A STUDY OF ACCESSIBILITY TO HEALTH FACILITIES FOR ELDERLY PEOPLE IN METRO ATLANTA USING A CATEGORICAL MULTI-STEP FLOATING CATCHMENT AREA METHOD

by

ZHAOYING WEI

(Under the Direction of Xiaobai Yao)

ABSTRACT

This study proposes a categorical multi-step floating catchment area method to measure spatial accessibility to health facilities for elderly people. This research is motivated to reveal the landscape of elderly people's spatial accessibility to different types of health facilities in various areas. The new method is revised and enhanced from the three-step floating catchment area method by modeling the categorical structure of health facilities and involving the competition between different categories of health facilities. Health facilities for the aged are divided into several different types and accessibility to different types of health facilities are calibrated independently. In this way, not only the big picture of the accessibility to different health facilities for elderly people can be shown, but also a competition-involved categorical accessibility to diverse types of health facilities for the aged can be identified. Finally, a case study of accessibility specifically for elderly people aged 65 and over is conducted in 28 counties of metropolitan Atlanta.

INDEX WORDS: Spatial Accessibility, Elderly People, Health Facility, Categorical

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INTRODUCTION

1.1 Accessibility to Health Care

Access to health care has been an important theme in public health policy in the United States and other countries for many years. Which communities and populations have poor geographical access to health services? This question has always been the issue that health planners are concerned about. Lots of efforts have been made to document potential accessibility, which is about the geographical linkage between people and essential services. At its core, the concept refers to the separation between services and population−how much distance, cost, time and effort are involved in reaching service facilities (Cromley and McLafferty 2011). Accessibility concerns the relative ease by which the locations of activities, such as work, shopping and health care, can be reached from a given location (BTS 1997). Access to health facility in a given location is the measurement of opportunities available to that health facility within certain distance or travel time. It is influenced by many factors, including the availability of health services in the area (supply), the number of people living in that location (demand), the population's health status, the socio-economic and financial resources available to the population, people's knowledge about health and the health care system, and geographical impedance between population and health services (Aday and Andersen 1974). The spatial access focuses on spatially uneven distribution of providers and consumers (spatial factors). Non-spatial access emphasizes on the variations among population groups because of their different socioeconomic and demographic characteristics (non-spatial factors). To ensure adequate access to health facility, health service planners and policy makers need reliable measures of accessibility so that true health facility shortage areas can be accurately identified and resources allocated to those needy areas to alleviate the problem.

Numerous methods have been proposed to estimate spatial access to medical facilities. These methods include the regional availability model (Khan 1992), kernel density models (Silverman 1986, Guagliardo 2004), and gravity models (Joseph and Bantock 1982, Luo and Wang 2003, Schuurman, Randall and Berube 2011). The regional availability method compared the sum of healthcare capacity and the population demand within an area. This method has been criticized for its two problematic assumptions: (1) people are restricted to one area and do not go beyond the area to seek health care and (2) all individuals within an area have equal access to the service regardless of how far away they live or work from healthcare sites. The kernel density model, which calculated medical supply and demand using a kernel function, was superior to the regional availability measure in estimating spatial access to health care because it considered both the distance decay effect and the cross-boundary healthcare-seeking behaviors (Guagliardo 2004). However, the kernel function was problematic for estimating medical service areas and population density (Yang, Goerge and Mullner 2006). Gravity-based spatial access models assumed that a population's spatial access to medical services decreases with the increase of its distance to nearby medical sites in a gravitational way (Joseph and Bantock 1982). Gravity models were conceptually more complete and more flexible to realize than the above-mentioned two models, but it was not intuitive to interpret. (Luo and Qi 2009). An improvement of the basic gravity model was the two-step floating catchment area (2SFCA) method, which was first proposed by Radke and Mu (2000), modified by Luo and Wang (2003), and recently enhanced by Luo and Qi (2009). The two-step floating catchment area (2SFCA) method defined the service area of physicians by a threshold travel time while accounting for the availability of physicians by their surrounded demands. The method required two point data sets: data on the locations and capacities of service providers and data on the locations of population in need of services. The 2SFCA moved between these two data sets in a two-step process. First, they constructed a threshold travel distance/time around each service provider j and computed the provider to population ratio R_j within that window. Second, for each population location i, they searched all provider locations within a threshold travel distance /time and sum up the R_j values for those providers. The resulting value was the accessibility score for the population at place i. Higher values indicated better spatial access to health care providers. Compared to gravity model, it's simpler and easier to interpret. However, it was limited in that it assumes all population locations within the catchment to have equal access and disregards the distance impedance within the catchment (Luo and Wang 2003). McGrail and Humphreys (2009a) used and enhanced 2SFCA to evaluate the spatial accessibility of primary care physicians in Victoria, Australia. Enhanced two-step floating catchment area (E2SFCA) method was an improvement because it considered the distance impedance within the catchment. Its limitation lied in that it may overestimate the demand for some service sites because people's demand on one service site can get lower when other sites are available at the same time. A three-step floating catchment area (3SFCA) is proposed to minimize the demand overestimation problem. Conceptually, it assumed that a population's healthcare demand for a medical site is influenced by the availability of other nearby medical sites (Wan, Zou and Sternberg 2012b). Though the 3SFCA method had notable advantages, several issues deserve special attention when implementing this method in health service accessibility studies. First, the determination of the catchment size could be more flexible. As claimed by previous studies (Yang et al. 2006, McGrail and Humphreys 2009a), the catchment size could vary with neighborhood characteristics and the specific type of medical service in demand. For instance, smaller catchment size should be used for urban than rural areas and for acute care services rather than for long-term care services. A second issue is that the competitions on either the supply or demand side have not been considered in current models. On the supply side, health facilities in the same or even different categories may provide overlapping types of services. The facilities may compete for the same potential clients. On the demand side, different population subgroups can be classified by demographic, socioeconomic, or insurance status. These people may seek service opportunities at the same facilities of high demand. How to model the competition remains a research topic.

1.2 Research Objectives

This study proposes a categorical multi-step floating catchment area method to measure the spatial accessibility of elderly people to different types of health facilities. This research is motivated to reveal the landscape of elderly people's spatial accessibility to different types of health facilities in various areas. The Categorical Multi-Step Floating Catchment Area (CMSFCA) method is revised and enhanced from the Three-Step Floating Catchment Area Method (3SFCA) that modeled categorical structure to calculate accessibility to health facilities. Health facilities for elderly people are divided into several different types and accessibility of different types of health facilities is calibrated. Taking the previous questions mentioned before in 3SFCA into consideration, the proposed method distinguishes different types of health facilities in a categorical structure. We plan to use diverse catchment sizes for different types of health facilities. Also, the relative competition ability of each type of health facilities in the area is used to dictate the accessibility of elderly population to each type of health facilities. A case study of accessibility specifically for elderly people aged 65 and over is conducted in 28 counties of metropolitan Atlanta. Four types of health facilities and services that elderly people are more prone to use are included. Finally, the new competition-involved categorical accessibility is compared with the categorical accessibility to validate the performance of new CMSFCA method. The objectives of this research are as follows:

1. Propose a categorical multi-step floating catchment area method to measure spatial accessibility to different types of health facilities for elderly people.
2. Conduct a case study for people who are 65 and over in metropolitan Atlanta MSA.

1.3 Expected Significance

In recent years, as population ageing has grown into a “defining global issue”, concerns have emerged regarding policy interventions that are appropriate for older people (Gorman and Heslop 2002, Barrientos and Lloyd‐Sherlock 2002), especially in the area of elderly health care.

Medicare is a federal health insurance program established by the US Congress in 1965 as Title of 18 of the Social Security Act. Medicare is designed to assist individuals aged 65 and over, some disabled individuals under the age of 65, as well as patients with end-stage renal (kidney) disease. Unlike Medical Assistance, Medicare is not based on income or assets. After almost 50 years since its enforcement, what would we find if we measure the access to health facilities for people who are eligible for Medicare?

Though accessibility to health facilities has been widely studied, the accessibility specifically of elderly people to healthcare services has rarely been touched. Elderly people have limited regenerative abilities and are much more likely to suffer mobility, health and disability problems, thus placing a strain on government finances and health care facilities. Worldwide, the number of elderly people is increasing faster than ever before, especially in developed countries such as the United States. Further, the elderly have many privileges from government agencies.

They are eligible for Medicare that provides health care coverage for those aged 65 or older, no matter what their income or worth is. However, the focus of this study is on the method for measuring spatial accessibility to health care facilities. I will not consider race or income disparity due to time constraint and data unavailability.

1.4 Thesis Design

In the following chapters, I will present a review of the pertinent literature in the areas of access study in public health, accessibility research in geography, including spatial access and non-spatial access, a general framework of spatial accessibility to health facilities for elderly people, a detailed methodology regarding the application of multi-step floating catchment area method, a case study that utilizing the new proposed method, and a summary of the results analysis from the proposed methodology, and general conclusions. Chapter 2 examines the history and application of accessibility calculation methodology in relation to health care services. This literature review bridges the methodological innovation of competition-involved categorical accessibility with the theoretical considerations of involving diverse catchment size and competition between different kinds of health facilities. Chapter 3 outlines the methodology of competition-involved categorical spatial accessibility to health facility for elderly people used in this thesis. Chapter 4 detailed the data and study area of the case study in this thesis. The necessary source of the data and parameter value we used in this research are introduced. Chapter 5 presents and summarizes the thesis results including mapped categorical accessibility value, the final competition-involved categorical accessibility value. Finally, Chapter 6 summarizes the thesis, acknowledges methodological limitations, and suggests directions for future study beyond the scope of this thesis.

CHAPTER 2

LITERATURE REVIEW

The aim of health services is to improve health and well-being. Although we typically think of biomedical health service providers, such as physicians and hospitals, a much broader array of activities contribute to health, including education services, water supply and sanitation facilities, mental health care, and social services. There are two general ways of providing health care. Informal health care is provided by families and communities in a home or community setting, such as the care provided by the elderly's adult children or relatives. Informal care is neither monetized nor assigned a value through market mechanisms or budgeting processes. Women provide well over half of informal health care delivered in the United States and worldwide (Navaie-Waliser, Spriggs and Feldman 2002). In contrast, formal health care is provided by public, private, and voluntary organizations, through providers, such as hospitals or physicians. Formal care takes place in a variety of settings, including clinics, workplaces, schools, and, increasingly, in individuals' homes. In the formal sector, caregivers typically receive a monetary wage for their services, and government regulation of services is common. This study focuses primarily on formal health services; however, it is noted that important links exist between the two types of health care that can be examined geographically. Changes in the intensity and structures of formal health care affect the need for informal health services and vice versa.

Accessibility can be generally divided into two types based on different influential factors−spatial accessibility and non-spatial accessibility. Access to healthcare varies across space because of uneven distributions of healthcare providers and consumers (spatial factors), and also varies among population groups because of their different socioeconomic and demographic characteristics (non-spatial factors). Accordingly, spatial access emphasizes the importance of geographic barriers (distance or time) between consumer and provider. However, non-spatial access stresses nongeographic barriers or facilitators, such as social class, income, insurance status, ethnicity, age, sex, etc. Early research in the public health field focused more on the non-spatial accessibility. Though the accessibility researchers in public health field started to realize the importance of spatial accessibility, most of the research only utilizes the existing method of measuring spatial accessibility. Few of them involve improved methodologies. However, in geography field, the research deals with both methodology and application. Non-spatial access is widely studied and applied by both public health researchers and geographers.

2.1 Accessibility in Public Health

Many studies about health care access are conducted in the field of public health. Some simple ways of measuring potential accessibility are utilized in public health research. One of them is to calculate the distance from the population in need of service to the nearest service provider. Differences in average distance to health facilities can highlight variation in geographical access to care. In most countries, rural residents travel significantly farther for care than their urban counterparts (Probst et al. 2007). To examine geographical access to pediatric medical services in the United States, Mayer (2006) used geocoded provider locations by subspecialty. Distances from each ZiP Code centroid to the nearest provider were calculated and weighted by the under-18 population. Comparison of population-weighted average distance across pediatric subspecialties showed substantial variations in access to care. Lawson et al. (2013) used a geospatial method to evaluate the spatial distribution of trauma center care in relation to the spatial distribution of severely injured patients. The proportion of major trauma cases within one hour travel time of a Level I or Level II trauma center is determined to represent spatial access to trauma center care.

In addition to average distance, examining the frequency distribution of distances can shed light on spatial access to services. These kinds of analyses are important for providing population-based evaluations of geographical access to health services at the national and regional scales. Onega et al. (2008) estimated travel time to the nearest cancer center in the United States, and they compared travel time statistics among sociodemographic population groups. Excessive travel burdens for Native Americans and nonurban populations were highlighted. To compare spatial access to health care among population groups in Wales, Christie and Fone (2003) created travel-time frequency distributions for each group for three travel speed scenarios. Spatial access problems were most acute among rural residents and, under certain scenarios, among the elderly and residents of deprived areas. Analyzing the distribution of distances can offer potent insights into the equality and inequality of spatial access among population groups. Crespo-Cebada and Urbanos-Garrido (2012) analyzed the inequalities in the use of primary care for elderly people. Their results show the presence of poor equality in both the access and the frequency of use for GP services for elderly people in Spain. Inequality in health care access leads to disparities in various health outcomes, including different rates in infant mortality and birth weight, vaccination and complications from preventive and common diseases, among others. Distance measurements can also be used in defining catchment areas for health service providers. A maximum distance or travel time threshold delineates the area in which people have reasonable access to care. Schuurman et al. (2006) employed a 1-hour travel time threshold to identify catchment areas for hospitals in British Columbia.

2.2 Accessibility in Geography

People started to realize the use of GIS to analyze access to health services in the dynamic context. GIS played a major role in providing and managing information about health service locations the measurement of geographical access to services, and the analysis of changing service distribution patterns.

In geographical field, accessibility is a crucial indicator to measure how well a facility's ability can be accessed. In the absence of individual-level health data, measures often focused on place accessibility (Kwan 1998). Accessibility measures need to account for both spatial and non-spatial factors (Khan 1992). Spatial access emphasizes the importance of spatial separation between supply (i.e., health care providers) and demand (i.e., population) and how they are connected in space (Joseph and Bantock 1982). Non-spatial factors include many demographic and socioeconomic variables such as social class, income, age, sex, race, and so on, which also interact with spatial access (Meade and Emch 2010).

2.2.1 Spatial Accessibility in Geography

One of the previous approaches to measure spatial accessibility is gravity-based accessibility model. Supply and demand located in different areas and has been applied in studying health care access (Joseph and Bantock 1982) and other areas, such as job access (Shen 2011). Accessibility at location i (A_i) is written as

$$A_i = \sum_{j=1}^{n} \left[S_j d_{ij}^{-\beta} / \left(\sum_{k=1}^{m} P_k d_{kj}^{-\beta} \right) \right] \qquad (1)$$

where P_k is population at location k, S_j is the capacity of the health care provider (e.g., number of doctors or hospital beds) at location j, d is the distance or travel time between them, β is the travel friction coefficient, and n and m are the total numbers of physician locations and population locations, respectively. Although conceptually advanced, this model has the limitation that its distance friction parameter β requires additional data and work to define and might be region specific (Huff 2000).

The floating catchment area (FCA) method is a special case of the gravity-based accessibility method (Luo and Wang 2003). Earlier version of FCA method resembles kernel estimation (for example, Bailey and Gatrell 1995), in which a ‘window’ (kernel) is moved across a study area, and the density of events within the window is used to represent the density at the center of the window. In estimating the density, one may use a gravity model to weigh events by the inverse of distances from the center (Peng 1997).

Radke and Mu (2000) developed the spatial decomposition method to measure access to social services. The method computes the ratio of suppliers to residents within a service area centered at a provider’s location and sums up the ratio for residents at each residential location. Like the earlier versions of FCA approach, they used straight-line distances.

An improvement of this methodology is the two-step floating catchment area (2SFCA) approach introduced by Luo and Wang (2003), building on earlier work by Radke and Mu (2000). This relatively sophisticated technique better accounts for the interactions between patients and physicians across administrative boundaries. It evaluates accessibility as the ratio between supply and demand, both determined within travel-time catchments. In step one, catchments are computed around each supply point j (e.g., a physician practice) and from the estimated population and the number of physicians within the practice, a physician-to-population ratio (R_j) is established. In step two, travel-time catchments are computed around demand centers (e.g., population centroids) and service accessibility is measured by summing all R_j values contained within this zone. The final accessibility measure (A_i) reports the balance between doctor availability (physician-to-population ratio) and service accessibility (sum of all supply points within a given travel- time of the demand center), returning higher values as accessibility increases.

$$A_i = \sum_{j \in \{d_{ij} \le d_0\}} R_j = \sum_{j \in \{d_{ij} \le d_0\}} \left(S_j / \sum_{k \in \{d_{kj} \le d_0\}} P_k \right) \quad (2)$$

The method's major limitation is its dichotomous approach that defines a doctor inside catchment as accessible and one outside the catchment as inaccessible.

Several studies attempt to enhance the 2SFCA. Their major difference lies in the method of defining the catchment size. Enhanced two-Step Floating Catchment Area **(**E2SFCA) method is based on the two-step floating catchment area method (Luo and Qi 2009). It presents an enhancement to the 2SFCA method by applying weights to differentiate travel time zone, thereby accounting for distance decay. The first step of enhanced floating catchment method is to compute the weighted facility-to-population ratio for each health facility point. Within each catchment, compute three travel time zones with different minute breaks. Search all population locations that are within the catchment area. In the second step, calculate the accessibility to health facilities of population at each population location. For each population location, search all health facilities that are within the catchment area, and sum up the weighted facility-to-population ratio. McGrail and Humphreys (2009a) proposed a constant weight within ten minutes, a zero weight beyond sixty minutes and a weight of gradual decay between. In the research of Shi et al. (2012), he assigned the value of 1 to the weight. A kernel density function (Guagliardo 2004) or a Gaussian function (Dai 2010) have been proposed to model the distance decay effect (i.e., a continuously gradual decay within a threshold distance and no effect beyond). The catchment radius might also vary by provider types or neighborhood types (Yang et al.

2006). Bell et al. (2013) developed a method that generates an access ratio at the neighborhood and census tract level by averaging the 2SFCA access ratios for all dissemination area level.

A further development based on E2SFCA is three-step floating catchment area (3SFCA) method. A spatial impedance-based competition scheme is incorporated into the E2SFCA method to minimize the overestimation of demand for some service sites (Wan et al. 2012b). The first step is to search all facility sites within the catchment of population location and a Gaussian weight is assigned to each facility site based on the sub-zone in which the site lies. It's a travel-time based competition weight and it assumes population's healthcare demand for a medical site is influenced by the availability of other nearby health facility site. In the second step, all population locations within the catchment of facility sites are searched. The physician-to-population ratio of each facility site is computed according to its sub-zone. The third step is to search all facility sites within the catchment of each population site, and sum up the spatial access of facility sites based on sub-zone. The 3SFCA method effectively minimizes the demand overestimation and presents a more reasonable geographic pattern of spatial access to primary care than the E2SFCA method.

The aforementioned methods have different assumptions for conceptualizing distance decay in patient–physician interactions. By generalizing the distance decay effect as a term f(d), we can synthesize all measures of spatial accessibility in a model similar to the models in Equations (1) and (2):

$$A_i = \sum_{j=1}^{n} \left[S_j\, f(d_{ij}) / \left(\sum_{k=1}^{m} P_k\, f(dk_j) \right) \right] \qquad (3)$$

Some studies of accessibility of population subgroups are explored recently. The idea is that different subgroups usually compete with each other for opportunities, and different opportunity groups may attract people from various population subgroups (Wang 2007). Wang (2007) calculated the accessibility of a subgroup of users on the demand side to a sub-opportunity set by adding two location-quotient-type terms measuring the relative abundance of opportunities in the sub-opportunity set and competition from users in a sub-population group (Wang 2011). Ngui and Apparicio (2011) weighted the total population at each location (the demand) by the proportion of subgroups of medical clinic users. Measuring sub-accessibility concerning population and opportunity subgroups helps to make the estimation of potential accessibility more accurate. Sub-accessibility is calculated on the basis of categorical accessibility and is a function of elderly population share and each kind of health facility share in the target area. If the elderly population share is the same as the share of one particular kind of health facility, the accessibility of elderly people to that kind of health facility is the same as categorical accessibility–that is, the opportunity for an elderly person to go to one particular type of health facility is the same as the opportunity for any resident in the neighborhood to go to that type of health facility. If the elderly population share is higher than the share of one particular kind of health facility, sub-accessibility is lower than categorical accessibility, as elderly population will compete with each other to go to that type of health facility. If the elderly population share is smaller than the share of one particular kind of health facility within the travel threshold, elderly people will face a relatively abundant supply of that kind of health facility and their accessibility to that kind of health facility will be higher than their categorical accessibility to all types of health facilities.

2.2.2 Non-spatial Accessibility in Geography

Recent studies on non-spatial factors regarding people's access to healthcare majorly focus on the variables including demographics (e.g., seniors, children, women of childbearing ages), socioeconomic status (e.g., poverty, female-headed households, homeownership, and median income), housing conditions (e.g., crowdedness, basic amenities), and linguistic barriers and education (Wang 2012). The common method to measure non-spatial access is statistics. Field (2000) used the results from a patient survey into utilization behaviour to define and model the determinants of the need for health care based on components of relative need and accessibility. All indicators, including health status, socioeconomic status, environment, transport availability, personal mobility, and service awareness, were standardized according to a normal distribution, and then combined to produce a final composite score. A composite measure of accessibility is given by the chi-square score derived from the eight indicators that reflect transport availability, personal mobility and service awareness. The underlying assumption was an equal weight for each variable. However, sociodemographic variables are often correlated and a simple aggregation of the indicators may not be appropriate.

Wang and Luo (2005) used factor analysis to group various variables into three factors including socioeconomic disadvantages, socio-cultural barriers, and high healthcare needs. One of the advantages of FA is that a large number of variables are consolidated into just a very few factors for easy interpretation and mapping. Another advantage is that explained variances clearly indicate the relative importance of different factors and thus differentiate primary and secondary factors.

Generalized estimating equations form of multilevel models is used in the analysis to obtain robust population-level effect estimates for each state from individual-level data with binary response (Mobley et al. 2012). They separately and independently estimated cancer screening models for each state and each cancer site. All models included the same set of multilevel predictors.

Logistic regression was employed to test whether there is a significant relationship of each demographic and socioeconomic variable with treatment continuity (Mennis, Stahler and Baron 2012). The analytical procedure was carried out in five stages, where first the characteristics of the individual patient were entered into the regression equation, then the institutional set- ting of the discharge address was entered, then the accessibility measure was entered, followed by the five neighborhood socioeconomic characteristics, and then the socioeconomic gradient variables.

Comber, Brunsdon and Radburn (2011) used logistic generalized linear models to analyze the extent to which different variables predict difficulty in access to general practitioners and Hospitals. The dependent variable was the survey response to the appropriate access question. To examine the spatial variation in these relationships, Geographically Weighted Regression (GWR) was used to generate spatially explicit logistic regression models. GWR allows one to consider and test for the possibility that relationships vary geographically. It is an approach that deals with spatial non-stationarity in multivariate regression by estimating regression coefficients locally using spatially dependent weights, under the assumption that the effect of the predictor variables on the dependent variable will vary continuously over space.

2.2.3 The Combination of Spatial and Non-spatial Accessibility

Non-spatial factors also interact with spatial access. For example, transit-dependent residents might be considered a non-spatial issue because of their age, medical condition, or lack of economic means, but they also tend to travel longer times to health care providers, thus affecting their spatial access (e.g.Lovett et al. 2002, Martin, Jordan and Roderick 2008). Various population groups might also have different levels of health care needs and travel behavior (Morrill and Kelley 1970). The Agency for Healthcare Research and Quality identified seven priority populations (racial and ethnic minorities, low-income groups, women, children, older adults, residents of rural areas, and individuals with disabilities or special health care needs) for high health care needs. McGrail and Humphreys (2009a) used principal component analysis to consolidate seven sociodemographic variables into one summary score of health needs. This allows non-spatial factors to be used to adjust the definition of demand in spatial accessibility measures, providing one way of integrating spatial access and non-spatial factors in a unified accessibility measure.

2.3 Summary

In conclusion, differential access to health care has been important theme in public health policy in the Unites States and other countries for many years. The access problems of rural residents who often travel long distances to the nearest health care provider are well documented, as are the problems of low-income urban residents whose choices are limited by time-space constraints, lack of insurance, poor transportation access. The restructuring of health care and efforts to control health care costs will continue to alter these patterns. Various methods have been proposed to measure health care accessibility, accounting for both spatial and non-spatial factors. Various measures of spatial accessibility differ in ways of conceptualizing the distance decay effect as a continuous function, a discrete variable, or a hybrid of the two. The selection of an appropriate model needs to be based on analysis of real-world health care utilization behavior. Non-spatial factors include a wide selection of demographic and socioeconomic variables, which can be consolidated into a few independent factors by factor analysis. The increasing complexity of accessibility models hinders its implementation and adoption by public health professionals and calls for the development of simplified and transparent proxy measures.

While the existing methods of measuring spatial accessibility have been improved a lot in recent years, they have their limitations. First, what is the appropriate functional form for the distance decay weights? As mentioned previously, various functional forms are used in current studies. The functional form should be decided depending on the type of accessibility. Second, what is the scale of temporal resolution for estimating travel time? This can be varied according the type of accessibility and the resolution needed. Third, the determination of the catchment size could be more flexible. The catchment size could vary according to the neighborhood characteristics and the specific type of medical services in demand. Last, it is likely that all methods may overlook the competition between different types of health facility group, so that the accessibility to each type of health facility is overestimated. The new method that we propose mainly contributes to overcome the last two shortcomings. We incorporate competition mechanism between different types of health facilities to minimize the overestimation problem. Also, diverse catchment size is used for different types of health facilities in the new method.

CHAPTER 3

METHODOLOGY

In consideration of the limitations of previous measurement methods, a new method is needed to generate more reliable and reasonable spatial accessibility values. In order to customize different services of health facilities for the calculation of accessibility to different subgroups, we propose a CMSFCA method based on the 3SFCA method (Wan et al. 2012a) to personalize the computing of accessibility to different target subgroups. The model in this study is based on a more reasonable assumption of healthcare demand and supply mechanism of medical services. As in 3SFCA, conceptually, the CMSFCA assumes that a population's healthcare demand for a medical site is influenced by the availability of other nearby medical sites. Practically, CMSFCA assigns a travel-time-based competition weight for each pair of population-medical sites as the methodology outlined in 3SFCA. This weight is then used in the calculation of the demand of services sites to minimize overestimation. Different catchment sizes will be selected for different types of facilities. Additionally, competition from the demand and supply are included. A categorical computing algorithm will be assigned when accessibility to different target subgroups is calculated. The method is implemented in four steps (shown in Figure 3.1):

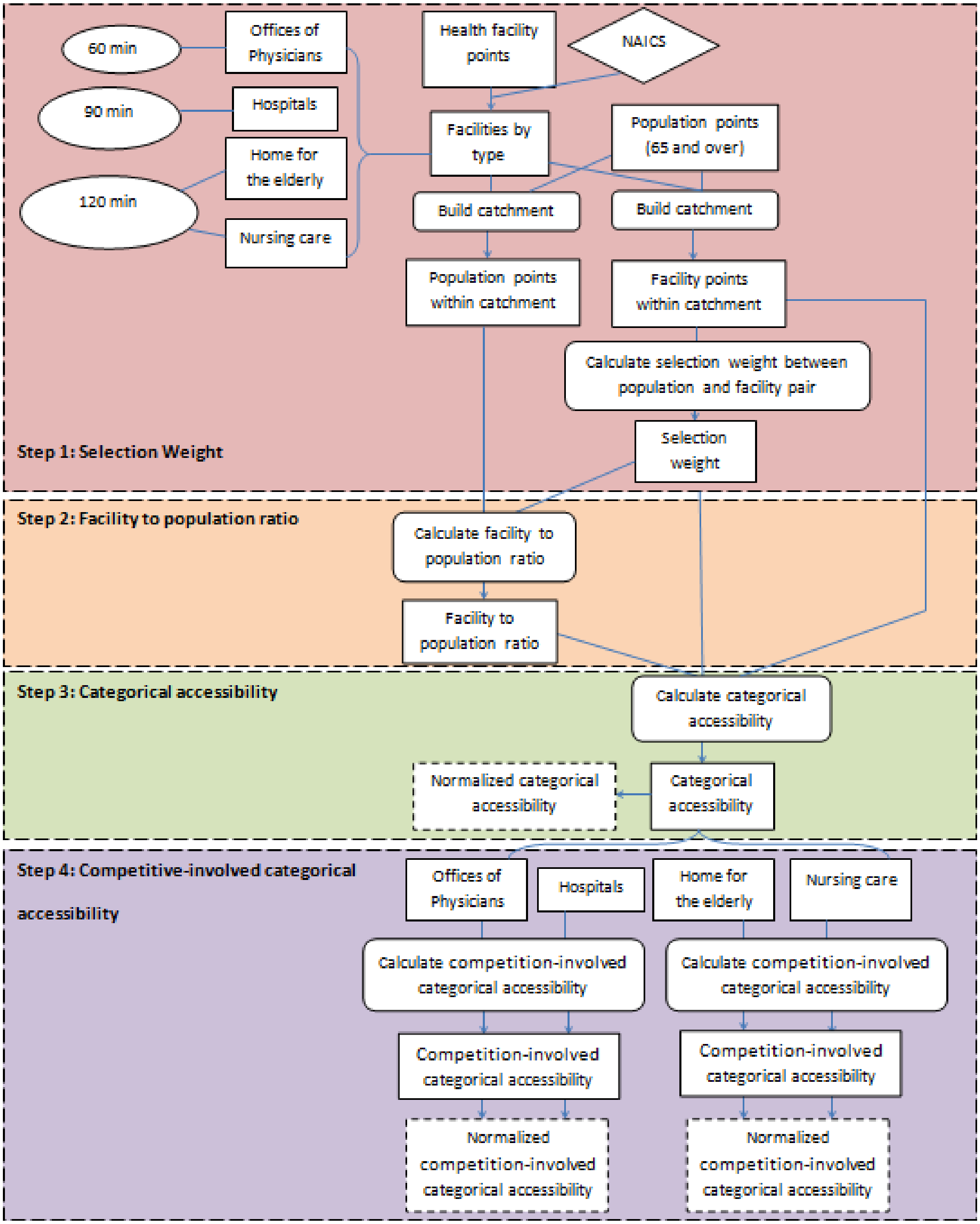


Figure 3.1: Flow diagram illustrating procedure of thesis methodology

3.1 Determining on the Likelihood of Selecting a Health Facility at Population Locations

The first step calculates a selection weight between each population site and health facility pair, which is essentially the likelihood of choosing a health facility at one population location. For one type of facility, the catchment of a population location i must be determined. Next, all health facilities are searched within the catchment size and a gravity-based weight to each health facility can be assigned based on distance from i. A selection weight between i and each health facility j can be calculated by

$$W_{ij} = \frac{G_{ij}}{\sum_{k \in \{Dist(i,k) < d_0\}} G_{ik}} \quad (4)$$

$$G_{ij} = e^{-\beta d_{ij}} \quad (5)$$

where W_{ij} is the selection weight between population location i and health facility j, Dist(i, k) is the travel cost (minutes) from i to any service site k within the catchment, and d_0 is the catchment size (i.e., driving time of 90 minutes for hospitals). G_{ij} and G_{ik} are the assigned weights for j and k, respectively. d_{ij} is the distance and β is the distance impedance parameter. In the case of hospitals, for example, all hospital service sites can be searched within the 90 min catchment; a weight can be assigned to each hospital; and the selection weight can be calculated.

In this study, we borrow the distance decay function from the transportation field to assign weight between each health facility and population location. Distance decay functions are of particular interest in transportation and land use planning activities because historically they have been associated with gravity models, a form of spatial interaction model that is conventionally used to forecast trip distribution in transportation planning models.

Although there are many other ways to measure distance decay, some researchers have discovered the results don’t have much variation when different models are used. The distance decay is usually specified by the gravity model. A common specification of the gravity model is negative exponential function $f(d_{ij}) = e^{-\beta d}$, where d is a variable representing distance. The distance decay function in this step would be $G_{ij} = f(d_{ij}) = e^{-\beta d_{ij}}$, in which d_{ij} is the travel time. The appropriate distance impedance parameter β will depend on the impedance function use. In a distance decay function, the parameter β is of great importance, since it specifies the level of deterrence or impedance to travel created by distance. Alternatively, this parameter may be interpreted as the willingness of individuals to travel between locations, given the conditions of the transportation network and the distribution of activities. The value of the impedance coefficient, β, could significantly influence the values of the spatial access index (Wan et al. 2012b).

Researchers have used statistical methods to find an appropriate impedance function (Thill and Kim 2005, Wang 2007, Scott and Horner 2008). Using empirical data related to patient travel to health services, one can determine the exponent that best fits actual travel patterns. In an analysis of Chinese immigrants' spatial access to physicians in Toronto, Wang (2007) used data from a survey of Chinese immigrants to determine an appropriate impedance function. Differences in transportation and mobility can also be incorporated. Research on physician accessibility in East Anglia, England (Lovett et al. 2002) calculated potential accessibility based on network travel times.

Another approach is to use an impedance function that is calibrated for one study area to predict potential accessibility in another study area. Knox (1978) did so in estimating intraurban patterns of potential accessibility to general practitioner services. The precise form of the distance function ($e^{-1.52 d_{ij}}$) was taken from an earlier study of general practitioner use. The empirical value of distance impedance parameter was used in this method. In the 2008 report of Minnesota Department of Transportation, a parameter estimation used real clinic trips that allowed for inferences regarding health care access-related travel and a negative exponential decay function fitted to the health care data. The β value calculated based on the real data was 0.11. Although no information was obtained on choice of mode, the inclusion of a large number of longer-distance trips suggests predominance of auto travel. Due to the lack of sample data in our study area, we utilize the value of the impedance coefficient in that particular model, which is 0.11, as the arbitrary value in our method to calculate accessibility to offices of physicians. In general, the β value in the distance decay function changes in the same direction with sensitivity to distance. When β is relatively large, impedance is high, and sensitivity to distance is higher. In other words, in the case of a higher β, people are reluctant to travel long distances. We assume that office visit of physicians is most sensitive to travel distance and the long term care facility (including home for the elderly and nursing care facility) is the least sensitive to distance. Accordingly, the offices of physicians have the highest β; the hospitals have the second highest β; and the long term care facilities have the lowest β. The impedance coefficients β are listed in Table 3.1, for hospitals, offices of physicians, and long term care facilities, respectively.

Table 3.1：Different types of health facilities and the corresponding catchment size and distance impedance coefficient

Health facility type	Catchment Size (min)	Distance impedance coefficient β
Offices of Physicians	60	0.11
General Medical and Surgical Hospitals	90	0.08
Homes for the elderly	120	0.05
Nursing care facility	120	0.05

3.2 Obtaining the Ratio between Medical Capacity of Health Facilities to Demand of Elderly Population

The second step is to compute the facility-to-population ratio at each health facility to obtain the medical capacity of one health facility that can supply to elderly population. The elderly population number, which represents the demand, is weighted by the selection weight from the first step and the distance impedance. The corresponding catchment area of each health facility j can be determined. All population locations within the catchment can be searched and weighted facility-to-population ratio (R) of j can be computed by

$$R_j = \frac{S_j}{\sum_{k \in \{Dist(j,k) < d_0\}} P_k G_{jk} W_{jk}} \qquad (6)$$

where S_j is the medical capacity of health facility j, G_{jk} is the distance impedance between health facility j and population site k, W_{jk} is the selection weight between health facility j and population site k, and P_k is the population size of k.

3.3 The Categorical Spatial Accessibility without Including Competitions between Groups

The third step calculates the categorical spatial access to one particular type of health service at each population location i. The categorical spatial access of one elderly population location is achieved through the sum of facility-to-population ratio of all health facility points that fall within the catchment area of this population site. The corresponding catchment area of each population location i can be determined. All facility sites within the catchment can be searched and the spatial access of population site i can be computed by

$$CA_i = \sum_{j \in \{Dist(i,j) < d_0\}} R_j G_{ij} W_{ij} \qquad (7)$$

where R_j is the weighted facility-to-population ratio of health facility j within the catchment, W_{ij} is the selection weight between i and j, and G_{ij} is the distance impedance between population site i and health facility j.

Then the categorical accessibility for each census tract is normalized to represent the relative categorical accessibility and make the results easier to be compared. The normalized categorical accessibility is calculated as the ratio between a census tract's categorical accessibility and the mean categorical accessibility of all census tracts.

3.4 The Competition-involved Categorical Spatial Accessibility Including Competitions between Groups

The last step calculates the competition-involved categorical spatial access by means of multiplying categorical spatial access from the last step by a competition ratio. Diverse health facilities usually compete with each other for opportunities. The spatial accessibility is influenced by the supply of other health facilities within the travel-threshold. This step is based on the assumption that there is no competition exists between acute care services and long term care services.

Generally, the spatial accessibility of people aged 65 and over to one type of health facility is influenced by the supply of other health facilities within the travel-threshold. In elderly population location i, the competition-involved categorical accessibility is determined by the corresponding categorical accessibility multiplying a fraction which represents the proportion of competition ability of one particular type of facility among all types of health facilities that have competition with this particular type of facility. This fraction represents the possibility that one type of health facility is chosen among all types of health facilities for elderly people within the catchment size of census tract i.

$$CCA_i^F = CA_i^F * \frac{PR^F \sum_{j\in\{Dist(i,j)<d_0\}} S_j^F G_{ij}}{\sum_{\{H\epsilon H_N,\ \ N=1,2,3\ldots\}} PR^H \sum_{j\in\{Dist(i,j)<d_0\}} {S_j}^H G_{ij}} \qquad (8)$$

CCA_i^F denotes the competition-involved categorical spatial accessibility of elderly people in census tract i to one particular type of health facility F. CA_i^F represents the categorical accessibility of elderly people in census tract i to that type of health facility F calculated in the third step. PR^F is the preference score of one type of facility F. PR^H is the preference score of one type of facility H. S_j^F is the number of employee of one type of health facility F in location j. S_j^H is the number of employee of one type of health facility H in location j. G_{ij} is the distance impedance between population site i and health facility j. H belongs to the set of all types of acute health facilities H_N or all types of long term care facilities H_N.

The preference score can be influenced by several demographic and socioeconomic factors, such as people's knowledge of health facilities, the quality of health care service, the insurance acceptance of health facilities, the language preference. These attributes are all important impact factors on the decisions of who make choices about visiting health care facilities.

Last, the competition-involved categorical accessibility for each census tract is normalized to indicate the relative difference of competition-involved categorical accessibility among different categories of health facilities. The normalized competition-involved categorical accessibility is calculated as the ratio between a census tract's categorical accessibility and the mean competition-involved categorical accessibility of all census tracts.

Chapter 4

Case Study

4.1 Study Area

This study chose the Atlanta metropolitan statistical area (MSA) as a study area in which to implement the new proposed categorical multi-step floating catchment area method (shown in Figure 4.1; Figure 4.2 shows the larger detail of Atlanta MSA). Atlanta MSAs are defined by the U.S. Office of Management and Budget, who announced updates to metropolitan statistical areas as of December 2009, based on the Census Bureau's July 1, 2007 and July 1, 2008 population estimates for cities and towns, and in specified circumstances, local opinion. The Atlanta MSA area contains 28 counties, including Barrow, Bartow, Butts, Carroll, Cherokee, Clayton, Cobb, Coweta, Dawson, DeKalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Haralson, Heard, Henry, Jasper, Lamar, Meriwether, Newton, Paulding, Pickens, Pike, Rockdale, Spalding and Walton. The area is composed of both metropolitan areas (e.g., Dekalb and Fulton) with highly concentrated health care facility sites and suburban areas (e.g., Jasper and Lamar) where health facility sites are few. The Atlanta MSA area is the ninth-largest MSA in the United States. It is the most populous metro area and economic, culture and demographic center of Georgia. The 2010 census recorded 5,268,860 people in the 28- county metro area. This population represented an increase of 1,020,879 versus the same 28-coutny in 2000. The percent of increase was 24.0%, and was among the nation’s ten largest metropolitan areas.

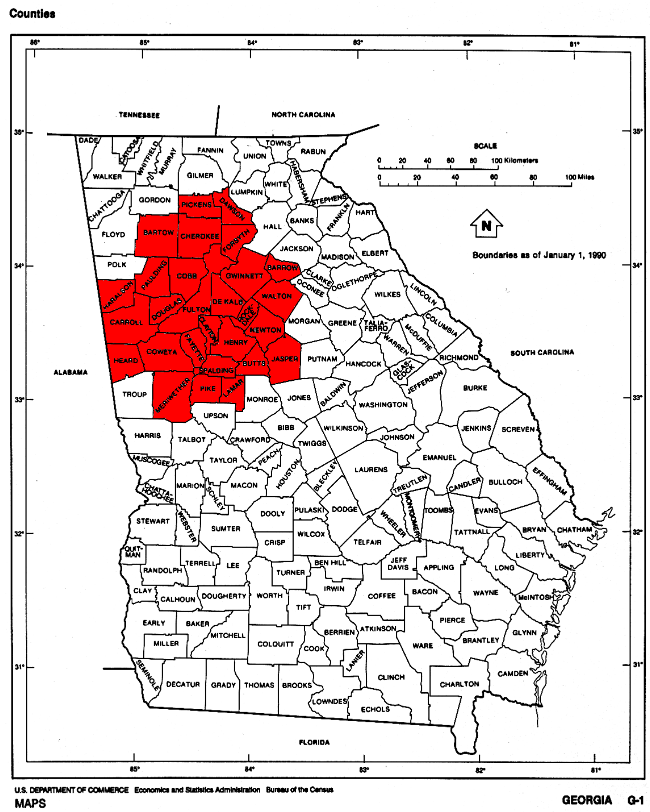


Figure 4.1: Atlanta MSA study area

Figure 4.2: Enlarged view of Atlanta MSA study area

4.2 Dataset:

4.2.1 The Demand Data: Elderly Population

The demographic data that includes the number of elderly population aged 65 and over within 946 census tracts were extracted from the Georgia Census 2010 Summary File 1 (US Bureau of the Census 2011a). The census tract level is used to group data in consideration of both data availability and result fineness. The corresponding census tract and county geographic boundaries were obtained from 2010 Census TIGER/Line dataset (US Bureau of the Census 2011b). The label point is used to represent location of each census tract. There are 471,753 elderly people in the study area, who comprise 9% of total population in Atlanta MSA. Figure 4.3 displays geographical distribution of the elderly population in the Atlanta MSA.

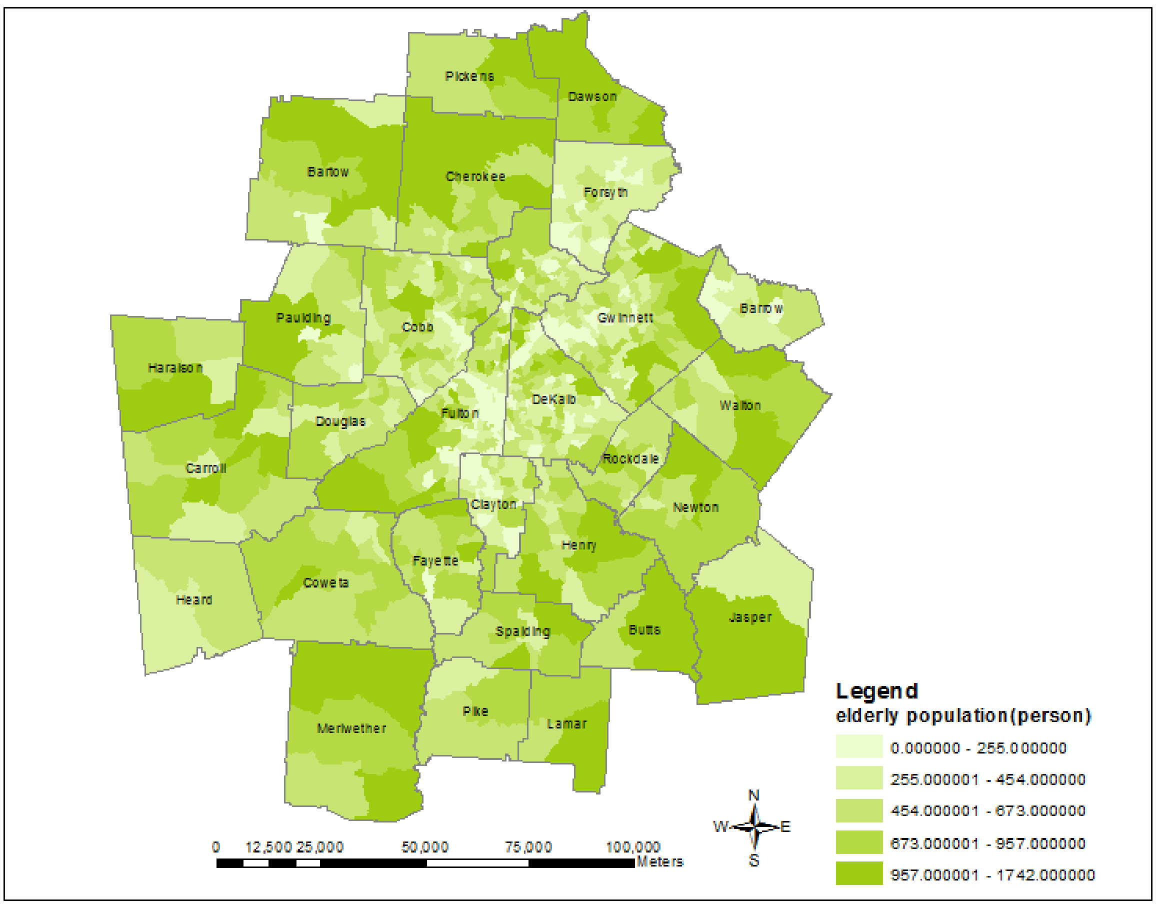


Figure 4.3: Geographic distribution of elderly population (aged 65 and over) in Atlanta MSA

4.2.2 The Supply Data: Health Facilities for Elderly People

The health business points, which include the information of a variety of health facilities in the state of Georgia, are gained from complete 2008 business point data provided by the MapInfo Company. The health business points are labeled as HTH under the business category field. Different types of health facilities are categorized based on its North American Industry Classification System (NAICS) code. The 6-digit 2010 edition NAICS code table of 2010 edition was retrieved from American Fact Finders. The NAICS code and its corresponding label are shown in Appendix 1. We chose to include four types of health facilities in this case study, based on the special needs of the target population of elderly people. These four types of health facilities were selected according to their NAICS code. The acute care facility codes are 621111 for Office of physicians (except mental health specialist) and 622110 for general medical and surgical hospitals. The long-time care facility codes are 623312 for homes for the elderly and 623110 for nursing care facilities. This dataset includes 234 general medical and surgical hospitals, 5414 offices of physicians, 388 homes for the elderly, and 742 nursing care facilities. Some manual editing was performed to offices of physicians points in order to exclude the facility points that were irrelevant to elderly people, such as pediatric or obstetric and gynecological care. Almost 80 percent (4336 health facility points) of the original data were kept in the group of offices of physicians points.

We used the actual number of employees at each business location to represent a facility's capacity. Although the number of employees at one of the facilities might not be an accurate representation of its capability for health care, to our knowledge the two factors have a close relationship as the number of employee is some of the best data available to us that is relatively consistently available across geographic areas. Data that included the number of employees is obtained from the attribute table of these supply points. Figure 4.4-4.7 shows the health facility geographic distribution and the corresponding number of employees at each health facility of offices of physicians, general medical and surgical hospital, nursing care facilities, and homes for the elderly, respectively.

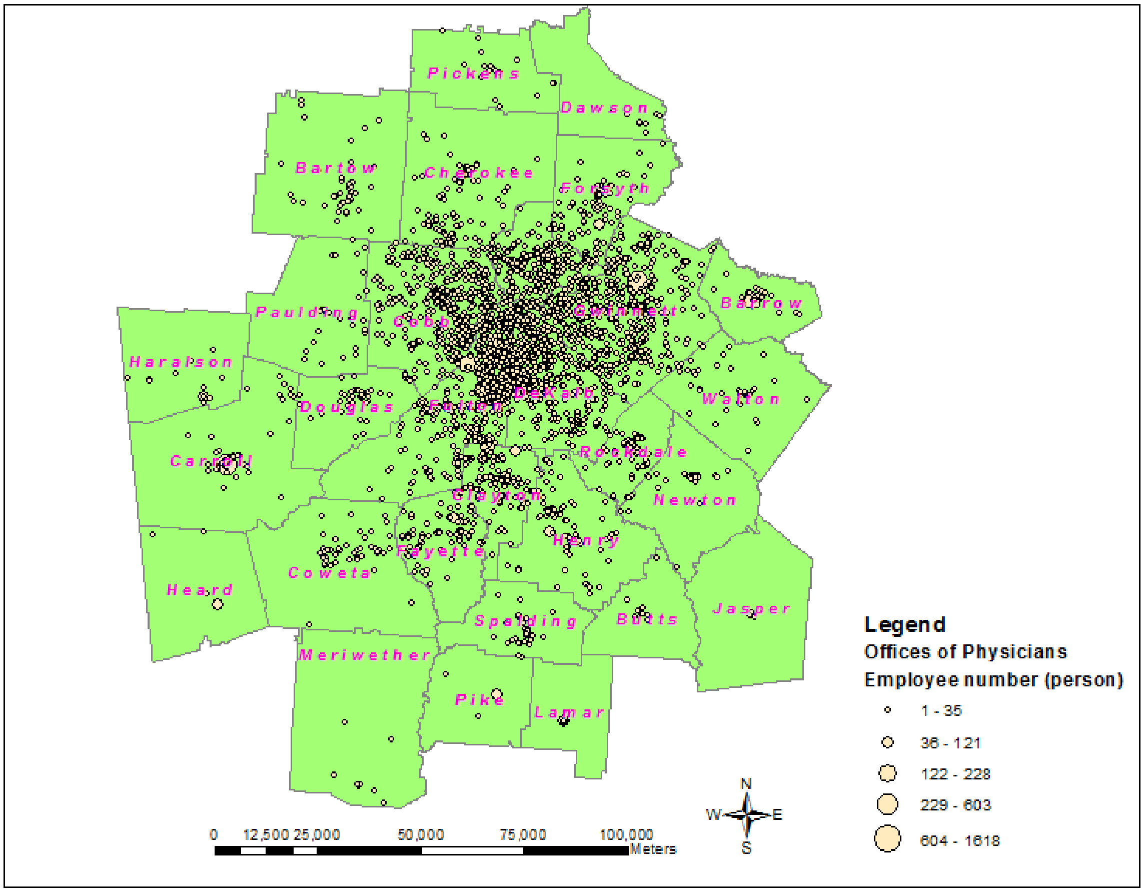


Figure 4.4: Offices of Physicians in Atlanta MSA

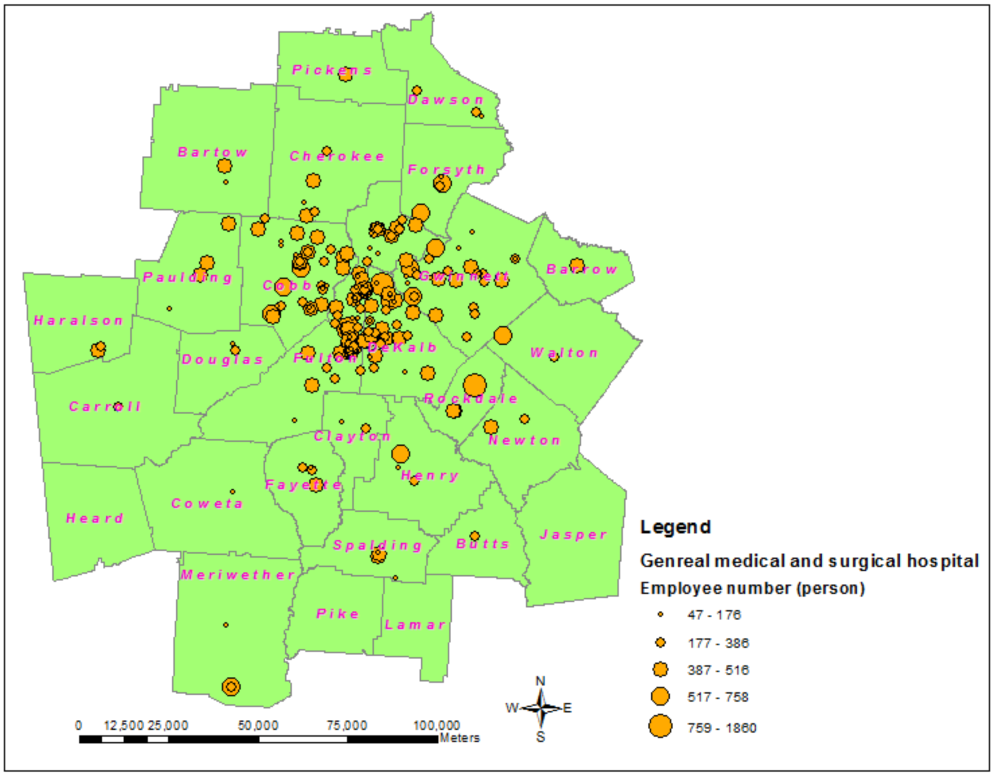


Figure 4.5: General medical and surgical hospitals in Atlanta MSA

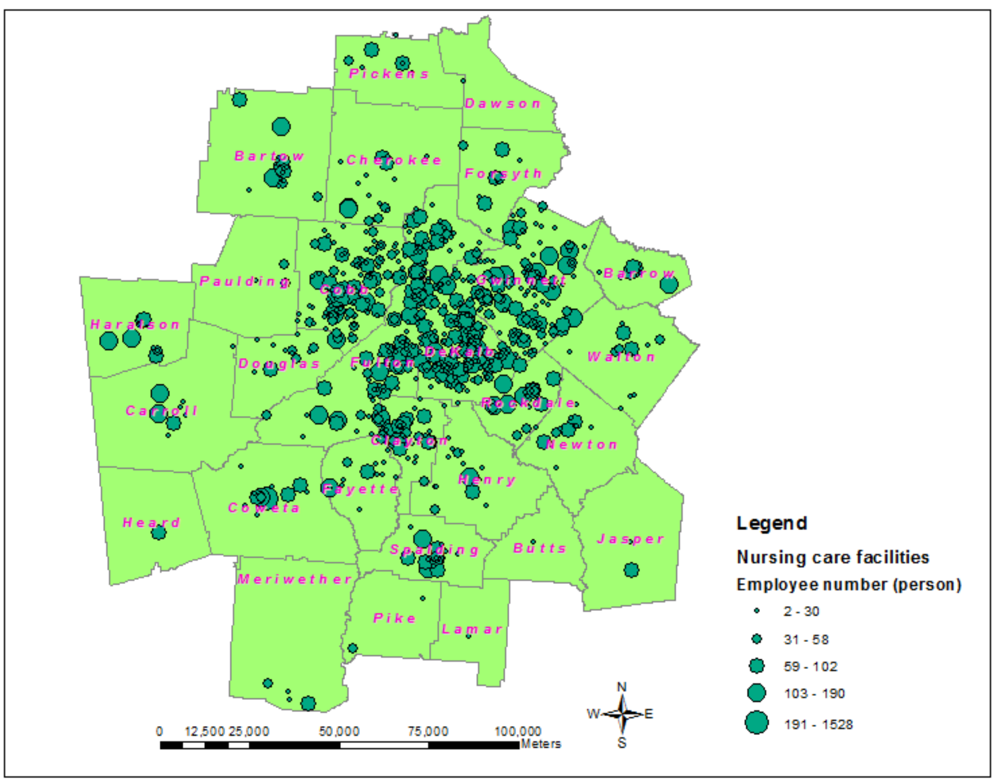


Figure 4.6: Nursing care facilities in Atlanta MSA

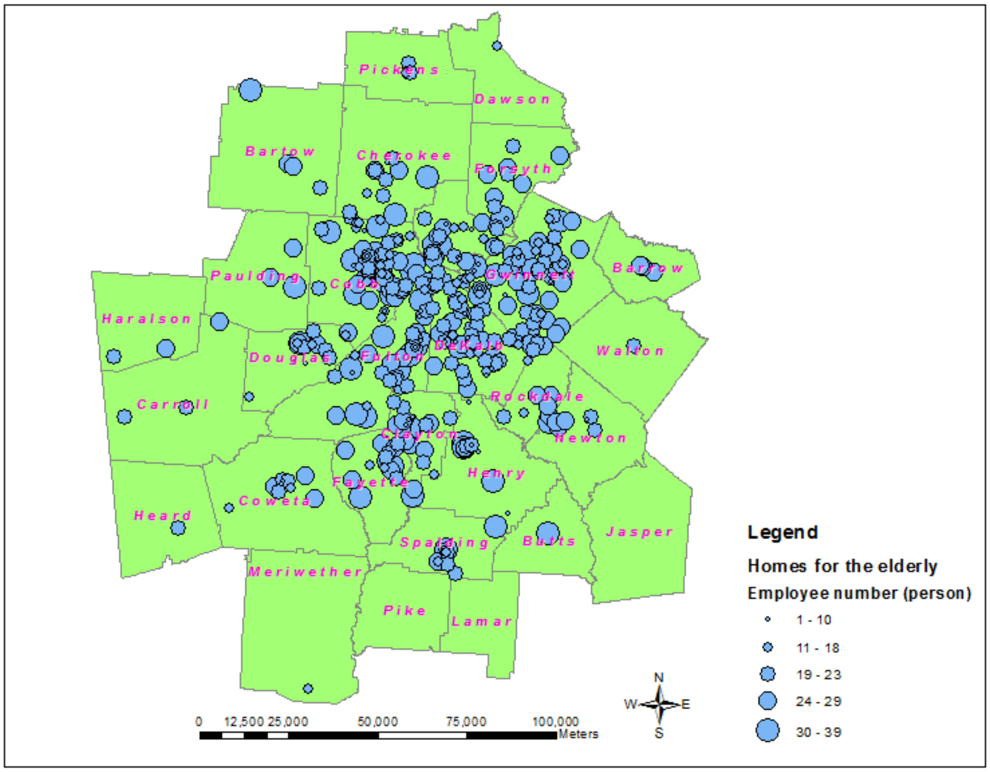


Figure 4.7: Homes for the elderly in Atlanta MSA

4.2.3 Measuring Travel Distance

One of the most important parameters in measuring spatial accessibility is the distance between the supply and the demand locations. Various measures of distance ranging from Euclidian distance to travel times can be identified in the literature. This research uses detailed street network data that come from US transportation department 2005 dataset and ESRI ArcGIS Network Analyst 10.0 to accurately estimate travel time to health facility locations. Using the road network and a set of origin points (census tract centroids) and destination points (health facility locations) as inputs, an Origin-Destination Cost Matrix function created a matrix that showed the travel time between all origin and destination pairs within a travel time threshold. Three groups of threshold travel time values were assigned according to the categorical level of health facility. For example, 60 minutes catchment size for offices of physicians, 90 minutes for hospitals, 120 minutes for home health care and nursing care. Thirty minutes has been suggested an appropriate catchment size for analyzing spatial access to physician health care (Lee 1991, Luo and Wang 2003). This study extends the catchment size to 60 minutes, so isolated rural regions can be included in the computation (McGrail and Humphreys 2009b, Wan et al. 2012a). The sub-zone of 30–60 minutes represents the extended region for physician health care.

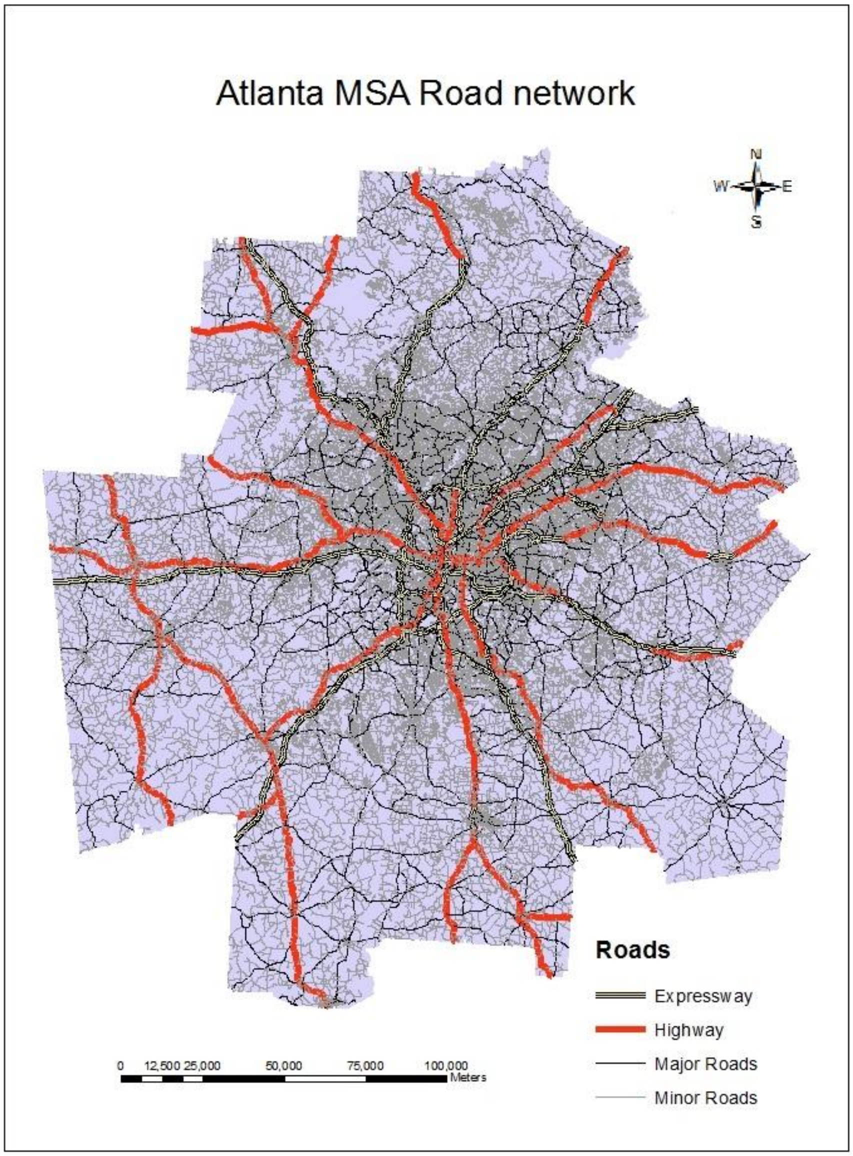


Figure 4.8: Road network in Atlanta MSA

4.3 Methodology Implementation

To illustrate the advantages of the CMSFCA method, we apply this method to examine the spatial accessibility to four types of health facilities, including offices of physicians, general medical and surgical hospital, nursing care facilities, and homes for the elderly in a group of 946 census tracts in the Atlanta MSA. The whole calculation process of all these four steps is completed in the python stand-alone scripts. The final results were compared with those derived only from the third step.

4.3.1 Determining on the Likelihood of Selecting a Health Facility at Population Locations

This step determines selection weight between each health facility and population location pair. In this step, the OD matrix of each type of health facility is set as input. The selection weight from each health facility to the census tract population location within the catchment size is computed for each type of health facility. Additionally, the selection weights for each health facility within the catchment size were calculated for all four types of health facilities.

The distance decay function that we choose to use in this case study is the negative exponential function $f(d_{ij}) = e^{-\beta d_{ij}}$. The distance impedance parameter β for physician facilities was set as 0.11 based on the result of empirical data from the Minnesota Department of Transportation 2008 report as mentioned before. The value of impedance parameter β for hospitals and two long-term care facilities are deduced from this distance impedance for offices of physician according to the regular pattern of β, which are 0.08 and 0.05, respectively.

4.3.2 Obtaining the Ratio between Medical Capacity of Health Facilities to Demand of Elderly Population

As mentioned before (section 4.2.2), the employee number was chosen to represent the medical capacity at one health facility site. In this step we set each type of health facility points as inputs respectively. Different catchment was generated for all health facilities of different types of health facility points; next the supply-demand ratio at each health facility for different types of health facilities was calculated.

Unlike previous methods, we used a continuously gradual decay (i.e. negative exponential function) within a threshold distance and no effect beyond to model the distance decay effect. We can gain more accurate distance information through this process.

4.3.3 The Categorical Spatial Accessibility without Including Competitions between Groups

This step calculates the selection-weighted categorical spatial access of census tract as the sum of weighted supply-to-demand ratios of all health facilities from one type of health facility within the catchment around the centroid of census tract. The same catchment size as before was used for each type of health facility. Then normalization was conducted to the categorical accessibility result of each census tract. In this study, we normalized the categorical accessibility of each census tract based on the mean of categorical accessibility of all census tracts. However, other normalization function could be used. For example, the mean of both categorical accessibility and competition-involved categorical accessibility could be combined in the normalization to make the difference between these two accessibility results more interpretable.

4.3.4 The Competition-involved Categorical Spatial Accessibility Including Competitions between Groups

This step is based on the assumption that no competition exists between acute care services and long term care services, which means we don't consider preference between acute care type and long term care type. In the proposed method, a preference score should exist for each type of health care facility. In this study, we did not intend to incorporate the complex interactions of those factors that impact people's choice of visiting health facilities because data about how people balance such factors when they visit health care facilities are difficult to obtain. We assigned the preference score to different types of health facilities on the scale of 1 to 10 (1 refers to the slightest preference, and 10 means the strongest preference). Different preference score combinations are tested using the scheme in Table 4.1.

Table 4.1 Different preference score combinations

Scenarios of preference	Facility Type 1	Facility Type 2
no preference	5	5
Slight preference to Type 1	10	5
Strong preference to Type 1	10	1
Slight preference to Type 2	5	10
Strong preference to Type 2	1	10

Nursing care services, for instance, would have the function with same preference between nursing care services and homes for the elderly

$$CCA_i^{F_1} = CA_i^{F_1} * \frac{\sum_{j\in\{Dist(i,j)<120\}} S_j^{F_1} G_{ij}}{\sum_{j\in\{Dist(i,j)<120\}} S_j^{F_1} G_{ij} + \sum_{k\in\{Dist(i,k)<120\}} S_k^{F_2} G_{ik}} \quad (9)$$

Similarly, the function for homes for the elderly would be

$$CCA_i^{F_2} = CA_i^{F_2} * \frac{\sum_{k\in\{Dist(i,k)<120\}} S_k^{F_2} G_{ik}}{\sum_{j\in\{Dist(i,j)<120\}} S_j^{F_1} G_{ij} + \sum_{k\in\{Dist(i,k)<120\}} S_k^{F_2} G_{ik}} \qquad (10)$$

$CCA_i^{F_1}$ denotes the competition-involved categorical spatial accessibility of elderly people in census tract i to nursing care service. $CCA_i^{F_2}$ denotes the competition-involved categorical spatial accessibility of elderly people in census tract i to homes for the elderly. $CCA_i^{F_1}$ represents the categorical accessibility of elderly people in census tract i to that type of nursing care service calculated in the third step. $S_j^{F_1}$ and $S_k^{F_2}$ are the employee number of nursing care service in location j and homes for the elderly in location k, respectively. G_{ij} is the distance impedance between population site i and nursing care service facility j calculated in equation (5). G_{ik} is the distance impedance between population site i and homes for the elderly facility k calculated in equation (5). At last, the same normalization process was repeated as that in the third step. The ratio between a census tract's competition-involved categorical accessibility and the mean competition-involved categorical accessibility of all census tracts was calculated for normalization.

In this step, the final accessibility score is determined by the proportion of one type of health facility's all entities' distance-weighted medical capacity among all types of health facilities'. Modification is made to categorical accessibility measures. Nursing care services and homes for the elderly compete with each other for the elderly people in each tract, so accessibility to nursing care service is influenced by the supply of the homes for the elderly within the travel threshold.

CHAPTER 5

RESULTS

5.1 Geographic Patterns of Spatial Accessibility

The geographic patterns of categorical spatial accessibility is computed using Steps one to three of the CMSFCA method, and the competition-involved categorical spatial accessibility to offices of physicians with different preference score combinations is computed using Steps one to four of the CMSFCA method. Before normalization, the results are less stable and comparable. After normalization, the results are easier to interpret and to be made comparison between different types of health facilities and different preference score combinations. The geographic distribution of spatial accessibility also becomes smoother.

In the case of offices of physicians, for example, the results of both categorical accessibility and competition-involved categorical accessibility with no preference are shown in Figure 5.1 and Figure 5.2. As shown in Figure 5.1 and 5.2, categorical accessibility and competition-involved categorical accessibility with no preference derive similar geographic patterns of spatial accessibility, which shows that the major metropolitan areas had high access ratios (0.053508-0.095701) while suburban areas have low access ratios (0-0.011398). The reason why access in center is higher than the peripheral area in both categorical and competition-involved categorical access possibly due to low density of elderly population residence and high density of health facilities. However, competition-involved categorical accessibility reveals lower access ratios than did categorical accessibility for offices of physician points. Generally, the competition-involved categorical accessibility is lower than the categorical accessibility for the same census tract. Specifically, the peripherals of metropolitan areas are characterized by low access ratios in terms of competition-involved categorical accessibility but very high access ratios by categorical accessibility. Several counties, such as Clayton, Heard, and Lamar are identified as very high access areas in the categorical accessibility results, while they appear to be medium or even low access areas in the competition-involved categorical results.

Figures 5.3-5.6 show the results after normalization of all the four types of health facilities respectively. In the case of offices of physicians, the normalized results have a smoother geographic distribution of categorical accessibility and competition-involved categorical accessibility. By comparing Figure 5.3(a) and Figure 5.3(b), we notice that the normalized results don’t change too much in the counties that locate in the peripheral area of study area. Only the accessibility to offices of physicians in the Heard county and the Carroll county enhance after including the competition from other categories. It’s probably because there are more options after including other types of health facilities. When looking at the competition-involved categorical accessibility, the results are higher in central Atlanta MSA than those in peripheral Atlanta MSA. With different preference score combinations, the major change in the Heard County and the Carroll County is also observed. With the preference to offices of physicians declining, the competition-involved categorical accessibility increases. The competition-involved categorical accessibility results in the central Atlanta MSA, such as the Fulton County and the DeKalb County, also have a slight improvement with the preference to general medical and surgical hospitals. However, in some census tracts of the Cobb County, the competition-involved categorical accessibility decreases following the decline of preference score of offices of physicians. For hospitals (Figure 5.4), nursing care facilities (Figure 5.5), and homes for the elderly (Figure 5.6), the major changes also locate in the center of Atlanta MSA if the preference score combinations vary. But there is still some exception, for example, the competition-involved categorical accessibility in the Coweta County change obviously with different preference score combinations.

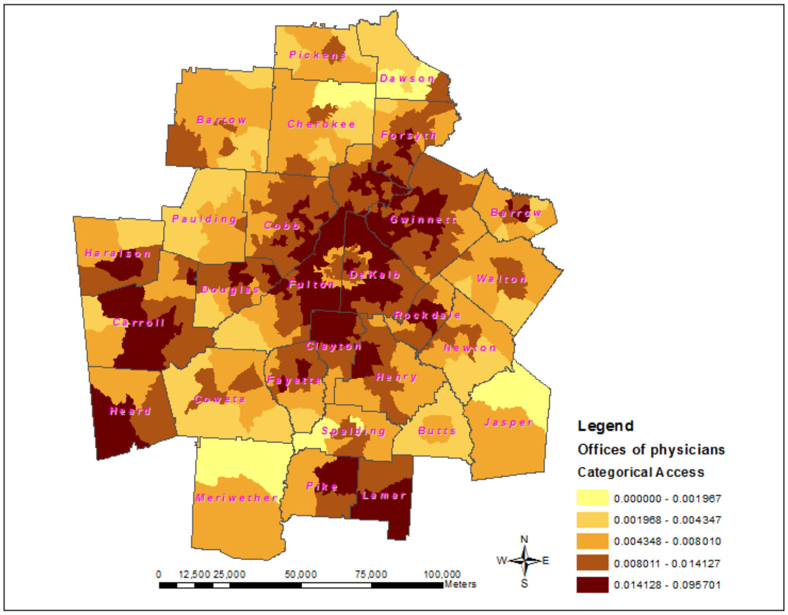


Figure 5.1: Categorical accessibility to Offices of physicians

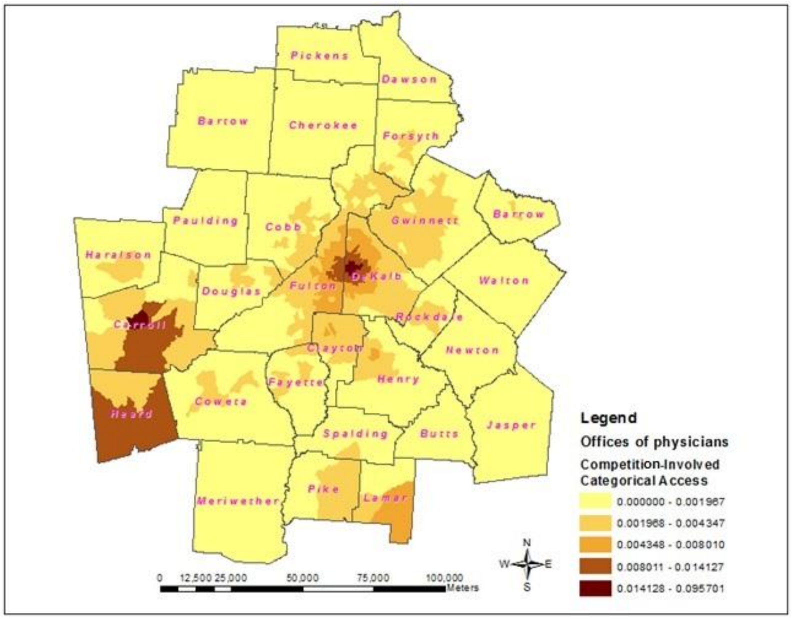
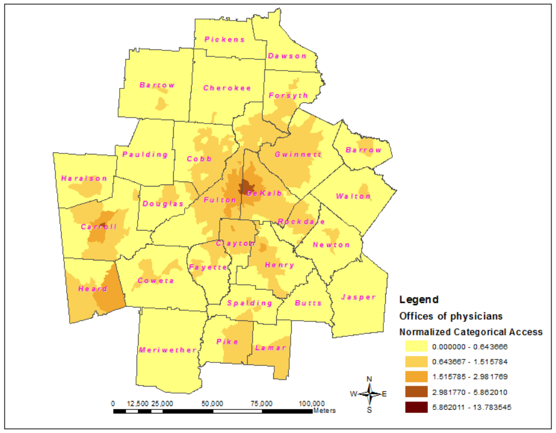
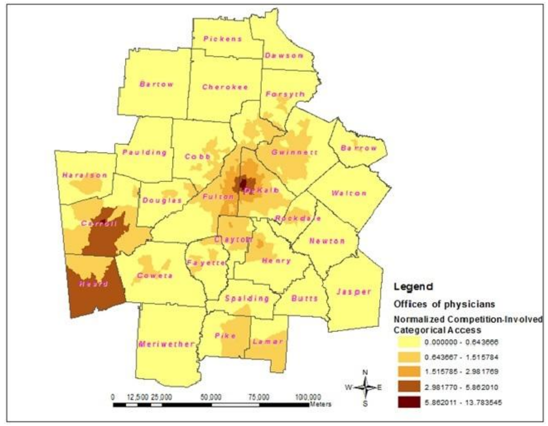


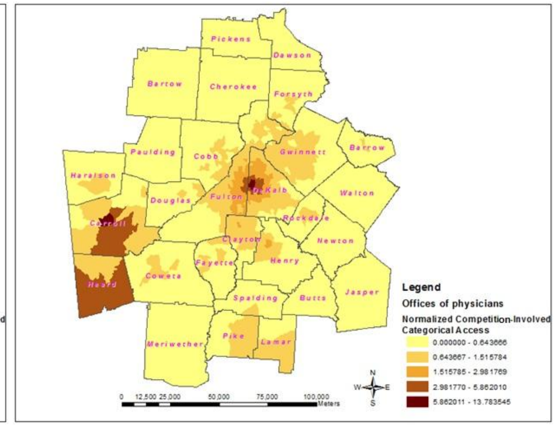
Figure 5.2: Competition-involved Categorical accessibility to Offices of physicians with no preference



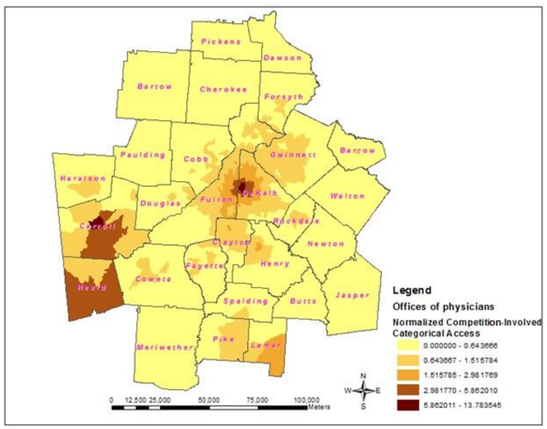
(a)competition not involved



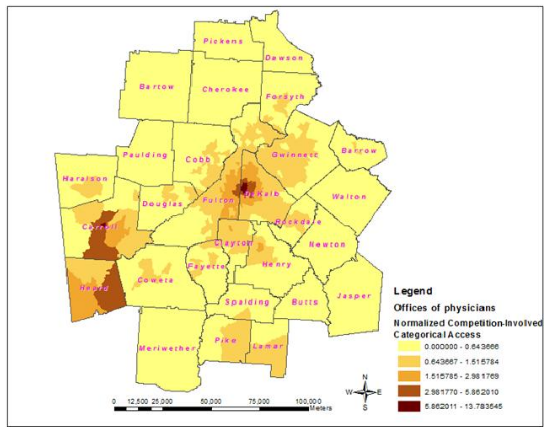
(b)no preference



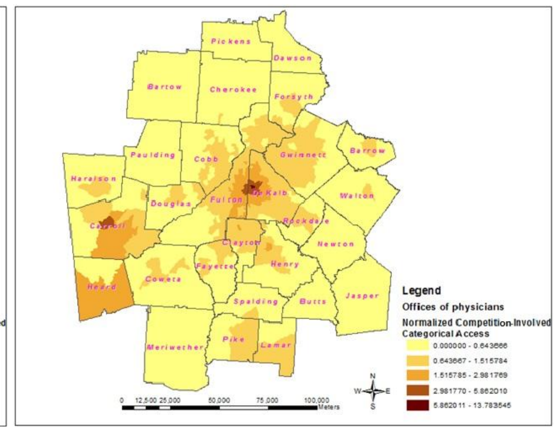
(c)slight preference to Hospitals



(d)strong preference to Hospitals

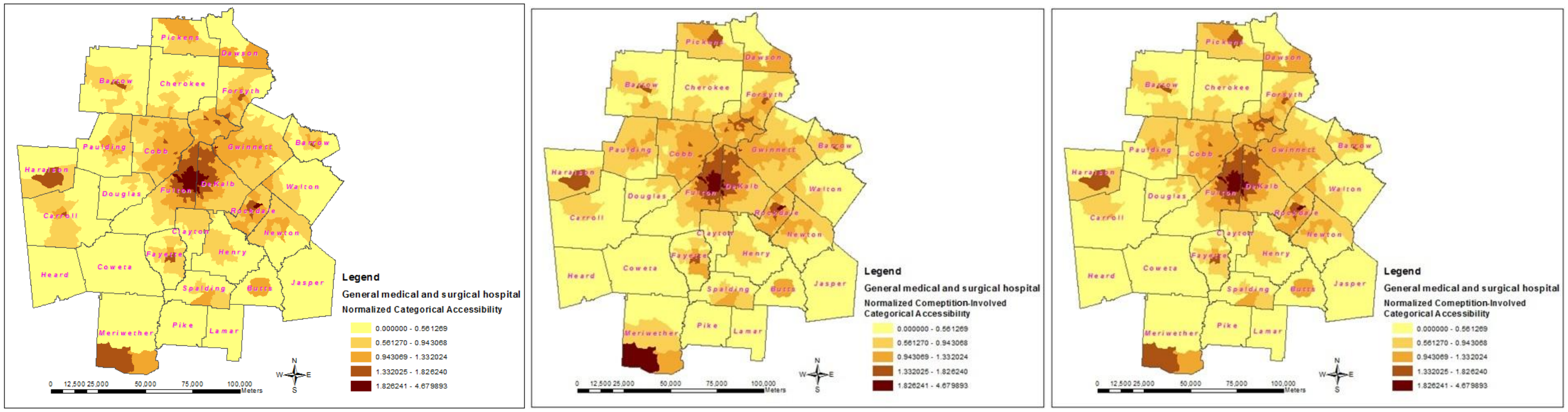


(e)slight preference to Offices of physicians

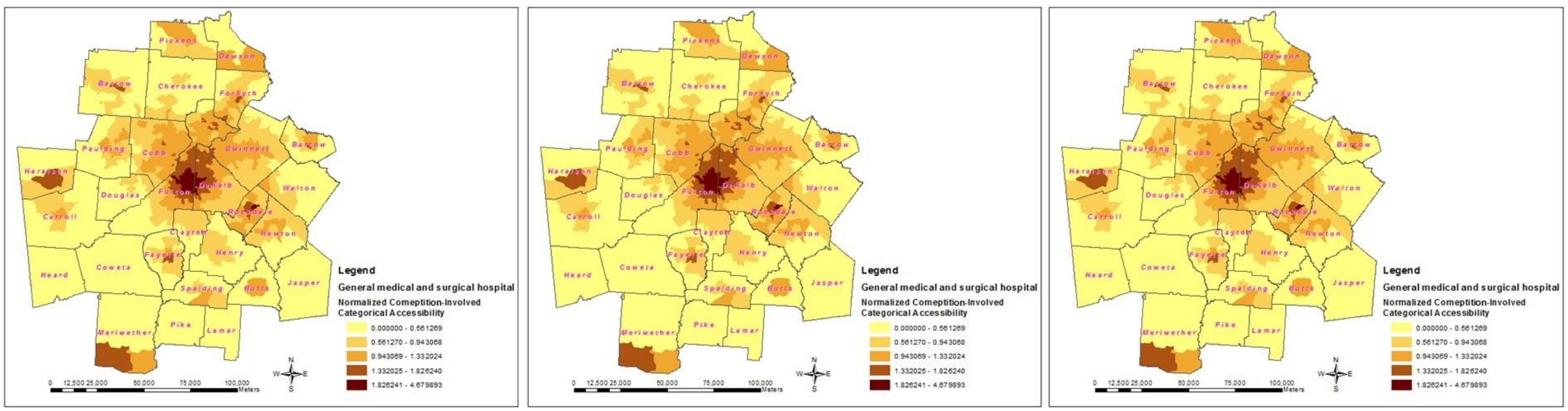


(f)strong preference to Offices of physicians

Figure 5.3: Categorical accessibility to Offices of physicians and Competition-involved Categorical accessibility to Offices of physicians with difference preference score combinations

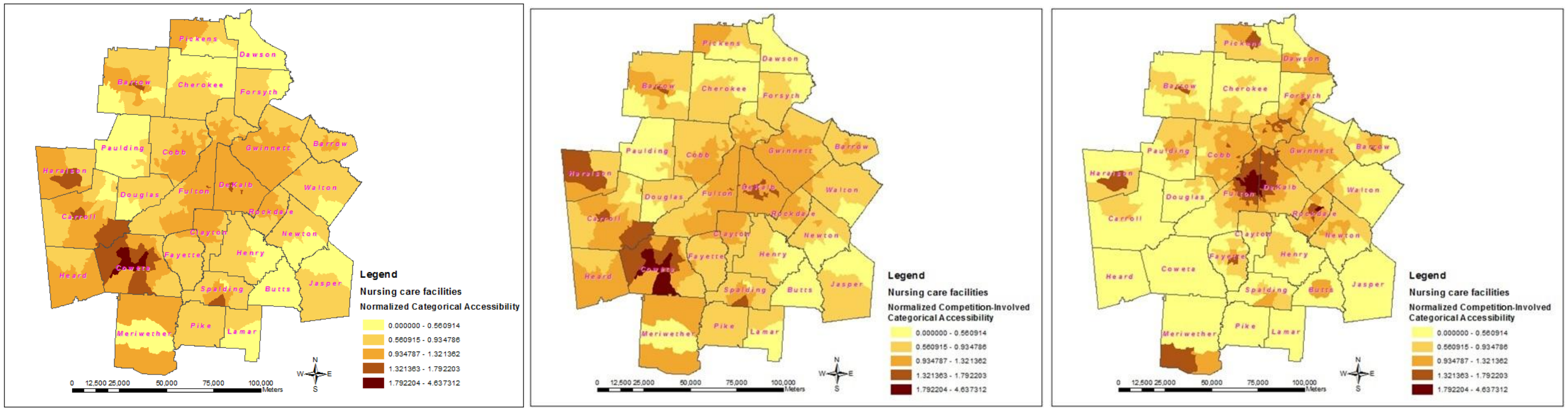


(a)competition not involved (b)no preference (c)slight preference to Hospitals

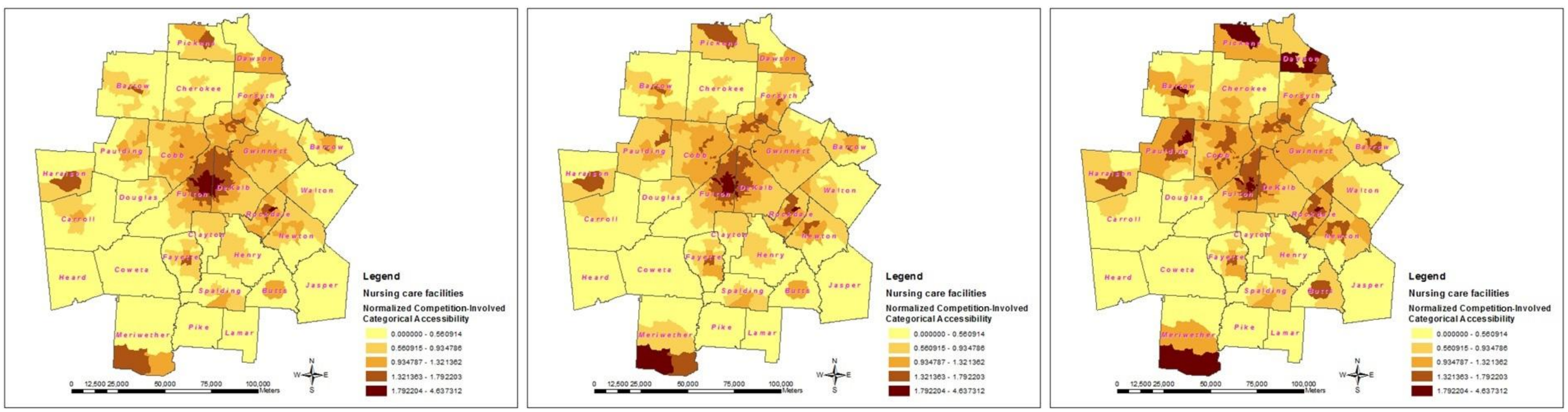


(d)strong preference to Hospitals (e)slight preference to Offices of physicians (f)strong preference to Offices of physicians

Figure 5.4: Categorical accessibility to Hospitals and Competition-involved Categorical accessibility to Hospitals with difference preference score combinations

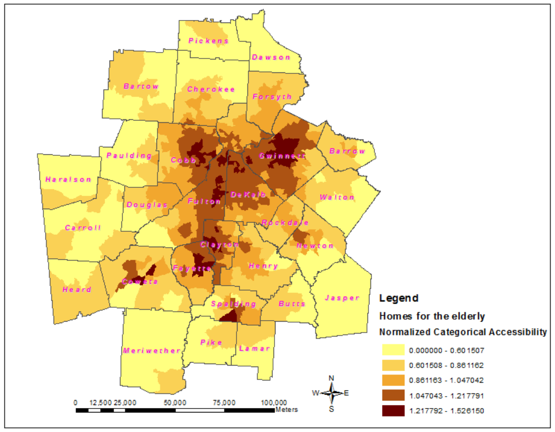


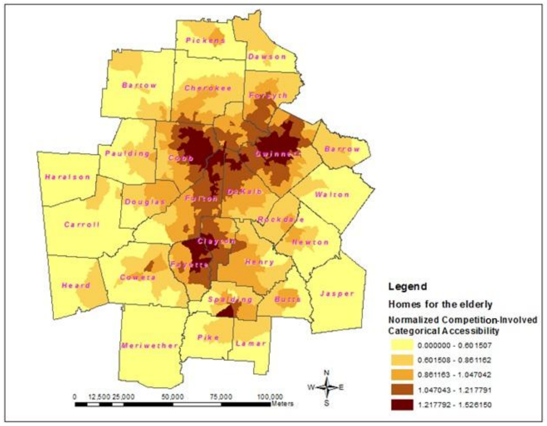
(a)competition not involved (b)no preference (c)slight preference to Nursing care

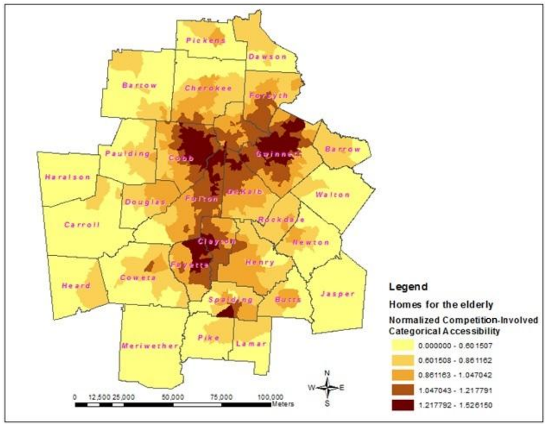


(d)Strong preference to Nursing care (e)slight preference to Homes for the elderly (f)strong preference to Homes for the elderly

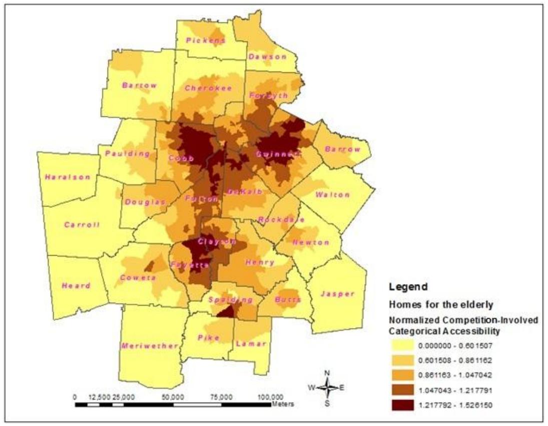
Figure 5.5: Categorical accessibility to Nursing Care facilities and Competition-involved Categorical accessibility to Nursing Care facilities with difference preference score combinations

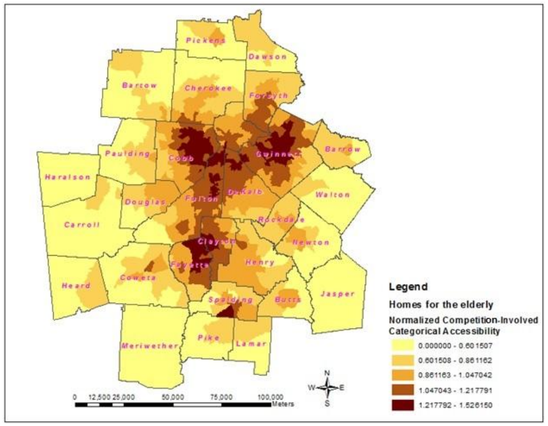


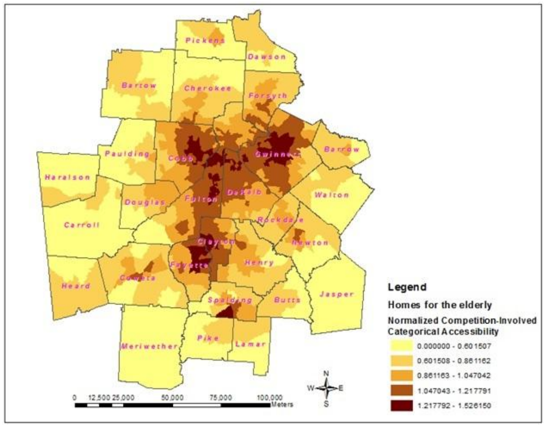




(a)competition not involved (b)no preference (c)slight preference to Nursing care







(d)Strong preference to Nursing care (e)slight preference to Homes for the elderly (f)strong preference to Homes for the elderly

Figure 5.6: Categorical accessibility to Homes for the elderly and Competition-involved Categorical accessibility to Homes for the elderly with difference preference score combinations

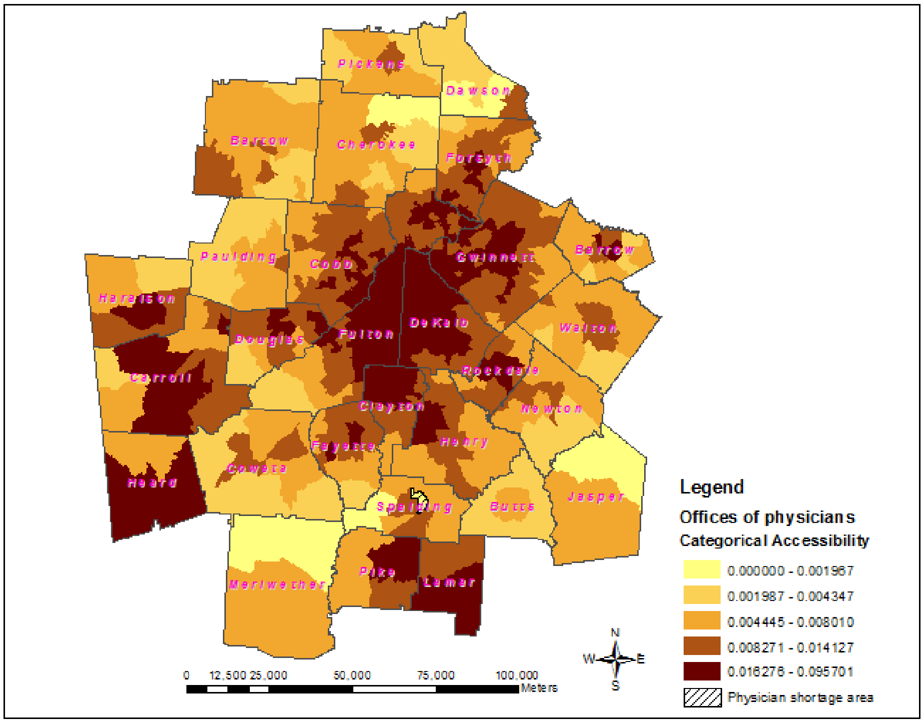


Figure 5.7: Physician shortage area based on categorical accessibility results

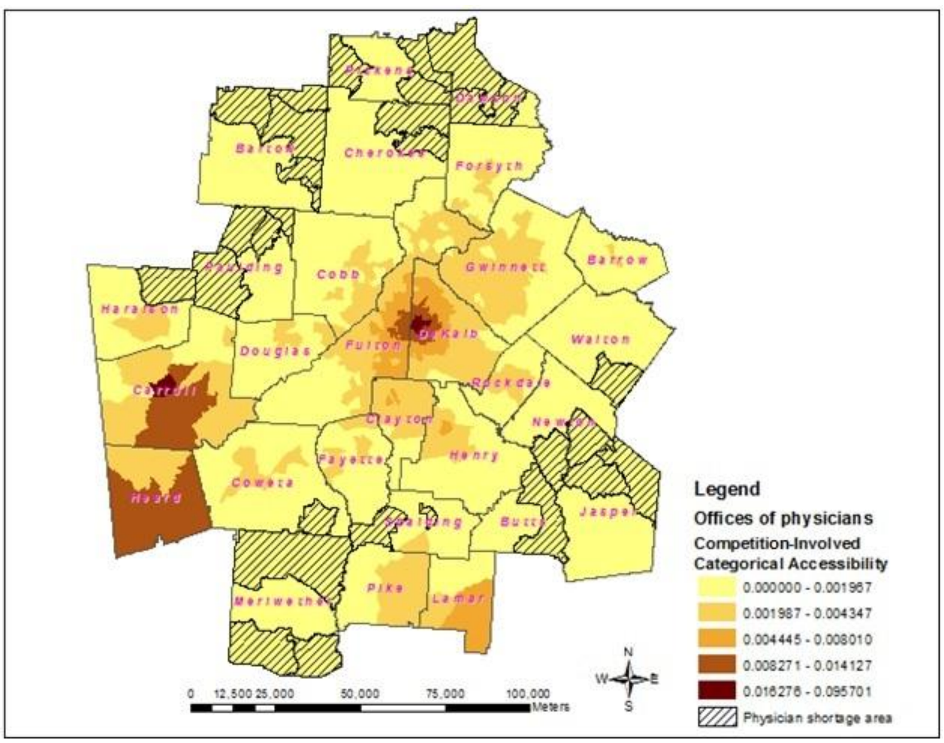


Figure 5.8: Physician shortage area based on competition-involved categorical accessibility with no preference

We use 1:3500, the national threshold value for designating health professional shortage areas (HPSAs), to identify physician shortage areas.(Ricketts et al. 2007). As shown in Figure 5.7, the categorical accessibility only detects 1 census tract in Spalding County as physician shortage area. This may be false because some peripheral areas of the Atlanta MSA contain a small supply of physicians. In contrast, the competition-involved categorical accessibility in Figure 5.8 detects 29 physician shortage census tracts which either were far from the metropolitan center or had few offices of physicians sites within. Compared to the categorical accessibility, the competition-involved categorical accessibility suggests a more rational distribution of physician shortage areas.

5.2 The Differences between Categorical and Competition-involved Categorical Spatial Accessibility

Figure 5.9 (a) - (d) illustrates the plot of normalized competition-involved categorical spatial accessibility and normalized categorical spatial accessibility for each type of health facility. Differences between the two results are mixed. Fractional polynomial function is used to generate the fitted line. In Figure 5.9, for all of these four types of health facilities, the fitted lines are almost linear when there is no preference. With the preference score combination changes, the fitted lines in Figure 5.9(a) – 5.9(c) tend to become curve. And the larger the relative disparity between preference scores is, the more the fitted line is curved. This indicates the competition from other types of health facilities is more influential when there is a strong preference to one type of health facility exists. In case of general medical and surgical hospitals, for example, the relative difference between normalized categorical accessibility and normalized competition-involved categorical accessibility with strong preference to offices of physicians is remarkable because the fitted line is largely curved. Figure 5.10 shows the geographic distribution of absolute difference between its categorical accessibility and its competition-involved categorical accessibility. The differences decrease from the center of metropolitan area, such as the Fulton County and the DeKalb County, to the suburban area. The difference for each census tract has a high value throughout the entire study area. In the plot for homes for the elderly (Figure 5.9(d)), however, all the fitted lines with different preference score combinations stay linear, which means that the relative difference between normalized competition-involved categorical accessibility and normalized categorical accessibility is least remarkable. Figure 5.11 represents geographic distribution of the absolute difference between competition-involved categorical accessibility and normalized categorical accessibility to homes for the elderly. Overall, the absolute difference in the central Atlanta MSA is higher than that in the peripheral Atlanta MSA. But the value of entire absolute differences for homes for the elderly is much lower than that for other types of health facilities, e.g. general medical and surgical hospitals (Figure 5.10). The insufficiency of geographic distribution and medical supply of homes for the elderly probably leads to little change of categorical accessibility after including the competition from other categories.

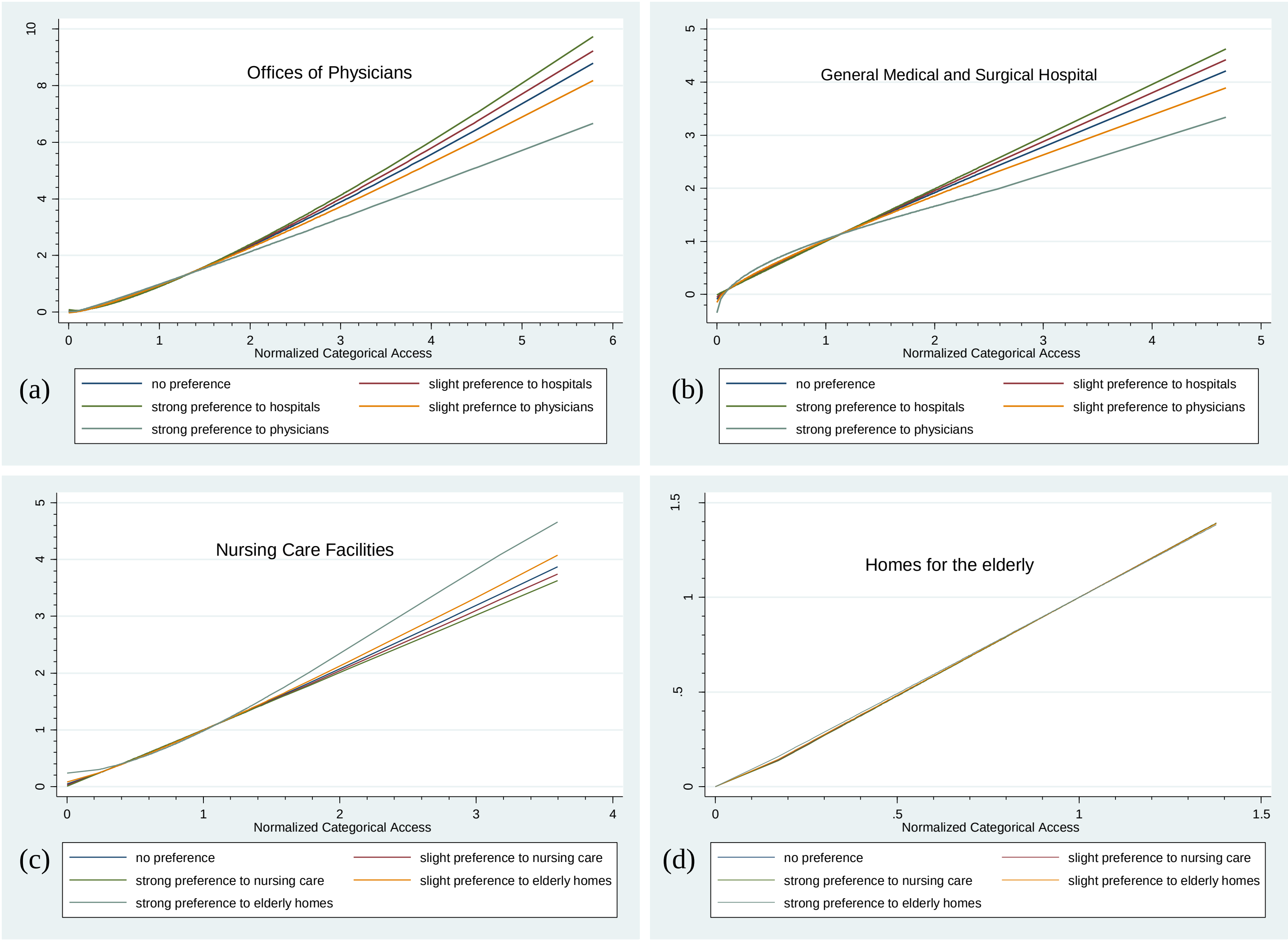


Figure 5.9: Comparison between categorical accessibility and competition-involved accessibility with different preference score combination

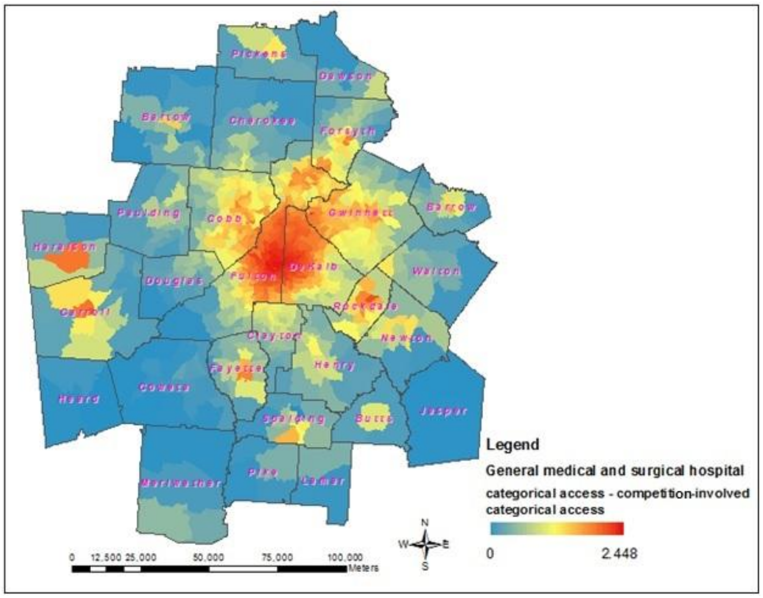


Figure 5.10: Geographic distribution of differences between the categorical accessibility to hospitals and competition-involved categorical accessibility to hospitals with strong preference to offices of physicians

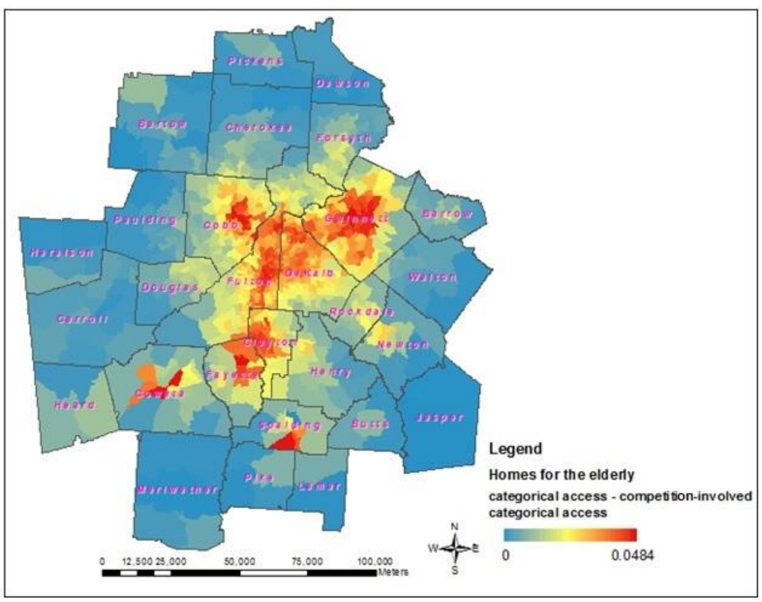


Figure 5.11: Geographic distribution of differences between the categorical accessibility to Homes for the elderly and competition-involved categorical accessibility to Homes for the elderly with no preference

CHAPTER 6

DISCUSSION AND CONCLUSION

This article proposes a CMSFCA method to encompass the competition from different groups of health facilities and to overcome the overestimation problem of previous spatial access models. As indicated by the case study in the Atlanta MSA of Georgia, the CMSFCA method can effectively minimize the overestimation problem. The new proposed CMSFCA method addresses the shortcomings of previous methods but maintains some their advantages such as the assumption of competition between health facilities within one health facility group, as well as the distance decay effect. The major advantage of the CMSFCA method over previous models lies in its more reasonable assumption of competition between different groups of health facilities. Using a competition scheme that involves travel time, medical capacity, and elderly people's preferences, the new method reveals a relative lower access for medical sites, thus minimizing the overestimation problem. This method leads to a more smoothed geographic pattern of spatial access to health facilities and derives more reasonable healthcare shortage areas. The avoidance of overestimation may result from the competition scheme between several groups of health facilities. In other words, competition from the other types of health facilities reduces the opportunity to access one type of health facility and increases the options to choose. When elderly people access health facilities, they not only face the selection of which nursing care facility they should select, but they also make their choices about whether they should select nursing care facilities or homes for the elderly, for example.

Though the CMSFCA method has notable advantages, several limitations deserve special attention when implementing this method in health facility accessibility studies. First, what is the appropriate functional form for the distance decay weights and how should the distance impedance parameter β be determined? In this study, we used the negative exponential model from the 2008 report of Minnesota Department of Transportation to account for the distance decay because of the lack of real observed data. Applying impedance functions from one study area to another has certain limitations as the effects of distance can vary over time and space, which could lead to errors in estimating potential accessibility. Similarly, the frictional effect of distance can differ substantially among population groups, reflecting differences in income, access to transportation and sociocultural factors. Another problem is that the distance exponent depends in part on the spatial configuration of service opportunities (Haynes and Fotheringham 1984). Research indicates that the distance exponent tends to be closer to zero for centrally located zones that are accessible to a large number of service facilities than for peripheral zones that are located far from service opportunities. If this situation is the case, the distance exponent will not be transferable from one study area to another unless the two areas contain similar geographical arrangements of service opportunities and population groups— a highly unlikely situation. To address this problem, we can calculate potential accessibility over a range of exponent values and explore the stability of the observed accessibility patterns in the future.

Second, what is the appropriate catchment size? In our study, we use varied catchment sizes according to the type of provider as Yang et al. (2006) explained. Catchment size may also vary according to type of neighborhood (Luo and Qi 2009). For instance, in rural areas, the catchment size may be larger and smaller in urban areas. Optimal size can be determined by incrementally increasing the size of the catchment until the base population within the catchment meets a threshold value (Tiwari and Rushton 2005). In addition, the catchment sizes do not have to be constant at different steps. The health facilities in an urban center may serve a large area, including surrounding small towns, requiring a large catchment for the second step, but population in an urban center is less likely to seek care in a nearby small town, which could result in a small catchment size for the third step (McGrail and Humphreys 2009b).

Third, as this is a spatial accessibility study, we don’t consider socio-demographic factors such as poverty rate, race, and linguistic barriers, which are important variables that can impact elderly people’s access to health facilities. However, integrating existing competition methods (e.g., those used in job accessibility studies) and patient survey and health facility admission data would greatly enhance the applicability of the CMSFCA method.

As our proposed method is designated to calibrate spatial accessibility to health facilities for elderly people, members of this age group basically all have access to health facilities as a result of their eligibility for the Medicare program. However, for people from other age groups, factors such as income, health insurance status, and education need to be considered in the accessibility study. The proposed method, which is more rational than the previous methods, can be combined with socio-demographic factors in future applications by using various integration methods (Wang and Luo 2005).

Fourth, edge effect exists for census tracts which locate at the border of study area. Elderly population who live in those census tracts could possibly seek health facilities in other nearby census tracts outside the study area. To account for the edge effect, a buffer zone (e.g. 2 hours) could be extended from the borders of the Atlanta MSA, but only the results within the Atlanta MSA are used as the final results.

Additionally, the suitable parameter to represent medical capacity needs to be further discussed. In some research including this research, employee number is chosen as the medical capacity parameter. In other studies, bed count at one health service location is used to represent medical capacity at that location. It's hard to judge which parameter is more reliable and accurate. A model with all parameters that are likely to influence the medical capacity can be built to obtain a comprehensive medical capacity index. Last but not the least, it is possible that there is an overlap between physicians in hospitals and physicians in the offices of physicians, which means some physicians could possibly work in both of these two places. To properly address all of these concerns, detailed surveys of actual utilization of health facilities would be necessary.

In conclusion, built on previous research, this paper presents an important improvement to the existing 3SFCA method for measuring spatial accessibility by introducing competition between different types of health facilities. This method effectively minimizes the overestimation problem of the existing methods. The distinct consideration of catchment size for different kinds of health facilities is justified, and distance decay is considered consistently in every step of this method. Additionally, factors that influence preference on visiting a health facility are added into the model, which makes the accessibility results more fitted to real life. Despite the limitations that were mentioned previously in this chapter, this study represents an important step in incorporating a different target group in a health accessibility study. The research that is methodology developed in this paper could also be useful for research on accessibility in other fields.

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APPENDIX A

NAICS CODE

NAICS.id	NAICS.display-label
621111	Offices of physicians (except mental health specialists)
621112	Offices of physicians, mental health specialists
621210	Offices of dentists
621310	Offices of chiropractors
621320	Offices of optometrists
621330	Offices of mental health practitioners (except physicians)
621340	Offices of physical, occupational and speech therapists, and audiologists
621391	Offices of podiatrists
621399	Offices of all other miscellaneous health practitioners
621410	Family planning centers
621420	Outpatient mental health and substance abuse centers
621491	Health maintenance organization medical centers
621492	Kidney dialysis centers
621493	Freestanding ambulatory surgical and emergency centers
621498	All other outpatient care centers
621511	Medical laboratories
621512	Diagnostic imaging centers

621610	Home health care services
621910	Ambulance services
621999	All other miscellaneous ambulatory health care services
622110	General medical and surgical hospitals
622210	Psychiatric and substance abuse hospitals
622310	Specialty (except psychiatric and substance abuse) hospitals
623110	Nursing care facilities
623210	Residential mental retardation facilities
623220	Residential mental health and substance abuse facilities
623311	Continuing care retirement communities
623312	Homes for the elderly
623990	Other residential care facilities
624110	Child and youth services
624120	Services for the elderly and persons with disabilities
624190	Other individual and family services
624210	Community food services
624221	Temporary shelters
624229	Other community housing services
624230	Emergency and other relief services
624310	Vocational rehabilitation services
624410	Child day care services

APPENDIX B

ACRONYM LIST

2SFCA: Two-Step Floating Catchment Area

3SFCA: Three-Step Floating Catchment Area

CMSFCA: Categorical Multi-Step Floating Catchment Area

E2SFCA: Enhanced Two-Step Floating Catchment Area

HPSA: Health Professional Shortage Area

MSA: Metropolitan Statistical Area

NAICS: North American Industry Classification System