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Examining Healthy Food Accessibility in Baton Rouge, Louisiana Using A Huff-modified 2SFCA Method

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EXAMINING HEALTHY FOOD ACCESSIBILITY IN BATON ROUGE, LOUISIANA USING A HUFF-MODIFIED 2SFCA METHOD

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ABSTRACT

Food accessibility refers to people's ability to access the service of food providers. Disparities in healthy food accessibility have long been a public health concern. This study proposes a new approach modified from the popular *2-Step Floating Catchment Area (2SFCA)* method to measure spatial access. By incorporating a self-adaptive kernel density function extracted from the Huff Model, the proposed new method is termed the *Huff-modified 2SFCA* method. It is then applied to measure the healthy food accessibility in East Baton Rouge Parish, Louisiana. The research accounts for the economically disadvantaged groups that may walk or depend on public transit for transportation. Also, the relationships between spatial accessibility of healthy food and other demographic and socio-economic factors are examined. The results show that socio-economically disadvantaged neighborhoods tend to have higher accessibility scores to healthy foods but population without a private vehicle suffers from poor healthy food accessibility. The research clearly differentiates spatial and non-spatial factors in food accessibility and inequalities across the study area, thus helps planners to scientifically design strategies of improving healthy food access.

CHAPTER 1. INTRODUCTION

Food accessibility refers to people's ability to obtain the services of food providers. Poor access to reasonably priced, nutritious and good-quality food may lead to poor diet with low consumption of fruits and vegetables and high consumption of energy-dense, nutritionally inferior foods (Dai and Wang, 2010; Roos et al., 2013). Low accessibility of healthy food in some geographic areas and demographic groups increases the risk of health problems such as obesity, diabetes and cardiovascular diseases (Darmon et al., 2002; Edelstein et al., 1997; Helling and Sawicki, 2003; Kyle and Blair, 2007; Larsen and Gilliland, 2008; Must et al., 1999; Pearce et al., 2006), and has increasingly become a public health concern. Previous literature (Larson et al., 2009; Morland et al., 2006; Wang et al., 2007) suggests that people with better access to providers of healthy (high-quality, fresh, low-fat and nutritious) however affordable food, such as supermarkets and fruit and vegetable markets, tend to have healthier diets and lower levels of obesity. As "a growing health concern for children, adolescents and adults in the United States and other countries" (Michimi and Wimberly, 2010, n.p.), the issue of "food desert," as well as the influence of neighborhood food environment on human health, has been widely discussed in the literature.

The term *food desert*, originally reported in Scotland in the early 1990s, refers to an area characterized by relatively poor access to healthy and affordable food. It may contribute to social disparities in diet and diet-related health outcomes (Cummins, 2007; Wrigley, 2002; Zenk et al., 2005). While the research of food desert focuses on the insufficiency of food providers in a defined area, its natural extension examines "differential accessibility of healthy and affordable food between socio-economically advantaged and disadvantaged areas and population groups" (Beaulac et al., 2009, A105). These spatial accessibility barriers are often linked to and interact with non-spatial factors such as race and poverty issues, partly because of people of specific ages and income with limited mobility (Apparicio et al., 2007) and partly because of uneven geographic distributions of providers and consumers that force people to travel long to purchase food (Wang and Luo, 2005).

By incorporating a self-adaptive kernel density function extracted from the Huff Model, this thesis proposes a new method, termed the *Huff-modified 2-Step Floating Catchment Area (H2SFCA)* method, to measure the healthy food accessibility in East Baton Rouge Parish, Louisiana. The research accounts for the economically disadvantaged groups that may walk or depend on public transit for transportation. Also, the relationships between spatial accessibility of healthy food and other demographic and socio-economic factors are examined. The accessibility was mapped and the spatial regression analysis was performed using ArcGIS 10.2 (ESRI (http://www.esri.com/)). The statistical analysis was executed using Excel 2013 (Microsoft (http://www.microsoft.com/)) and SPSS Statistics 20 (IBM (http://www.ibm.com)). The results from the research will help planners to scientifically design strategies of improving healthy food access.

The remainder of the thesis is structured as follows. In Chapter 2, a literature review is provided with an emphasis on the methods for measuring spatial impedance and accessibility; and the study objectives are outlined. The study area and data preparation issues are articulated in Chapter 3. Chapter 4 presents detailed implementation for the spatial accessibility measure; and the method is applied to the study area. Chapter 5 mainly analyzes how the study area's demographic and socio-economic characteristics shape the neighborhood's spatial accessibility of healthy food. A brief summary and some discussion of future improvements are covered in Chapter 6.

CHAPTER 2. LITERATURE REVIEW

A variety of studies in the U. S. or other parts of the world have been conducted to closely examine the spatial accessibility of food. The choice of accessibility measure is essential since accessibility is a function of the indicators used (Talen, 1998; Talen and Anselin, 1998). This chapter provides a literature review with an emphasis on the methods for measuring spatial impedance and accessibility.

The Risk Factor Monitoring and Methods Branch at the National Cancer Institute (NCI) (http://appliedresearch.cancer.gov/about/rfmmb/) recommends two simple measures of accessibility – the nearest distance to food stores in order to evaluate immediate proximity, and counts of the number of food stores within a specific area, to evaluate the richness of food providers. While these two methods capture some important elements in an individual consumer's decision making when selecting food providers, they do not account for other consumers' competition for the service of food providers. A number of studies in the U. S. have asserted that people in rural (Fisher and Strogatz, 1999; Kaufman, 1999; Liese et al., 2007), low-income (Moore and Roux, 2006; Morland et al., 2002; Powell et al., 2007; Zenk et al., 2006) and minority concentrated (Morland and Filomena, 2007; Powell et al., 2007; Sloane et al., 2003; Shannon N. Zenk et al., 2005) residential communities are most affected by food access inequalities. One major reason is that people in these areas experience more competition for food as the population density there is high and supermarkets and quality grocery stores with healthful food are few. Accounting for consumers' choices and competition for food, many existing studies (Michimi and Wimberly, 2010; Moore and Roux, 2006; Raja et al., 2008) use a measure that calculates the ratio of the number of food providers to population within an administrative unit, or a defined area within a fixed range from a residential area by the *Floating Catchment Area* (FCA) method. Although this method is straightforward and considers the match ratio between population and food resources, it comes short in capturing the spatial interaction between them. Specifically, it ignores two aspects in interaction across boundaries of residential areas: competition for food providers from adjacent neighborhoods and competition for customers from food stores in nearby residential units (Dai and Wang, 2010).

Luo and Wang (2003) have developed the popular *2-step floating catchment area (2SFCA)* method to measure spatial accessibility by accounting for the match ratio between supply and demand and possible spatial interaction beyond boundaries of analysis units. However, like any FCA method, it does not consider the gradual effect of distance decay in spatial interaction. The *kernel density based 2SFCA* (*KD2SFCA*) method proposed in a

Mississippi study in 2010 (Dai and Wang, 2010) addresses the issue of distance decay within a threshold range that the original 2SFCA method fails to account for. However, it still has some deficiencies as outlined below:

1. The kernel density function that attenuates the quantitative amounts is fixed, not adaptive. That is to say, this method assumes that the effect of events declines with distance according to a unified pattern, despite the possible difference in population distribution, store ratings and travel time between residential units and stores.

2. In residential units where consumers have to travel long to access the even nearest food stores, the kernel density function underestimates the availability of those stores. However, for rural consumers who usually own automobiles, those stores are often the sole choice of food resource and reasonably available.

A study in southwest Missouri integrates the *Huff Model* with the Floating Catchment Area method to measure the spatial accessibility of health care facilities (Luo, 2014). The Huff Model (Huff, 1963) provides a way to solve those problems for a couple of reasons:

1. It provides a measure to estimate the probability that a customer chooses a certain store, given that within a travel time threshold, the customer has multiple choices of food resource. The probability value is related with the length of travel time and the attractiveness (weight) of the target store so that it can be considered adaptive while simultaneously following the distance decay rule. Replacing the fixed kernel density function with the "Huff core" (measure of probability that a customer purchases in a certain store) hence rescales a store's visiting population adaptively to travel time and store condition. The rescaled population is the expected value of visiting population.

2. The mechanism of probability measure tends to highlight the importance of remote stores in areas where food resources are sparse. Because of the limited number of food stores, the probability of visiting a store could be high despite a lengthy distance or travel time. Under extreme circumstances, where solely one store serves a wide stretch of residential areas, the probability that every customer visits this store is 100%. The demand for food is a rigid demand for human beings and is not solely and simply decayed by the trip length.

The "Huff core" is specifically designed from a store's perspective to measure its probability being visited and hence its potential serving population. However, from a customer's view, the availability of a store is still influenced by its capacity and the travel cost (time or distance) to the store. The "Huff core" becomes inapplicable when rescaling store availability. In addition, much of the aforementioned literature assumes that every consumer has access to automobiles for food. However, residents without vehicles "have to rely on public transit, walking or bicycles" (Wang, 2003, 261). As a result, food stores beyond a tolerable walking distance or time cannot be considered accessible for people without personal vehicles.

The common path taken by these studies is to identify spatial or non-spatial variables in affecting food accessibility, which include but are not limited to, "distance, mobility, economic and social capital, and behavioral factors (e. g. preference for convenient foods)" (Widener et al., 2013, 2). Some researchers focus on spatial factors such as urban versus rural areas (Morton and Blanchard, 2007; Powell et al., 2007; Sharkey and Horel, 2008). Others emphasize non-spatial factors such as: income (Baker et al., 2006; Chung and Myers, 1999; Fisher and Strogatz, 1999), ethnicity (Baker et al., 2006; Block and Kouba, 2006; Fisher and Strogatz, 1999; Horowitz et al., 2004; Hosler et al., 2006) and other variables (Alwitt and Donley, 1997; Horowitz et al., 2004; Jetter and Cassady, 2006; Morland et al., 2002a, 2002b). An interesting task is to analyze how spatial and non-spatial factors are related to each other.

Based on the above critical review of existing literature, this study proposes an accessibility measure termed "*Huff-modified 2SFCA*" method as an improvement over the original *2SFCA* and *KD2SFCA* method. It incorporates the probability concept used in the Huff Model and uses it to replace the kernel density function in the first step of the KD2SFCA method to rescale consumer population. Furthermore, both scenarios – traveling with private vehicle and walking/public transit – are considered when measuring the spatial accessibility. The relationship between spatial accessibility and socio-demographic factors is also examined to shed light on how spatial and non-spatial factors intersect in an urban-rural continuum in the study area.

CHAPTER 3. DATA SOURCES AND PREPARATION

3.1 Study area

This research selects East Baton Rouge Parish as the study area. A parish is a county-equivalent unit in Louisiana. The study area includes urban, suburb and rural areas (see Figure 1). Census block group is chosen as the analysis unit as most of socio-demographic variables are available at this level. The City of Baton Rouge is the parish seat of East Baton Rouge Parish with the largest area and population. Other cities and towns in the parish also include Baker, Zachary and Greenwell Springs. In order to account for possible edge effect (i.e., interaction between consumers and food resource beyond the parish boarder), the study area is expanded by a 2500-meter buffer zone around East Baton Rouge Parish to include some adjacent cities such as Port Allen, Brusly, Addis, Denham Springs, Prairieville, Lobdell, Saint Gabriel and Watson outside the parish boundary. The area includes the whole spectrum of urban, suburb and rural areas.

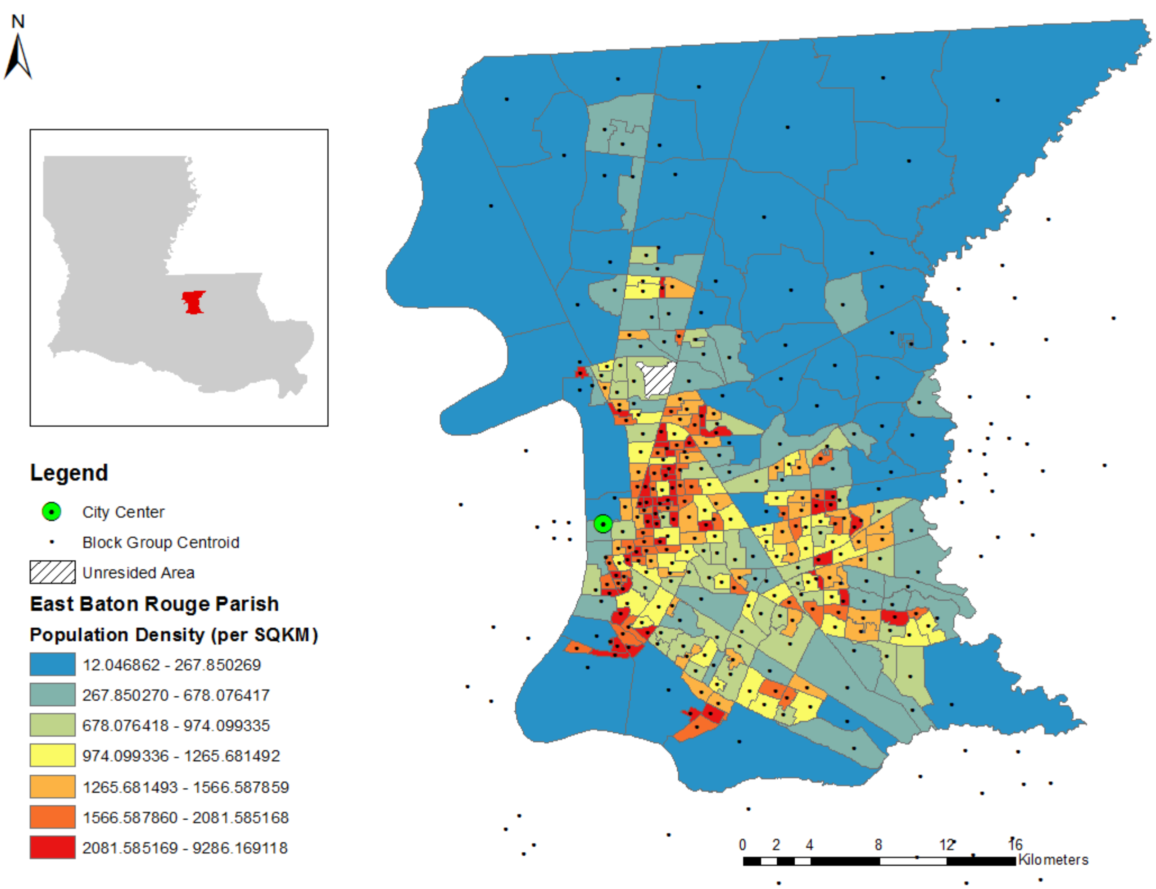


Figure 1 Population density in census block groups in East Baton Rouge Parish in 2010

Some descriptive statistics are presented in Table 1 for the study area.

Table 1 Descriptive statistics for the study area in 2010

Total population	440,171
Number of occupied housing units	26,104
Number of block groups	360
Number of resided block groups	302

3.2 Census data

The spatial data at the block group level is from the *2010 Census TIGER (Topologically Integrated Geographic Encoding and Referencing)/Line Shapefiles* for the United States and Puerto Rico (http://www.census.gov/). This study is based primarily on the block group level because it is the smallest census unit with socio-demographic variables needed for the analysis and it also well reflects patterns of social interaction that evolves with street and road networks (Grannis, 1998). The socio-economic data at block group level is from the *American Community Survey 5-Year Estimates, 2008 – 2012 Detailed Tables* (http://www.census.gov/)) and contains socio-economic variables such as race/ethnicity, family structure, income and education. As previously discussed, it also includes an important variable for the study, namely vehicle availability.

Figure 1 shows that population density is the highest around the city center and gradually decreases as the distance from the city center increases. The unresided area in the middle-north part of the study area, donated by the black-white shade, is the Baton Rouge airport.

3.3 Food store data and classification

The food store data with street addresses is from the Baton Rouge Yellow Pages (http://www.yellowpages.com). According to the categorization defined by the National Cancer Institute (NCI) (http://www.cancer.gov/), the "food store environment" consists of grocery stores, supermarkets, convenience stores, snack bars, specialty food stores, farmer's markets, bodegas and food banks. For our purpose of focusing on healthy foods, snack bars and bodegas are excluded.

According to the data collected from the Yellow Pages, there are nearly 400 food stores within the metropolitan area surrounding East Baton Rouge Parish. Only 297 stores are retained for the study by excluding those with addresses outside of the study area, or incorrect or missing addresses, or online stores. 247 stores out of 297 are located in the East Baton Rouge Parish and the remaining 50 are located in nearby cities and towns, as shown in Figure 2.

To determine the *attractiveness* for each food store, all 297 stores are classified into 6 categories: supermarket, grocery store, health food retail, convenience, farmer's market and uncategorized store, based on the primary *Standard Industrial Classification* (SIC) codes provided by the Reference USA database service (http://www.referenceusa.com/). The Reference USA database includes individual business information, from which this study adopted the primary SIC code, primary SIC code description, employment size and business area (square footage).

To differentiate the quality of each category, a weight score 1 – 10 is assigned to represent the attractiveness level for each food store on the basis of the primary SIC code description, employment size and business area (square footage). Enlightened by earlier studies (Dai and Wang, 2010; Moore et al., 2008; Raja et al., 2008), supermarkets and department stores with SIC codes of 531102, 531110 and 549909 with more than 200 employees and larger than 40,000 square feet receives the highest attractiveness score 10. Grocery stores, whose primary SIC codes include 541105, 542107, 541101, etc., are further classified into 3 categories according to the employment sizes and business area, with attractiveness scores of 7, 5 and 3 assigned to corresponding subcategories. Other smaller stores such as convenience stores, farmer's markets and service stations received even lower attractiveness scores (3, 2 and 1) due to their limited sizes. This simple weighting scheme is adopted because of the lack of more detailed and reasonable information such as food price and food quality. It also differs from previous studies (Dai and Wang, 2010; Moore et al., 2008; Raja et al., 2008), and considers a store's square footage and employment size. "The quality of produce is generally high in medium and large stores, while wilted, damaged, or spoiled produce in not uncommon in smaller stores" (Raja et al., 2008, 470), so this weighting scheme reflects store's capacity in terms of healthy food to some extent. Still, as a previous study suggests (Roos et al., 2013), specific food store surveys can be conducted to acquire more scientific information that considers food price, availability and quality to improve the categorizing and weighting scheme.

Figure 2 shows the store density by using a simple Floating Catchment Area (FCA) method with a search range of 15-minute driving time around block groups and applying the aforementioned weighting scheme to all food stores. It indicates that the food store density tends to be high in and around the central city and relatively low in the rural areas.

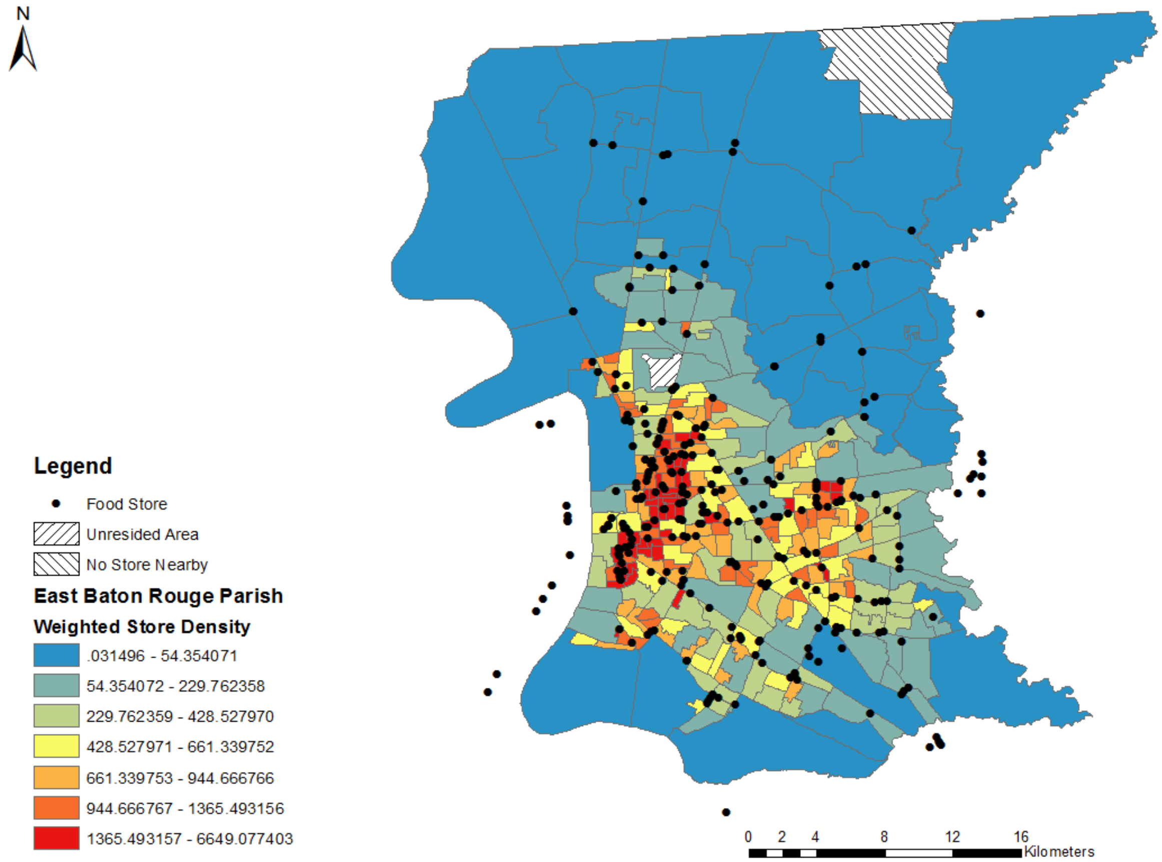


Figure 2 Food store density

A simple illustration of food store categories is presented in Table 2 in Page 11.

1. Stores with an employment size larger than 50 or an area more than 40,000 square feet are considered large, with a weight score of 7 assigned.

2. Stores with an employment size between 10 and 50 or an area between 10,000 and 40,000 square feet are considered medium, with a weight score of 5 assigned.

3. Stores with an employment size smaller than 10 or an area less than 10,000 square feet are considered small, with a weight score of 3 assigned.

Table 2 Food store categories and examples

Food store category	SIC code	Employment size	Square footage	Weight	Example
Supermarket	531102 531110 549909	200+	40,000+	10	Wal-Mart, Sam's Club.
Grocery Store	541105 542107 541101 514101	50 – 200 10 – 50 1 – 10	40,000+ 10,000 – 40,000 0 – 10,000	7 5 3	D & H Grocery, Maxwell's Market.
Healthy food retail	543101 549901	1–10	0 – 10,000	3	Southside Produce Market, Fruit Land Inc.
Convenience	541103 539901 593222	1–10	0 – 10,000	2	Dollar General, Asian Food Market.
Farmer's Market	543102 204102	1–10	0 – 10,000	2	El Tio Supermarket, Cargill Food Flour
Uncategorized	581208 554101 533101	1–10	0 – 10,000	1	Jeff's Food Mart, L & S Foods

3.4 Transportation – road network and public transit

The road network database is obtained from the 2012 ESRI data CDs (http://www.esri.com). The road network database includes all levels of roads and streets with information such as zip code range, speed limits and directions. According to the book *Getting to know ArcGIS Desktop* (Ormsby, 2004), the aforementioned attributes in the Baton Rouge street layer most closely match the "US Address – Dual Ranges" address locator style, which is used to reference the road network dataset for geocoding to obtain food store locations.

People without access to automobiles may utilize the public transit system to purchase food. Figure 3 shows the Baton Rouge's transit system, namely the Capital Area Transit System (CATS) (http://www.brcats.com/). Some routes (Route No. 80, Route No. 102, Route No. 103 and Route No. 105) are not included because they do not provide full seven-day service. Louisiana State University's bus system – the Tiger Trails (http://www.lsu.edu/), and Southern University's shuttle lines (http://www.subr.edu/) are not included for the same reason.

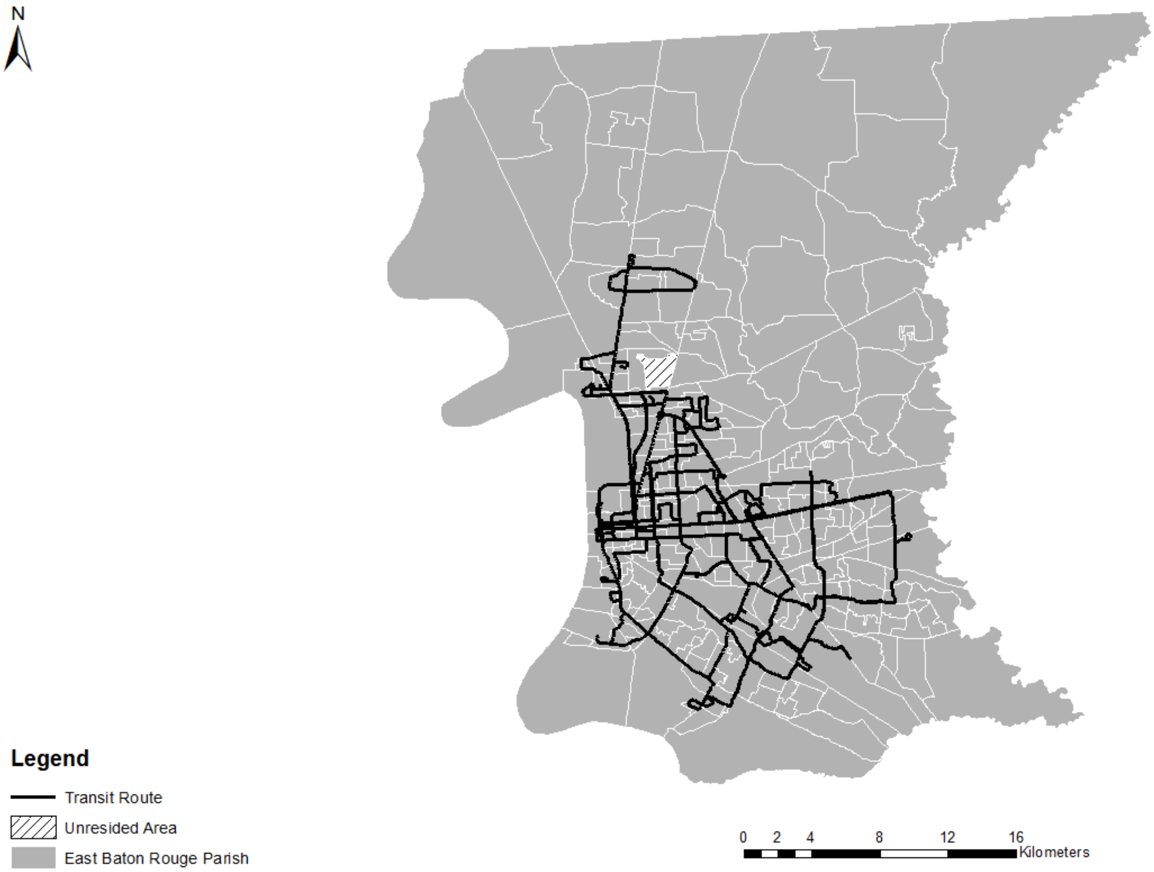


Figure 3 Transit routes in Baton Rouge

3.5 Technical issues in data preparation

Several technical issues in data preparation merit some discussion here.

First, 58 non-resided block groups in the study area are excluded from analysis, resulting in 302 valid block groups as residential locations. Population-weighted mean center is used as the centroid for each block group to represent its location more accurately. As suggested by Jane and Rollow (2000), the population centroid instead of the geographic centroid would provide more accurate estimate in trip distance or travel time between areal units.

Secondly, people on the edge of the study area may visit stores outside the parish border or travel through the roads outside the parish to purchase food. On the other side, people in adjacent parishes may also use the stores inside the parish boundary, and thus reduce the availability of these food stores. Confining the data to the parish itself may lead to the edge effect, i.e., the results for block groups on the edge are not as reliable as other areas.

Therefore, a 2500-meter buffer around the parish is applied to also include grocery stores and road network in the analysis of spatial accessibility of food stores in the parish.

Thirdly, the measure of spatial impedance is the shortest travel time through the road network by following the speed limits. For people taking the public transit system, the total time is composed of (1) walking time from residential block group centroid to the nearest transit station with a confortable speed for a healthy human at approximately 1.3 meters/second (or 0.05 miles per minute) (Bohannon, 1997; Nishimori and Ito, 2014), (2) travel time on the public transit, and (3) walking time from the transit's destination station to a store. When a block group is close to a store without the need of riding the transit system or in an area without any transit route, the second component through the public transit can be 0, and the first and third components are consolidated to simple walking time between them.

CHAPTER 4. SPATIAL ACCESSIBILITY OF HEALTHY FOOD

This study proposes the Huff-modified 2SFCA method. Different from the original KD2SFCA method, when rescaling store's serving population, the kernel density function is substituted by the probability of residents visiting a store calibrated in the Huff Model. This chapter begins with a brief review of both the original 2SFCA and its revision KD2SFCA, and then introduces the Huff-modified 2SFCA method.

4.1 2-Step Floating Catchment Area (2SFCA) method

The original 2SFCA method is the foundation of the KD2SFCA and Huff-modified 2SFCA methods, and works as follows (Wang, 2006).

First, for each food store j (supply location), search all block group centroids k (demand locations) that are within a travel time threshold t_0 from the food store location to form a catchment area and then sum the total population within the catchment area up as the *availability* for this food store j. Then compute the store-to-population (supply-to-demand) ratio R_j within each catchment area to measure the *availability* of each store:

$$R_j = \frac{S_j}{\sum_{k \in \{t_{kj} \leq t_0\}} D_k} \tag{4.1}$$

where D_k is the total demanding population of block groups whose centroids fall into the catchment area of the store j ($k \in \{d_{kj} \leq d_0\}$); t_{kj} is the travel time between the store j and each block group while t_0 is the aforementioned travel time threshold; S_j is the weight score for the store j (supply) as discussed in Chapter 3.

Next, for each block group i, search all food stores j that are within the same travel time threshold t_0 as in the first step and sum up again the store-to-population ratios R_j to obtain the *accessibility* at the block group:

$$A_i = \sum_{j \in \{t_{ij} \leq t_0\}} R_j = \sum_{j \in \{t_{ij} \leq t_0\}} \left(\frac{S_j}{\sum_{k \in \{t_{kj} \leq t_0\}} D_k} \right) \tag{4.2}$$

where R_j is the availability of stores that fall into the catchment area of the block group i; t_{ij} is the travel time between block group i and the store j.

4.2 Kernel Density 2-Step Floating Catchment Area (KD2SFCA) method

To account for the distance decay rule, or the *first law of geography* (Tobler, 1970), between food providers and consumers, the KD2SFCA incorporates a kernel function (KD) within the catchment range t_0 in the 2SFCA. That is to say, both the demand population D_k and stores' availability R_j are discounted by travel time by a

KD function and become 0 when travel time exceeds the threshold. Specifically, the KD function rescales the population at each demand location k according to its travel time to a store location j in the first step:

$$R_j = \frac{S_j}{\sum_{k \in \{t_{kj} \le t_0\}} [D_k \cdot f(t_{kj})]} \tag{4.3}$$

Similarly, in the second step, the KD function again rescales R_j according to the travel time:

$$A_i = \sum_{j \in \{t_{ij} \le t_0\}} [R_j \cdot g(t_{kj})] \tag{4.4}$$

Consequently, the KD2FCA method is written as:

$$A_i = \sum_{j \in \{t_{ij} \le t_0\}} [R_j \cdot g(t_{kj})] = \sum_{j \in \{t_{ij} \le t_0\}} \left\{ \frac{S_j \cdot g(t_{kj})}{\sum_{k \in \{t_{kj} \le t_0\}} [D_k \cdot f(t_{kj})]} \right\} \tag{4.5}$$

4.3 Huff-modified 2SFCA method

As "the Huff Model is a widely accepted method for quantifying the probability of people's selection on a service site out of multiple available ones" (Luo, 2014, 440), the probability part of Huff Model is chosen as the kernel function to rescale population. Proposed in one of Huff's studies on shopping center trade area analysis in 1963 (Huff, 1963), the Huff Model works as follows:

$$\mathrm{P}(C_{ij}) = \frac{\frac{S_j}{{t_{ij}}^{\lambda}}}{\sum_{j=1}^{n} \left(\frac{S_j}{{t_{ij}}^{\lambda}} \right)} \tag{4.6}$$

where $\mathrm{P}(C_{ij})$ is the probability of a consumer at a given point of origin i traveling to a given store j; S_j is the attractiveness of the store j; t_{ij} is the travel time involved in getting from a consumer's base and λ is a parameter which is to be estimated empirically to reflect the effect of travel time on various kinds of shopping trips, or, the "distance friction coefficient" (Wang, 2015).

So in this case, the KD function associated with the demand side D_k in the KD2SFCA method is revised to be the probability of residents visiting a store, written as:

$$
\begin{cases} f(t_{ij}) = \dfrac{\dfrac{S_j}{{t_{ij}}^{\lambda}}}{\sum_{j=1}^{n}\left(\dfrac{S_j}{{t_{ij}}^{\lambda}}\right)} & t_{ij} \le t_0 \quad (4.7a) \\ f(t_{ij}) = 0 & t_{ij} > t_0 \quad (4.7b) \end{cases}
$$

Meanwhile, following the distance decay rule, the KD function that rescales store availability remains intact. However, for consistency with the power function used in the Huff model in Equation (4.7a), the distance decay of the supply side is also captured by the power function such as:

$$
g(t_{kj}) = \frac{1}{{t_{kj}}^{\lambda}} \tag{4.8}
$$

The λ value has decreased over time because improvements in transportation technology or road network reduces the effect of travel time on (Wang, 2015). However, for population without access to vehicles, the λ value still remains relatively higher. Several empirical studies using the Huff model suggested $\lambda \approx 1$ (Huff and Blue, 1960; Haines Jr. et al., 1972; Markham et al., 2014). For convenience, this research uses $\lambda = 1$ as the distance friction coefficient for residents with vehicles.

This Huff-modified 2SFCA is similar to the method developed by Luo (2014). However, an important difference is that Luo incorporated the "Huff core" to rescale not only a facility's serving population but also its availability. We argue that it is problematic to do so because a facility cannot "select" its customers. In our case, the availability of food store simply declines according to the inverse distance function.

4.4 Different measures related to mobility

The accessibility measure differs between the population group with private vehicles and that without. Denote the population without access to private vehicles at residential site k by D_k^w, approximated as:

$$
D_k^w = r_k^w \cdot D_k = \frac{H_k^w}{H_k} \cdot D_k \tag{4.9}
$$

where r_k^v is the ratio of the number of households that own at least 1 vehicle, H_k^w, to the total number of households at block group k, H_k; and D_k is the total population within that block group. From the census data discussed in

Chapter 3, H_k^w and H_k at the household level are available but D_k^w and D_k at the individual level are not available. The above approximation assumes a uniform household size.

Similarly, the population with access to vehicles, D_k^w is estimated as:

$$D_k^v = D_k - D_k^w = (1 - r_k^w) \cdot D_k = \left(1 - \frac{H_k^w}{H_k}\right) \cdot D_k \tag{4.10}$$

Based on Equations (4.9) and (4.10), Figure 4 shows the distribution of population without access to a private vehicle. The percentage of mobility-disadvantaged population is generally higher in central city and also noticeable in rural areas.

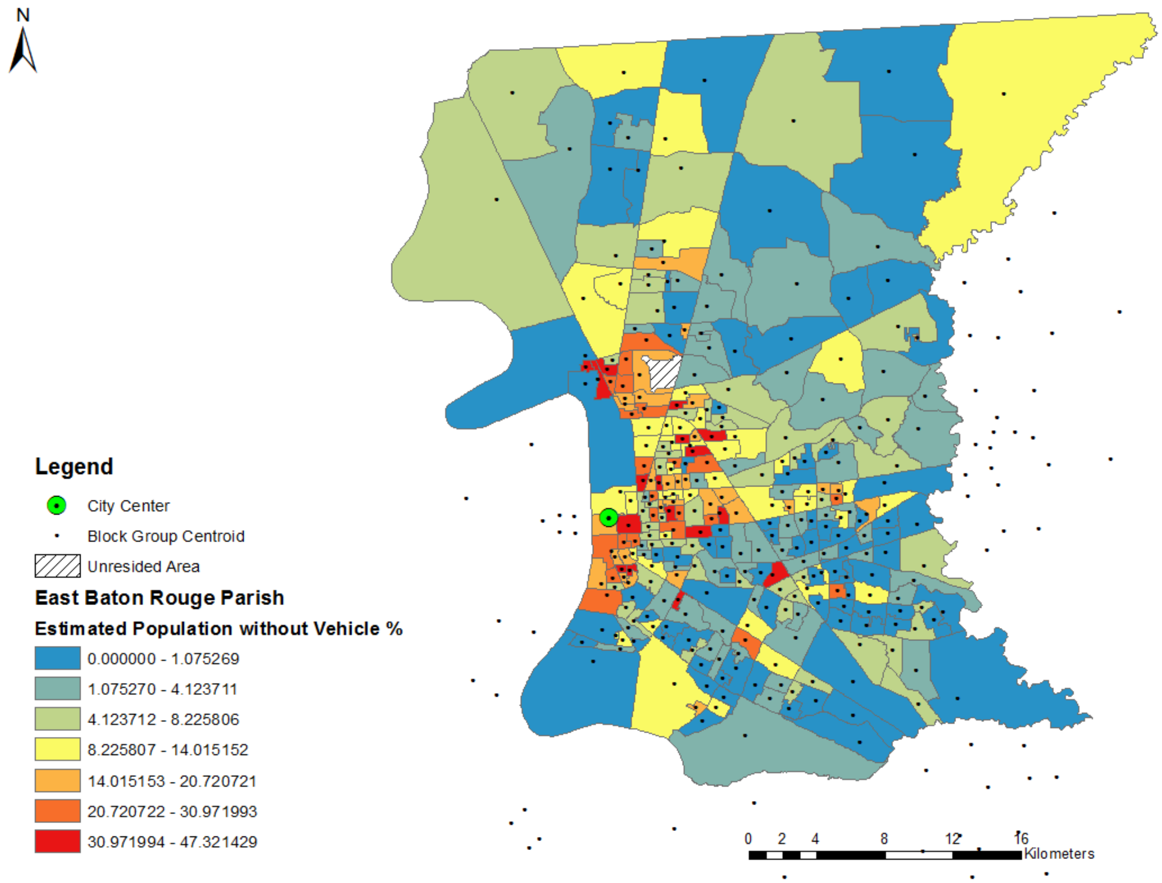


Figure 4 Percentage of population without personal vehicles

With population separated by mobility, the population served by stores should be calculated separately. The availability of food store in Equation (4.3) is updated as:

$$R_j = \frac{S_j}{\sum_{k\in\{t_{kj}\le t_0\}}\left[D_k^X \cdot f^X(t_{kj})\right]} \quad (4.11)$$

where “X” stands for different population groups: private vehicle, walking or public transit.

Similarly, food stores’ accessibility of each block group should be the weighted average of accessibility of both population groups in the block group:

$$A_i = m \cdot \frac{\sum_X \left\{D_k^X \cdot \sum_{j\in\{t_{ij}\le t_0\}}\left[R_j \cdot g^X(t_{kj})\right]\right\}}{D_k} \quad (4.12)$$

4.5 Defining threshold travel time for food purchase

In the above formulations for spatial accessibility, it is critical to define the threshold travel time t_0. According to a study on people’s travel behavior and pattern by vehicle (Yang and Diez-Roux, 2012), the mean value for an average American’s travel time on vehicle for daily purposes is approximately 14.9 minutes.

Table 3 reports basic statistics of estimated travel time by personal vehicle for all trips between block groups and food stores. The median value of travel time is 14.3 minutes in the study area. In summary, it is reasonable to set the threshold travel time by personal vehicle as 15 minutes for this study.

Table 3 Descriptive statistics for estimated travel time by personal vehicle

Mean	15.74346
Median	14.29668
Standard deviation	8.577884
Observations	106920

As for trips by walking, a study at New York (Rundle et al., 2007) suggests a 10-minute range for walking for everyday purposes, which is adopted for this study.

For population that relies on public transits, a food-purchasing trip is composed of walking between house/store and transit stop and outbound/inbound transit ride. According to a study about the walking distance to light-rail stations in Calgary, Canada (O’Sullivan and Morrall, 1996), the preferred walking distance threshold is suggested as 326 meters. In the study area, 100 block groups (out of 360) and 204 food stores (out of 297) are beyond this threshold from any transit stations, and are thus considered inaccessible and excluded from our analysis. The bus-riding time is computed similarly to the travel time by private vehicle. The bus-riding time threshold t_0 for one-way trips was also set at 15 minutes.

4.6 Spatial accessibility of healthy food

The overall healthy food accessibility is computed according to Equation (4.12), and then rescaled between 0 and 100 as shown in Figure 5.

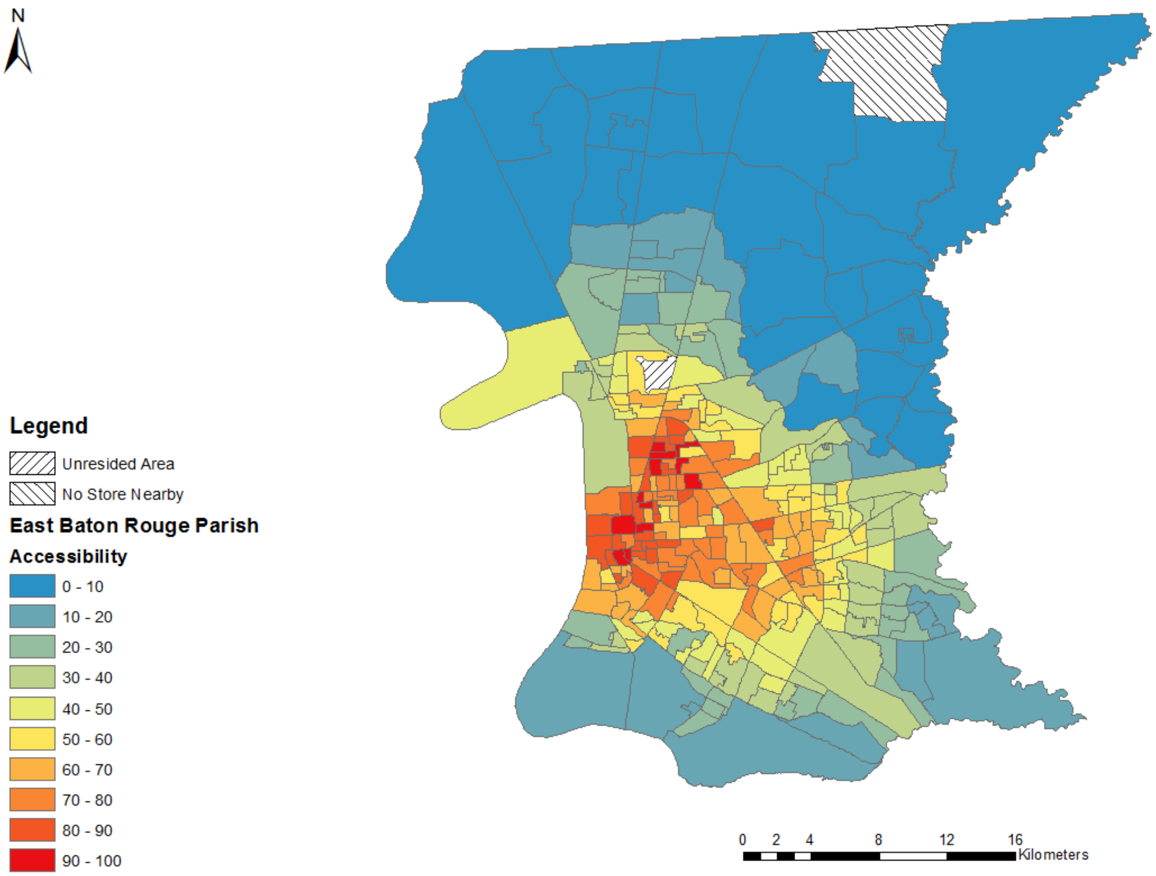


Figure 5 Healthy food accessibility in Baton Rouge by Huff-modified 2SFCA method

Figure 5 shows that overall accessibility scores conform to a concentric pattern, i.e., declining with distance from the city center. Figure 6 further validates the pattern. Low spatial accessibility of healthy food is pervasive in rural areas while central city residents enjoy good access. Note that an area on the northeast part of the study area is inaccessible to any food stores within a 15-minute driving time.

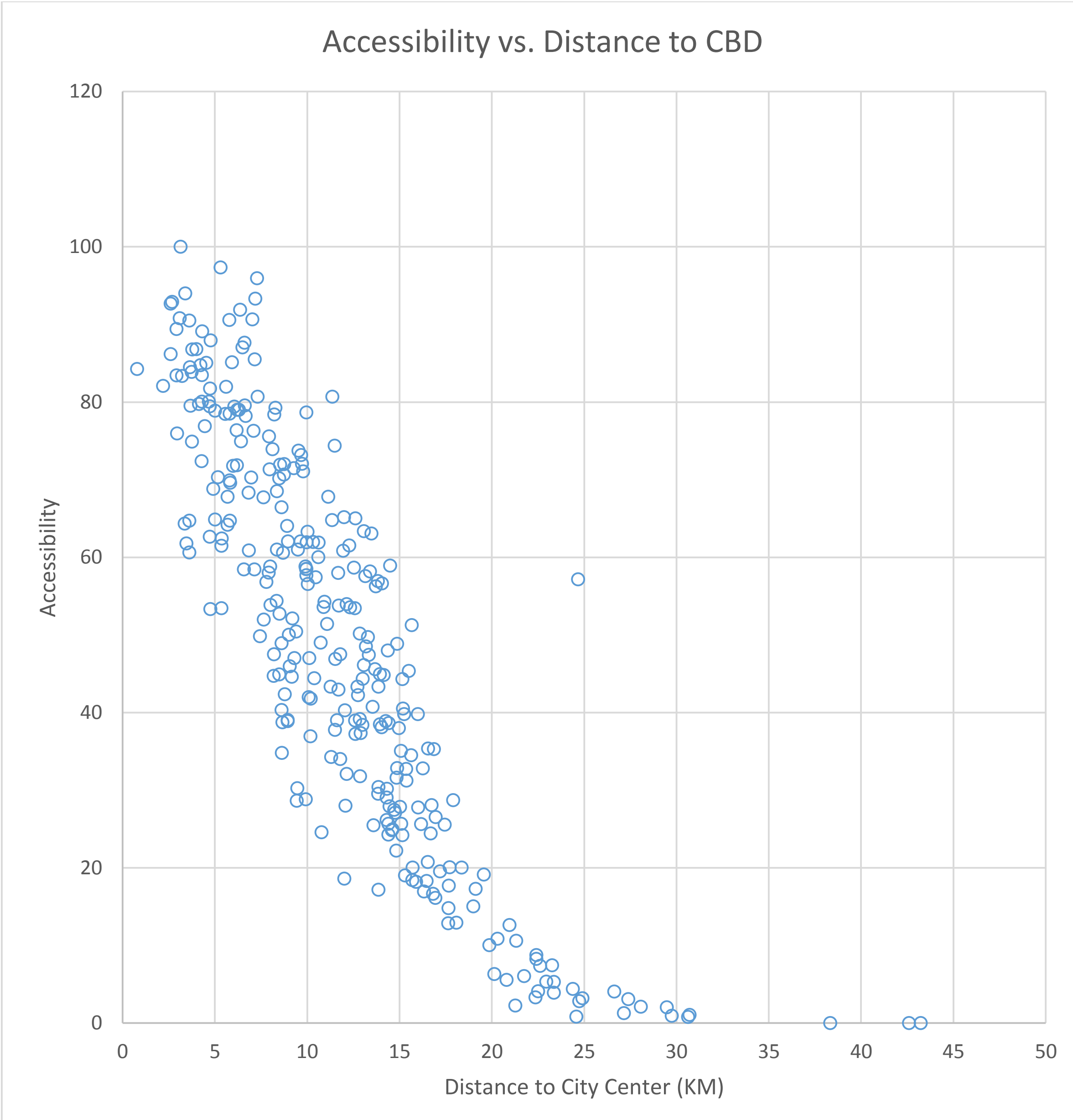
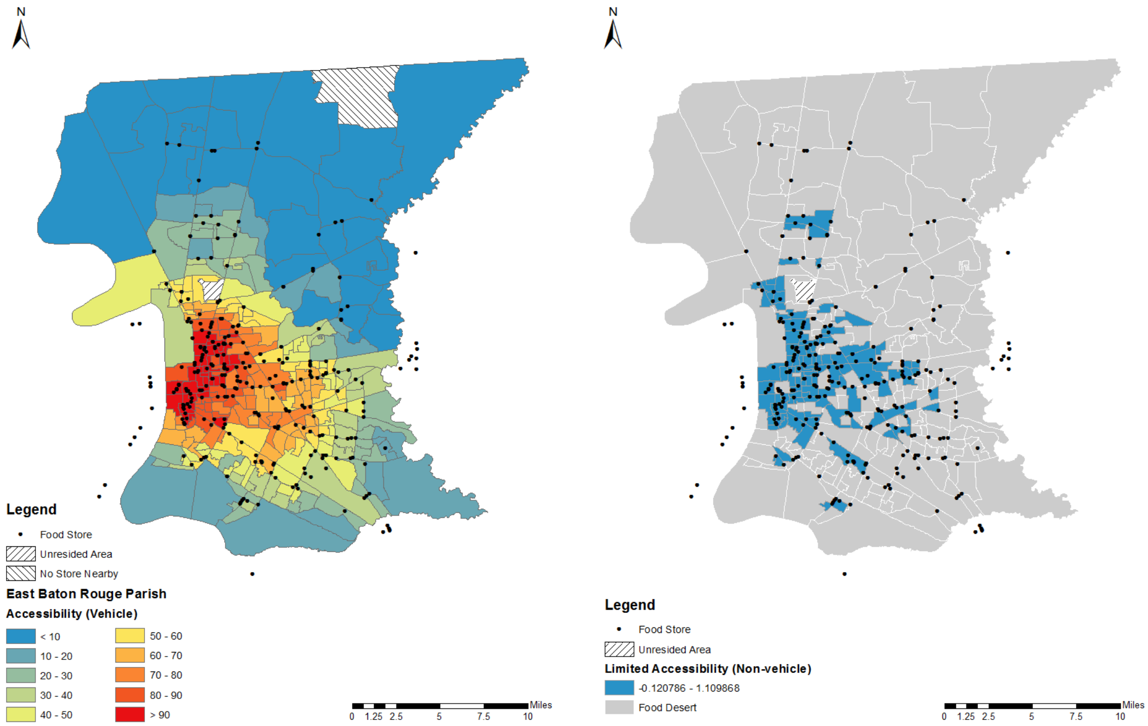


Figure 6 Spatial accessibility versus distance from city center in Baton Rouge

Figures 7(a) and 7(b) show the accessibility scores for population with personal vehicles and those without, respectively. Figure 7(a) is very similar to the overall accessibility pattern shown in Figure 5, because population without access to private vehicle only accounts for a small percentage (shown in Figure 4). For this small yet significant portion of the population, the spatial accessibility of healthy food is seriously limited with accessibility scores ranging 0 – 1. In much of the suburban and rural areas, residents without vehicle are completely inaccessible to any food stores. While the disadvantaged people tend to concentrate in the central city, the urban poor without personal vehicles also have very poor access to healthy food.



(a) (b)

Figure 7 Spatial accessibility for: (a) population with vehicles and (b) population without vehicles

For comparison, the spatial accessibility by the more commonly used KD2SFCA method, with the standard normal distribution function as its KD function, was also obtained.

The results are also rescaled to 0 - 100 as shown in Figure 8. Generally speaking, the results from the two methods are consistent with each other: accessibility scores are higher in and around central city and gradually decline to suburban and rural areas.

Figure 9 further validates the consistency between the two.

While the Huff-modified 2SFCA method is more conceptually sound than the KD2SFCA, we cannot declare the superiority of one over another until an empirical study is conducted to establish the connection between accessibility and actual utilization of food stores. Such a task is beyond the scope of this study.

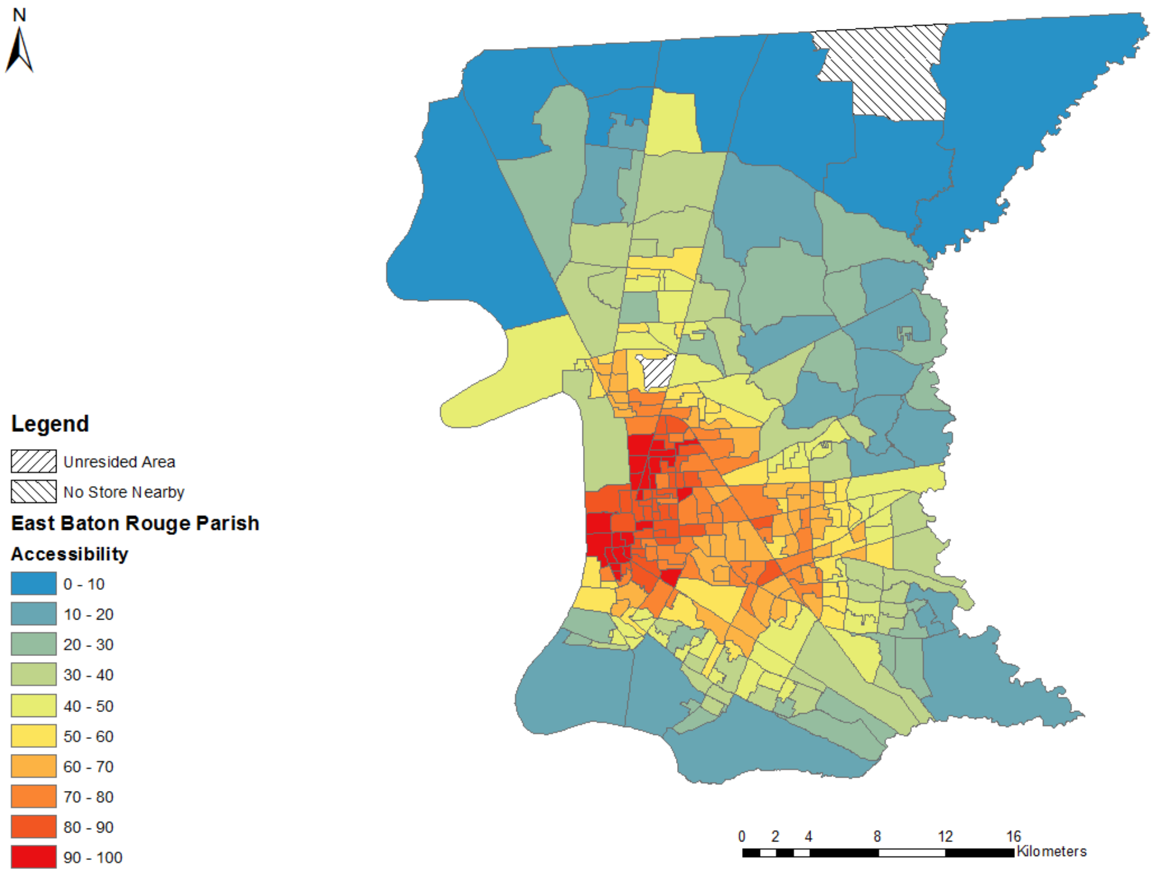


Figure 8 Healthy food accessibility in Baton Rouge by KD2SFCA method

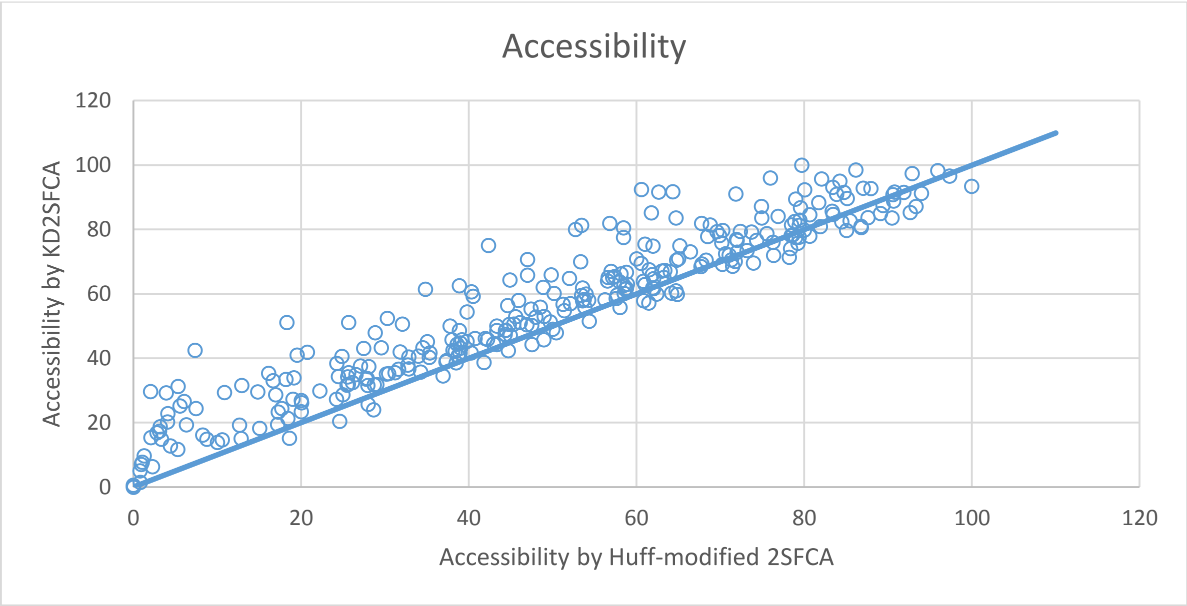


Figure 9 Spatial accessibility scores by KD2SFCA vs. Huff-modified 2SFCA

CHAPTER 5. SPATIAL ACCESSIBILITY AND NEIGHBORHOOD FEATURES

This chapter analyzes how demographic and socio-economic characteristics are related to the spatial accessibility of healthy food among the neighborhoods in the study area.

5.1 Correlation analysis

The initial assessment is by a bivariate correlation analysis between the spatial accessibility scores and each of the 12 socio-demographic variables. The results are reported in Table 4.

Table 4 Correlation coefficients between spatial accessibility and neighborhood characteristics

Variable	Code	Mean	Correlation Coefficient	
			Huff-modified 2SFCA	KD2SFCA
Female-male ratio	A	1.141	0.018	0.082
Non-white population percentage	B	55.283	0.327**	0.430**
Percentage of population with a disability	C	11.904	0.192**	0.300**
Female householder percentage	D	19.493	0.198**	0.298**
Percentage of population without a high school diploma	E	13.972	0.277**	0.418**
Linguistically isolated population percentage	F	0.269	0.000	0.030
Poverty rate (%)	G	19.055	0.276**	0.325**
Median household income ($)	H	50998	-0.377**	-0.468**
Unemployment rate (%)	I	33.736	0.049	0.096
Percentage of renter-occupied housing units	J	38.092	0.338**	0.385**
Percentage of housing units with >1 occupant per room	K	2.681	0.054	0.099
Percentage of housing units without kitchen facilities	L	3.615	0.181**	0.242**

*: Correlation is significant at 0.05 level (2-tailed); **: Correlation is significant at 0.01 level (2-tailed)

Number of observations: 302

Both measures reveal that higher spatial accessibility scores tend be associated with higher ratios of minority population, the disabled, female-headed households, people of lower educational attainment, people under the poverty line, people with lower income, renters, and housing lack of basic amenities. That is to say, the socially or economically disadvantaged groups actually enjoy better spatial accessibility of food, primarily because of their residential locations closer to central city. Among the socio-demographic variables significantly correlated with spatial accessibility scores, the correlations are higher with the original KD2SFCA scores than the Huff-modified 2SFCA scores.

Table 5 presents the Pearson's correlation coefficient matrix for each pair of demographic and socio-economic variables (see Table 4 for the variable names). Correlation coefficient scores higher than 0.5 are marked in bold to highlight highly correlated pairs. Two clusters of highly correlated variables are observed: the first one contains non-white percentage, female household percentage and percentage of population without a high school diploma, and the second one includes poverty rate, median household income and percentage of renter-occupied housing units. This indicates that some of the variables capture similar features of neighborhoods and are thus duplicated to some extent. The analysis paves the way to the principle components analysis in the next section.

Table 5 Correlation coefficients between 12 demographic and socio-economic characteristics

	A	B	C	D	E	F	G	H	I	J	K	L
A	1											
B	0.154 **	1										
C	0.072	0.501 **	1									
D	0.253 **	0.723 **	0.403 **	1								
E	0.141 *	0.720 **	0.548 **	0.657 **	1							
F	-0.067	-0.012	-0.053	-0.067	-0.029	1						
G	0.158 **	0.452 **	0.310 **	0.414 **	0.529 **	0.004	1					
H	-0.205 **	-0.628 **	-0.409 **	-0.473 **	-0.593 **	-0.021	-0.706 **	1				
I	0.120 *	0.217 **	0.372 **	0.201 **	0.345 **	-0.034	0.268 **	-0.249 **	1			

(Table 5 continued)

	A	B	C	D	E	F	G	H	I	J	K	L
J	0.107	0.295 **	0.123 *	0.236 **	0.337 **	0.082	0.670 **	-0.643 **	-0.035	1		
K	0.147 *	0.346 **	0.141 *	0.376 **	0.428 **	0.025	0.323	-0.283 **	0.099	0.198 **	1	
L	0.158 **	0.404 **	0.261 **	0.367 **	0.339 **	-0.050	0.282	-0.312 **	0.143 *	0.145 *	0.243 **	1

*: Correlation is significant at 0.05 level (2-tailed); **: Correlation is significant at 0.01 level (2-tailed)

5.2 Determining principle components

The *principle component analysis* (PCA) method (Wang, 2009) is used here to amalgamate significantly correlated variables into a small number of independent factors.

Table 6 presents the *eigenvalues* and corresponding percentage of variance explained by each initial component. Three components with corresponding eigenvalues greater than 1, marked in bold, are retained, and collectively capture 63.75% of the total variance of the original 12 variables. The scree plot in Figure 10 shows that the eigenvalues level off significantly after the 3rd component and thus further validate the choice of keeping three components.

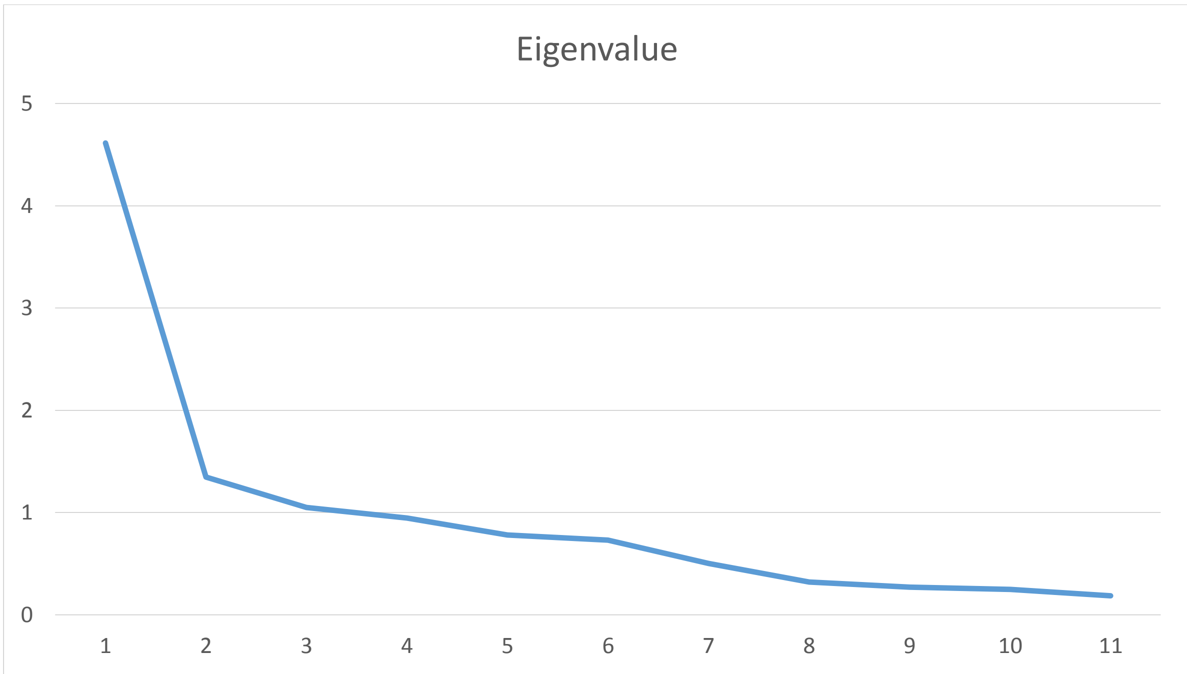


Figure 10 Scree plot for 12 components

Table 6 Eigenvalues from the principle components analysis

Component	Initial Eigenvalue	Proportion	Cumulative
1	4.615	41.958	41.958
2	1.349	12.262	54.22
3	1.048	9.531	63.75
4	0.947	8.605	72.356
5	0.78	7.095	79.45
6	0.732	6.655	86.105
7	0.503	4.57	90.675
8	0.321	2.918	93.593
9	0.272	2.469	96.062
10	0.248	2.254	98.316
11	0.185	1.684	100

The *Oblimin with Kaiser Normalization* rotation technique is used to polarize the loadings for the convenience of easy interpretation of derived components. This is commonly referred to as the principle components factor analysis. The result is shown in Table 7 with *factor loadings*, which "indicates the strength of relations between variables and factors" (Wang, 2009, 4).

Table 7 uses bold font to highlight which variable contributes to what factor with the highest score of factor loading, and thus forms the structure for labeling the factors

Table 7 Factor loadings from the principle components factor analysis

Variable	Factor 1	Factor 2	Factor 3
A	-0.045	0.112	0.563
B	0.624	0.532	0.674
C	0.811	0.297	0.261
D	0.516	0.423	0.753
E	0.694	0.57	0.606
G	0.362	0.875	0.365
H	-0.458	-0.86	-0.443
I	0.729	0.11	0.052
J	0.023	0.896	0.211
K	0.119	0.314	0.665
L	0.295	0.234	0.602
Variance Explained	0.649	0.584	0.844

Factor 1 explains 41.96% of the total variance, and incorporates 3 neighborhood feature variables:

1. Percentage of population with a disability;

2. Percentage of population without a high school diploma;

3. Unemployment rate.

For lack of a better term, this factor is named as *social disadvantage*, and its spatial pattern is mapped in Figure 11.

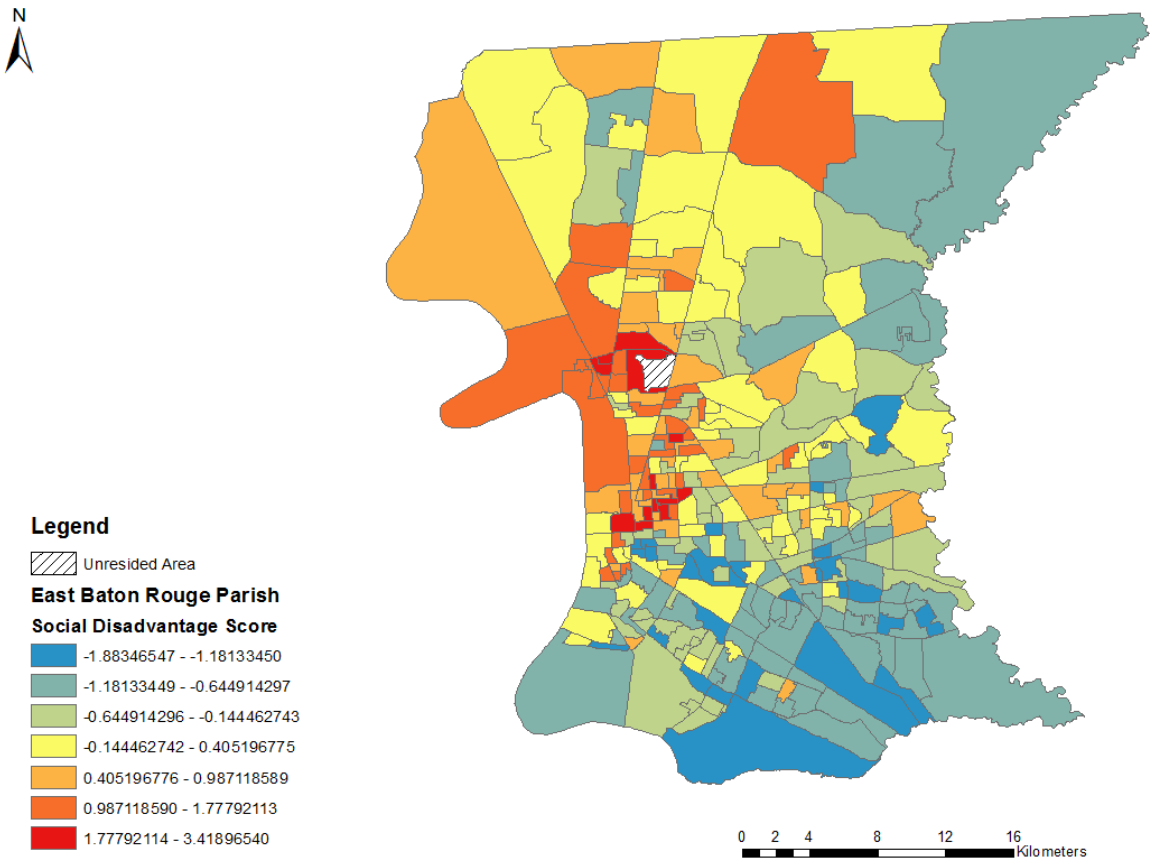


Figure 11 Social disadvantage score

A higher social disadvantage score indicates a more socially disadvantageous neighborhood. Although roughly, the map shows that the inner city and a long stretch toward the north sector suffer major social disadvantages.

Factor 2 explains 12.26% of the total variance, and integrates 3 variables:

1. Percentage of renter-occupied housing units;

2. Poverty rate;

3. Median household income.

This fact can be labeled as *economic disadvantage* and is mapped in Figure 12. A higher economic disadvantage score implies a more economically deprived neighborhood. The map shows a generally improved situation toward suburban and rural areas.

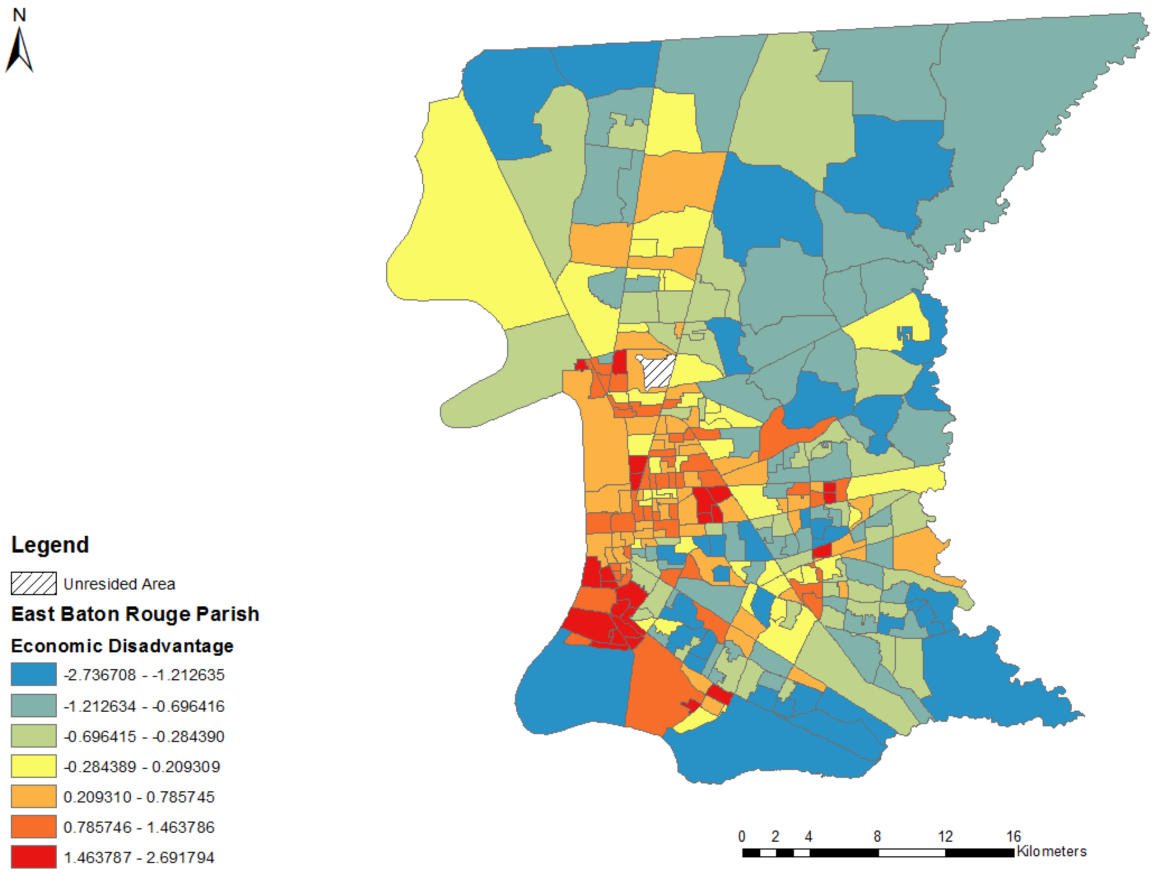


Figure 12 Economic disadvantage score

Factor 3 explains 9.53% of the total variance, and captures 6 variables:

1. Female-male ratio;
2. Non-white population percentage;
3. Female householder percentage
4. Linguistically isolated population percentage
5. Percentage of housing units with more than 1 occupant per room;
6. Percentage of housing units without kitchen facilities.

It is labeled "*minority disadvantage*" and mapped in Figure 13. Its pattern is less clear but also reveals a disadvantaged stripe toward the north.

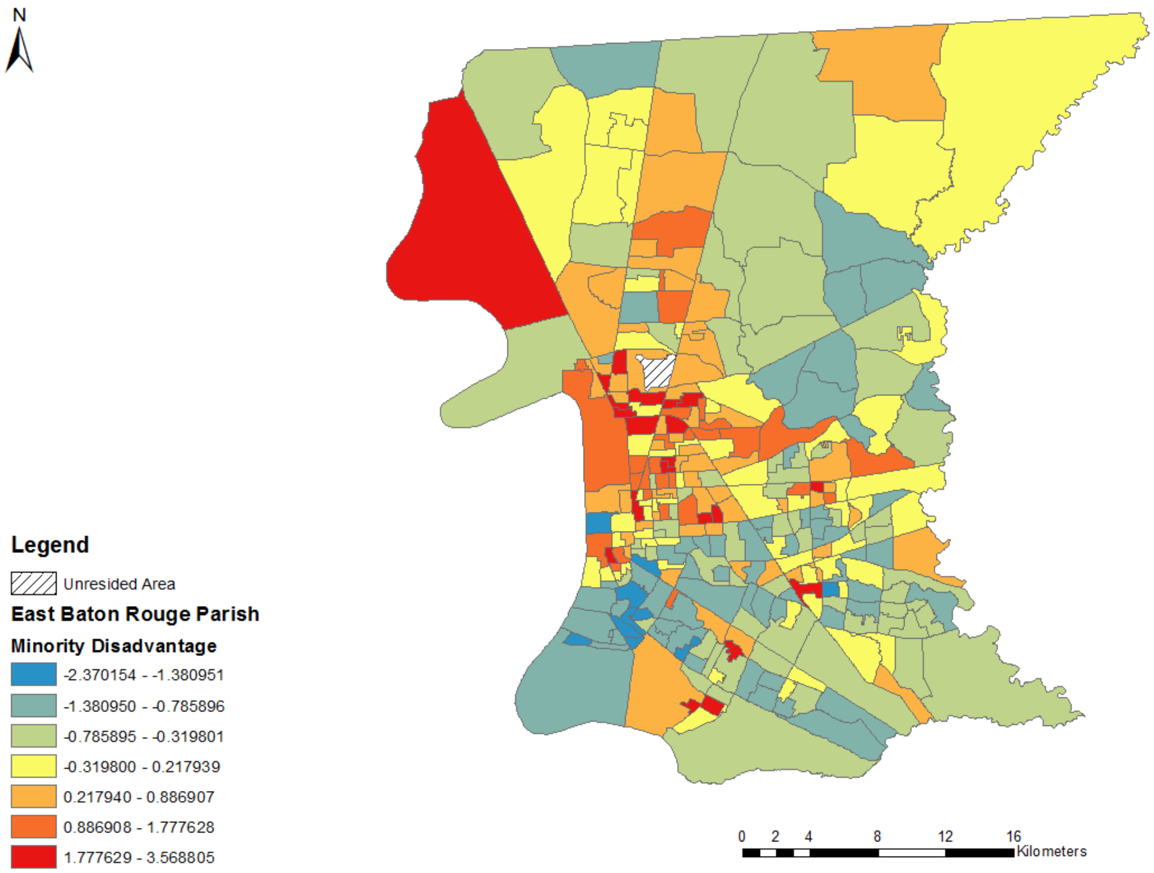


Figure 13 Minority disadvantage score

5.3 Relationships between spatial accessibility and neighborhood factors

Table 8 presents the result of correlation analysis between healthy food accessibility and each of the disadvantage factors. All the disadvantage factors are positively correlated with the spatial accessibility of healthy food, and the correlations are statistically significant. The significance is the highest for the economic disadvantage factor, followed by the social disadvantage factor and then the minority disadvantage factor. Also see Figures 14-16 for their positive correlation trends.

This further validates the finding from the correlation analysis of original socio-demographic variables and spatial accessibility. The socio-economically disadvantaged population groups are mainly located in urban areas with more food store outlets, and enjoy better spatial access to healthy food. If healthy food access remains an issue for these groups, it is not because of “where they are” rather possibly “who they are” such as whether they have private vehicles or possesses necessary financial means of actually purchasing healthy food.

Table 8 Correlation coefficients between disadvantage factors and spatial accessibility

Factor	Correlation Coefficient	Probability	Standard Deviation
Social disadvantage	0.196	0.001**	1.029
Economic disadvantage	0.359	0.000**	1.037
Minority disadvantage	0.170	0.003**	1.040

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

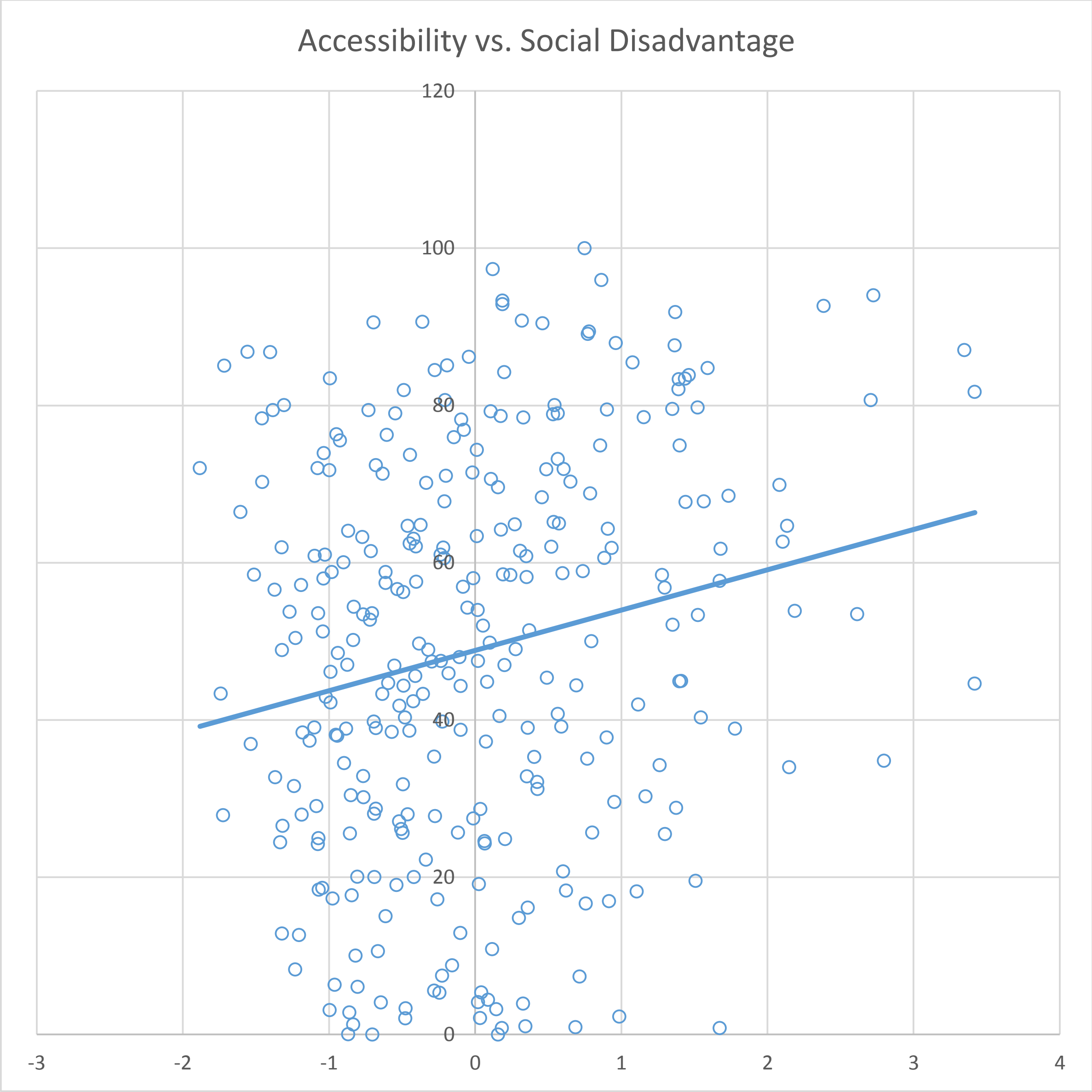


Figure 14 Spatial Accessibility and social disadvantage

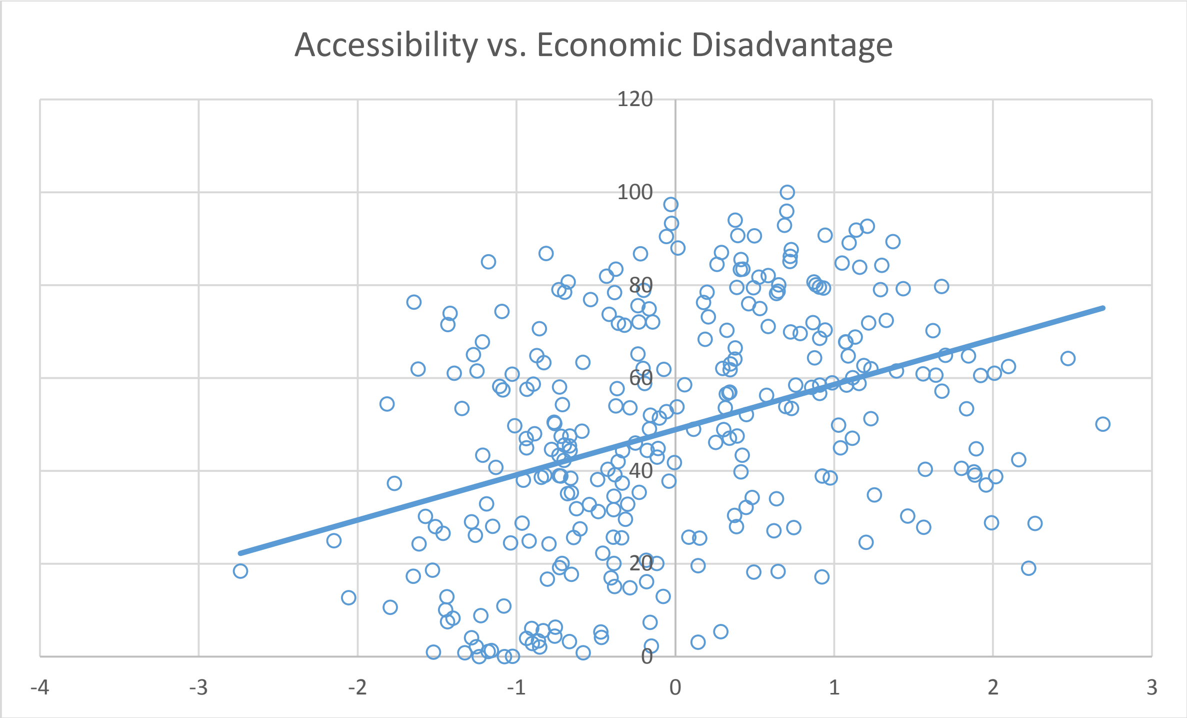


Figure 15 Spatial Accessibility and economic disadvantage

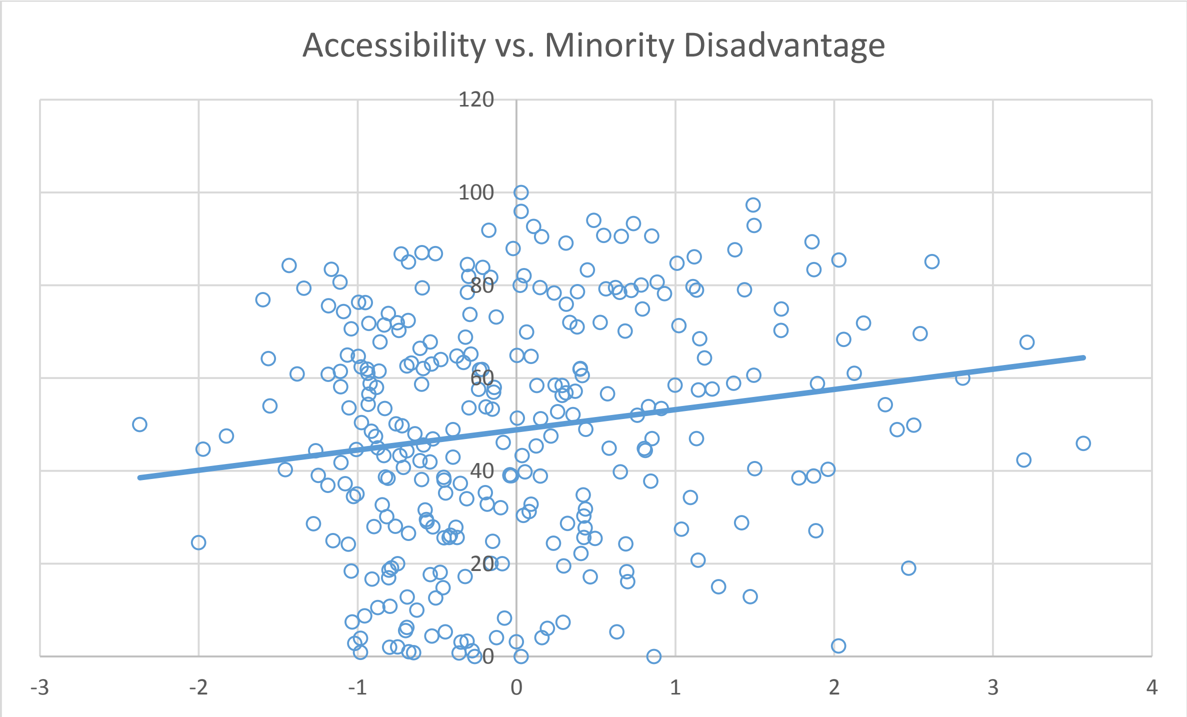


Figure 16 Spatial accessibility and minority disadvantage

CHAPTER 6. DISCUSSION AND CONCLUSIONS

Examining and mitigating disparities to public services has always been of great interest to urban planners and public policy analysts. In addition to food access (Algert et al., 2006), public services may also include health care facilities (Vega et al., 2003), public green spaces (Irvine et al., 2009), public transportation (Murray et al., 1998) and even digital resource (Driskell and Wang, 2009). Any meaningful planning or policy design begins with scientific assessment of the disparities for access to such a service. This paper proposes an alternative to the commonly used 2SFCA or its improved version KD2SFCA – the Huff-modified 2SFCA method in attempt to more accurately capture the very essence of spatial accessibility.

Compared with the traditional 2SFCA method, the Huff-modified 2SFCA method utilizes the probability measure in the Huff Model to rescale the amount of supply-to-demand interaction within a catchment. Based on the original KD2SFCA method, the Huff-modified 2SFCA method rescales interaction in a more reasonable way: (1) it uses an adaptive kernel density function, instead of a fixed one, to account for distance decay in the supply-to-demand interaction, and (2) it adopts a "Huff Kernel" to formulate the competition intensity for a store's service as possible population visiting the store instead of simply distance-decayed demands. While the Huff-modified 2SFCA method is more conceptually sound than the KD2SFCA, we cannot declare the superiority of one over another until an empirical study is conducted to establish the connection between accessibility and actual utilization of food stores. Such a task is beyond the scope of this study.

The result of healthy food accessibility derived by the Huff-modified 2SFCA method indicates a largely concentric pattern that central city and urban areas have better access to healthy food retailers than suburb and rural areas. This is contradictory to the common notion that the urban poor in central city do not have adequate access to healthy and affordable food. However, the advantage in spatial accessibility of healthy food for these neighborhoods may not be transferrable for a small percentage of people who are deprived of access to a private vehicle. This population group is small yet significant, and suffers from the lowest healthy food accessibility because they rely on much slower transportation modes such as walking or public transit services.

Recent literature suggests that the linkage between built environment and obesity prevalence varies a great deal across geographic settings, and some built environment factors such as street connectivity and walkability seem to be only relevant in influencing physical activity and obesity risk in suburban areas but not in central city or rural area (Xu and Wang, 2014). Our research suggests that the spatial accessibility tied to one's location is certainly not the barrier that prevents the urban poor from obtaining and developing a healthy diet. What matters more is the complex interaction among socio-economic attributes, spatial accessibility and consumer behavior. Socio-economic conditions can heavily influence people's dietary habit – disadvantaged people may have no choice but to purchase energy-dense, nutritionally inferior but cheap foods, even with sufficient healthy food supply around their neighborhoods (Helling and Sawicki, 2003; Larson et al., 2009). In other words, from a public policy perspective, the focus should not be on the spatial aspect of "food desert" rather on the non-spatial dimensions.

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