comparison of food desert locator simple, we followed the same criteria and just changed the distance requirement to transit travel-time. In terms of the validation findings, i.e. identifying the low-income low-access (LILA) block-groups as food deserts, the comprehensive travel time (TTCransit) – a spatiotemporal - technique is a better measure than the only spatial Euclidean and Network distances. The TTC combines two modes of transportation (car and public transit), accounts for time variation on a given day, and between weekday and weekend due to traffic flow operations. Thus, TTC has the provision of calculating realistic and accurate travel time distances for researches and policy makers. Fourth, by using Euclidean and Network distances, more low-income low access (LILA) have been identified which might not be the true picture. The affluent residents of the suburbs are less likely to depend on public transport for their groceries and low-income residents of the city with no access to vehicles are dependent on public transportation for their routine activities. This disparity in access might affect the decisions of the policy makers in urban communities to whether allocate resources to improve existing supermarkets or open new stores (Martin et al. 2014). For example, Martin et al. (2014) pointed out that improving the quality of food, and store appearances in urban stores may influence purchasing decisions of low-income households who lack adequate transportation, and improve poor dietary intake linked to health disparities and food insecurity.

This study also has few limitations. First, since the free Google API has a limit of 2500 requests per day, users will have to either split their calculations over several days if the dataset is large or pay extra money ($0.50 USD / 1000 additional requests, up to 100,000 daily). However, to address this limitation at free of cost and in a relatively user-friendly way, the proposed toolbox provides two parameters, Offset (allows a user to choose a particular row to start calculating travel time) and Span (allows user to specify how many rows to calculate at one time). These parameters help to split and manage big datasets with ease. Second, travel time by bus and car may vary by day of the week, time of the day, and also by the study area. This research chose Wednesday and Saturday as representative weekday and weekend day respectively. The times chosen, 10 am and 5 pm, were also representative of morning and evening commute. It is possible that the travel times could be different for other days and times; however, we believe that the overall results and conclusions will remain the same. Third, due to insufficient prior literature and this being the first attempt to use travel time in identifying block-groups with low-access and low-income criteria, we used both the 6 and 7 minutes as the time threshold to define low-access. It is possible that in a different study setting, the comprehensive time threshold could be longer, thus, indicating the need for more research on this topic. (Widener et al. 2013a)

Chapter 3: Spatial Supermarket Redlining and Neighborhood Vulnerability: A Case Study of Hartford, Connecticut

3.1 Introduction

Supermarket redlining is a term used to describe a phenomenon when major chain supermarkets are disinclined to locate their stores in inner cities or low-income neighborhoods and usually relocate existing stores to the suburbs (Eisenhauer 2001). Compared to the more explicit reasons for familiar types of redlining such as banking, insurance and housing based on race (Holloway 1998, Holmes 2000, Zenou and Boccard 2000, Squires 2003), the causality of redlining in retail sectors, including supermarkets, is unclear (D'Rozario and Williams 2005). This is primarily due to the difficulty of obtaining detailed empirical data on perceived discriminatory practices by retailers based on race, income or other urban obstables (Eisenhauer 2001, D'Rozario and Williams 2005). These urban obstacles include lower demand, higher costs of urban land, labor, and utilities, lower profit margins from perishable food items, or risk of theft in inner cities (Eisenhauer 2001). Coupled with these perceptions, other drivers of supermarket redlining are difficulties of finding locations for new supermarkets (typically 50,000 square feet or more), purchasing multiple adjacent plots, or competition from other investments. For example, a proposal for a minor-league baseball stadium threatens plans for a supermarket just north of Downtown Hartford. City officials argue that the approximately $60 million stadium will boost city's economy. However, opening the supermarket addresses a much greater, and critical, public health issue related to obesity in Connecticut's capital city (Ghosh 2014).

Since the process of supermarket redlining is complex, with multiple related drivers, which may or may not be racially motivated, we will initially clarify how we have positioned the

supermarket redlining definition in our study. First, we do not restrict the vulnerable population to any particular racial or ethnic group. Instead, it includes all low-income people with limited access to healthy and affordable food. Second, we primarily focus on the spatial segregation (or discrimination) of supermarket redlining, whereby chain supermarkets typically either close or relocate from inner city to suburbs (Bell and Burlin 1993, Eisenhauer 2001, D'Rozario and Williams 2005). To emphasize this geographical pattern, we extend the definition of supermarket redlining to *spatial supermarket redlining*, where chain supermarkets either – i) close down, ii) relocate to suburban areas, or iii) new stores do not open in urban areas not only to due to racially discriminatory reasons but also for a host of other related factors (Eisenhauer 2001). Third, spatial supermarket redlining is not defined as individual instances of grocery store closures but a combination of the three scenarios mentioned above. Even though supermarket redlining is a disputable issue, and perhaps hard to prove empirically, assessing the impact of potential supermarket redlining is worthy of investigation because of its disproportionate impact on vulnerable populations. If a neighborhood's supermarket closes with limited chances of a new one opening, what remains are vacant buildings and demoralized residents. Supermarkets also tend to drive smaller grocery stores out of business when they move in; so when they relocate or close down, residents face difficulties in accessing healthy and affordable food—thus widening the *grocery gap*, increasing *food insecurity*, and perhaps creating a *food desert.* More studies on this issue can only help to make the more vulnerable (i.e. those that are supermarket redlined) among us become less so.

In Connecticut, according to the Federal Government's survey, the percentage of households with food insecurity rose by approximately 33% from 7.6% in 2000-2002 to 11.4% in 2007–2009 (HartfordFoodSystem 2013). During 2010–2012, the value further increased to 13.4%

of households. Out of these households, 36.6% were categorized in the critical level of food insecurity (Coleman, Nord, and Singh 2012). Recently, Russell and Heidkamp (Russell and Heidkamp 2011) found that a food desert was created when Shaw's (http://www.shaws.com) closed down in New Haven, a city with similar indicators of income inequality and health disparities as that of Hartford. The Shaw's supermarket, located in an urban neighborhood, was the most successful retail anchor for the surrounding Dwight Street neighborhood. It was the *only* full-service supermarket in the nearby residential area within walking distance from hundreds of households with limited or no access to cars. The other retail stores were in the suburban area, which could only be accessed by a car. In Hartford, in the past, 11 out 13 chain supermarkets (almost 85% of the stores) left the city between 1968 to 1984 (Kane 1984) and few supermarkets opened since then to lessen the grocery gap. Even today, residents living in Downtown Hartford and Downtown North (or DoNo) neighborhoods are at a distance of more than a mile from large to medium sized stores indicating an urban food desert (Martin et al. 2014). In some areas, especially in the neighborhoods of Blue Hills in the north and South End in the south, there is not a single full service grocery store within a distance of 2 miles (Martin et al. 2014).

There is plethora of studies identifying food deserts - both in rural (Hendrickson, Smith, and Eikenberry 2006, Smith and Morton 2009, Hubley 2011) and urban settings (Whelan et al. 2002, Wrigley 2002, Gallagher 2006, Hendrickson, Smith, and Eikenberry 2006, Larsen and Gilliland 2008, Hallett and McDermott 2011) and at different geographies (Cummins and Macintyre 2002, Wrigley et al. 2002, Morton et al. 2005, Pearson et al. 2005, Zenk et al. 2005, Smoyer-Tomic, Spence, and Amrhein 2006, Apparicio, Cloutier, and Shearmur 2007, McClintock 2008, Raja, Ma, and Yadav 2008, Ball, Timperio, and Crawford 2009, Coveney and O'Dwyer 2009, Sparks, Bania, and Leete 2011). Similarly there are studies measuring food insecurity (Kendall,

Olson, and Frongillo 1996, Carlson, Andrews, and Bickel 1999, Olson 1999, Alaimo, Olson, and Frongillo 2001, Hamelin, Beaudry, and Habicht 2002, T.Vozoris and Tarasuk 2003, Drewnowski 2004, Lopez et al. 2005, Tchumtchoua and Lopez 2005, Center 2011); however, there is no study to our knowledge, particularly from an empirical approach, that focuses on potential spatial supermarket redlining as an early indicator of risk for food deserts and food insecurity. The objectives of this study, therefore, are twofold: first, describe an empirical approach to model the impact of spatial supermarket redlining in a Geographic Information Science (ArcGIS) environment, and second, to understand the effects of potential spatial supermarket redlining on food access in disadvantaged neighborhoods of Hartford, Connecticut.

The organization of the paper is as follows. Section 3.1.1 and 3.1.2 briefly discuss the background literature of supermarket redlining in relation to food deserts and food insecurity and section 3.2 describes methodology including the underlying conceptual framework (section 3.2.1), the details of the study area (section 3.2.2), datasets (3.2.3) and analytic approach (3.2.4) employed in this paper. Sections 3.3 and 3.4 then follow with results, and discussion respectively.

3.1.1 Food Desert and Food Insecurity

The literature on food desert and food insecurity have increased tremendously in the last decade with several prominent studies, systematic reviews, and case studies (Avilés-Vázquez and Bussmann 2009, Beaulac, Kristjansson, and Cummins 2009, Larson, Story, and Nelson 2009, McKinnon et al. 2009, Walker, Keane, and Burke 2010).

The term *food desert* describes a phenomenon where affordable and healthy food is difficult to access. The concept of food desert was first used in the United Kingdom (T.Vozoris and Tarasuk 2003) in the 1990s to describe the rapidly decreasing number of grocers in urban, low

income neighborhoods after World War II (Whelan et al. 2002). The term was first used in the context of public sector housing schemes in Scotland in the early 1990s for the Low Income Project Team of the Nutrition Task Force (Beaumont et al. 1995). Since then, several researchers have attempted to define food deserts from different perspectives. Earlier, Acheson (1998) defined it as where "*cheap and varied food is only accessible to those who have private transport or are able to pay the cost of public transport"* (p.65). Some of the recent literature has identified socioeconomically disadvantaged neighborhoods with limited or inadequate physical or economic access to healthy and affordable food as food deserts (Whelan et al. 2002, Wrigley et al. 2002, Wrigley, Warm, and Margetts 2003, Smoyer-Tomic, Spence, and Amrhein 2006, Apparicio, Cloutier, and Shearmur 2007, Larsen and Gilliland 2008). The United States Department of Agriculture (USDA) measures food desert in the following way: A census tract is considered a food desert if it meets a certain threshold of poverty, and if at least 500 people or one-third of the population reside more than a mile from a large grocery store (USDA). Currently the USDA's definition of food desert is the most widely used.

In terms of methodological exploration, researchers have used different techniques to delineate food desert and there was no clear agreement on what measures were absolutely necessary in identifying food deserts. Initially researchers focused on the number of food stores, ratio of stores per unit area in a neighborhood (Cummins and Macintyre 2002, Morland et al. 2002, Moore and Roux 2006, Block and Kouba 2006), or the minimum distance to the nearest food stores (Zenk et al. 2005). Researchers who argued that food deserts did not have clear boundaries began using GIS, remote sensing, and complex modeling techniques to delineate food deserts (Hallett and McDermott 2011, Sparks, Bania, and Leete 2011, Sadler, Gilliland, and Arku 2011). Some had also used mixed methods to measure accessibility to food stores (Hallett and McDermott 2011).

“Food insecurity” describes a condition where people have limited access to sufficient, safe, and nutritious food to meet their daily need for healthy living (Olson 1999, Hamelin, Beaudry, and Habicht 2002, Lopez et al. 2005). Typically, residents living in a food desert with limited access to healthy food experience issues of food insecurity but the impact is disproportionately higher among vulnerable populations due to lower socioeconomic status, ethnic minority status, old age, and existing negative health outcomes (Morland et al. 2002, Zenk et al. 2005, Raja, Ma, and Yadav 2008). Zenk et al. (2005) found that, even within low-income neighborhoods, residents living in areas with higher proportion of African-American population had to travel on an average 1 to 1.25 miles more to the nearest supermarket than neighborhoods with predominantly white population. White neighborhoods, on the other hand, had almost 4 times more supermarkets compared to neighborhoods with significantly higher black population (Morland et al. 2002). In terms of prices, the majority of research showed that the poor had to pay more for healthy food (Chung and Myers 1999, Morland et al. 2002, Hendrickson, Smith, and Eikenberry 2006, Jetter and Cassady 2006). In a case study conducted in the Twin Cities Metropolitan Area of Minnesota, Chung and Myers pointed out that big chain supermarkets had much lower price but were not likely to locate in poor areas (Chung and Myers 1999). Non-chains and small stores were more likely to be located in impoverished areas, where typically choices for fresh food were limited but with an abundant variety of high-calorie packaged foods at higher prices (Chung and Myers 1999). Researchers, from other countries had different findings. Unlike in the United States, study sites in Canada, Australia and New Zealand (Smoyer-Tomic, Spence, and Amrhein 2006, Apparicio, Cloutier, and Shearmur 2007) showed that middle-income communities had the most access to supermarkets and were better served by food stores. Cummins and Macintyre (2002) argued that in United

Kingdom, wealthier and poor neighborhoods had no statistically significant differences in access to supermarkets, food prices, or food availability.

3.1.2 Spatial Supermarket Redlining

The concept of retail redlining is less explored in the literature and adaptation of this abstract idea to *spatial supermarket redlining* is even more limited and perhaps challenging and controversial. Redlining, in general, is a practice in banking and insurance companies when they decide to deny, stop, or charge higher from residents living in marginalized and vulnerable neighborhoods (Kane 1984). Typically, a *red-line* will be marked on a map to delineate those specific areas (Sagawa and Segal 1999). Later D'Rozario and Williams (2005) defined retail redlining as "*A spatially discriminatory practice among retailers, of not serving certain areas, based on their ethnic-minority composition, rather than on economic criteria, such as the potential profitability of operating in those area*" (p.175). As mentioned earlier, in our study, we further extend the definition of supermarket redlining to *spatial supermarket redlining* where chain supermarkets either – i) close down, ii) relocate to suburban areas, or iii) new stores do not open in urban areas not only to due to discriminatory reasons but also for a host of other related factors. These factors can be broadly divided into two categories – i) stereotypes as perceived urban obstacles (Eisenhauer 2001) and ii) logistical obstacles related to retail business (Shaffer 2002, Raja, Ma, and Yadav 2008).

Examples of perceived urban obstacles in a city are as follows. i) *Profitability:* Supermarket chains often cite low profit margins and higher cost of overheads as barriers to investment in neighborhoods where demand for food items is low due to low-income shoppers, lower volume of sales per customer, and smaller per trip purchases (Eisenhauer 2001, Shaffer

2002). ii) *Crime*: Higher crime rates in low income urban neighborhoods including employee theft, shoplifting, and dishonesty are also central to the reasons for supermarket closures (Shaffer 2002). High crime is also related to higher rates of insurance and greater difficulty of getting loan approvals to open new stores. iii) *Cultural Biases*: Another important reason why supermarkets avoid inner-city neighborhoods is a perceived anxiety based on cultural biases about the inner city and minorities (Zenk et al. 2005, Raja, Ma, and Yadav 2008, Ball, Timperio, and Crawford 2009, Sugrue 2014). In Morland et al.'s multi-site study (Morland et al. 2002) the racial discrepancy was evident from their findings that predominantly white neighborhoods had 4-times as many supermarkets than black neighborhoods. Mark Green – former New York Consumer Affairs Commissioner (Shaffer 2002) said there is a "*knee-jerk premise that blacks are poor and poor people are a poor market*"(p.25). Logistical obstacles on other hand include: i) difficulties of finding locations for new stores, which are typically 50,000 square feet or more, ii) purchasing multiple adjacent plots, iii) higher cost of tax rates, insurance, and utilities (Eisenhauer 2001, Shaffer 2002), iv) zoning restrictions and contamination of sites that may require remediation before new stores can be constructed (Shaffer 2002), v) investors may not understand the diversity of food needs and desires of the racially mixed population, and v) hindrances from local politics (Shaffer 2002).

In the United States, isolated incidents of supermarket closures or possible supermarket redlining incidents began in 1960s and since then the trend had been on the rise (IFDP 1997). For example, in Boston, Massachusetts, 34 out of 50 big chain supermarkets have closed since 1970s. In Los Angeles county in California, the number of supermarkets decreased from 1068 in 1970 to 694 in 1990 (Turque 1992). Safeway, a well-known supermarket chain, closed more than 600 stores in the country from 1978 to 1984 (Eisenhauer 2001). Many of these stores were the primary

or only source of affordable, safe, and acceptable quality of meat and produce in their neighborhoods. In Hartford, 11 out 13 chain supermarkets (almost 85% of the stores) left the city between 1968 to 1984 (Kane 1984). Incidents of such kind are still happening today (Eisenhauer 2001, Raja, Ma, and Yadav 2008, Russell and Heidkamp 2011).

In recent years, the city of Hartford also experienced several supermarket closures leaving behind unhappy residents and an even wider grocery gap. Market at Hartford 21, an upscale grocery store located in Downtown Hartford was *only* open for six months when it finally closed in September 2011 (Haar 2011). It used to provide various healthy and nutritious ready-to-eat meals, some fresh produce, and even few organic items. It was becoming "a downtown favorite" as quoted by Tiff (2011) and *"it's very nice having a basic grocery store with some basic needs close by"* (Jimmy 2011). Central Supermarket, located in the Farmington Avenue of Hartford, was closed on May 2014 which has been described as "*a huge loss to the West End since this area does need a grocery store"* (Emily 2012). West Hartford's Crown Supermarket also plans to close after more than seven decades of service to the community. A local resident, who had shopped at Crown for her entire life said, *"I don't know what I'll do. I'll be devastated if it closes. I am there once a week for a big order"* (Jacobson 2014).

Incidents of possible supermarket redlining caused due to either closing down of existing supermarkets, relocation of supermarkets to the suburbs, lack of investments to construct new ones, or combination of these scenarios will disproportionately affect neighborhoods with low-income vulnerable residents. It will increase the difficulty of accessibility and availability of healthy food choices. Low-income residents usually do not have enough economic support and/or access to transportation (e.g. personal cars) to travel that "extra" distance to buy healthy food from other stores or from the chain supermarkets in the suburbs. In terms of affordability, low-income

consumers often have to pay more for shopping at the local stores where stock is limited and sometimes of poor quality (Kaufman et al. 1997, Morland et al. 2002, Hendrickson, Smith, and Eikenberry 2006, Andreyeva et al. 2008). Therefore, as stores close, vulnerable urban residents are either traveling farther to purchase nutritious, competitively priced groceries or perhaps paying inflated prices for low quality, processed foods at the corner stores. These situations, affecting both the individual health and health of neighborhoods, would widen the urban grocery gap, increase food insecurity, and perhaps create a food desert.

3.2 Method

3.2.1 Conceptual Framework

Supermarket Redlining Index (SuRI) is an index that ranks a chain supermarket based on certain parameters. These parameters are location of the supermarket, presence of local grocery stores in close proximity, sales volume, employee count, accepts SNAP (Supplemental Nutrition Assistance Program) and/or WIC (Women, Infants, and Children) coupons, and size and population density of the service area. Detailed specifications of the index with variable definitions are explained later in section 3.4.3. If a supermarket with high SuRI value closes in an inner city or relocates to a suburb with limited possibilities of a new store being open, the risk of spatial supermarket redlining increases. Given such risk, the *Supermarket Redlining Impact Model* or SuRIM identifies *places* or location of neighborhoods where the impact of food access vulnerability will be critical. This model is an extension of Cutter's hazards-of-place model of social vulnerability (Figure 3.2.1) (Cutter 1996, Cutter, Mitchell, and Scott 2000, Cutter, Boruff, and Shirley 2003).

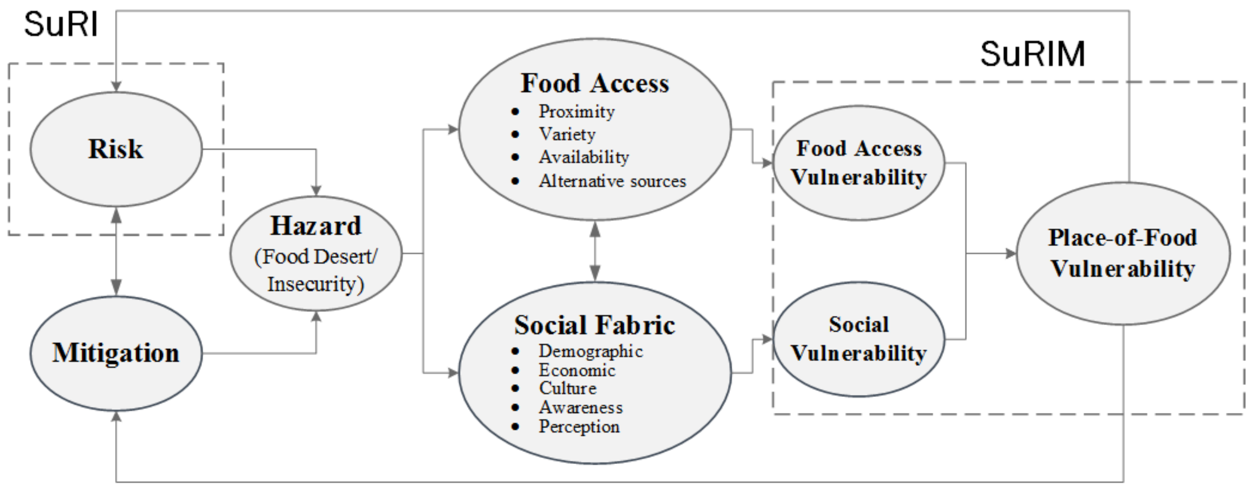

Figure 3.2.1: Conceptual Framework

(Notes. SuRI: Supermarket Redlining Index; SuRIM: Supermarket Redlining Impact Model)

According to Cutter's model, risk and mitigation interact to create an initial hazard potential (Cutter, Mitchell, and Scott 2000, Cutter, Boruff, and Shirley 2003). In our framework, *risk* is the likelihood of the occurrence of spatial supermarket redlining i.e. scenarios where a supermarket closes down and/or relocates to suburban neighborhoods from inner cities. The magnitude of the risk will further depend upon parameters such as 1) the source of the potential risk (e.g. location of the store), 2) type of the risk (e.g. rank of the store calculated from SuRI), and 3) the impact of the risk (high-consequence: if it is the only full-sized supermarket in the neighborhood, and low-consequence: if there are other alternatives to fill the grocery gap). The risk of spatial supermarket redlining then interacts with *mitigation* (e.g. increasing investments to open new stores, increasing stocks of fresh produce in the existing corner stores of the neighborhood, presence of alternate sources for fresh food such as farmers' markets, community gardens) to produce the *hazard* potential of increasing food insecurity and food deserts. Risks can either be reduced by good mitigation policies or amplified by poor or nonexistent mitigation

practices. The latter is typical for inner city urban areas where a combination of perceived and logistical obstacles creates disinvestment for new stores and increases the likelihood of food insecurity and food deserts.

The hazard of increasing food security or difficult access to healthy food interacts with the underlying *social fabric* of the neighborhoods to create *social vulnerability*. The social fabric (including sociodemographic, economic, and cultural characteristics, awareness, perception, and experiences of the neighborhood residents) affects the overall capacity to respond to food insecurity. For example, if an important supermarket closes down in a neighborhood, the impact would be disproportionately more among low-income residents with limited access to cars compared to others who have the resources to travel farther for buying fresh produce. The *food access* filter includes indicators describing the food environment or foodscapes of the neighborhoods. The indicators are proximity to other smaller grocery and corner stores, availability of fresh produce in these stores, variety or diversity of food items to satisfy the need for ethnically diverse population, and alternative sources of healthy food at seasonal farmers' markets and community gardens. Similar to social vulnerability, the impact of the hazard will be disproportionally higher for residents with fewer food access indicators to fill their grocery needs. Finally, the social and food vulnerability parameters are mutually related and produce the places-of-food vulnerability outcome or in other words *locations of disadvantaged neighborhoods with maximum food vulnerability*. Similar to Cutter's model, the places-of-food vulnerability has a feedback loop to the initial risk (spatial supermarket redlining) and mitigation (to reduce the risk of spatial supermarket redlining), allowing for enhancement or reduction of both risk and mitigation, which in turn lead to increased or decreased places-of-food vulnerability (Figure 3.2.1) (Cutter, Mitchell, and Scott 2000, Cutter, Boruff, and Shirley 2003).

To operationalize this conceptual framework, we focused on one input element (Walker et al.) and three outcome elements (food access vulnerability, social vulnerability, and place-of-food vulnerability) of the model. SuRI measures the location and magnitude of risk from potential spatial supermarket redlining; the social fabric and food access indicators contribute to social vulnerability and food access vulnerability respectively. The final outcome of place-of-food vulnerability is the product of social and food access vulnerabilities (Figure 3.2.1 and 3.2.4).

3.2.2 Study Area

Hartford, the capital city of Connecticut, has diverse demographic, socioeconomic, and health disparity indicators. The total population in 2012 was 124,893, which were predominantly urban (ESRI 2011). The Hispanic population comprised the biggest ethnic group with 43.4%, followed by 34.1% of non-Hispanic blacks and 15.8% of non-Hispanic whites (City-Data 2012). Hartford has an estimated poverty rate of 32.9%, more than double the Unites States' poverty rate of 15% (Martin et al. 2012, United-States-Census-Bureau 2013b). The unemployment rate in Hartford in April 2013 was 14.8% (Connecticut-Department-of-Labor 2013), compared to approximately 7% nationally (US-Bureau-of-Labor-Statistics 2014). The 2011 median household income was estimated at $29,169, which is less than half of the estimated median household income for the Hartford County and below the median for the Unites States ($50,502) (United-States-Census-Bureau 2013a, 2012). 47.9% of children in Hartford live below the poverty line compared to the Unites States' child poverty rate of 21.8%. The youngest members of Hartford are at increased risk of diet-related diseases due to nutritionally imbalanced access to foods in their neighborhoods. A 2012 study found that 37% of preschool children in Hartford were overweight or obese, making the prevalence of childhood obesity among preschoolers more than twice as high

as Centers for Disease Control and Prevention (CDC) age and gender body mass index guidelines (University-of-Connecticut's-Center-for-Public-Health-and-Health-Policy 2012).

3.2.3 Data

The data for this study was grouped into four categories of retail food stores, relevant GIS shapefiles, socioeconomic and demographic characteristics, and travel-time to stores. Food store data were collected from two sources: Connecticut Department of Energy & Environmental Protection's (DEEP 2011) food residual generation mapping project and ESRI's Business Analysis (ESRI 2011). We followed the criteria used in DEEP's grocery store mapping project to categorize the stores included in our study into three groups: 1) large supermarkets with employee count greater than 15 persons (e.g. Shop and Stop), 2) small supermarkets with employee count between 4-14 persons (e.g. Carlos Supermarket), and 3) convenience stores (e.g. 7-Eleven). Based upon this criterion and within a 3-miles buffer around the city of Hartford, we identified 33 large supermarkets, 17 small supermarkets and 73 convenience stores. A 3-miles buffer were used for two reasons, first, the residents of Hartford often shop outside their town limits, and second, to minimize errors from edge effects in the subsequent mapping and spatial analysis (Haefner et al. 1991, Lawson, Biggeri, and Dreassi 1999, Laurance 2000). A variety of methods were used to ensure sample completeness, including online yellow pages, business listings, and more importantly "ground-truthing" by driving through neighborhoods to verify store names. Out of the 33 identified large supermarkets within a 3-miles buffer around Hartford, 9 were located in the city (Figure 3.2.3). For each large supermarket, we further obtained the following information: sales volume, employee count, SNAP/WIC coupon status, size of the service area, and population density of the service area.

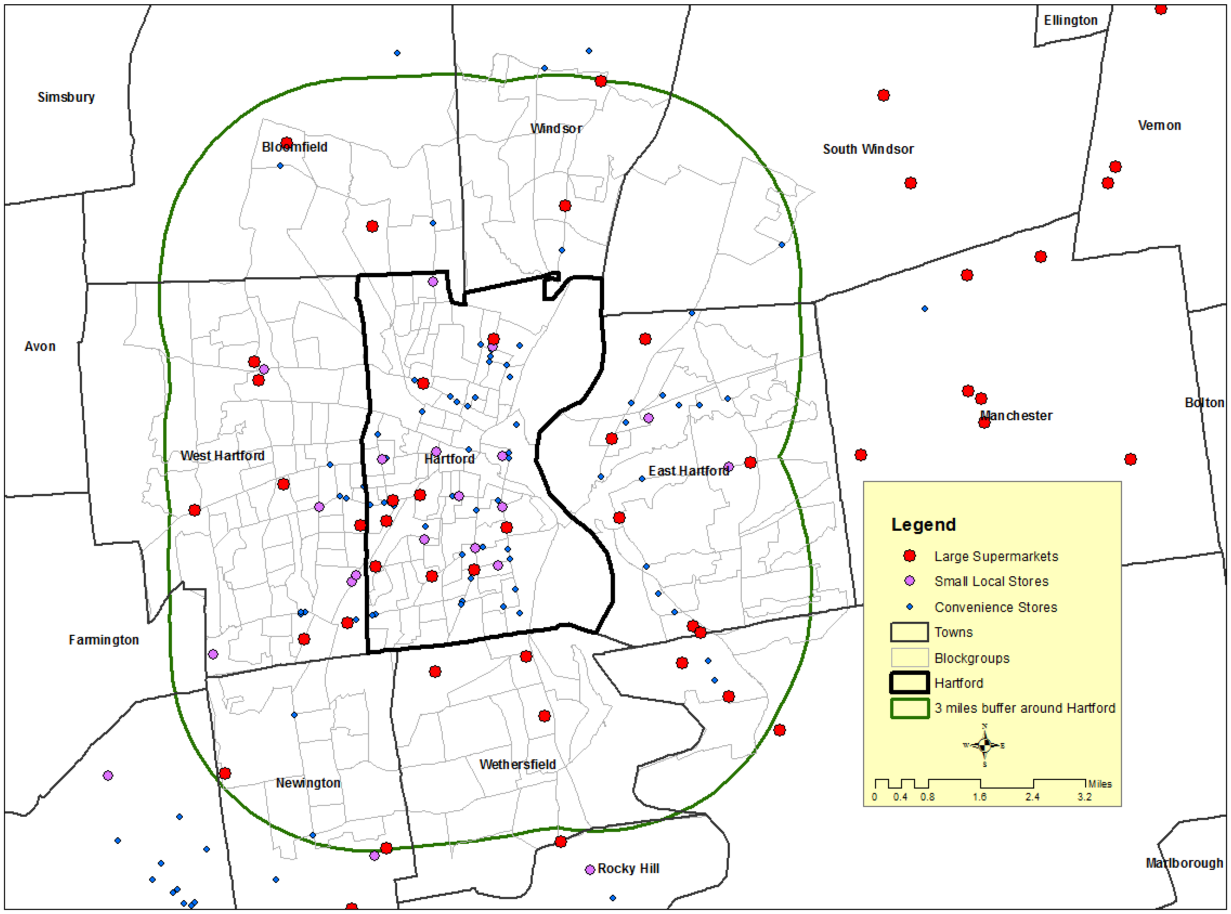

Figure 3.2.3: Location of three categories of food retailing stores in Hartford with a 3-mile Buffer

The GIS shapefiles such as Connecticut's roads were obtained from ESRI's Business Analysis dataset, and state, town, and census block-group boundary shapefiles from the Map and Geographic Information Center at University of Connecticut (MAGIC 2013). The socioeconomic and demographic variables were selected from ESRI's Business Analysis dataset at the block-group level. The variables selected for the social fabric indicator of the SuRIM model were: percentage of elderly population (65+ years), minority and ethnic population (Black and Asian), diversity of race and ethnicity, population with less than high school education, renter occupied household units, unemployment rate, and low income population. The data on travel time by bus

and by car from the population centroids of block-groups to the retail food stores were obtained by using Google Direction API application. This is a free service provided by Google that calculates the direction (and distance) including the time between locations using an HTTP request with a limitation of 2,500 requests per 24-hour period. We will introduce the details of this technique in a future paper, which is currently under preparation.

3.2.4 Methodology

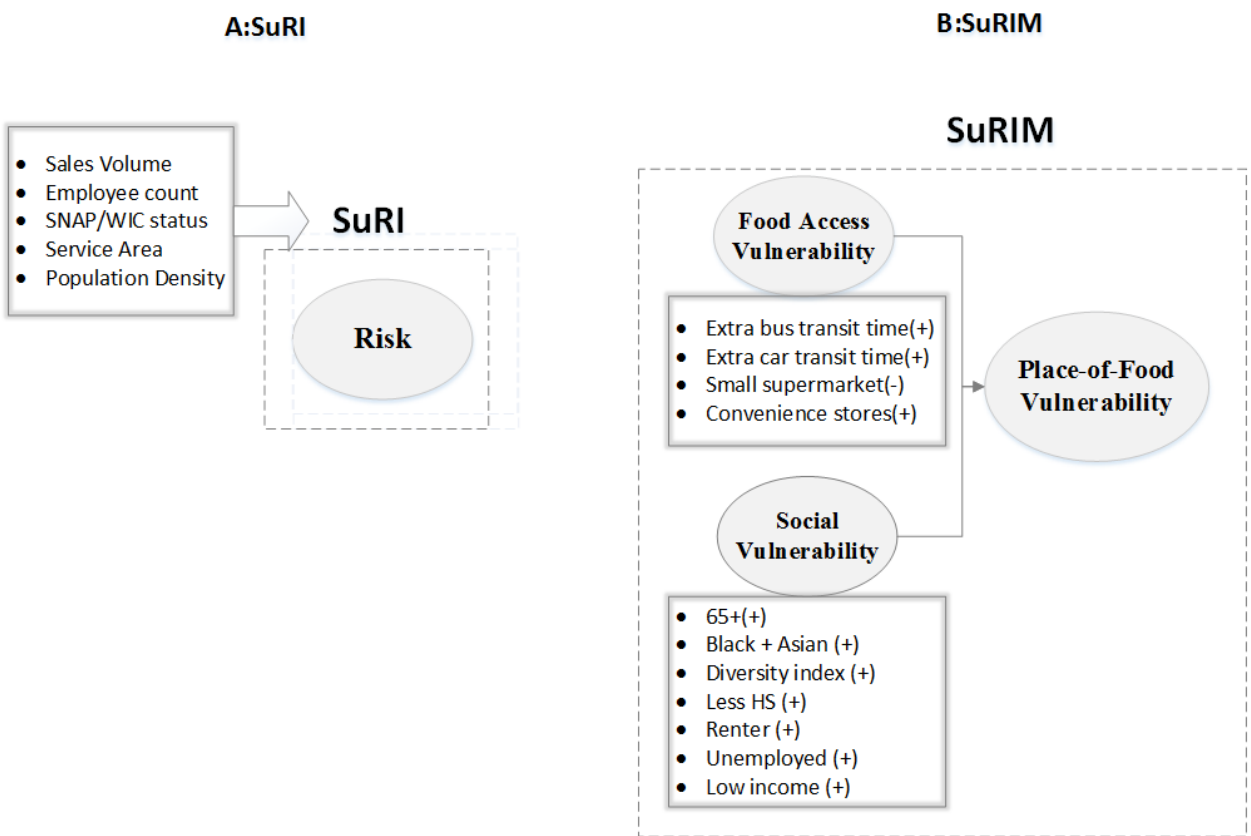

Figure 3.2.4: Operational framework of Supermarket Redlining Index (SuRI) and Supermarket Redlining Impact Model (SuRIM)

(Notes. SuRI: Supermarket Redlining Index; SuRIM: Supermarket Redlining Impact Model, SNAP: Supplemental Nutrition Assistance Program; WIC: Women, Infants, and Children; HS: High School)

We first calculated the potential Supermarket Redlining Index (SuRI) at the store level using five variables (Figure 3.2.4A): sales volume ($), number of employee (count), whether the store accepts SNAP and/or WIC coupons (yes or no, coded as 1 and 0 respectively), size of the service area (number and area of all block-groups that were assigned to the store as the closest supermarket), and population density (number of person per square mile) of the service area. Sales volume and employee count were the characteristics of the supermarket, which indicated how important that particular supermarket was in serving the community. SNAP-WIC status indicated whether the supermarket accepted coupons from the federally funded food assistance programs designed for low-income households. The service area of the supermarket was determined by using ArcGIS 10.1's Network Analyst functions where a road-network database and the 'Closest Facility' tool were used to calculate the path from each block-group population centroid to its closest supermarket. The average population density of the service area was then calculated and assigned to each supermarket as the fourth variable. So neighborhoods with sparse supermarkets had a larger service area and thus larger proportion of urban residents would be at risk if that store closed down.

Since the units of these variables were different, each variable was standardized by calculating the ratio of its value to the total value divided by the highest ratio among the block-groups (See formula 2).

$$SD(x) = \frac{x_i}{\sum x_i} \Big/ \max \frac{x_i}{\sum x_i} \qquad \text{(Formula 2)}$$

$SD(x)$ is the standardized Redlining Indicator; where

i is the store

x_i is the variable value of each store;

$\sum x_i$ is the sum of each variable;

$\frac{x_i}{\sum x_i}$ *is the ratio of each variable.*

Value of each standardized variable ranged between zero to one. To generate an aggregate value for SuRI, standardized values were summed for each supermarket. Due to the lack of prior literature and statistical evidence needed to assign specific weights to calculate supermarket redlining index, all indicators were given the same importance of equal weights (Wood, Burton, and Cutter 2009, Laurance 2000). The final result was rescaled from 0-10 to be comparable with the values from the SuRIM. These steps are summarized in Table 3.2.4.

Table 3.2.4: Methodology of Supermarket Redlining Index (SuRI)

Creating Supermarket Redlining Index	Example using the 'Sales Volume' variable
Step 1: Sum of each variable for all stores	Sum of sales volume ($)
Step 2: Computing the variable ratio for each store	Sales Ratio = sale volume of a store /sum of sales volume for all stores
Step 3: Calculating the Variable Indicator for each store	Sales indicator= Sales ratio/ maximum value of sales ratio
Step 4: Calculating a composite index of SuRI for each store including all the variable indicators	SuRI=[sales indicator + service area indicator + …..+ population density indicator]

Note: The left column lists the steps and the right column provides an example for each step.

Next, we built the Supermarket Redlining Impact Model (SuRIM) at the block-group level using 11 variables (Figure 3.2.4B). We used 7 socioeconomic and demographic variables to describe the *social vulnerability* (SoVI) component of the SuRIM (See Fig. 3.2.4B). For the *food access vulnerability* (FaVI) component, 4 variables related to access to healthy food in a situation when existing supermarket closed down or relocated to suburbs were included. In figure 3.2.4B, variables with "+" and "-" represent positive and negative effect on the SuRIM respectively. The

7 socio-economic-demographic variables were percentage of elderly population (65+ years), minority and ethnic population (Black and Asian), diversity of race and ethnicity, population less than high school education; renter occupied household units, unemployment rate, and low income population. All these social fabric variables had positive impact and increased the value of SoVI or in other words increased the impact of risk (spatial supermarket redlining) on the hazard of potential food insecurity and food deserts.

For FaVI, the transit-time variables were the *additional* travel time that the neighborhood residents would have to travel for groceries by a public transport or by a car in a situation of potential spatial supermarket redlining. Google Direction API application was used to calculate these transit time variables (by bus and by car) for each block-group from their closest supermarket to the second closest one with the assumption that longer transit time would increase the difficulties for accessing healthy food. Travel time by a bus included walking to a bus stop, time on the bus to the store, and then off the bus and walking to the store. The other two variables described the alternative sources of fresh food in a time of supermarket closures. The variables were the presence and absence of small sized local supermarkets with employee count between 4 and 14 persons and convenience stores. When a supermarket stopped business and the second closest supermarket was too far away, these stores would become the primary or sometimes the *only* source of groceries. Local small supermarkets might still shelve limited fresh produce but the convenience stores would typically not have fresh food items at all. Small supermarkets were aggregated by block-groups and the count showed the availability of alternative access to limited healthy food (Martin et al. 2014). We assumed that these stores decreased the impact of the risk of supermarket redlining and used 1 minus the standardized value when calculating the FaVI. In contrast, convenient stores typically with no fresh food, would increase the food vulnerability. This variable was also

aggregated at the block-group level and higher the count, the higher was the FaVI value indicating increase in the risk of exposure to low nutrition food environments.

All of these 11 variables were then standardized using the same method described for the SuRI to create the SoVI (social vulnerability) and the FaVI (food access vulnerability) components. The final outcome of place-food-vulnerability in the SuRIM was the product of FaVI and SoVI (FaVI * SoVI = place-food-vulnerability). Since there were no prior studies that modeled the impact of supermarket redlining and provide insight in choosing the weights, we assigned equal weights to FaVI and SoVI in calculating the product (Cutter, Boruff, and Shirley 2003).

3.3 Results

Table 3.3.1: Descriptive Statistics of SuRI

	N	Min.	Max.	Mean	Std. Deviation	Percentiles		
						25	50	75
SuRI	33	2.1	6.2	4.11	0.86	3.55	3.8	4.62

Table 3.3.1 shows the descriptive statistics of SuRI values, which ranges from 2.1 to 6.2 with a mean value of 4.1. Based on these values, 33 large supermarkets were grouped into three categories of low (SuRI <3.0), medium (SuRI 3.00 – 4.99), and high (SuRI >= 5.00) SuRI values. There were 3 supermarkets with a service area of 4 block-groups in the low category, 25 supermarkets with a service area of 192 block-groups in the medium category, and 5 supermarkets with a service area of 74 block-groups in the high category. Higher SuRI values indicated higher *risk* of potential spatial supermarket redlining and resulting higher *hazard* of food insecurity and food deserts. Conversely, if in a neighborhood, a store with low SuRI value closed down or relocated to suburb with limited mitigation efforts to fill the gap, the residents of that neighborhood

would either had other supermarkets to shop from in that same neighborhood or had access to car (and or public transportation) to travel to distant stores.

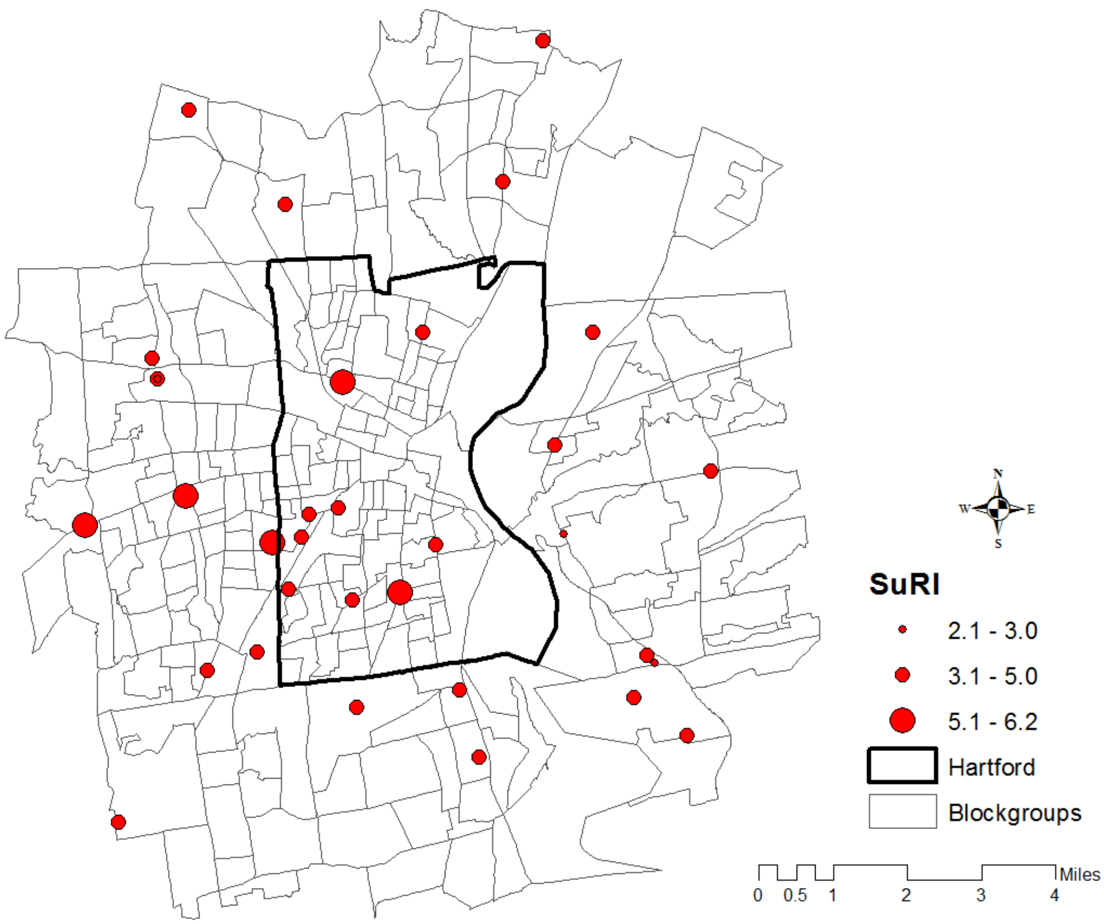

Figure 3.3.1: Spatial distribution of Supermarket Redlining Index (SuRI)

Figure 3.3.1 is a proportional circle map showing the spatial distribution of stores with SuRI values. Of the 33 large supermarkets, only 9 (27%) were located in Hartford and most of them were in the west and south. The supermarket with highest SuRI value (Bravo Supermarket) was located in northwest of Hartford in Albany Ave. Given there were no other supermarkets or even a small store, this store played an important role as the only provider of fresh food for the residents of the surrounding 27 block-groups in the northwest region of Hartford. A Walmart,

which opened in 2013 at the border of Hartford and West Hartford, had a lower SuRI value, even though it had a higher sales volume and employee count than the other stores. This was due to the presence of other large supermarkets such as Super Stop & Shop and Save-A-Lot in close proximity. Closure of any one of these stores, will therefore, not be a critical loss for the residents.

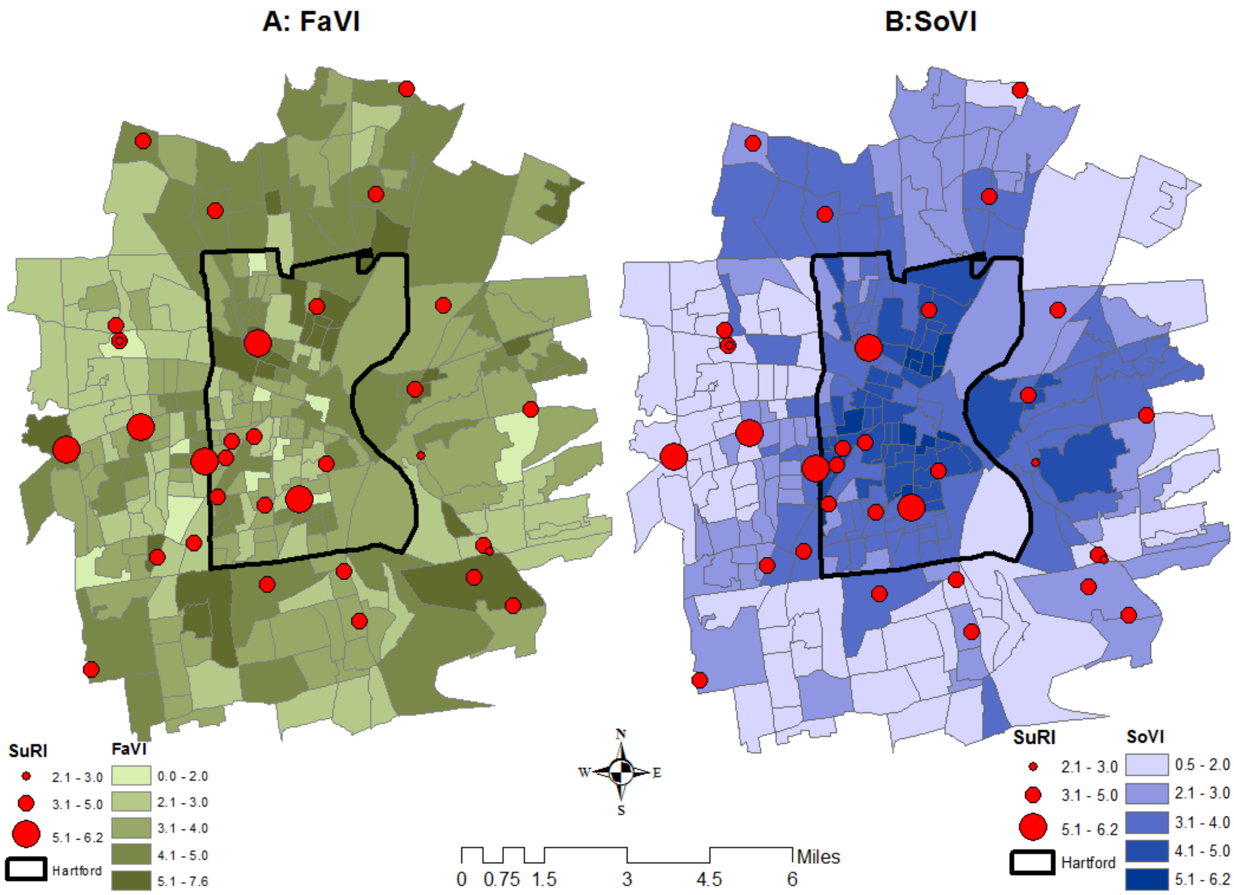

Figure 3.3.2: Spatial distribution of Food Access Vulnerability Index and Social Vulnerability Index

Figure 3.3.2 shows the spatial distribution of the two components of SuRIM – food access vulnerability index (FaVI) and social vulnerability index (SoVI) with SuRI values at the census block-group level. Although FaVI did not show strong spatial clustering of either high or low

values in the study area, several important findings emerged. First, north Hartford and areas just outside the northern city boundary had higher food access vulnerability due to a lack of large supermarkets, small-sized local stores, or limited public bus services. Second, block-groups with higher FaVI values (5.1 – 7.6) were located in the downtown, DoNo, and northwest. Third, the supermarket with the highest SuRI value was located in a block-group in DoNo with highest FaVI, indicating a positive correlation between SuRI (Walker et al.) and FaVI (one of the outcome of SuRIM). This supermarket was the store closest to the surrounding 27 block-groups with no other alternative food stores in the vicinity. Overall, the SoVI was higher in Hartford than the surrounding suburbs. Within Hartford, the inner-city areas in the central and north-central region had the highest values with 41-96% of black population and 38-50% of low-income population. Block-groups located in the downtown area with higher SoVI also had higher FaVI (5.6 – 7.6) and several supermarkets with medium (3.1-5.0) to high (5.1-6.2) values of SuRI. This indicated a stronger positive correlation between SoVI and FaVI, and a weaker positive correlation between SoVI and SuRI.

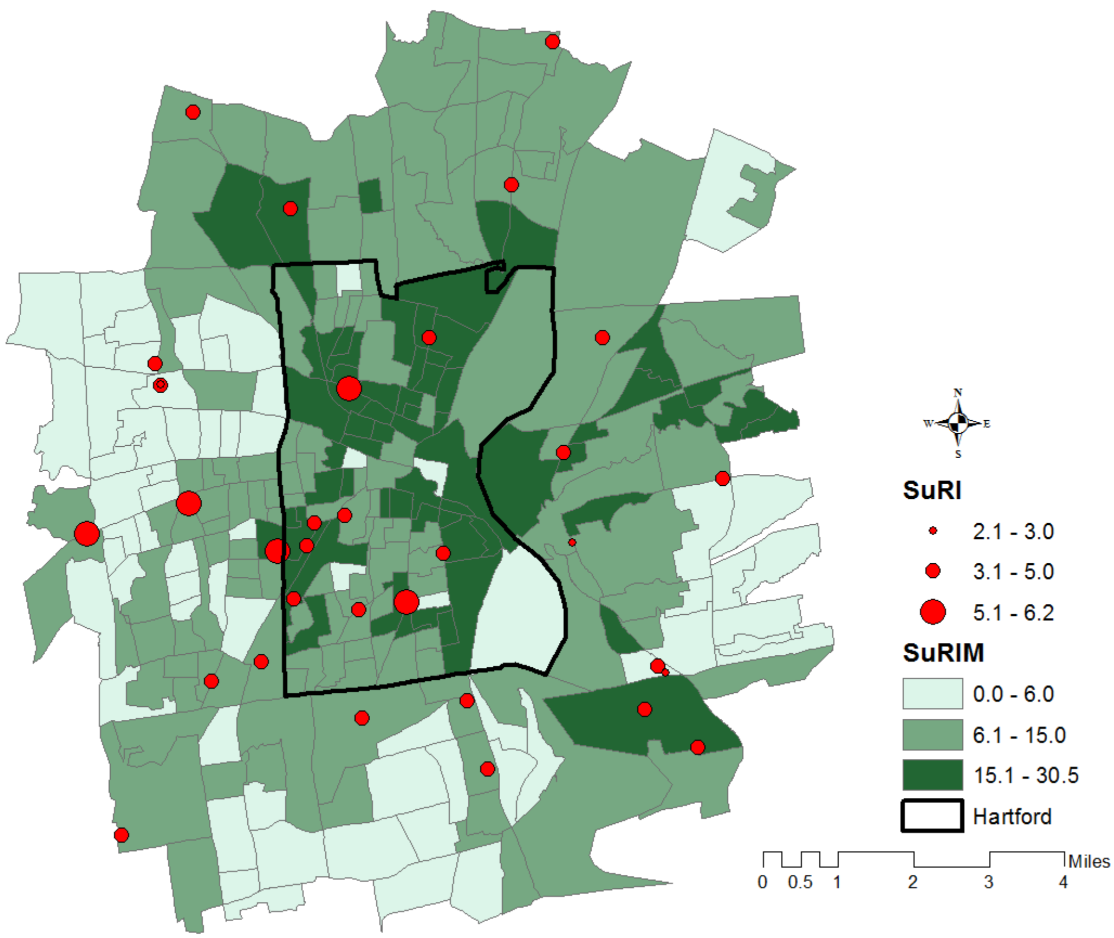

Figure 3.3.3: Spatial distribution of Supermarket Redlining Impact Model (SuRIM)

The final outcome of SuRIM or the place-food-vulnerability value (FaVI * SoVI = place-food-vulnerability) is shown along with the SuRI values in Figure 3.3.3. Based on the SuRIM values, the 263 block-groups in the study area were divided into three categories of low (66 block-groups), medium (132 block-groups), and high (65 block-groups) values. Our first observation was that the *places* or neighborhoods of inner city Hartford suffered a higher impact of place-food-vulnerability (higher SuRIM values) from the risk of potential spatial supermarket redlining (higher SuRI values). The neighborhoods in the northwest of Hartford had the highest SuRIM values between 15 and 30 with only one supermarket. The impact of potential supermarket closures

on these neighborhoods was further accentuated by the socioeconomic vulnerability of the residents and limited choice and access to healthy food. On the contrary, some affluent suburban areas (West Hartford, Newington and south of Wethersfield) located to the west of Hartford, had lower SuRIM values indicating that the residents living in these neighborhoods were less vulnerable to the hazard of potential food insecurity and food desert even if their large supermarket closed down. This was because the residents were not dependent on a single store and had higher socioeconomic status and easy access to other alternative stores. The pattern, however, was different for the suburbs located east and northeast of Hartford. Towns such as Bloomfield, South Windsor, East Hartford, and Manchester had medium to high values of SuRIM (6.1-15.0) and lower values of SuRI (2.1-3.0).

Table 3.3.2: Cross-tabulation of SuRI and SuRIM

SuRIM	No. of Block-groups	SuRI					
		Low: < 3.0		Medium: 3.00-4.99		High: >=5.00	
		No. of Supermarket	No. of Block-groups in service area	No. of Supermarket	No. of Block-groups in service area	No. of Supermarket	No. of Block-groups in service area
Low: < 6	66	2	0	2	13	0	0
Medium: 6.0-14.99	132	1	4	17	144	2	31
High: >= 15	65	0	0	6	35	**3**	**43**
Total	263	3	4	25	192	5	74

The cross-tabulation between SuRI (Walker et al.) and SuRIM (place-food-vulnerability) are shown in Table 3.3.2. In the lower right cell (i.e. high SuRI and high SuRIM values), there are three large supermarkets, whose services are critical for providing fresh and healthy food to the residents of their service area (43 block-groups). Of these three stores, two (Bravo Supermarket) are located in Hartford and one store (Shop Rite Supermarket) is located on the western edge of

Hartford. The socioeconomic status of the residents (approximately 62,000 population) living in these 43 block-groups is vulnerable: over half of the population (51%) live in rented properties, 11% have less than high school education, there is a significant black population (69%), average unemployment rate is at 21%, and 26% with low income. Therefore, the continued operation of these stores is vital because if any of these stores close down or relocate to the suburbs without efficient mitigation efforts to close the grocery gap, a significant number of population who are socioeconomically vulnerable would experience the hazard of food insecurity and food deserts. Residents will either have to drive long distances to another big supermarket or shop at the nearby small local stores, which might not be able to provide fresh fruits and vegetables at affordable prices.

3.4 Discussion and Limitations

We highlight the major findings of our study here. First, the service areas (block-groups) of the supermarkets with higher SuRI values (vital source of food availability) were also the areas with higher impact of place-food-vulnerability (high SuRIM values). These areas were located in the inner-city neighborhoods of Hartford, especially in the north, east, central, and south-central parts. In these neighborhoods, once a nearby supermarket closes (or relocates) and if the mitigation efforts are slow, a large proportion of vulnerable residents might face food insecurity and related negative health outcomes. However, residents who have the resources or the means to travel the extra miles to an alternate supermarket will be less vulnerable to the hazard of food insecurity. The mitigation efforts (e.g. increasing investments to open new stores, increasing stocks of fresh produce in the existing corner stores, encouraging seasonal farmer's markets and community gardens) will affect the severity of the hazard and the final outcome of place-food-vulnerability.

Second, some suburban areas such as northwest of West Hartford, Newington and south of Wethersfield have low SuRI and SuRIM values. This indicates that residents living in these neighborhoods are less vulnerable and the existence of clusters of large supermarkets in close proximity provided choices and more options for buying fresh groceries. These places are typically affluent suburban neighborhoods (only 4% low income population and unemployment rate at 5%) with a predominantly white population (over 80%) and with easy access to a number of large chain supermarkets (average number is 4).

Third, GIS algorithms, particularly network analyses and travel-time data obtained from the Google Direction API service were appropriate in building the supermarket redlining index (SuRI) and the Supermarket Redlining Impact Model (SuRIM). These analytic approaches aided in illustrating the major findings. The spatial analysis and correlation between SuRI and SuRIM identified urban neighborhoods that will face increasing difficulty of accessing healthy and nutritious food if full-service supermarket closes. It raises concerns about food insecurity and food deserts and urges city officials to consider stronger but feasible mitigation policies to fill the possible grocery gap.

Since it is not always feasible to open a large supermarket in inner cities due to lack of investments, stable markets, and lack of infrastructure related to easy access to highways, large loading docks for large trucks to unload, or distribution networks (Shaffer 2002, Martin et al. 2014), we suggest other mitigation policies. These suggestions are: a) investing more in fresh food stocks at the existing local medium to small sized grocery stores and corner stores (Martin et al. 2012), and b) encouraging more urban farms and community gardens to increase options for healthy foods for at least few months of the year. At present, there are 7 farmer’s seasonal markets of varying sizes and few established community gardens (e.g. KNOX Inc and gardens in the Trinity College).

Martin et. al. (2014) in their recent study indicated that improvement of quality of food and appearance of the existing smaller local stores can potentially impact the food purchasing decisions of low-income residents in Hartford and mitigate the negative impacts of food insecurity (Martin et al. 2014). Many of the storeowners from small and medium-sized markets in Hartford live locally. Therefore, efforts to improve the business infrastructure and sales of these markets will also support the local economy, which is in line with the principles of healthy, sustainable food systems. Studies have shown that storeowners' established friendships between owners and patrons fosters store loyalty, especially in neighborhoods without a large supermarket (Bloemer and De Ruyter 1998, Walker, Block, and Kawachi 2012). In comparison, large supermarkets tend to be owned by national or often international companies where revenues are not reinvested into the city and the owners might not be at the same level of enthusiasm to develop friendship with the local patrons.

The study also had a few limitations. First, due to insufficient literature and to our knowledge this being the first attempt to model the impact of spatial supermarket redlining, we used equal weights of FaVI and SoVI in the SuRIM (SuRIM or place-food-vulnerability was the product of FaVI and SoVI) (Cutter, Boruff, and Shirley 2003). It is possible that in a different study design, FaVI could be more critical than SoVI or vice versa. Second, we calculated accessibility to grocery stores by car and by public transportation. Due to a high incidence of crime in some parts of the inner-city neighborhoods of Hartford, residents are disinclined to walk to services and therefore walking distance is not included. It is however possible that some residents still walk to grocery stores. Third, we included small supermarkets (with employee count between 4 and 14) as an alternative source for access to fresh food in a situation of potential spatial supermarket redlining i.e. when supermarket closes or relocates to suburbs. However, some small

supermarkets may not stock fresh produce or a variety of food items for the ethnically diverse population of Hartford. The prices of food items in these local stores may also vary significantly. If these small supermarkets have higher prices and a limited variety, will the residents consider these stores as an alternative for large chain supermarkets? If not, then these local supermarkets are not an alternate source for healthy foods and therefore will increase the impact of supermarket redlining instead of decreasing the impact. To answer this question empirically in this study, we analyzed data from a survey, which collected detailed data on price, quality, and variety of available food items, and external and internal appearances of the medium and small sized grocery stores in Hartford and adjacent towns in Chapter 3 with more detailed information. Last but not the least, because of the controversial meaning of the word redlining specially in the retail sector, the authors want to reemphasize two aspects here. First, it should be remembered that in all its variation, retail redlining (including supermarket redlining) is not blatantly practiced based only on race compared to the financial and housing sectors. As discussed in the paper, the process of supermarket redlining is complex with multiple related drivers, which may or may not be racially motivated. Second, this study is the first attempt to empirically understand the effects of potential spatial supermarket redlining on food insecurity among vulnerable populations. For that we have built an index and an impact model in a GIS environment and not a predictive model.

Chapter 4: What actually get sold in food stores? A multidimensional assessment of local grocery stores in Greater Hartford Area of Connecticut, USA

4.1 Introduction

The concept of the term *food access* is not only subjective but also multidimensional. Food and Agriculture Organization (FAO) of the United Nations defines food access as *"access by individuals to adequate resources for acquiring appropriate foods for a nutritious diet"* (FAO 2006). The measurement of food access and their indicators, however, vary across different settings such as rural vs urban or high-income vs low-income neighborhoods (Chung and Myers 1999, Ross and Murphy 1999, Morland et al. 2002, Rose and Richards 2004, Lewis et al. 2005, Block and Kouba 2006, Moore and Roux 2006, Liese et al. 2007, Powell et al. 2007, Mojtahedi et al. 2008, Larson, Story, and Nelson 2009, McKinnon et al. 2009, Mavoa et al. 2012, Tribby and Zandbergen 2012). Residents of low income neighborhoods, face more barriers in accessing nutritious food in terms of number of stores, distance to stores, prices, as well as quality of food items sold in the stores than residents in affluent neighborhoods located in the suburbs (Andreyeva et al. 2008, Chung and Myers 1999, Ball, Timperio, and Crawford 2009, Larsen and Gilliland 2008, Moore and Roux 2006, Morland et al. 2002, Powell et al. 2007). This exacerbates food insecurity perhaps leading to the formation of food deserts. Food insecurity describes a condition where people have limited access to sufficient, safe, and nutritious food to meet their daily need for healthy living (Hamelin, Beaudry, and Habicht 2002, Lopez et al. 2005, Olson 1999). Typically, community residents living in a food desert face situations of food insecurity, which further affects the overall health of a community.

Researchers use different techniques to measure food access, the most common being measuring geographic distance to grocery stores (Azar, Ferreira, and Wiggins 1994, Nyerges 1995). Advances are also made on the computation of geographic distance, that is, from the Euclidean distance or as the 'crow flies' to distance on road network (Aultman-Hall, Roorda, and Baetz 1997, Liu and Zhu 2004, Widener, Metcalf, and Bar-Yam 2011, Wu and Murray 2005), to travel time (Liu and Zhu 2004, Hillman and Pool 1997, O'Sullivan, Morrison, and Shearer 2000, Gent and Symonds 2005, Lei and Church 2010, Widener and Shannon 2014) by a car (Couclelis 1992, Van Bemmelen et al. 1993, Handy and Niemeier 1997, Bamford et al. 1998, Talen and Anselin 1998, Cervero, Rood, and Appleyard 1999, Fortney et al. 1999, Witten, Exeter, and Field 2003, Liu and Zhu 2004, Zenk, Schulz, Israel, et al. 2005, Goodchild, Yuan, and Cova 2007, Apparicio, Cloutier, and Shearmur 2007, Jones et al. 2010) and public transit (Witten, Exeter, and Field 2003, Liu and Zhu 2004, Hadas and Ranjitkar 2012, Hadas 2013). Although widely used, this indicator of access is still one-dimensional and only measures the spatial relation of location of households and food stores. Many researchers in the field of healthcare (Aday and Andersen 1974, Salkever 1976, Penchansky and Thomas 1981, Dutton 1986, Frenk and White 1992, Margolis et al. 1995, Gulliford et al. 2002, Haddad and Mohindra 2002, Peters et al. 2008, Levesque, Harris, and Russell 2013, Shengelia, Murray, and Adams 2003, Gibson et al. 2014) argue that access is a multidimensional concept. For example, while some health studies still focused on geographic accessibility to healthcare facilities (Arcury et al. 2005, Pilkington et al. 2012), other studies used affordability of receiving care (Guagliardo 2004, Wang and Luo 2005) or variety of healthcare services provided at the facilities (Guagliardo 2004) as a measure of access. Amongst them, Penchansky and Thomas (1981) described a robust taxonomy of access to healthcare facilities including dimensions such as *availability, accessibility, accommodation, affordability, and*

acceptability. This concept has been further adapted by several other researchers from public health, social work, and economics (Gulliford et al. 2002, Peters et al. 2008, Levesque, Harris, and Russell 2013, Gibson et al. 2014). Gulliford et al. (2002) pointed out that access in terms of utilization is dependent on the affordability, physical accessibility and acceptability of service and not mere adequacy of supply. In another study, Penchansky's dimensions were conceptualized to 1) approachability, 2) acceptability, 3) availability and accommodation, 4) affordability and 5) appropriateness (Levesque, Harris, and Russell (2013)). While the concepts of acceptability (ability to seek), availability and accommodation (ability to reach), and affordability (ability to pay) was similar to Penchansky's, approachability and appropriateness were defined as ability to perceive and ability to engage respectively.

There is no study to our knowledge, which has applied Penchansky and Thomas (1981) robust framework to understand access to grocery stores either from a seller or a buyer's perspectives. Therefore, the primary objective of this paper is to conduct a thorough assessment of access to local stores with two secondary objectives: one, recommend improvements for making them more accessible to buyers and second, whether such improvements are cost effective compared to opening a big chain supermarket. The paper is organized as follows. Section 4.1.1 provides a short review of the prior and current research on measuring multidimensional food accessibility; Section 4.2 describes the study area (4.2.1), data (4.2.2), methodology (4.2.3); Section 4.3 explains the results with further discussions and limitations mentioned in Section 4.4.

4.1.1 Measuring multidimensional accessibility

Several studies have considered availability of a variety of healthy food items (Cheadle et al. 1991, Edmonds et al. 2001, Jekanowski, Binkley, and Eales 2001), their quality (Schultz, Yeh,

and Katz 2003, Furst et al. 1996), and price (Shankar and Klassen 2001, Reicks, Randall, and Haynes 1994, Glanz et al. 1998, French, Story, and Jeffery 2001, Drewnowski and Specter 2004, Schultz, Yeh, and Katz 2003, Furst et al. 1996) as determinants of purchasing decisions and dietary practices (Zenk, Schulz, Hollis-Neely, et al. 2005).

Availability: Availability describes *the relationship between the volume and type of existing food stores to the volume and types of household needs (Penchansky and Thomas 1981).* In other words, it also refers to the adequacy of the supply of different types of food items in stores and their impact on the combined demand of households in a given neighborhood. In the US, there is scarcity of large chain supermarkets in low-income urban neighborhoods (Alwitt and Donley 1997, Eisenhauer 2001, Morland et al. 2002) but typically have non-chain small grocery stores. Such local stores are more likely to have limited choices of fresh foods but with an abundant variety of high-calorie packaged foods (Chung and Myers 1999, Jetter and Cassady 2006). For example, Jetter and Cassady (2006) in their research pointed out that the small independent stores had very limited availability of healthier food items with much higher prices, while chain supermarkets had a wider range that they offered customers compared to the small grocery stores. Using statistical tests, Bustillos et al. (2009) indicated that large supermarkets had wider selection of fresh food items than small grocery stores and also smaller stores carried less variety of fresh fruit (8 ± 0.7 vs 4.7 ± 0.3; $P< 0.01$) and vegetables (10.7 ± 0.2 vs 6 ± 0; $P< 0.001$) than supermarkets.

Affordability*:* Affordability is *the relationship between prices of food and the consumers' income, ability to pay, and other social-economic indicators (Penchansky and Thomas 1981).* In terms of prices, the majority of research in the US showed that people with lower income had to pay more for healthy food (Chung and Myers 1999, Morland et al. 2002, Hendrickson, Smith, and Eikenberry 2006, Jetter and Cassady 2006). In a case study conducted in the Twin Cities

Metropolitan Area of Minnesota, Chung and Myers pointed out that big chain supermarkets had much lower price but were not likely to locate in poor areas (Chung and Myers 1999). Researchers from other countries, however, had different findings. The study sites in Canada, Australia and New Zealand (Smoyer-Tomic, Spence, and Amrhein 2006, Apparicio, Cloutier, and Shearmur 2007) showed that middle-income communities had the most access to supermarkets and were better served by the food stores in their neighborhoods. In contrast, Cummins and Macintyre (2002) argued that in United Kingdom, wealthier and poor neighborhoods had no statistically significant differences in access to supermarkets, food prices, or food availability.

Acceptability*:* Acceptability describes *the relationship between consumers' attitudes towards characteristics of food stores (including internal quality and external quality) and the quality of food they provide (Penchansky and Thomas 1981).* Shoppers are both attracted and troubled by a store's physical characteristics, including internal quality and external quality and they enjoy visiting upscale supermarkets with varieties of fresh and attractive produce well stocked and organized (Webber, Sobal, and Dollahite 2010). Few recent studies on food environment, however, have explored the food accessibility on the acceptability dimension based on the store level. Martin et al. (2014) in their research surveyed all small, medium and large-sized supermarkets within a 2-mile buffer of Hartford, CT. In their study, they found that produce quality, internal, and external store appearances, which were the items describing the acceptability dimension, were significantly lower in the stores in Hartford compared to the suburban stores.

Accommodation: Accommodation describes the relationship between the manner in which the grocery stores are organized for ease of shopping (including parameters such as weekly hours of operation and number of people per cashier or open cash counter) and the consumers' ability to accommodate these factors and their perception of their appropriateness *(Penchansky and Thomas*

1981). Webber, Sobal, and Dollahite (2010) in their qualitative research found that one of the most important characteristics of shoppers' ideal store should be "convenience", which conveyed several meanings including the physical closeness and compatible time schedules of a grocery store. Shoppers even would like to pay more dollars for the convenience of shopping in the stores (Webber, Sobal, and Dollahite 2010). Longer hours of operation, pleasant and helpful staff, and efficient and well trained cashiers are all attractive accommodative factors that customer would like during shopping. To our knowledge, there has been no prior attempt to measure the accommodation dimension of shopping in grocery stores as an indicator of overall accessibility.

4.2 Method

4.2.1 Study Area

Our study area is the Greater Harford Area, located at the central part of the state of CT. In 2015, Greater Hartford Area, with 29 townships, had a total population of 758,868. Over the years, however, the region is becoming more ethnically diverse. The minority population in the Greater Hartford area increased 34.3% between 1990 and 2000, which contributed to the region's population growth from 20.8% to 27.5%. Townships such as Harford, East Harford, and Bloomfield especially have higher proportion of minority population than the other towns and cities in the study area. In 2012, median household income in the Greater Hartford area ranged from a low of $26,415 in Hartford to a high of $120,903 in the Town of Avon. In 2015, the median household income for the region increased to $85,997 with a low of $30,630 in Hartford to a high of $123,894 in the town of Avon, further increasing the income inequality.

In Connecticut (CT), according to the Federal Government's survey, the percentage of households with food insecurity rose by approximately 33% from 7.6% in 2000-2002 to 11.4% in

2007–2009 (HartfordFoodSystem 2013). During 2010–2012, the value further increased to 13.4% of households. Out of these households, 36.6% were categorized in the critical level of food insecurity (Coleman, Nord, and Singh 2012).

4.2.2 Data

The data was grouped into the following four categories.

(1) Location of 99 grocery stores (employee count greater than 4 persons) in the Greater Hartford Area of CT within a 5-miles buffer from the town limit were obtained from ESRI's Business Analysis 2014 dataset and Connecticut Department of Energy & Environmental Protection (DEEP). A 5-miles buffer was used for two reasons: first, the residents of Hartford often shop outside their town limits, and second, to minimize errors from edge effects in the subsequent mapping and spatial analysis (Haefner et al. 1991, Lawson, Biggeri, and Dreassi 1999, Laurance 2000, Zhang and Ghosh 2015).

(2) The Geographic Information System (GIS) shapefiles of CT's roads were obtained from ESRI's Business Analysis dataset (2014). The state, town, and the US census block-group boundary shapefiles were from the Map and Geographic Information Center at University of Connecticut (MAGIC 2013).

(3) Neighborhood median household income data and public safety data such as crime rates were obtained from Neighborhood Scout (NeighorhoodScout 2015).

(4) Data on price, availability, and quality of food items were collected using a self-conducted survey (Appendix B) from all the 99 grocery stores in the study area in May 2014. The survey was adapted from Martin et al.'s study (Martin et al. 2014) and USDA's report (Carlson

A and Frazão 2012). Thirty-eight standard and non-seasonal food items were categorized into seven groups of dairy, protein, grains, fruits, vegetables, beverage and canned/staple. These selected items represent a standard basket of healthy food for people's daily lives during all seasons (Martin et al. 2014).

4.2.3 Method

From the above–mentioned data, we calculated the four dimensions of assessments with the following items:

i) availability: number of standard and non-seasonal items out of 38 food items in a basket of food;

ii) affordability: average price of a market basket of food;

iii) acceptability: quality of fresh produce, internal appearance including lighting, cleanliness, and organization, and external appearance including lighting, parking, median household income, and crime rates of the store's neighborhood; and

iv) accommodation: hours of operation, and number of people per open cash counter.

4.2.3.1 Availability

We calculated a percentage value of food items available out of the selected 38 items as the availability score for each store. The value of availability ranges from 0 to 100.

4.2.3.2 Affordability

The food price data was used to measure the affordability dimension for each store. We adapted the methodology from Martin et al.'s study (Martin et al. 2014) to calculate an average food basket price based on the unit price of each items noted on the survey. If an item was not

present in the store at the time of the survey, we noted it as unavailable (NA) in the dataset and used the average price of this missing item during the calculation of food basket price. Higher food basket price is expected to lead to lower affordability i.e. negative impact on overall access.

4.2.3.3 Acceptability

This dimension has 3 sets of indicators with 11 variables:

i) external quality: variables included are appearance, lighting, parking, neighborhood income, and public safety),

ii) internal quality variables included are appearance, lighting, cleanness, organization, and number of other shoppers in a store, and

iii) quality of the available fresh food items.

All of these variables were measured on a Likert scale of 1 (very poor condition/quality) to 5 (very good condition/quality). Out of the 11 variables, two variables were obtained from the Neighborhood Scout (NeighorhoodScout 2015): neighborhood income (median household income based on the neighborhood level) and public safety (annual crime rate by neighborhood) for external quality. The other nine variables were from the survey.

For the fresh produce (fruits and vegetables) listed in the survey, we also collected data on their quality on a 5 point Likert scale: 1 = Very Poor: all or most of the item is of poor quality (brown, bruised, overripe, wilted); 2 = Mixed quality; more poor than good; 3 = Mixed quality; some good some poor; 4 = Mixed quality; more good than poor; 5 = Very good: All or most of the item is of good quality (very fresh, no soft spots, excellent color). We calculated an AQ (availability * quality) score which is the product of availability (available or not, coded as 1 and

0 respectively) and quality (coded as 1 – 5) of the fresh produce for each store to present the quality of the existing fresh food items.

Since the units of these variables were different, each variable was standardized by calculating the ratio of its value to the total value divided by the highest ratio among the stores (See formula 2).

First, each variable was standardized to build the three indicators then each indicator was standardized and equally weighted to build the acceptability dimension with values ranging from 0 to 100.

4.2.3.4 Accommodation

For each store, we collected hours of operation for every day from Monday to Sunday, total number of people waiting (in the check-out area) and open cash counters at the time of the survey. We calculated the total hours of operation per week and the density of open cash counters per people. Longer operation hours and more cashiers per people have positive impact on accommodation, providing more ease and conveniences for shopping. These two variables were standardized (see Formula 2) and weighted equally to build the accommodation dimension of each stores with values ranging from 0 to 100.

Finally, we used the methodology from Zhang and Ghosh's research (Zhang and Ghosh 2015) to calculate the dimensions for the block-groups level from the stores level. By using ArcGIS 10.1's Network Analyst functions a road-network database has been built and the 'Closest Facility' tool were used to calculate the path from each block-group population centroid to its closest three grocery stores (Figure 3.2.3.4). Each block-group were then assigned the average availability, affordability, acceptability, and accommodation values of the closest three stores.

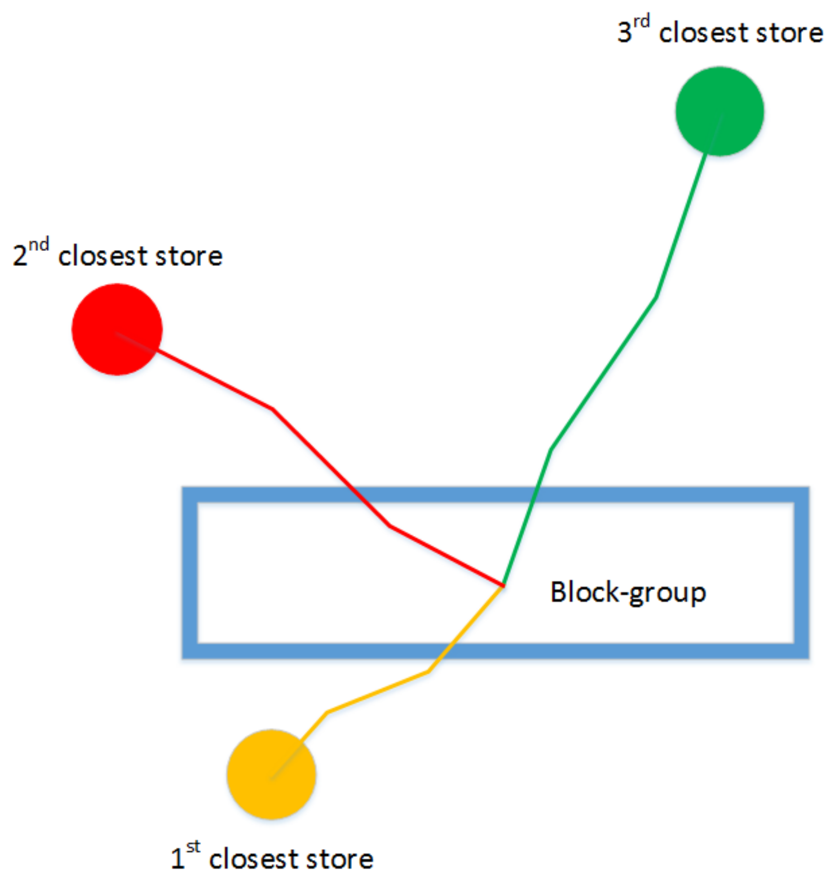

Figure 4.2.3.4: Block-group and its closest three stores

4.3 Results

Out of the 99 grocery stores located in the study area, 75 (75.8%) were located in the 29 towns of the Greater Hartford Area, while the other 24 (24.2%) were in the 5-miles buffer area. The towns of Hartford and West Hartford had the highest number of grocery stores (11 for each town), followed by East Hartford (6), Glastonbury, Granby, and Vernon (5 for each towns). These 6 towns combined, had almost half of the stores (43.4%) of our study area. The towns of Andover, Bolton, East Granby, Marlborough, and Windsor Locks do not have any grocery stores with employee count greater than 4 persons.

4.3.1 Availability

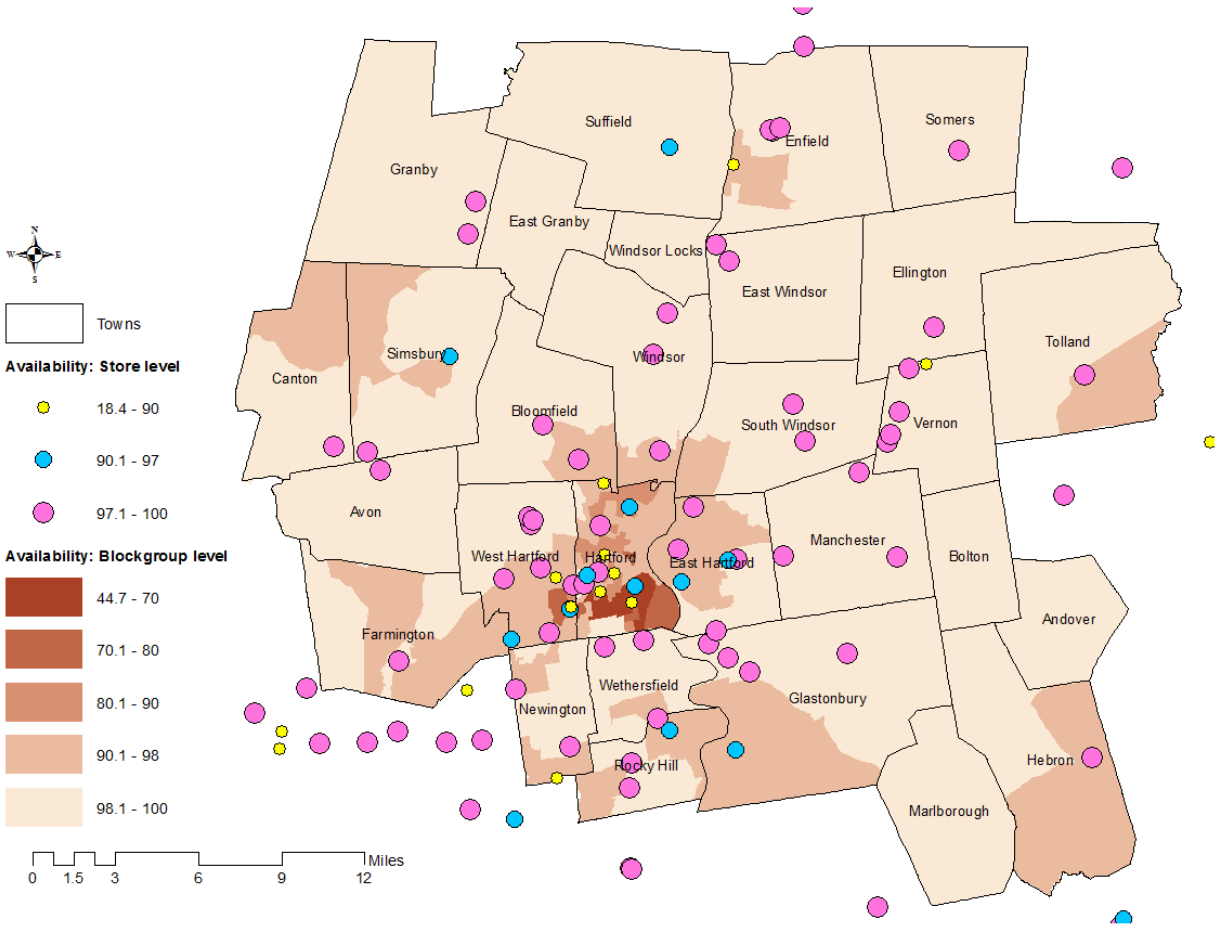

Figure 4.3.1: Availability dimension of grocery stores in Greater Hartford Area of Connecticut

Figure 4.3.1 shows the availability dimension of grocery stores at both the store level (proportional circles) and at the block-group level (polygons). At the store level, 60 out of 99 grocery stores (60.6%) had all the surveyed items with the maximum availability score (100), and 32 grocery stores (32.3%) had the scores between 80 and 99. Five stores had the lowest scores of equal or below 50, which means more than half of the surveyed items were not available in the

store. Three (out of those five stores) were in the 5-miles buffer area and the other two were located in Hartford (44.7) and West Hartford (50).

At the block-group level it was more obvious that the block-groups in Hartford, especially those in the south-central part had the lowest availability score (which is the average standardized availability value of the closest three stores). There were 16 out of 97 block-groups (16.5%) in Hartford that had availability score less than 70, and 8 of them were even below 50, indicating that a large number of items from the food basket were missing in the stores in those communities which might result in higher risk of food insecurity.

In Table 4.3.1, towns of Andover, Bolton, East Granby, Marlborough, and Windsor Locks were excluded since they do not have any grocery stores with employee count greater than 4 persons. The remaining 24 towns were assigned the average availability values for each group categories and the overall availability. Hartford had the highest number of grocery stores (11) but the lowest average overall availability score (84.9%) for the selected 38 food basket items. It also had the lowest availability for 4 out of 7 categories including fruits (93.2%), vegetables (77.9%), dairy (72.7%) and beverage (90.9%). Especially for the average availability of vegetables, Hartford (77.9%) was much lower than the 2nd lowest town of Tolland (85.7%) and the 3rd lowest town of East Hartford (88.1%). Also for the average availability of dairy, Hartford (72.7%) was much lower than the 2nd lowest town of Vernon (80%) and the 3rd lowest town of West Hartford (97%). For fruits, only Hartford (93.2%), Rocky Hill (93.8%), and West Hartford (97.7%) did not have 100% availability. In the meanwhile, Hartford (90.9%) and West Hartford (90.9%) were the only two towns which did not have 100% availability for beverage.

Table 4.3.1: Average availability scores for each town

Town	No. of Stores	Fruits	Vegetables	Dairy	Protein	Grains	Canned	Beverage	Overall Availability
Hartford	11	93.2	77.9	72.7	84.4	87.3	94.8	90.9	84.9
Vernon	5	100	91.4	80	82.9	84	85.7	100	87.4
W Hartford	11	97.7	94.8	97	90.9	89.1	88.3	90.9	92.6
Suffield	1	100	100	100	100	100	71.4	100	94.7
Newington	3	100	100	100	100	100	76.2	100	95.6
E Hartford	6	100	88.1	97.2	100	100	97.6	100	96.9
Hebron	1	100	100	100	100	100	85.7	100	97.4
Tolland	1	100	85.7	100	100	100	100	100	97.4
Canton	1	100	100	100	100	100	85.7	100	97.4
Farmington	1	100	100	100	100	100	85.7	100	97.4
Simsbury	2	100	100	100	85.7	100	100	100	97.4
Enfield	4	100	100	100	92.9	100	92.9	100	97.4
Rocky Hill	4	93.8	100	100	100	100	96.4	100	98.7
Glastonbury	5	100	100	100	100	96.0	97.1	100	98.9
Ellington	1	100	100	100	100	100	100	100	100
Somers	1	100	100	100	100	100	100	100	100
Avon	1	100	100	100	100	100	100	100	100
Bloomfield	2	100	100	100	100	100	100	100	100
E Windsor	2	100	100	100	100	100	100	100	100
Granby	2	100	100	100	100	100	100	100	100
S Windsor	2	100	100	100	100	100	100	100	100
Wethersfield	2	100	100	100	100	100	100	100	100
Manchester	3	100	100	100	100	100	100	100	100
Windsor	3	100	100	100	100	100	100	100	100

4.3.2 Affordability

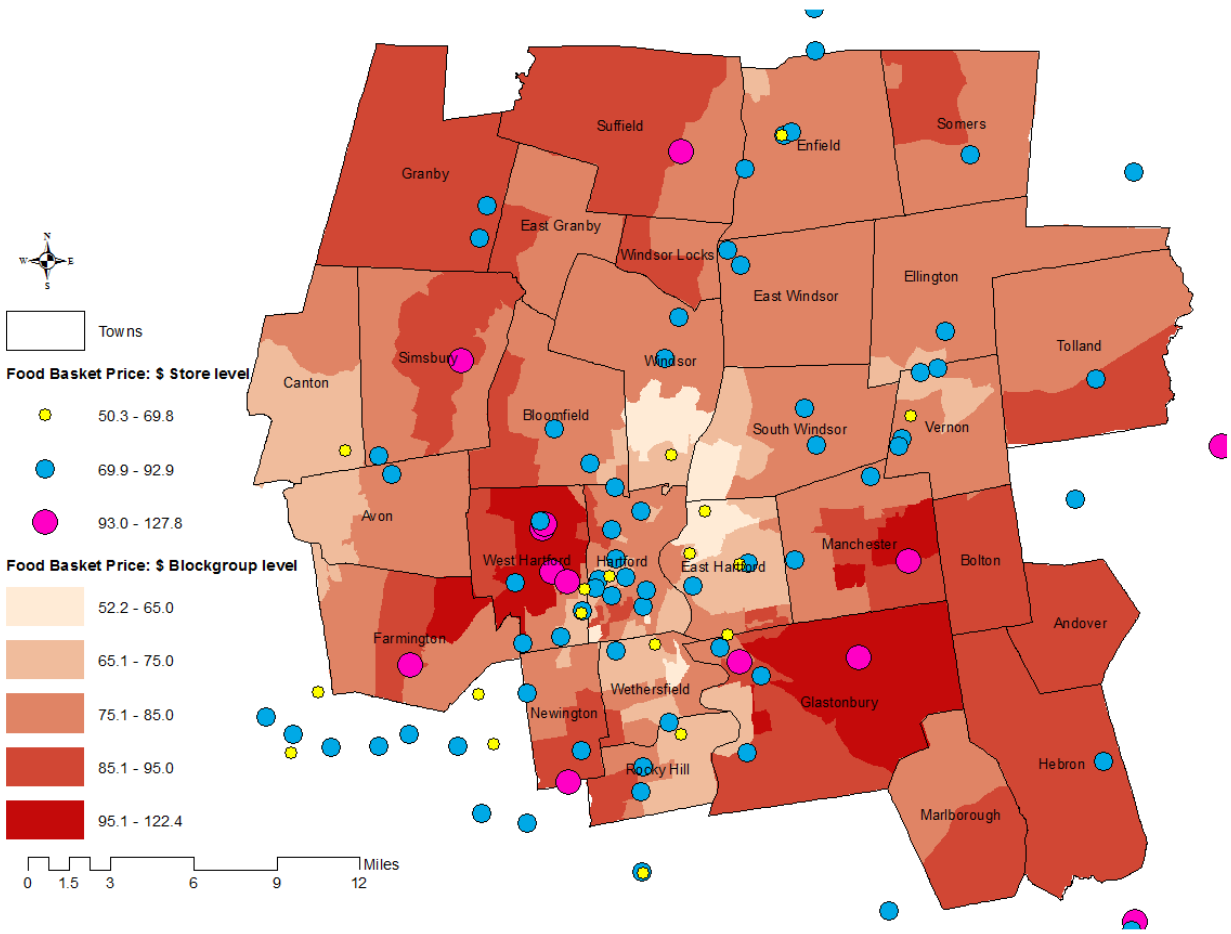

Figure 4.3.2: Affordability dimension of grocery stores in Greater Hartford Area of Connecticut

There were 18 out of 99 surveyed stores (18.2%) that had low food basket prices between $50 and $70 (Figure 4.3.2). Five of them were located in the buffer area and Hartford (2), East Hartford (3), and southeast of West Hartford (2) had more stores with low food basket price ($50 - $70). These cheaper price grocery stores are Price Rite, Aldi, Save-a-lot, and Shop Rite. In contrast, 13 out of 99 stores (13.1%) had highest food basket prices between $95 and $128 and three of them were located in the buffer area. Stores in West Hartford (4) Glastonbury (2), Manchester (1), Farmington (1), Suffield (1), and Simsbury (1) had the most expensive food basket

prices. These expensive grocery stores were Whole Foods, Highland Park, Stew Leonard's (a chain of five supermarkets in CT and New York), and Fitzgerald's Food (a local store).

Table 4.3.2: Average food basket price and neighborhood income ratio for each town

Town	No. of Stores	Food Basket Price ($)	Neighborhood Income ($)	Food basket price/ Income (%)
Hartford	11	78.6	27835	0.282
East Hartford	6	68.0	37261	0.182
Bloomfield	2	79.0	61478	0.129
Enfield	4	78.7	63320	0.124
West Hartford	11	88.5	71827	0.123
Newington	3	88.4	72491	0.122
Vernon	5	77.1	65244	0.118
East Windsor	2	79.9	68212	0.117
Manchester	3	84.6	75690	0.112
Farmington	1	93.6	86316	0.108
Suffield	1	95.4	91151	0.105
Rocky Hill	4	75.7	73614	0.103
Wethersfield	2	67.2	65614	0.102
Granby	2	83.0	82312	0.101
Windsor	3	71.9	72240	0.100
Glastonbury	5	95.0	96883	0.098
Ellington	1	77.6	86310	0.090
Somers	1	87.5	100911	0.087
Tolland	1	86.8	100714	0.086
South Windsor	2	80.1	94147	0.085
Canton	1	67.7	80990	0.084
Avon	1	78.2	100386	0.078
Simsbury	2	88.8	121890	0.073
Hebron	1	80.0	111521	0.072

Based on Table 4.3.2, Suffield ($95.4), Glastonbury ($95), and Farmington ($93.6) were the towns with the highest average food basket price. Comparing with that, Hartford had a much lower average food basket price ($78.6), with the highest price-income ratio (0.282%) due to its lowest neighborhood income ($27,835). This means that even the food basket price was lower in

Hartford, the cost of food still played a much more important role in residents' budget comparing with that of other towns.

4.3.3 Acceptability

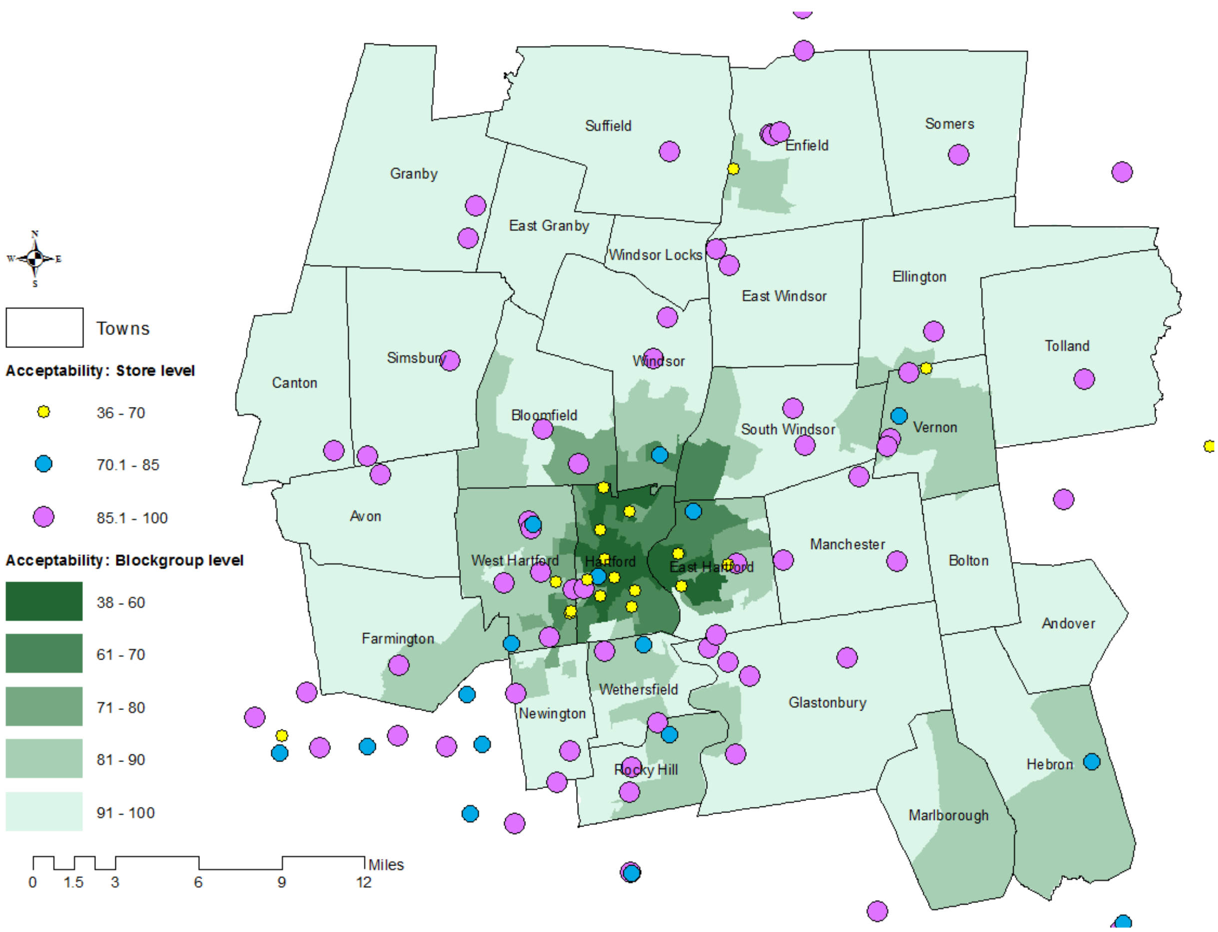

Figure 4.3.3: Acceptability dimension of grocery stores in Greater Hartford Area of Connecticut

We combined the external quality, internal quality, and quality of fresh food items to build the acceptability dimension of grocery stores (Figure 4.3.3). The majority of the surveyed stores (63.6%) located in the suburban towns had higher acceptability scores (85-100). Typically, they

were the large chain stores. However, 19 out of 99 stores (19.2%) had lower scores between 35 and 70. Two of them were in the buffer area. The rest 17 stores were predominantly located in Hartford (9), West Hartford (3), and East Hartford (3). The representatives of low acceptability stores were all small local grocery stores such as C-Town, Carlos, Glorimar and Bravo. The internal, external, and fresh produce quality of these stores were usually in poor condition (rated as 2), and some were even in very poor condition (rated as 1), especially those stores in Hartford such as Glorimar, Carlos, and El Gitano. Combined with low median household income (HartfordFoodSystem 2006, Martin et al. 2014, Jacobson 2014, Zhang and Ghosh 2015) and higher crime rates (mean = 43.2 per 1000 people annually), the residents of these neighborhoods had also limited access to acceptable quality food items in the stores which were not clean, well lit, disorganized, and lacked safe parking options.

4.3.4 Accommodation

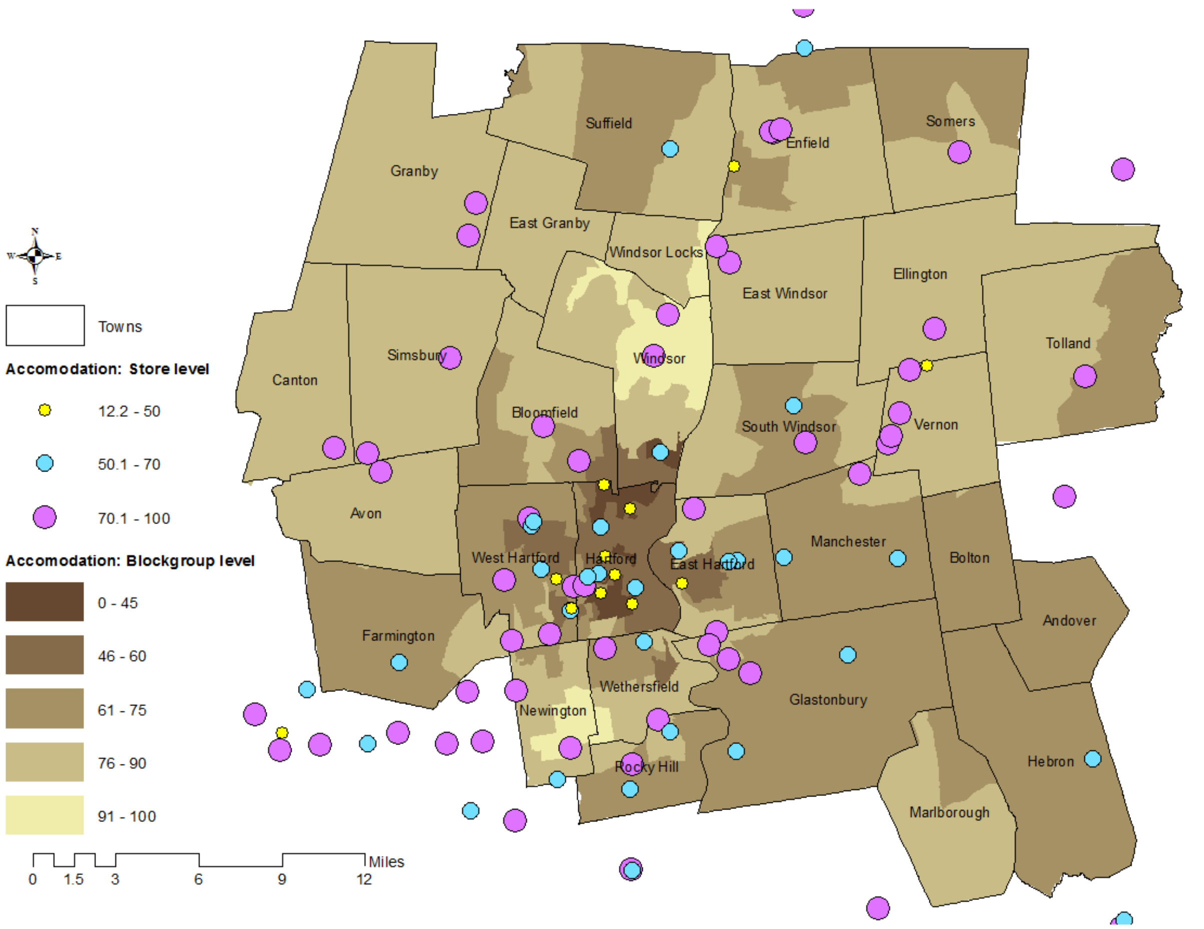

Figure 4.3.4: Accommodation dimension of grocery stores in Greater Hartford Area of Connecticut

Figure 4.3.4 shows the accommodation dimension, which was built on each grocery stores' hours of operation per week and density of open cash counters per people waiting. Thirteen stores (13.1%) had lower accommodation scores (12-50). Two of them were in the buffer area and Hartford had the most stores (6) with the lowest accommodation score, followed by West Hartford (2), and East Hartford (1). Statistical results from the Pearson's Correlation showed high negative correlation between the accommodation score with the neighborhood's crime rate, poverty level, unemployment rate, and ethnic diversity (significant at 0.01 level). This means food store's accommodation score was worse in areas with high crime rate, low median household income,

high percentage of unemployment rate, and ethnic diversity. Food stores located in rich neighborhoods (higher median household income) were organized to accommodate for easy and convenient shopping experiences.

4.4 Discussion and Limitations

We highlight the major contributions of our study here. First, we conducted an exhaustive survey (Appendix B) for collecting data on price, availability, and quality of 38 standard and non-seasonal food items from all the grocery stores (employee count greater than 4 persons) in the Greater Hartford Area of CT with a 5-mile buffer zone from the town limits. Additional information was also collected through this survey such as the internal/external appearance, lighting, cleanliness, parking, organization, hours of operation and number of people waiting per open cash counters during the survey. To the best of our knowledge, we believe that this is the first attempt to compile such a detailed database of grocery stores in the Greater Hartford Area. Second, no prior studies have conceptualized and measured a multidimensional taxonomy of access to grocery stores incorporating dimensions of *availability*, *affordability*, *acceptability* and *accommodation.*

Table 4.4: Average availability, acceptability and accommodation for each town

Town	Availability	Acceptability	Accommodation
Hartford	84.9	68.7	47.0
East Hartford	96.9	80.7	68.3
Hebron	97.4	82.9	54.7
Canton	97.4	87.5	73.2
Vernon	87.4	88.2	78.5
West Hartford	92.6	88.4	67.4
Simsbury	97.4	91.6	77.2
Tolland	97.4	92.9	74.8

Rocky Hill	98.7	93.1	72.8
Granby	100	93.7	78.6
Enfield	97.4	95.6	72.0
Bloomfield	100	96.2	79.9
Wethersfield	100	96.2	67.1
Manchester	100	96.7	67.0
Windsor	100	96.7	80.2
Farmington	97.4	97.5	63.4
Suffield	94.7	97.5	69.6
East Windsor	100	97.5	77.1
Glastonbury	98.9	97.6	71.2
Newington	95.6	99.2	78.7
Avon	100	100	73.4
Ellington	100	100	81.0
Somers	100	100	76.1
South Windsor	100	100	73.7

One of the major findings is the significant variability of the average availability, acceptability and accommodation, with Hartford faring much worse than that of other towns (Table 4.4). Most of the stores in Hartford are small and medium-sized local markets such as Bravo, C-town, Carlos, Glorimar and El Gitano. Comparing with the large chain supermarkets (such as Stop & Shop, Whole Foods, and Big Y) located in the suburban towns, the external quality, internal quality, and quality of fresh food items were generally rated lowest for stores in Hartford leading to the lowest average acceptability. The lower quality (internal quality, external quality and fresh produce quality) may impact customers' willingness to shop in these stores or to purchase fruits and vegetables that contribute to a healthy diet, which can help prevent or mitigate chronic diseases (Webber, Sobal, and Dollahite 2010). Besides that, those small and medium-sized stores in Hartford had the lowest average hours of operation per week (73 h) comparing with that of large chain supermarket such as Big Y (98 -111 h, average of 106 h) and Stop and Shop (104 - 125 h, average of 121 h) in other suburban towns. Comparing with the expensive and upscale grocery stores (such as Whole Foods, Highland Park, Stew Leonard's and Fitzgerald's Food) in the affluent

towns such as Suffield, Glastonbury, and Farmington, those small and medium sized stores in Hartford had a much lower average food basket price ($78.6), but the highest price-income ratio due to its lowest neighborhood income ($27,835). In overall, even though non-chain grocery stores in Hartford offered lower price of non-seasonal and standard food items, these stores were lacking in terms of other dimensions of access such as availability and quality of food, internal/external quality (such as appearance, lighting, organization, and cleanness), and hours of operation.

Such variability of different dimension of access to grocery stores in Hartford raises concerns about food insecurity and food deserts and urges city officials to consider stronger but feasible mitigation policies to fill the possible grocery gap. The policy question to consider here is whether to propose and invest funding in Hartford for more chain large supermarkets or invest on improving the availability of quality food items and external and internal appearances of the existing small to large local grocery stores. Zhang and Ghosh (Zhang and Ghosh 2015) in their recent research provided examples of perceived urban obstacles (lower profit margins, higher crime, and cultural biases about the inner city and minorities) and logistical obstacles (difficulties of finding locations for new stores and purchasing multiple adjacent plots, highest cost of tax rates, insurance and utilities, zoning restrictions, unfamiliarity of needs and desires from investors and hindrances from local politics) to open new chain supermarkets in a city.

Since it is not always feasible to open new stores in cities, already struggling with low income, due to lack of investments, stable markets, and lack of infrastructure related to easy access to highways, large loading docks for large trucks to unload, or distribution networks (Shaffer 2002, Martin et al. 2014), we suggest other mitigation policies to improve access to healthy food items and the grocery gap. These include: a) investing more in not only fresh food (vegetables and fruits) stocks but also other food basket items (such as dairy) at the existing local small to medium-sized

grocery stores (Martin et al. 2012, Zhang and Ghosh 2015). Result from this study shows that Hartford had the highest number of grocery stores but the lowest availability for fruits (93.2%), vegetables (77.9%), dairy (72.7%), and beverage (90.9%). Especially for the average availability of vegetables (77.9%) and dairy (72.7%), Hartford was much lower than other towns (ranged from 85.7% - 100% for vegetables, and 80% - 100% for dairy). When stores carry a greater variety of fruits and vegetables, customers tend to buy them (Martin et al. 2012). Customers are more likely to purchase fresh food when there is a wider variety in the store. b) In the meanwhile, improving both internal and external quality (such as appearance, lighting, organization, parking), quality of fresh produce and longer operation hours of stores in Hartford. Comparing with the large chain supermarkets located in the suburban towns, the internal/external quality of those small to medium-sized stores in Hartford (such as Glorimar, Carlos, and El Gitano) were usually in poor condition (rated as 2) and some were in very poor condition (rated as 1). Food items in those stores were disorganized, floors were not clean, appearance and quality of food were not acceptable. Improving the acceptability and quality of food will potentially improve food purchasing and consumption patterns of low-income residents in Hartford and a potential improvement to food insecurity (Blitstein, Snider, and Evans 2012, Martin et al. 2014).

We hope this study can help influence recommendations for the Hartford Advisory Commission on Food Policy and promote action from other city agencies to improve food availability and quality and store internal/external in Hartford stores. In addition, this research may contribute to decisions by policymakers in other urban communities to allocate resources to improve existing small and medium-sized markets before creating new large stores. Improving the availability and quality of food, and store internal/external quality in urban stores are relatively more plausible than locating a large chain supermarket.

This study also had few limitations. First, we adapted the survey from Martin et al.'s study (Martin et al. 2014) and USDA's report (Carlson A and Frazão 2012) and categorized the selected 38 food items into dairy, protein, grains, fruits, vegetables, beverage and canned/staple seven groups. It was possible that the items in the categories were not exhaustive. For example, in the grains category, we did not look at crackers, chips, or bagels, but instead focused on bread, cereals, and pastas. We guided our selection based on the assumption that the market basket represented a standard basket of healthy food items for people's daily lives during all seasons. Second, the scale used to assess internal, external and produce quality was a subjective measure of quality based on the researcher's own perception although clear and consistent guidelines on how to rate the quality were provided. Data was collected from all the stores by the same researcher to keep the perceptions consistent and minimize bias. Third, this survey was administered in a single month of May in 2014. Although produce supply may vary seasonally, we assumed that the quality, availability, and price of the items were fairly stable over time (Martin et al. 2014).

Chapter 5: ‘Measuring Access to Food by a Robust ‘5A-indicator’

5.1 Introduction

In Chapter 4, we reviewed the concept of food access, food insecurity, and food desert. In terms of methodology, researchers use different techniques and indicators to measure food access which vary across different settings such as rural vs urban or high-income vs low-income neighborhoods (Chung and Myers 1999, Ross and Murphy 1999, Morland et al. 2002, Rose and Richards 2004, Lewis et al. 2005, Block and Kouba 2006, Moore and Roux 2006, Liese et al. 2007, Powell et al. 2007, Mojtahedi et al. 2008, Larson, Story, and Nelson 2009, McKinnon et al. 2009, Mavoa et al. 2012, Tribby and Zandbergen 2012). Some research focused on the accessibility to the number of food stores, or ratio of grocery store to all stores per unit area in a neighborhood (Cummins and Macintyre 2002, Morland, Wing S, and AV. 2002b, Moore and Diez Roux 2006, Block and Kouba 2006) or the minimum distance to the nearest food stores (Zenk SN, Schulz AJ, and Hollis-Neely T et al. 2005). The most common being measuring geographic distance to grocery stores (Azar, Ferreira, and Wiggins 1994, Nyerges 1995). Advances are also made on the computation of geographic distance, that is, from the Euclidean distance or as the ‘crow flies’ to distance on road network (Aultman-Hall, Roorda, and Baetz 1997, Liu and Zhu 2004, Widener, Metcalf, and Bar-Yam 2011, Wu and Murray 2005), to travel time (Liu and Zhu 2004, Hillman and Pool 1997, O'Sullivan, Morrison, and Shearer 2000, Gent and Symonds 2005, Lei and Church 2010, Widener and Shannon 2014) by a car (Couclelis 1992, Van Bemmelen et al. 1993, Handy and Niemeier 1997, Bamford et al. 1998, Talen and Anselin 1998, Cervero, Rood, and Appleyard 1999, Fortney et al. 1999, Witten, Exeter, and Field 2003, Liu and Zhu 2004, Zenk, Schulz, Israel, et al. 2005, Goodchild, Yuan, and Cova 2007, Apparicio, Cloutier, and Shearmur 2007, Jones et

al. 2010) and public transit (Witten, Exeter, and Field 2003, Liu and Zhu 2004, Hadas and Ranjitkar 2012, Hadas 2013). Although widely used, this indicator of access is still one-dimensional and only measures the spatial relation of location of households and food stores. Many researchers in the field of healthcare (Aday and Andersen 1974, Salkever 1976, Penchansky and Thomas 1981, Dutton 1986, Frenk and White 1992, Margolis et al. 1995, Gulliford et al. 2002, Haddad and Mohindra 2002, Peters et al. 2008, Levesque, Harris, and Russell 2013, Shengelia, Murray, and Adams 2003, Gibson et al. 2014) argue that access is a multidimensional concept. For example, while some health studies still focused on geographic accessibility to healthcare facilities (Arcury et al. 2005, Pilkington et al. 2012), other studies used affordability of receiving care (Guagliardo 2004, Wang and Luo 2005) or variety of healthcare services provided at the facilities (Guagliardo 2004, Wang and Luo 2005) as a measure of access. Amongst them, Penchansky and Thomas (1981) described a robust taxonomy of access to healthcare facilities including dimensions such as *availability, accessibility, accommodation, affordability, and acceptability*. This concept has been further adapted by several other researchers from public health, social work, and economics (Gulliford et al. 2002, Peters et al. 2008, Levesque, Harris, and Russell 2013, Gibson et al. 2014). Gulliford et al. (2002) pointed out that access in terms of utilization is dependent on the affordability, physical accessibility and acceptability of service and not mere adequacy of supply. In another study, Penchansky's dimensions were conceptualized to 1) approachability, 2) acceptability, 3) availability and accommodation, 4) affordability and 5) appropriateness (Levesque, Harris, and Russell (2013). While the concepts of acceptability (ability to seek), availability and accommodation (ability to reach), and affordability (ability to pay) was similar to Penchansky's, approachability and appropriateness were defined as the ability to perceive and ability to engage respectively.

There is no study to our knowledge, which has applied Penchansky and Thomas (1981) robust framework to understand access to grocery stores from availability, acceptability, affordability, accommodation and accessibility those five dimensions. Therefore, the main objective of this paper is to describe an empirical approach to model the access to local stores from the above 5A indicators and identify the critical area with lower food accessibility. The paper is organized as follows. Section 5.1.1 provides a short review of the prior and current research on measuring multidimensional food accessibility; Section 5.2 describes the study area (5.2.1), data (5.2.2), methodology (5.2.3); Section 5.3 explains the results with further discussions and limitations mentioned in Section 5.4.

5.1.1 Measuring geographic accessibility

In section 2.2.1, we reviewed the existing approaches of measuring geographic accessibility into two broad categories of spatial (travel distance) and spatiotemporal (travel distance and travel time) approaches for both car and public transit. We further divide these categories by popular data models and methods used in a GIS such as the object-based vector model (Euclidean travel distance) and the field-based raster model (travel cost distance) (Sander et al. 2010). The vector data model can also be extended to incorporate network or graph features and is referred to as a network data model (see Table 2.1.1).

Euclidean distance is the most widely used technique of measuring geographic accessibility and it is easy to calculate and conceptually straightforward. However, people usually travel along road or sidewalk network and thus may not perceive distances as straight lines. From the measurement perspective, Euclidean distance is simplistic and does not incorporate transportation structures (density of road network, road type), travel time (speed limit, traffic congestion at a

particular time), and modality (private car or public transit). Vector-based road-network distance calculates ‘travel distance’ and is a significant improvement over straight-line distance. Even though this measure may correspond more accurately to human perceptions of geographic or spatial accessibility, it lacks to incorporate temporal impedances such as speed limits (van Eck and De Jong 1999, Liu and Zhu 2004), diurnal variation of travel time due to traffic congestion, or variation of travel time between week or weekend days (Arentze, Borgers, and Timmermans 1994, O'Sullivan, Morrison, and Shearer 2000, Polzin, Pendyala, and Navari 2002, Kim and Kwan 2003, Leggat et al. 2012, Mavoa et al. 2012, Farber, Morang, and Widener 2014).

Travel time, instead, is a much more accurate measure of accessibility and calculating time by different modes of transportation such as car or public transit is even more realistic to understand the equity of access among different groups of population. Despite the growing evidences of representing geographic accessibility by car travel time (O'Sullivan, Morrison, and Shearer 2000, Liu and Zhu 2004, Burns and Inglis 2007a, Yigitcanlar et al. 2007, Lei and Church 2010, Delamater et al. 2012, Owen and Levinson 2013, Tallis 2014), there is relatively little research on calculating travel time using public transit (O'Sullivan, Morrison, and Shearer 2000, Huang and Wei 2002, Polzin, Pendyala, and Navari 2002, Liu and Zhu 2004, Currie 2004, Burns and Inglis 2007b, Yigitcanlar et al. 2007, Lei and Church 2010, Curtis and Scheurer 2010, Currie 2010, Mavoa et al. 2012, Owen and Levinson 2013, Farber, Morang, and Widener 2014, Tallis 2014). In Chapter 2, we designed and built a user-friendly ArcGIS toolbox first combining Google Direction API and GIS to calculate historical or real travel time for different modes of transportation. It does not need any additional detailed transit data (such as GTFS) but can provide a lot more accurate travel time results incorporating traffic condition, road works, waiting time for the public transit etc.

5.1.2 Measuring multidimensional accessibility

In Chapter 4, from either a seller or a buyer's perspectives, we explored multidimensional accessibility to grocery stores from 1) availability, 2) affordability, 3) acceptability and 4) accommodation those four aspects (Penchansky and Thomas 1981) by using food access survey which included price, quality, and variety of available food items, and external and internal appearances of the large to small sized grocery stores in Hartford and adjacent towns. Availability describes the relationship between the volume and type of existing food stores to the volume and types of household needs; affordability is the relationship between prices of food and the consumers' income, ability to pay, and other social-economic indicators; acceptability describes the relationship between consumers' attitudes towards characteristics of food stores (including internal quality and external quality) and the quality of food they provide; accommodation describes the relationship between the manner in which the grocery stores are organized for ease of shopping (including variables such as weekly hours of operation and number of cashier per people in the line) and the consumers' ability to accommodate these factors and their perception of their appropriateness.

This section further expended into the fifth dimension of access.

Accessibility: Accessibility describes the relationship between the location of food stores and the location of customer, taking account of the household transportation choices and travel time *(Penchansky and Thomas 1981)*. While a plethora of approaches exist to measure geographic accessibility, there is relatively little research on measuring accessibility by travel time. This is perhaps due to lack of availability of transit data, easy to use tools to calculate travel time, and more sophisticated analyses required due to the complexity of the trips that can be undertaken by

transit (Gulliford et al. 2002, Mavoa et al. 2012). Travel time, instead, is a much more accurate measure of accessibility and calculating time by different modes of transportation such as car or public transit is even more realistic to understand the equity of access among different groups of population. Despite the growing evidences of representing geographic accessibility by car travel time (O'Sullivan, Morrison, and Shearer 2000, Liu and Zhu 2004, Burns and Inglis 2007a, Yigitcanlar et al. 2007, Lei and Church 2010, Delamater et al. 2012, Owen and Levinson 2013, Tallis 2014), there is relatively little research on calculating travel time using public transit (O'Sullivan, Morrison, and Shearer 2000, Huang and Wei 2002, Polzin, Pendyala, and Navari 2002, Liu and Zhu 2004, Currie 2004, Burns and Inglis 2007b, Yigitcanlar et al. 2007, Lei and Church 2010, Curtis and Scheurer 2010, Currie 2010, Mavoa et al. 2012, Owen and Levinson 2013, Farber, Morang, and Widener 2014, Tallis 2014). Zhang et al.'s study (Zhang, Ghosh, and Liu 2017), to our knowledge, first combined Google Direction API and GIS and designed a customized ArcGIS toolbox – Transit Time Calculator (TTC) to calculate historical or real travel time for different modes of transportation. The users of the proposed toolbox (TTC) are not required to have a programming background or need to use additional detailed transit data. In this study, we will adopt TTC to calculate travel time by car and by public transit.

5.2 Method

5.2.1 Study Area

Our study area is city of Hartford, Connecticut (CT), which has a diverse population. The population is primarily urban with approximately 125,000 people in 2014 (ESRI 2014), of which 45.6% are Hispanics, followed by non-Hispanic blacks (35.2%) and non-Hispanic whites (13.9%) (ESRI 2014). The poverty rate is 32.9%, almost twice the poverty rate of United States (Martin et

al. 2012, United-States-Census-Bureau 2013b). Similar is the comparison of unemployment rates between Hartford (14.8%) and United States (7%) (Connecticut Department of Labor 2013; US-Bureau of Labor Statistics 2014). The median household income in 2013 was estimated at $27,417, which was less than half of both the median household incomes for the Hartford County and for the nation (United-States-Census-Bureau 2013a, 2012). In 2013, the crime rate per 1,000 residents was 52.27 including 11.96 violent crimes and 40.31 property crimes, which made Hartford one of high-crime cities in the Unites States (NeighorhoodScout 2015).

The residents of Hartford also experience health disparities. In 2013, approximately 48% of children in Hartford lived below the poverty line, which is almost 3.5 times higher than that of nation's child poverty rate of 14.3% (Zhang and Ghosh 2015). A study found that the prevalence of childhood obesity among preschool children in Hartford was more than twice as high as Centers for Disease Control and Prevention's (CDC) age and gender adjusted body mass index guidelines (University-of-Connecticut's-Center-for-Public-Health-and-Health-Policy 2012). Due to lack of access to nutritionally balanced foods in some neighborhoods, both the children and the adults of Hartford are at increased risk of diet-related negative health outcomes.

In terms of public transportation and connectivity, Hartford has over 30 local and 12 express bus routes. Many local routes operate 7 days a week and express services operate on weekdays only (CTTransit 2015). A large number of residents in Hartford avail by public transit, which is an inexpensive transportation option for their daily commute. The NeighorhoodScout (2015)'s research shows that more than 33% of households in the neighborhoods of downtown Hartford do not own a car. Out of 97 block-groups in Hartford, 57 block-groups (63.33%) have 10% or more households with no access to a vehicle (Census 2013). Residents living in these neighborhoods will likely depend on public transit for their daily activities and commute.

5.2.2 Data

The data was grouped into the following five categories.

(1) Location of 36 grocery stores (employee count greater than 4 persons) in the city of Hartford and its 3-mile buffer from the town limit were obtained from ESRI's Business Analysis 2014 dataset and Connecticut Department of Energy & Environmental Protection (DEEP). A 3-miles buffer was used for two reasons: first, the residents of Hartford often shop outside their town limits, and second, to minimize errors from edge effects in the subsequent mapping and spatial analysis (Haefner et al. 1991, Lawson, Biggeri, and Dreassi 1999, Laurance 2000, Zhang and Ghosh 2015).

(2) The Geographic Information System (GIS) shapefiles of CT's roads were obtained from ESRI's Business Analysis dataset (2014). The state, town, and the US census block-group boundary shapefiles were from the Map and Geographic Information Center at University of Connecticut (MAGIC 2013).

(3) Neighborhood median household income data and public safety data such as crime rates were obtained from Neighborhood Scout (NeighorhoodScout 2015).

(4) Data on price, availability, and quality of food items were collected using a self-conducted survey (Appendix B) from all the 36 grocery stores in the study area in May 2014. The survey was adapted from Martin et al.'s study (Martin et al. 2014) and USDA's report (Carlson A and Frazão 2012). 38 standard and non-seasonal food items were categorized into seven groups of dairy, protein, grains, fruits, vegetables, beverage and canned/staple. These selected items

represent a standard basket of healthy food for people's daily lives during all seasons (Martin et al. 2014).

(5) Travel time by public-transit and by car from the population centroids of the block-groups to the large supermarkets were calculated by using the proposed Transit Time Calculator (TTC) - a Google Direction API application based on prior research (Zhang, Ghosh, and Liu 2017). Travel time by a bus included walking to a bus stop, time on the bus to the store, and then off the bus and walking to the stores.

5.2.3 Method

From the above–mentioned data, we calculated the five dimensions of assessments with the following items:

v) availability: number of standard and non-seasonal out of 38 food items in a basket of food;

vi) affordability: average price of a market basket of food and neighborhood household income;

vii) acceptability: quality of fresh produce, internal appearance including lighting, cleanliness, and organization, and external appearance including lighting, parking, median household income, and crime rates of the store's neighborhood;

viii) accommodation: hours of operation, and open cash counters per waiting people; and

ix) accessibility: comprehensive travel time (by car and by public transit).

5.2.3.1 Availability

We calculated a percentage of food items available out of the selected 38 items as the availability score for each store. The value of availability ranges from 0 to 100.

5.2.3.2 Affordability

The food price data and neighborhood median household income data were used to measure the affordability dimension. We adapted the methodology from Martin et al.'s study (Martin et al. 2014) to calculate an average food basket price based on the unit price of each items noted on the survey. If an item was not present in the store at the time of the survey, we noted it as unavailable (NA) in the dataset and used the average price of this missing item during the calculation of food basket price. We divided food basket price by the neighborhood median household income got the price-income ratio which represented the importance of cost of food in residents' budget. We used 1 minus the price-income ratio to represent affordability which ranges from 0 to 1. Higher price-income ratio is expected to lead to lower affordability i.e. negative impact on overall access.

5.2.3.3 Acceptability

This dimension has 3 sets of indicators with 11 variables:

iv) external quality: variables included are appearance, lighting, parking, neighborhood income, and public safety,

v) internal quality variables included are appearance, lighting, cleanness, organization, and number of other shoppers in a store, and

vi) quality of the available fresh food items.

All of these variables were measured on a Likert scale of 1 (very poor condition/quality) to 5 (very good condition/quality). Out of the 11 variables, two variables were obtained from the Neighborhood Scout (NeighorhoodScout 2015): neighborhood income (median household income based on the neighborhood level) and public safety (annual crime rate by neighborhood) for external quality. The other nine variables were from the survey.

For the fresh produce (fruits and vegetables) listed in the survey, we also collected data on their quality on a 5 point Likert scale: 1 = Very Poor: all or most of the item is of poor quality (brown, bruised, overripe, wilted); 2 = Mixed quality; more poor than good; 3 = Mixed quality; some good some poor; 4 = Mixed quality; more good than poor; 5 = Very good: All or most of the item is of good quality (very fresh, no soft spots, excellent color). We calculated an AQ (availability * quality) score which is the product of availability (available or not, coded as 1 and 0 respectively) and quality (coded as 1 to 5) of the fresh produce for each store to present the quality of the existing fresh food items.

Since the units of these variables were different, each variable was standardized by calculating the ratio of its value to the total value divided by the highest ratio among the stores (See formula 2).

First, each variable was standardized to build the three indicators then each indicator was standardized and equally weighted to build the acceptability dimension with values ranging from 0 to 100.

5.2.3.4 Accommodation

For each store, we collected hours of operation for every day from Monday to Sunday, total number of people waiting (in the check-out area) and open cash counters at the time of the survey.

We calculated the total hours of operation per week and the density of open cash counters per people. Longer operation hours and more cashiers have positive impact on accommodation, providing more ease and conveniences for shopping. These two variables were standardized (see Formula 1) and weighted equally to build the accommodation dimension of with values ranging from 0 to 100.

Finally, we used the methodology from Zhang and Ghosh's research (Zhang and Ghosh 2015) to calculate the dimensions for the block-groups level from the stores level. By using ArcGIS 10.1's Network Analyst functions a road-network database has been built and the 'Closest Facility' tool were used to calculate the path from each block-group population centroid to its closest three grocery stores (Figure 4.2.3.4). Each block-group were then assigned the average availability, affordability, acceptability, and accommodation values of the closest three stores.

5.2.3.5 Accessibility

Comprehensive travel time (Formula 1) to the closest three grocery stores from each block-group centroid in the study area was calculated in Chapter 2. Food desert literature show evidences that it is likely we do not always buy groceries from the nearest store, and hence we chose the closest three grocery stores (Zhang and Ghosh 2015) and finally calculated the average comprehensive travel time value for each block-group.

$$Comprehensive\ Travel\ Time = NV \times PT + (1 - NV) \times CT \text{ .... (Formula 1)}$$

NV: Percentage of households without vehicles in a given block-group;

PT: Public transit time;

CT: Car travel time.

By using the variable, percentage of households without vehicles (NV), this equation combines travel time by both car and public transit for a given block-group. This provides a comprehensive and more realistic way to describe access to grocery stores because in a given block-group there will be households with both with and without access to cars. The value of the percentage of household without vehicles (NV) ranges from 0 to 1. If the value for a block-group is close to 1, it indicates that the block-group has very high proportion of households with no access to personal vehicles and is mostly dependent on public transit for transportation. On the contrary, if the value is close to 0, households of the block-group have access to vehicles and are not entirely dependent on public transit. We chose four representative times-points for our calculation: Wednesday at 10 am and 5 pm and Saturday at 10 am and 5 pm. The selected times-points reflect weekday, weekend, and rush hour commute times. In this study, we calculated the average car travel time, average bus travel time and the comprehensive travel time on the chosen four representative times-points.

5.2.3.6 5A Food Access Index

In this study, we adopted Penchansky and Thomas (1981)'s research, built a robust taxonomy of access to grocery stores including availability, acceptability, affordability, accommodation and accessibility. Since the units of these five indicators (five access dimensions) were different, each indicator was standardized by calculating the ratio of its value to the total value divided by the highest ratio among the block-groups (See Formula 2).

Due to the lack of prior literature and statistical evidence needed to assign specific weights to calculate the 5A index, all As were first given the same importance of equal weights (Laurance 2000, Cutter, Boruff, and Shirley 2003, Wood, Burton, and Cutter 2009) in Model 1 (Table 5.2.3.6

and Figure 5.2.3.6). The final 5A Food Access Index was rescaled from 0-100. Next, we built five other models to increase the weight of each As (from 20% to 40%) separately and kept the remaining As the same weight (15%) to test the sensitivities of each indicators (Table 5.2.3.6 and Figure 5.2.3.6). In Model 2, availability has been assigned more weight (40%) than the other 4As (15% for each), which means consumers would like to have a healthy diet and they don't want to miss any food basket items. In Model 3, acceptability has the highest weight (40%) means consumers focus more on the characteristics of food stores (including internal quality and external quality) and the quality of food they provide. They have higher food quality standard and would prefer shopping in a better and more pleasant environment. Model 4 describes a condition that affordability is more important to the consumers. Price of food is the priority criteria during their shopping experiences which might due to their limited financial situation. In Model 5, accessibility has been given the highest weight (40%) showing consumers may not be able to travel longer time/distance. Either they don't have a vehicle or dur to their limited financial situation.

Those six models were perhaps incomplete and do not reflect the real scenario. It is possible that residents would give different importance rate to each As. For instance, residents who are socioeconomic vulnerable living in the city of Hartford, especially in the northern neighborhoods, where 20% - 76% of the population do not have vehicles (ESRI 2011) might rate accessibility and affordability more important than other 3As. So model 4 and 6 will be more applicable to them. Affluent suburban neighborhoods with higher socio-economic status live in the suburbs might prefer to shop in grocery stores with more choices of fresh produce, and higher quality of food and service. Under this condition, they may rate availability (Model 2), acceptability (Model 3) and accommodation (Model 5) more important than accessibility and affordability since they are able to drive longer distance/time and afford higher food basket prices.

Table 5.2.3.6: 5A Weight Testing (%)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Availability	20	40	15	15	15	15
Acceptability	20	15	40	15	15	15
Affordability	20	15	15	40	15	15
Accommodation	20	15	15	15	40	15
Accessibility	20	15	15	15	15	40
Total	100	100	100	100	100	100

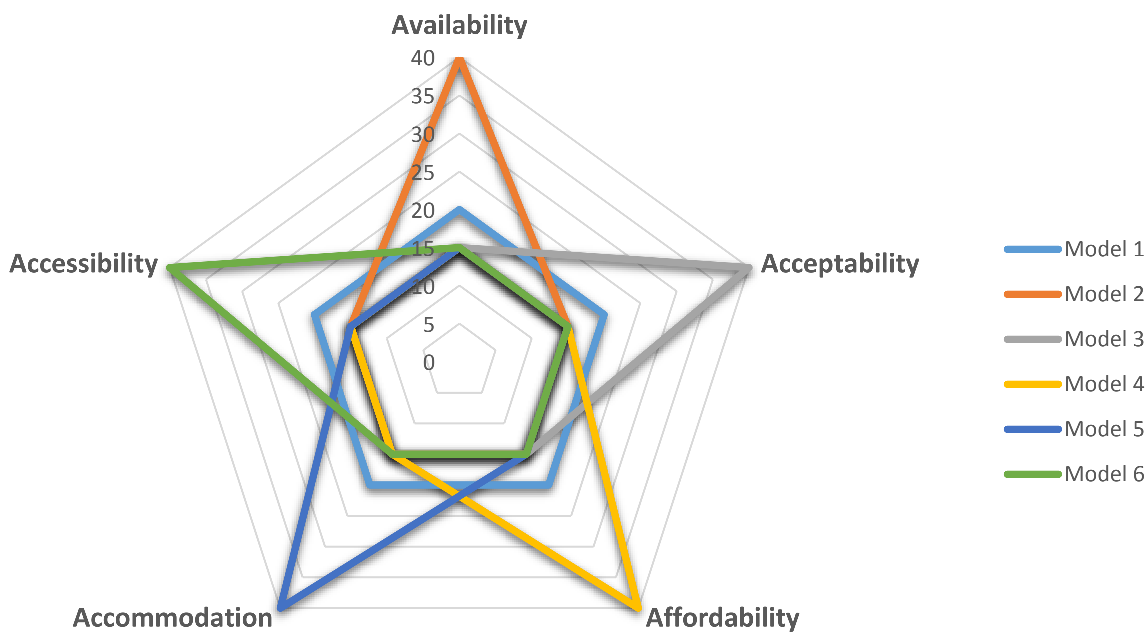

Figure 5.2.3.6: 5A Weight Testing

5.3 Results

Out of the 36 grocery stores located in the study area, 11 (30.6%) were located in the city of Hartford, while the other 25 (69.4%) were in the 3-miles buffer area.

5.3.1 Comprehensive Travel Time

The average car travel time ranged from 1 to 13 minutes for the study area. Figure 5.3.1A shows that from more than 58.6% of the block-groups in the study area, it took on average 4 – 8 minutes by car to travel to the nearest three grocery stores from their centroids on the chosen four representative times-points. While from 40% of the block-groups, it took on less than 4 minutes. However in the city of Hartford, 36% of the population did not have access to a car, especially for residents living in the northern neighborhoods, where 20%-76% of the population do not have to vehicles (ESRI 2011). Therefore, conceiving accessibility solely by car was not likely to adequately represent the population who have no vehicle availability and therefore need consideration the most. Figure 5.3.1B shows the travel time by public transit, in which 197 block-groups (75%) in deepest shade represent longer travel time (7.1 – 13 minutes) from the population centroids to the nearest three grocery stores on the chosen four representative times-points. These block-groups were located in and northeast of Hartford and suburbs beyond the city boundary. Forty-three block-groups (16.3%) which located in the suburbs were not able to be reached by the public transport for grocery shopping. It indicated that the public transportation is mainly focused in the city and that there is less connectivity between city and the suburbs. Figure 5.3.1C shows the average comprehensive travel time to the closest three grocery stores from each block-group centroid in the study area on the chosen four representative times-points. Thirty-four out of 263 block-groups (13.7%) in deepest shade represent longer travel time (7.1 – 12 minutes). Eighteen of them were from city of Hartford and the rest sixteen were in the 3-mile buffer.

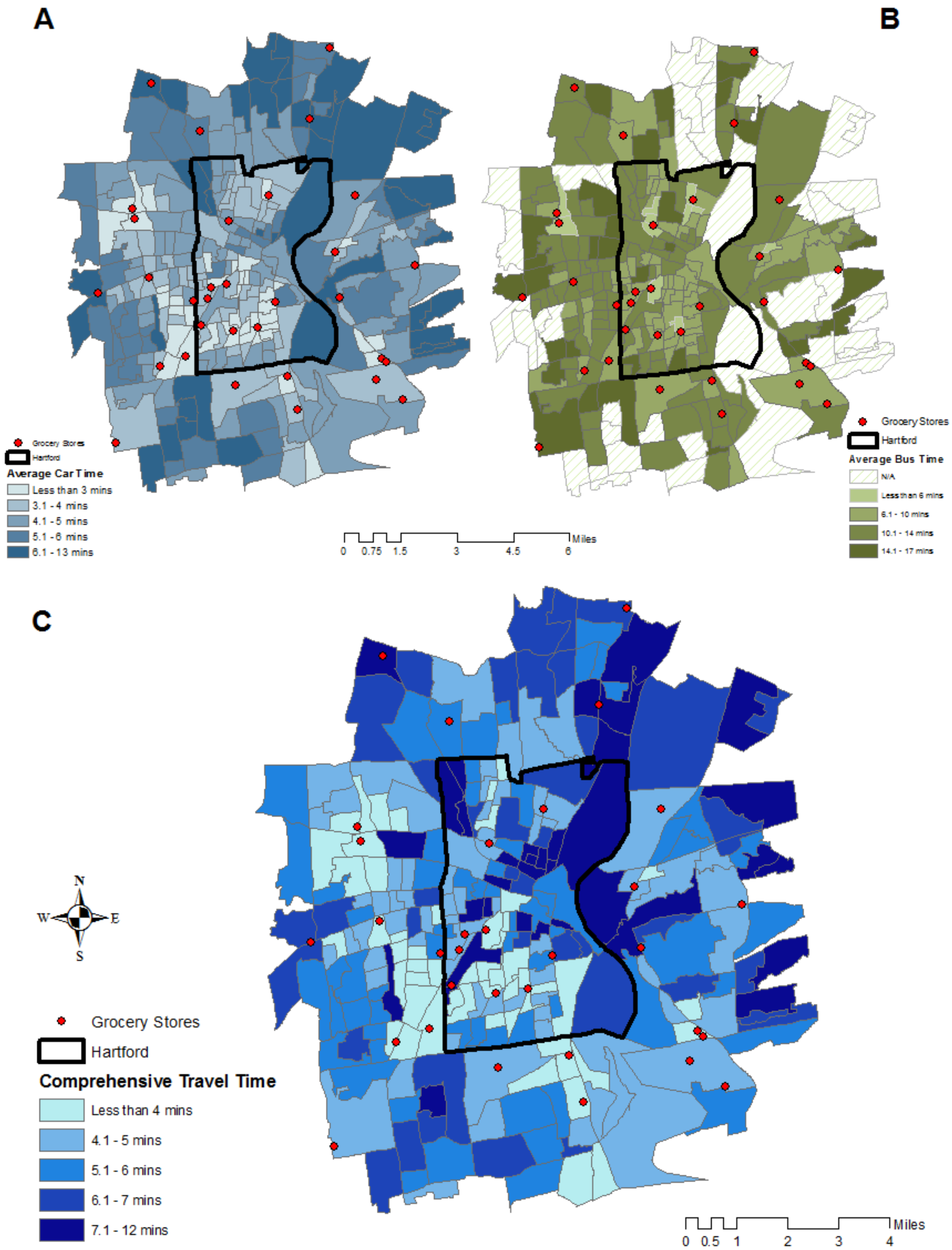

Figure 5.3.1: A) Average Car Travel Time; B) Average Bus Travel Time C) Average Comprehensive Travel Time

In Table 5.3.1, town of West Hartford (5.19 minutes), Wethersfield (5.49 minutes), Newington (5.7 minutes) and Hartford (6.08 minutes) had the relatively higher accessibility with shorter comprehensive travel time. While Andover (11.82 minutes), Hebron (11 minutes), Marlborough (10.28 minutes) and Granby (10.09 minutes) had the relatively lower accessibility with longer comprehensive travel time (Table 5.3.1).

Table 5.3.1: Average travel time by towns

Town	No. of BG	NV	Car Time (mins)	Bus Time (mins)	Comprehensive (mins)
Andover	5	0.9%	10.65	82.36	11.82
Hebron	10	0.5%	10.41	84.72	11.00
Marlborough	11	0.6%	9.99	89.06	10.28
Granby	14	2.1%	9.75	29.18	10.09
Tolland	14	1.8%	9.73	33.02	10.05
Canton	12	2.2%	9.48	34.79	9.85
Somers	12	0.8%	9.75	40.72	9.66
Bolton	13	1.6%	8.86	55.55	9.65
Suffield	19	2.6%	8.64	45.73	9.57
Farmington	25	2.5%	8.37	46.90	9.31
East Granby	16	2.1%	8.42	58.18	9.30
Simsbury	31	3.4%	8.15	43.00	9.22
Avon	25	2.8%	8.33	49.11	9.22
East Windsor	20	3.2%	7.40	47.79	8.20
Ellington	27	1.9%	7.95	31.09	8.14
Enfield	40	4.0%	6.92	40.32	8.01
Windsor Locks	18	2.6%	7.00	53.38	7.94
Bloomfield	32	5.6%	6.49	40.90	7.79
Glastonbury	32	2.0%	7.23	47.77	7.73
Windsor	43	4.2%	6.42	42.21	7.34
East Hartford	50	11.6%	5.54	22.38	6.91
South Windsor	26	2.0%	6.20	35.85	6.67
Rocky Hill	24	5.1%	5.03	32.54	6.64
Vernon	32	2.4%	6.10	29.21	6.58
Manchester	61	5.6%	5.51	25.12	6.34
Hartford	122	24.7%	4.14	13.81	6.08
Newington	36	4.5%	4.85	25.76	5.70
Wethersfield	37	6.2%	4.56	22.74	5.49
West Hartford	92	7.8%	4.46	17.28	5.19

The table 5.3.1 shows city of Hartford had higher accessibility due to the shortest average travel time to the grocery stores by both car (4.14 minutes) and public transit (13.81 minutes) with more low-income residents than the suburban areas (with more affluent residents). The affluent residents of the suburbs are less likely to depend on public transport for their groceries and low-income residents of the city of Hartford with no access to vehicles (24.7%) are dependent on public transportation. The comprehensive travel time combines the travel time by both car and public transit (Figure 5.3.1C) by using Formula 1. Suburban towns like Andover, Hebron, and Marlborough had the longest average car travel time (9.99 – 10.65 minutes) and bus travel time (82.36 – 89.06 minutes) which lead to the longest average comprehensive travel time (10.28 – 11.82 minutes) even they had relatively lower NV (percentage of households without vehicles) ranged from 0.5% - 0.9% (Table 5.3.1).

5.3.2 5A Food Access Index

Figure 5.3.2 shows the spatial distribution of six 5A Food Access Index models by giving different weights to each As at census block-group level in our study area. Our first observation was that block-groups in deepest shade representing the lowest 5A Food Access Index (less than 60) were all located in the city of Hartford. Majority of the block-groups in Hartford had 5A Food Access Index between 60 and 80. This indicated that residents living in city of Hartford with limited food access facing higher potential of food insecurity and food desert.

Figure 5.3.2: 5A Food Access Index

In Table 5.3.2.1 it was more obvious that city of Hartford had the lowest 5A Food Access Index (ranged from 59.63 to 70.62) from all the six models. Town of Vernon had the highest 5A Food Access Index in Model 1 (84.61, equal weight for 5As), Model 2 (88.33, availability had the highest weight), and Model 5 (84.17, accommodation had the highest weight). Town of Canton had the highest 5A Food Access Index (82.94) in Model 4 (affordability had the highest weight) and Newington had the highest Food Access Index (82.89) in Model 6 (accessibility had the highest weight).

Table 5.3.2.1: Average 5A Food Access Index for each town

Town	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Andover	78.28	83.36	81.58	77.89	75.09	73.48
Avon	83.26	87.17	86.10	82.62	80.94	79.47
Bloomfield	77.94	82.67	79.28	75.69	75.33	76.72
Bolton	80.86	85.50	84.10	79.60	77.83	77.30
Canton	83.31	87.09	86.12	82.94	81.45	78.96
East Granby	83.19	87.14	86.03	81.20	82.21	79.35
East Hartford	75.81	81.22	76.76	71.26	73.92	75.88
East Windsor	83.60	87.69	86.18	80.87	82.64	80.61
Ellington	83.48	87.56	86.18	80.74	82.36	80.57
Enfield	83.00	87.13	85.53	80.80	81.22	80.32
Farmington	80.96	85.23	83.80	79.52	78.60	77.67
Glastonbury	81.77	86.04	84.67	79.69	78.82	79.64
Granby	82.66	86.56	85.71	81.37	81.40	78.26
Hartford	65.26	70.62	65.14	59.63	62.21	68.68
Hebron	78.47	83.49	81.28	77.94	75.29	74.33
Manchester	82.51	86.83	85.29	79.89	79.15	81.40
Marlborough	80.77	85.26	83.64	80.09	78.16	76.68
Newington	83.76	87.29	85.38	79.89	83.37	82.89
Rocky Hill	82.67	86.42	84.56	80.55	80.58	81.26
Simsbury	83.71	87.46	86.56	82.72	82.01	79.80
Somers	82.73	87.04	85.89	81.26	80.74	78.69
South Windsor	82.44	86.67	84.00	79.11	81.36	81.06
Suffield	82.39	86.58	85.40	80.10	81.34	78.51
Tolland	82.24	86.37	85.07	80.08	81.71	77.99
Vernon	84.61	88.33	86.28	81.51	84.17	82.77
West Hartford	78.11	82.38	79.15	74.85	75.06	79.10

Wethersfield	82.55	86.37	84.00	79.65	80.56	82.17
Windsor	80.51	84.93	81.81	77.68	79.09	79.03
Windsor Locks	83.88	87.86	86.41	80.87	83.21	81.04

Table 5.3.2.2: Cross-tabulation of 5A Food Access Models and Study Area

Model			< 60	60 - 80	80 - 100	Total
Hartford	Model 1	No. of BGs	27	60	10	97
		Percentage	27.84%	61.86%	10.31%	100%
	Model 2	No. of BGs	12	70	15	97
		Percentage	12.37%	72.16%	15.46%	100%
	Model 3	No. of BGs	25	60	12	97
		Percentage	25.77%	61.86%	12.37%	100%
	Model 4	No. of BGs	54	33	10	97
		Percentage	55.67%	34.02%	10.31%	100%
	Model 5	No. of BGs	48	44	5	97
		Percentage	49.48%	45.36%	5.15%	100%
	Model 6	No. of BGs	9	74	14	97
		Percentage	9.28%	76.29%	14.43%	100%
Hartford 3-mile buffer	Model 1	No. of BGs	27	108	128	263
		Percentage	10.27%	41.06%	48.67%	100%
	Model 2	No. of BGs	12	87	164	263
		Percentage	4.56%	33.08%	62.36%	100%
	Model 3	No. of BGs	25	104	134	263
		Percentage	9.51%	39.54%	50.95%	100%
	Model 4	No. of BGs	54	91	118	263
		Percentage	20.53%	34.60%	44.87%	100%
	Model 5	No. of BGs	48	127	88	263
		Percentage	18.25%	48.29%	33.46%	100%
	Model 6	No. of BGs	9	119	135	263
		Percentage	3.42%	45.25%	51.33%	100%

In the Cross-tabulation table 5.3.2.2, Model 4 has the highest percentage of block-groups with 5A Food Access Index less than 60 in Hartford and its 3-mile buffer. This means in the condition when customers think affordability is more important than other indicators, there are more block-groups in Hartford facing food desert or food insecurity problems. This is realistic since many residents in Hartford are low-income population and there is very high possibility that

they might give more weights in affordability due to their financial limitation (limited budget on grocery shopping). However, for the affluent neighborhoods in the suburban towns, residents might give more weights in the availability and acceptability, model 2 (availability is more important, customers would like to have a healthy diet) and model 3 (acceptability is more important, customers have higher food quality standard, and would prefer to shopping in a better and more pleasant environment) will work better for them.

5.3.3 Identifying food desert areas: USDA vs. 5A Food Access Index

In Chapter 2, based on USDA's methodology of food deserts, which is well accepted in the food desert literature, we identified the low-income and low-access (LILA) block-groups in our study area by Euclidean and network distances to the closest supermarket from the population-based block-group centroids (Figure 5.3.3.1). Here the criteria are: LI - poverty rate of 20 percent or greater and LA - 0.5 miles' distance.

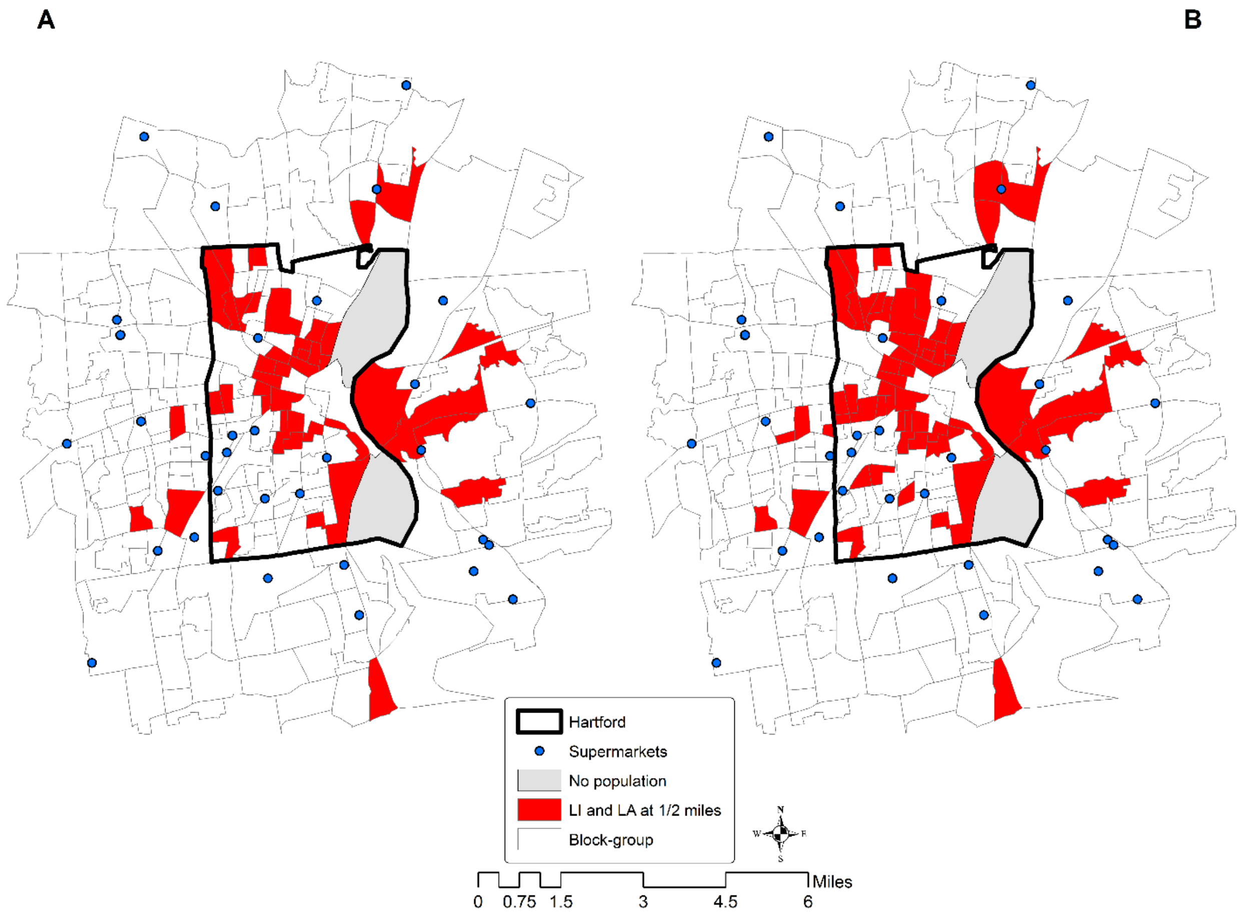

Figure 5.3.3.1: LI (Low Income) and LA (Low Access) at ½ miles (A: Euclidean B: Network)

We then compared the results with the 5A Food Access Index using the value of 60 as the food desert threshold (Figure 5.3.3.2). By reviewing the frequency tables and the histograms (not shown here) of the comprehensive time, we noticed that 60 is the threshold of 5A Food Access Index where the tail of the distribution starts to form. Also, due to lack of prior literature on using Penchansky and Thomas (1981) robust framework to identify food deserts and this being the first attempt to do so, we first attempt to use both 60 as the food access index thresholds to define food desert in our study area.

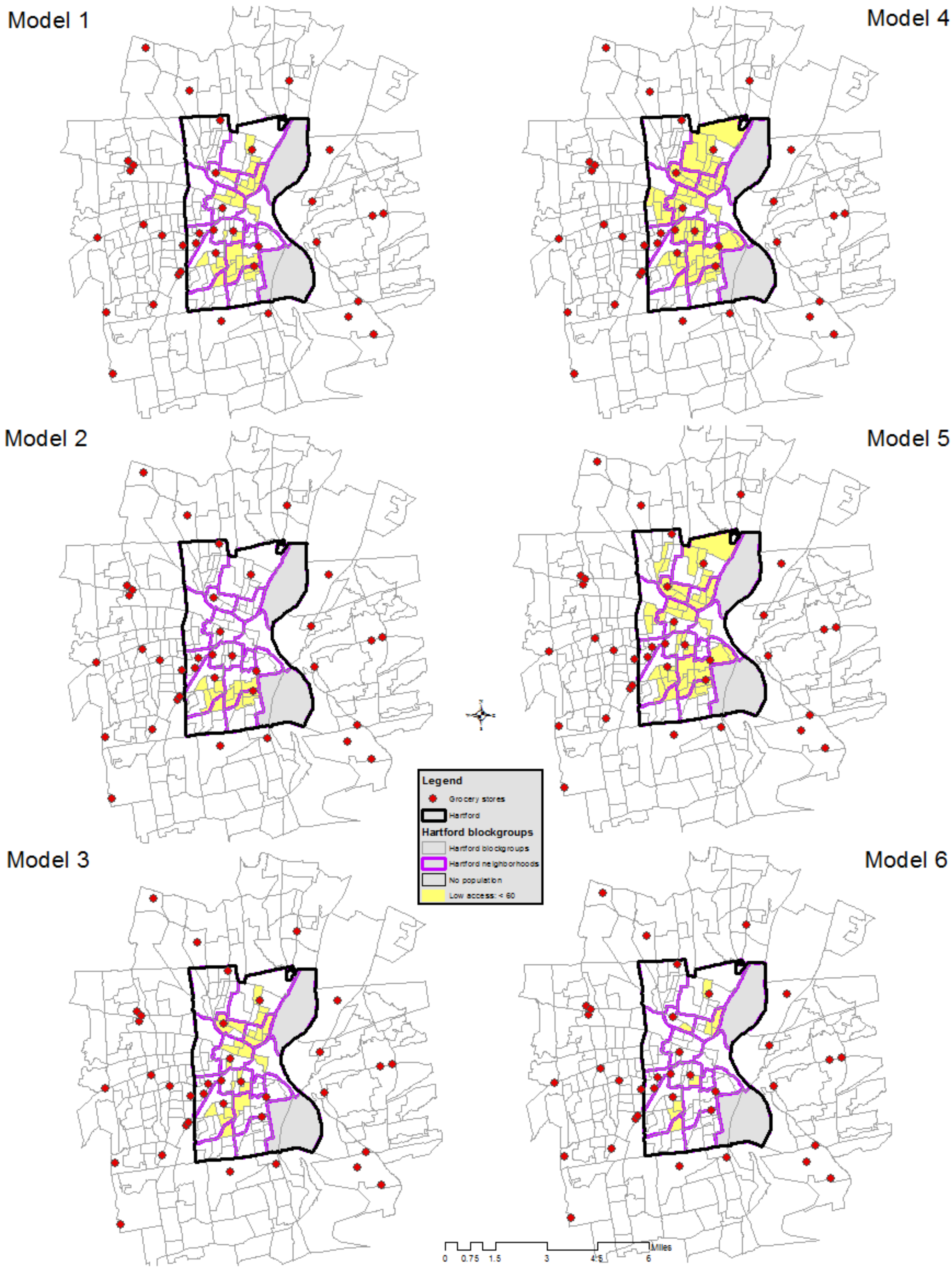

Figure 5.3.3.2: 5A Food desert area

Table 5.3.3.1: Comparison of food desert areas by Euclidean, Road-Network, and 5A Food Access

Food Desert Area		Within Hartford	Within 3-mile buffer
Total No. of BGs		97	263
Euclidean	No. of BGs	32	44
	Percentage	33.00%	16.70%
Network	No. of BGs	44	59
	Percentage	45.40%	22.40%
Model 1	No. of BGs	43	43
	Percentage	44.33%	16.35%
Model 2	No. of BGs	15	15
	Percentage	15.46%	5.70%
Model 3	No. of BGs	49	49
	Percentage	50.52%	18.63%
Model 4	No. of BGs	70	72
	Percentage	72.16%	27.38%
Model 5	No. of BGs	59	60
	Percentage	60.82%	22.81%
Model 6	No. of BGs	16	16
	Percentage	16.49%	6.08%

The comparison of food desert bock-groups is further tabulated in Table 5.3.3.1. Thirty three percent of block-groups in Hartford and 16.7% of block-groups in the suburbs has been identified as food desert by using the Euclidean method (Figure 5.3.3.1A and Table 5.3.3.1). While using Network distances, the percentage of food desert area changed to 45.4% and 22.4% in Hartford and the suburbs respectively (Figure 5.3.3.1B and Table 5.3.3.1). For the 5A Food Access Index, the distribution of the block-groups identified as food desert varied by the six models and by threshold of 60 (Table 5.3.3.1). Within Hartford the minimum number of block-groups identified as food desert was 15 (15.46%) in the Model 2 (availability is more important with the maximum weight of 40). The maximum was 70 block-groups (72.16%) identified in Model 4 (affordability is more important with the maximum weight of 40).

Table 5.3.3.2: **Low 5A food access areas (<60) in neighborhoods of Hartford, CT**

Neighborhood	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Blue Hills	0 (0%)	0 (0%)	0 (0%)	0 (0%)	3 (6.25%)	0 (0%)
North Meadows	1 (3.7%)	0 (0%)	1 (4%)	1 (1.82%)	1 (2.08%)	0 (0%)
West End	0 (0%)	0 (0%)	0 (0%)	4 (7.41%)	2 (4.17%)	0 (0%)
Upper Albany	1 (3.7%)	0 (0%)	3 (12%)	4 (7.41%)	4 (8.33%)	1 (11.11%)
Clay-Arsenal	5 (18.52%)	0 (0%)	5 (20%)	6 (11.11%)	5 (10.42%)	3 (33.33%)
Asylum Hill	3 (11.11%)	0 (0%)	4 (16%)	8 (14.81%)	6 (12.6%)	0 (0%)
Downtown	1 (3.7%)	0 (0%)	1 (4%)	1 (1.82%)	1 (2.08%)	0 (0%)
Frog Hollow	2 (7.41%)	0 (0%)	3 (12%)	7 (12.96%)	4 (8.33%)	1 (11.11%)
Parkville	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Sheldon Charter Oak	0 (0%)	0 (0%)	0 (0%)	2 (3.7%)	2 (4.17%)	0 (0%)
South Green	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Behind the Rocks	3 (11.11%)	4 (33.33%)	3 (12%)	4 (7.41%)	5 (10.42%)	2 (22.22%)
South Meadows	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Barry Square	5 (18.52%)	4 (33.33%)	1 (4%)	6 (11.11%)	6 (12.6%)	0 (0%)
South End	2 (7.41%)	3 (25%)	0 (0%)	3 (5.56%)	3 (6.25%)	0 (0%)
South West	1 (3.7%)	1 (8.33%)	1 (4%)	1 (1.82%)	1 (2.08%)	1 (11.11%)
Northeast	3 (11.11%)	0 (0%)	3 (12%)	7 (12.96%)	5 (10.42%)	1 (11.11%)
Total	27 (100%)	12 (100%)	25 (100%)	54 (100%)	48 (100%)	9 (100%)

Table 5.3.3.2 further summarizes the distribution of the food desert block-groups by the 17 neighborhoods of Hartford. Neighborhoods of Behind the Rocks has the highest average percentage (16.08%, ranges from 7.41% in Model 4 to 33.33% in Model 2) of food desert by the six models with the same cut-off as 60. Clay-Arsenal has approximately 15.6% (ranges from 0% in Model 2 to 33.33% in Model 6), followed by Barry Square (mean of 13.26%, ranges from 0% in Model 6 to 33.33% in Model 2) and Northeast (mean 9.6%, ranges from 0% in Model 2 to 12.96% in Model 4). These are the same neighborhoods with higher percentage of households with low-income, high racial and ethnic diversity, and with no large supermarkets within 1-2 miles (Martin et al. 2014, Zhang and Ghosh 2015).

5.4 Discussion and Limitations

This multi-dimensional measure of access goes beyond just distance to stores and incorporates the characteristics of food store, quality of food, and finally the relationship between stores and consumers. Therefore, this paper expanded upon the robust meaning of food access and had both topical and methodological contributions.

We highlight the major findings of our study here. First, city of Hartford had significantly lower 5A Food Access Index indicating higher risk of food insecurity. In this study, a robust taxonomy of access to grocery stores including availability, acceptability, affordability, accommodation and accessibility had been built based on Penchansky and Thomas (1981)'s research. Six models had been built to test the sensitivities of each access dimension. Hartford had the average lowest 5A Food Access Index for all the six models indicating the lowest overall food accessibility comparing with that of other towns. This indicates that no matter how we adjusted the weight, since Hartford had relatively lower scores in each of the As (see Table 5.3.2.1), residents living in Hartford always have the lowest overall food access and the highest potential of food insecurity and food desert.

Second, some suburban areas such as Vernon, Canton and Newington have relatively higher 5A Food Access Index indicates that residents living in these towns have better access to food. These places are typically affluent suburban neighborhoods with large chain supermarkets (such as Stop & Shop, Big Y) in close which can provide more choices and options of higher quality of food produces and better accommodation (longer operation hours and more working cashier) for easy of shopping.

Third, since these parameters are so subjective and to keep the comparison of food desert locator simple, we followed the USDA LILA criteria and just set the threshold of 5A Food Access

to 60. In terms of the validation findings, i.e. identifying the low 5A Food Access Index (<60) block-groups as food deserts, the 5A Food Access Index – a multi-dimensional robust taxonomy of access is a better measure than the only spatial Euclidean and Network distances. The 5A Food Access Index combines 5 dimensions of food access (availability, acceptability, affordability, accommodation and accessibility), accounts for weights variation on a given model for various target population. Thus, 5A Food Access Index has the provision of calculating comprehensive and realistic food access for researches and policy makers.

The study also had a few limitations.

First, we adapted the survey from Martin et al.'s study (Martin et al. 2014) and USDA's report (Carlson A and Frazão 2012) and categorized the selected 38 food items into dairy, protein, grains, fruits, vegetables, beverage and canned/staple seven groups. It was possible that the items in the categories were not exhaustive. For example, in the grains category, we did not look at crackers, chips, or bagels, but instead focused on bread, cereals, and pastas. We guided our selection based on the assumption that the market basket represented a standard basket of healthy food items for people's daily lives during all seasons.

Second, the scale used to assess internal, external and produce quality was a subjective measure of quality based on the researcher's own perception although clear and consistent guidelines on how to rate the quality were provided. Also, data was collected from all the stores by the same researcher to keep the perceptions consistent and to minimize bias.

Third, this survey was administered in a single month of May in 2014. Although produce supply may vary seasonally, we assumed that the quality, availability, price of the items were fairly stable over time (Martin et al. 2014).

Fourth, travel time by bus and car may vary by day of the week, time of the day, and also by the study area. This research chose Wednesday and Saturday as representative weekday and weekend day respectively. The times chosen, 10 am and 5 pm, were also representative of morning and evening commute. It is possible that the travel times could be different for other days and times; however, we believe that the overall results and conclusions will remain the same.

Fifth, due to insufficient literature and to our knowledge this being the first attempt to model a robust taxonomy of food access from multidimensional concept based on Penchansky and Thomas (1981)'s theory, we used equal weights of 5As first (Cutter, Boruff, and Shirley 2003), then separately increased the weight (from 20 to 40) of availability (Model 2), acceptability (Model 3), affordability (Model 4), accommodation (Model 5) and accessibility (Model 6). It is possible that in a different study design, each As could have different weights.

Sixth, due to lack of prior literature on using Penchansky and Thomas (1981) robust framework to identify food deserts and this being the first attempt to do so, we first attempt to use 60 as the food access index thresholds to define food desert in our study area. It is possible that in a different study setting, researchers can adjust the threshold to for their own study purpose.

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Appendix A: Transit Time Calculator Survey

1. How long have you used ArcGIS?
a) Less than 6 months b) 1- 3 years c) 3-5 year d) 5+ years

2. How would you rate your overall satisfaction with this toolbox?
a) Very satisfied b) Somewhat satisfied c) Neutral d) Somewhat dissatisfied e) Very dissatisfied

3. How likely is it that you would recommend this to a fiend/colleague?
a) Very likely b) Somewhat likely c) Neutral d) Somewhat unlikely e) Very unlikely

4. How would you describe this toolbox in one or more words? (Please circle the words)

The complete set of 118 Product Reaction Cards.				
Accessible	Creative	Fast	Meaningful	Slow
Advanced	Customizable	Flexible	Motivating	Sophisticated
Annoying	Cutting edge	Fragile	Not Secure	Stable
Appealing	Dated	Fresh	Not Valuable	Sterile
Approachable	Desirable	Friendly	Novel	Stimulating
Attractive	Difficult	Frustrating	Old	Straight Forward
Boring	Disconnected	Fun	Optimistic	Stressful
Business-like	Disruptive	Gets in the way	Ordinary	Time-consuming
Busy	Distracting	Hard to Use	Organized	Time-Saving
Calm	Dull	Helpful	Overbearing	Too Technical
Clean	Easy to use	High quality	Overwhelming	Trustworthy
Clear	Effective	Impersonal	Patronizing	Unapproachable
Collaborative	Efficient	Impressive	Personal	Unattractive
Comfortable	Effortless	Incomprehensible	Poor quality	Uncontrollable
Compatible	Empowering	Inconsistent	Powerful	Unconventional
Compelling	Energetic	Ineffective	Predictable	Understandable
Complex	Engaging	Innovative	Professional	Undesirable
Comprehensive	Entertaining	Inspiring	Relevant	Unpredictable
Confident	Enthusiastic	Integrated	Reliable	Unrefined
Confusing	Essential	Intimidating	Responsive	Usable
Connected	Exceptional	Intuitive	Rigid	Useful
Consistent	Exciting	Inviting	Satisfying	Valuable
Controllable	Expected	Irrelevant	Secure	
Convenient	Familiar	Low Maintenance	Simplistic	

Note: Developed by and © 2002 Microsoft Corporation. All rights reserved

5. What do you like best about this toolbox?

6. What do you like least about this toolbox?

7. What other products do you use to accomplish similar tasks?

8. Do you have any suggestions for improving this toolbox?

Thank you very much for your time and participation!

Appendix B: Food Access Survey

Survey Instruction:

- Capture the price for the least expensive brand/option available.
- Use the unit prices if it exists, if not available, note the size and price in the survey and do the calculation
- If the indicated item is not available, note 'NA'.
- If price is not available, ask an employee at the cash register or at customer service.
- Do not use a sale price unless it is the only price posted and write “sale price” in comments.

Type	Size	Price	Comments
Dairy			
Milk, cow's, fluid, 1% fat	Per quart		
Milk, cow's, fluid, 2% fat	Per quart		
Milk, cow's, fluid, whole	Per quart		
Cheese, processed, American cheddar, low fat	Per lb		
Yogurt, plain,no fruit	Per lb		
Yogurt, with fruit	Per lb		
Protein			
Grounded beef, 80% lean	Per lb		
Grounded beef, lean only	Per lb		
Chunk Ligh Tuna in Water	Per lb		
Chicken, thigh	Per lb		
Chicken, breast	Per lb		
Pork chop,lean only	Per lb		
Egg, large	Per dozen		
Canned and Staple			
Rice – White, medium	Per lb		
Rice - Brown	Per lb		
Canned beans, pinto, navy, kidney or cannellini	Per lb		
Canned tomatoes	Per lb		
Spaghetti Sauce	Per lb		
Pasta, Spaghetti	Per lb		
Peanut Butter	Per dozen		
Grains			
Multigrain bread	Per lb		
White bread	Per lb		
Oatmeal, cooked, regular, no fat added	Per lb		
Cheerios	Per lb		
Frosted flakes, Kellogg	Per lb		
Beverages			
100% Orange Juice	Per lb		
100% Apple Juice	Per lb		

Quality: Write the number that best describes the overall quality of the produce for each item.

1 = Very Poor: all or most of the item is of poor quality (brown, bruised, overripe, wilted); 2 = Mixed quality; more poor than good; 3 = Mixed quality; some good some poor; 4 = Mixed quality; more good than poor; 5 = Very good: All or most of the item is of good quality (very fresh, no soft spots, excellent color)

Fresh Produce	Size	Price	Quality, 1- 5	Comments
Fruit				
Apples	Per lb			
Bananas	Per lb			
Oranges	Per lb			
Grapes	Per lb			
Vegetable				
Carrots	Per lb			
Tomatoes	Per lb			
White potato	Per lb			
Broccoli	Per lb			
Iceberg Lettuce	Per lb			
Romaine Lettuce	Per lb			
Celery	Per lb			

	Rate 1-5	Comment
External		
Appearance		
Lighting		
Parking		
Internal		
Appearance		
Lighting		
Cleanliness		
Organization		
Other consumers		
	No.	Comment
Accommodation		
Open hours per week		
Total waiting people		
No. of working Cashier		