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Measuring Spatial Health Disparity Using a Network-Based Accessibility Index Method in a GIS Environment: A Case Study of Hillsborough County, Florida


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Measuring Spatial Health Disparity Using a Network-Based Accessibility Index Method in a GIS Environment: A Case Study of Hillsborough County, Florida

Abstract

In recent decades, the health care delivery system in the United States has been greatly transformed and more widely examined. Even with one of the most developed health care systems in the world, the United States still experiences great spatial disparity in health care access. Increasing diversity of class, culture, and ethnicity also has a significant impact on health disparity. The goal of this paper is to address the spatial disparity of health care access using a network-based health accessibility index method (NHAIM) in a Geographic Information System (GIS) environment. Ensuring a desired level of accessibility for patients is the goal of the health care delivery system, through which health care service providers are supplied to populations in need. GIS plays an increasing role in understanding and analyzing accessibility to health care by incorporating geographical physical barriers, network-based travel time, and transportation costs required for access to health care services. In this study, we develop a NHAIM to examine the spatial disparity in health care access in Hillsborough County, Florida, determining the locations of registered medical doctors and facilities using data from Medical Quality Assurance Services (MQA) and the U.S. Census. This research reveals the spatial disparity of health care accessibility and availability in this region and provides an effective method for capturing health care accessibility surplus and shortage areas for future health care service planning.

Keywords

health disparity, accessibility, GIS, Network-based Health Accessibility Index Method (NHAIM)

1. INTRODUCTION

Accessibility is the key element within the health care delivery system. Ideally, all should have equal access to quality health care. Such equal access has come to be recognized as being as essential to public health as individual health status (Aday and Andersen 1974; Culyer and Wagstaff 1993; Oliver and Mossialos 2004). Penchansky and Thomas (1981) described five dimensions of health access: availability, accessibility, affordability, acceptability, and accommodation. The first two are related to geographical locations and thus inherently spatial. Among them, accessibility reflects the travel impedance between population in demand and health facilities, and is usually measured in travel distance or time. Availability refers to the amount of health facilities available for population in demand to choose from. In health geography literature, the term “spatial accessibility” is used to refer to the combination of these two dimensions (Guagliardo et al. 2004; Luo and Wang 2003a; Luo 2004).

Generally speaking, the spatial distributions of health facilities and population in need are not matched perfectly over geographical space (Guagliardo 2004; Luo and Wang 2003b; Parker and Campbell 1998). Therefore, the goal to substantially reduce the inequality in accessing health care services is far from being achieved in the United States. According to Rosenberg and Hanlon (1996), middle and high income individuals are more likely to benefit from better access to family physicians, maintaining a higher health status and practicing preventive health care. Some other studies demonstrate that blacks are more likely to receive late-stage breast cancer diagnosis compared to whites and therefore have higher mortality rates. Additionally, African-Americans are more likely to experience the negative influence of socioeconomic disadvantages, such as low educational attainment and linguistic barriers over late diagnosis (McLafferty and Wang 2009; Meliker et al. 2009a; Meliker et al. 2009b; Wang et al. 2008). Since socioeconomic and neighborhood inequalities are significantly correlated with health care accessibility, it is not surprising that the shortage of health care supply is especially severe in rural areas and impoverished urban communities (COGME 1998; COGME 2000; Rosenblatt and Lishner 1991; Rosenthal et al. 2005; Shen 1998).

Thus, it is of great importance in understanding this dynamic context and exploring accessibility as a multidimensional concept contingent upon the interaction between a variety of spatial factors (e.g., geographical location, travel distance) and aspatial factors (e.g., socio-economic status, age, gender, and ethnicity) (Joseph and Bantock 1984; Meade and Earickson 2000; Penchansky and Thomas 1981). Theoretically, health facilities should be located according to potential demand such as in areas with high population density to ensure maximum coverage. However, population in demand might not necessarily be covered by the service range of health facilities in reality. Shi et al. (2012) identified “islands” with no coverage of major cancer care facilities at a national scale. For example, the most visible high-demand area for cancer care services is located at the contact of Kansas, Missouri, Arkansas and Oklahoma, which happens to be the biggest uncovered “island” in the Midwest. This spatial mismatch between the geographical locations of health facilities and population in demand raises the following question: how do we define, measure and evaluate the accessibility to health care services?

Geographers and public health researchers recognize the significance of measuring

accessibility and apply a broad spectrum of techniques to solve this issue. While some focus on mathematical modeling or statistical analysis (Field 2000; Gu et al. 2010; Higgs 2005; Joseph and Bantock 1982), others apply a more qualitative approach (Hanlon and Halseth 2005; Hawthorne and Kwan 2013; Kiwanuka et al. 2008). Within this body of literature, Geographic Information System (GIS) plays an increasingly significant role in understanding and analyzing accessibility to health care. In particular, the capability of GIS highlights the spatial dimensions of accessibility. For example, Langford and Higgs (2006) estimated 'demand-side' population, or potential health care client locations, by applying various spatial interpolation techniques. Yang et al. (2006) evaluated access to dialysis health care by using specialized gravity models. Luo and Wang (2003a) measured spatial accessibility to health care and identified health shortage areas in Chicago region. In conclusion, GIS enables researchers to store and manage sensitive yet complicated information for both patients and health service locations (Bullen et al. 1996; Gu et al. 2010; Verter and Lapierre 2002; Zhang et al. 2009), measure access to health services for populations in need (Curtis et al. 2006; Lo and Wang 2005; Wang 2006; Wang 2012), and analyze the evolving spatial distribution patterns of health facilities (Gesler and Albert 2000; Higgs 2005; Kurland and Gorr 2012; Pedigo and Odoi 2010; Ross et al. 1994).

In this paper, we present an alternative set of health accessibility measures, which comprehensively evaluate both spatial dimensions of health accessibility and availability in order to address spatial disparity problems. The goal of this paper is to measure and evaluate spatial accessibility to health care by using a *network-based health accessibility index method* (NHAIM) in a GIS environment. Based on data downloaded from the Florida Geographic Data Library Documentation and US Census Bureau, this paper demonstrates the application of NHAIM in measuring spatial accessibility to health facilities in Hillsborough County, Florida. Both dimensions of accessibility and availability are measured and presented as indexes to reveal patterns of health disparity, as well as to capture underserved areas.

This paper is organized as follows. In the next section, we provide a brief review of existing spatial accessibility measures. In the third section, we demonstrate the application of an alternative method – the *network-based health accessibility index method* (NHAIM), using Hillsborough County, Florida as a case study. The NHAIM consists of two sub-indexes to measure accessibility and availability respectively and a comprehensive index to evaluate the overall level of health disparity. The fourth section provides the analysis results of the case study, followed by conclusions in the fifth section.

2. SPATIAL ACCESSIBILITY AND DISPARITY IN HEALTH CARE SYSTEMS

Spatial accessibility to health service locations is usually measured through addressing the geographical barriers like travel distance or time (Cromley and McLafferty 2012; Guagliardo 2004). The interaction between population in need and health care providers decrease with increasing travel distance, following a function of distance decay. Shorter geographical distance can lead to more frequent visits to health facilities, and eventually

better health for individuals. For example, Buchmueller et al. (2006) found that increasing distances from hospitals result in higher death rates from heart attacks and unintentional injuries. Another study by Arcury et al. (2005) shows that a shorter distance between patients and physicians can increase the frequency of regular family physical exams. Other studies also confirm that early detection of disease and treatment is negatively associated with the spatial separation between medical services and patients (Campbell et al. 2000; Meyer 2012; Monnet et al. 2006; Onega et al. 2008). Distance decay is a fundamental aspect to measure spatial accessibility, and it varies for different types of medical practice and health care needs. For example, cardiovascular emergencies requires patients be delivered to an emergency center within a critical time window (Busingye et al. 2011; Hare and Barcus 2007). For routine health check-ups, there are much less restrictions over travel time or distance (Lovett et al. 2004).

Most existing measures of spatial accessibility are based on the potential interaction between health care providers (e.g., primary care physicians, cancer treatment centers, hospitals, etc.) and population in need, or supply and demand (Guagliardo 2004; Higgs 2005; Wang 2012). One commonly used measure is the supply-demand ratios, or provider-population ratios, which are computed within bordered areas. The ratios are effective for gross comparisons of supply between geographical units, and are widely applied to set minimal standards for local supply and identify underserved areas (Cervigni et al. 2008; Khan 1992; Perry and Gesler 2000; Radke and Mu 2000). For example, the U.S. Department of Health and Human Services (DHHS) uses a minimum population-physician ratio to identify Health Professional Shortage Areas (HPSA). However, this basic measurement has difficulty capturing the border crossing of patients among neighborhood spatial units. Detailed variations in accessibility across space and the distance dimension of access are ignored (Guagliardo et al. 2004; Wang 2012). Another basic method is to measure average travel distance to nearest providers (Fryer Jr et al. 1999; Goodman et al. 1992). This method applies the straight line distance between the population point and the location of the health provider. However, travel routes are rarely straight lines in reality. It also cannot fully represent clusters of health providers in an urban setting and ignores the availability dimension of access.

Gravity models, initially developed for land use planning, are also utilized to account for the spatial interaction between health care supply and demand (Hansen, 1959; Joseph and Bantock, 1982; Shen, 1998). The simplest formula for gravity-based accessibility A_i can be written as follows:

$$A_i = \sum_j^n \frac{S_j}{d_{ij}^\beta} \quad (1)$$

A_i is the index of spatial accessibility from population point i , such as a personal residence or population centroid of certain spatial unit. S_j is the service capacity of health facilities (e.g., the number of hospital beds or doctors) at location j . d_{ij} is the distance or travel time between i and j , and β is the travel friction coefficient. n is the number of health facilities. Spatial accessibility improves if the number of health facilities increases, the service capacity increases, or the travel distance decreases. The improved gravity-based accessibility model proposed by Joseph and Bantock (1982) adds a population

adjustment factor to the denominator. The formula can be written as:

$$A_i = \sum_{j=1}^n \frac{S_j d_{ij}^{-\beta}}{\sum_{k=1}^m P_k d_{kj}^{-\beta}} \quad (2)$$

P_k is the population at location k , d_{kj} is the distance or travel time between j and k , and the indexes n and m represent the total number of facility locations and population locations, respectively. The gravity-based accessibility model is essentially the ratio of supply to demand (Huff 1963, 2000; Luo and Qi 2009; Wang 2012). Despite its elegance in revealing geographic variation in accessibility, gravity models are not easy for public health professionals to interpret or implement. A large amount of geo-coded data for the locations of both population and health facilities are required to estimate the travel friction coefficient β . Sometimes the models also involve great effort of computation and programming (Luo and Whippo 2012; Taaffe et al. 1996).

Another development in spatial accessibility modeling is the two-step floating catchment area method (2SFCA) proposed by Luo and Wang (2003a and 2003b). The fundamental assumption of 2SFCA is that availability and accessibility are not mutually exclusive and they can compensate each other. A health provider is defined as accessible if located inside the catchment, and inaccessible if located outside of the catchment. The catchment of a provider location is defined as a buffer area within a threshold travel distance or time from the provider. The 2SFCA can be implemented in a GIS environment using two steps. First for each physician location j , search all population locations k that are within the catchment area and compute the provider – population ratio R_j . Then for each population location i , search all provider locations j that are within the threshold distance from location i , and sum up R_j derived from the first step at these locations. Eventually the accessibility index A_i can be written as follows (Luo and Wang 2003a):

$$A_i = \sum_{j \in \{d_{ij} \leq d_0\}} R_j = \sum_{j \in \{d_{ij} \leq d_0\}} \frac{S_j}{\sum_{k \in \{d_{kj} \leq d_0\}} P_k} \quad (3)$$

R_j is the measurement of potential service intensity of facility j , the provider-population ratio. S_j is the service capacity of facility location j , P_k is the population in need at location k , d_{kj} is the travel distance or time between k and j , and d_0 is the threshold.

The 2SFCA has been popular and used in a number of studies (Cheng et al. 2012; Dai 2010; McGrail and Humphreys 2009; Ngui and Apparicio 2011; Shi et al. 2012; Wan et al. 2013; Yang et al. 2006). However, Luo and Wang demonstrate that their model is not fundamentally different from the gravity-based accessibility model (Luo and Wang, 2003a, b). The 2SFCA overcomes the restriction of using pre-defined geographical boundaries. However, the limitation of 2SFCA is mainly found in assuming a health provider inside a catchment area is accessible and one outside the catchment area is inaccessible, which tends to be arbitrary, ignoring the possibility of overlapping areas in coverage. In addition, potential improvements may be made to account for different transportation options, as well as variable catchment sizes for different populations and health services. While the above methods make significant contributions in revealing

health disparity, we seek to complement such spatial accessibility literature by providing an alternative measure. Recognizing that spatial accessibility is a complex concept including both accessibility and availability, we seek to develop a method that can reveal and represent both dimensions respectively.

3. ANALYTICAL FRAMEWORKS AND STUDY AREA

3.1 NETWORK-BASED HEALTH ACCESSIBILITY INDEX METHOD (NHAIM)

The concept of spatial accessibility to health care includes both dimensions of accessibility and availability. In general, *accessibility* refers to the ease to reach health services from the demand side while *availability* emphasizes choices of local service locations from the supply side. Spatial accessibility to health services is primarily dependent on the geographical locations of health care providers and population in need, as well as the travel distance/time between them (Wan et al. 2013). Since distance decay is a fundamental aspect in understanding spatial accessibility, the following questions were raised when developing our methodology: [1] how to define travel distance and reflect distance decay, [2] how to represent both health care demand and supply, and [3] how to apply the most reasonable measure for travel distance to health care services. *Network distance* has gained certain popularity in recent literature as a replacement for Euclidean distance and Manhattan distance. It is considered to be a more accurate measurement for real travel distance and time (Brabyn and Beere 2006; Cheng et al. 2012; Dai 2010; Delmelle et al. 2013; Pearce et al. 2006; Shi et al. 2012; Wan et al. 2013). However, Apparicio et al. (2008) found that Euclidean and Manhattan distances are strongly correlated with network distances. However, local variations are still observed, notably in suburban areas. Thus in those areas, network-based distance may provide more accurate results. In our study, we applied network-based distance rather than Euclidean distance and Manhattan distance, since the study site includes both urban and suburban areas.

In NHAIM, the population centroid within each spatial unit is used to represent aggregated health care demand location. When health care demand is aggregated, the true distance to health care services from each individual or household is replaced by the distance from the aggregation point (Current and Schilling 1990). The aggregation method can reduce the complexity of location and routing problems as well as protect the privacy of the individual or household by masking their individual locations, especially in sensitive research. The population centroid for each health care demand area can be obtained in a GIS environment through preprocessing.

The fundamental issue in spatial accessibility literature is addressing the potential interaction between health care providers and population in need. However, it is difficult to predict people's choices and behaviors, especially with border crossing problems. The term "edge effect" is coined to describe the possibility of accessing health providers across borders (Cromley and McLafferty 2012; Guagliardo 2004; Higgs 2005; Wang 2012). The NHAIM tries to mitigate edge effect by evaluating and integrating both dimensions of health care accessibility and availability. As summarized in Table 1, the

NHAIM consists of three sub-indexes. The first sub-index, the *Network-Based Health Accessibility Supply Index* (NHA-SI), is developed from the supply side and reveals the availability of health care providers in each spatial unit. The second one, the *Network-Based Health Accessibility Demand Index* (NHA-DI), is developed from the demand side and evaluates health care accessibility for the population in demand residing within each spatial unit. The third sub-index, the *Network-Based Health Access Disparity Index* (NHA-DP), is a global index summarizing both dimensions. Ultimately, the NHAIM is designed to evaluate the interaction between health demand and supply, and present both sides of the interaction.

Table 1. The Indexes of NHAIM.

NHAIM	NHA-SI	Network-Based Health Accessibility Supply Index: <ul style="list-style-type: none"> • Reflects health care access from the supply side • Measures service availability in terms of health facilities
	NHA-DI	Network-Based Health Accessibility Demand Index: <ul style="list-style-type: none"> • Reflects health care access from the demand side • Measures overall health care accessibility for the population in demand
	NHA-DP	Network-Based Health Access Disparity Index: <ul style="list-style-type: none"> • Combines both the NHA-SI and NHA-DI • Measures both health care accessibility and availability

1) NETWORK-BASED HEALTH ACCESSIBILITY SUPPLY INDEX (NHA-SI)

The *Network Health Accessibility Supply Index* (NHA-SI) addresses health care access problems from the supply side. The NHA-SI is an indicator quantifying the availability of health care supply within the measured spatial unit.

As illustrated in Figure 1, the NHA-SI can be achieved through the following four steps in a GIS environment. The first step (Step 1 in Figure 1) is to represent health care demand locations using population centroids. As suggested by Current and Schilling (1990), the population centroid within each spatial unit can be used to represent the aggregated health care demand location. The demand aggregation method reduces the complexity of location problems and protects the privacy of individuals or households, especially in sensitive researches. Demand aggregation can result in over- or underestimation of true distance and health care supply coverage (Cromley and McLafferty 2012; Openshaw 1983). According to Hewko et al. (2002), aggregation error is a result of spatial separation between the distribution of individuals and the centroid of spatial unit. Thus accessibility measured for smaller units tends to be more reliable than that measured for larger spatial units. The second step (Step 2 in Figure 1) involves calculating the network demand area of health care for each population centroid. A health care demand area is defined as a network-distance travel zone from the population centroid. Coverage is measured based on travel distances calculated using road networks. The sizes of demand areas vary according to different types of health services. For example, cancer treatment centers generally cover larger demand areas than primary care providers. Luo and Qi (2009) defined the threshold travel distance to Primary Care

Physicians as 30 minute network travel distance. Wan et al. (2013) extended the travel time to 60 minute focusing on access to cancer screening and treatment facilities. Thus the thresholds for travel distances are flexibly set to reflect different types of health services. The size of a demand area expands as the threshold travel distance increases. In the third step (Step 3 in Figure 1), we calculate the population within each demand area i generated in the previous step. The calculated population is denoted by p_i . Next we search every demand area that covers health care facility j . This can be interpreted as the health care facility j serving n demand areas ($n \geq 0$; n = the number of demand areas covering facility j). In the end, we calculate P_j , the total population residing within n demand areas that facility j is serving, which is expressed by $P_j = \sum_i^n p_i$. Note that the population residing within the overlapping areas (i.e., intersections in Step 3 in Figure 1) is only counted once to get the most accurate result. The final step (Step 4 in Figure 1) calculates s_j , the health care accessibility for each facility j using following formula:

$$s_j = k \frac{C_j}{P_j}, \quad 0 < s_j < 1, \quad \forall j \tag{3}$$

where

C_j : the capacity of facility j (e.g., the number of beds/rooms as a proxy for supply capacity),

P_j : the total population residing within n demand areas that facility j is serving

k : is the scalar to adjust the ratio.

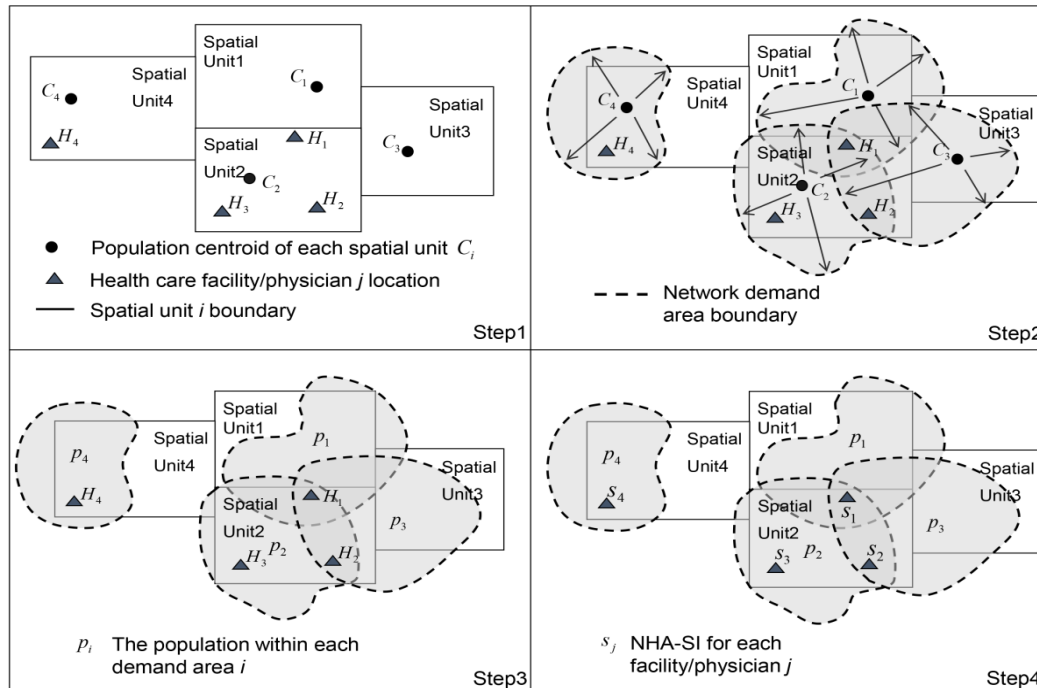


Figure 1. The procedure for calculating the Network-Based Health Accessibility Supply Index.

Now, as each spatial unit i will contain n ($n \geq 0$) health facilities j with attribute s_j , the S_i , the NHA-SI for spatial unit i is calculated as follows:

$$S_i = \sum_{j=1}^n s_j, \quad j \in R \quad (4)$$

where

R : the set of facilities j located within spatial unit i .

When the facility capacity is fixed, the NHA-SI index will be smaller if a greater health care demand is identified. Both higher facility capacity and smaller population in need will result in a larger NHA-SI value, which reflects less constraints over the facilities and represents a higher level of availability in the measured spatial unit.

2) NETWORK-BASED HEALTH ACCESSIBILITY DEMAND INDEX (NHA-DI)

The *Network Health Accessibility Demand Index* (NHA-DI) evaluates the overall accessibility from the demand side by calculating the percentage of population residing within the service ranges of health care facilities in each spatial unit, as well as taking the capacities of those facilities into consideration. It reveals the general level of health care accessibility in the measured spatial unit. As illustrated in Figure 2, the NHA-DI index is achieved in the following four steps.

In the first step (Step 1 in Figure 2), we identify the locations of health care facilities within each spatial unit. Next, we calculate the network service area for each facility j (Step 2 in Figure 2). The service area is defined as the network distance travel zone from facility j . Similar to the demand areas generated from population centroids when calculating NHA-SI, the sizes of service areas also vary for different types of health services according to different travel time thresholds (Luo and Qi 2009; Wan et al. 2013). In the third step (Step 3 in Figure 2), we calculate the population ratio covered by the network service area of facility j in spatial unit i : p_i^j/p_i ($p_i^j \leq p_i$). p_i^j is the population in spatial unit i that falls within the network service area of health facility j , while p_i is the overall population residing in spatial unit i . The final step (Step 4 in Figure 2) involves calculating D_i , the NHA-DI index for each spatial unit using the following formula:

$$D_i = k \sum_{j=1}^n C_j \frac{p_i^j}{p_i}, \quad 0 \leq D_i \leq 1, \quad \forall i \quad (5)$$

where

p_i^j/p_i : the ratio of population covered by the network service area of health facility j to the total population in spatial unit i . According to the formula, either a higher percentage of population covered by the network health service areas (p_i^j) or higher facility capacities results in a higher NHA-DI index. A higher NHA-DI index indicates that more people have access to higher capacity facilities, which is considered as having better health accessibility.

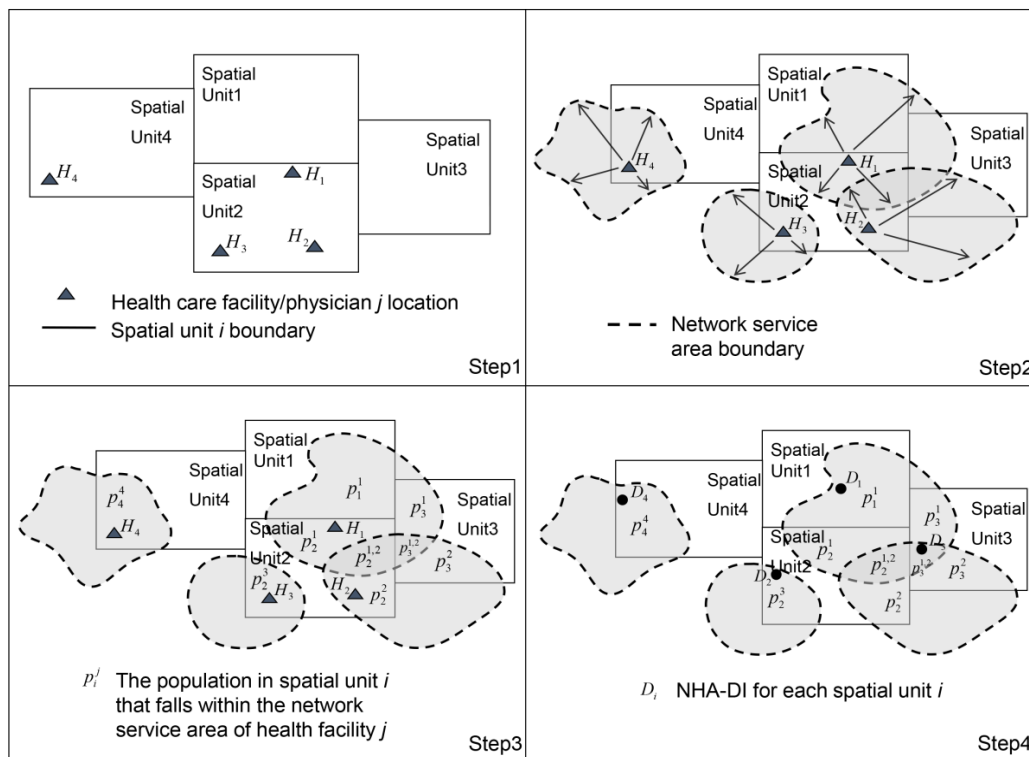


Figure 2. The procedure for calculating the Network-Based Health Accessibility Demand Index.

3) NETWORK-BASED HEALTH ACCESS DISPARITY INDEX (NHA-DP)

The *Network Health Access Disparity Index* (NHA-DP) is a comprehensive index that examines the balance between health care accessibility and availability at each spatial unit by evaluating both indexes: the NHA-SI and NHA-DI. Each spatial unit will contain two attributes: a population centroid in spatial unit i with attribute D_i and n health facilities with summed up attribute S_j . The level of spatial disparity A_i for each spatial unit i is represented as:

$$A_i = [\text{NHA-SI}, \text{NHA-DI}] = [D_i, S_i], \quad \forall i \tag{6}$$

Accordingly, spatial units in the study area can be categorized in four quadrants based on indexes A_i illustrated in Figure 3. In detail, the first quadrant (1Q) includes spatial units with *High Accessibility & High Availability* (HAc & HAv), indicating that a higher proportion of the population has access to higher-capacity health care facilities. There are little constraints over the facilities available for the population in need. This is considered to be the most ideal situation in the health care delivery system. The second quadrant (2Q) describes *Low Accessibility & High Availability* (LAc & HAv). Spatial units within this category are identified with sufficient health supply. Measured facilities have either high capacities or are serving a smaller population. However, the population in need have low access to the measured health facilities. Only a small percentage of population is covered

by the service areas of facilities, which indicates a mismatch between the spatial distribution of health care demand and supply. The third quadrant (3Q) represents the spatial units with *Low Accessibility & Low Availability* (LAc & LAv). In this case, the population in need has a low level of accessibility to health facilities within travel range. The facilities located inside the spatial unit are considered as being less ‘available’ due to great constraints. It could be a result of having no facilities within the spatial unit, or facilities serving a large population with limited capacities. This category includes spatial units with unsatisfied demand and limited supply, representing a great shortage in health care provision. The fourth quadrant (4Q) identifies spatial units with *High Accessibility & Low Availability* (HAc & LAv). Low availability indicates that facilities are over-constrained to serve a large population, or there are no facilities located within the spatial unit at all. Nevertheless, local residents are able to access facilities located across borders, which compensates the shortage of health care supply within the spatial unit.

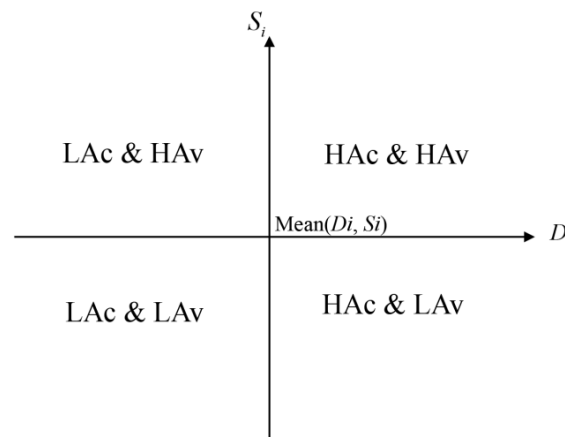


Figure 3. The classification of spatial units using the NHA-DP (Note: H=High, L=Low, Av=Availability, Ac=Accessibility).

Given this categorization, the results based on the NHA-DP are straightforward to interpret and easy to apply for any geographic scale. Notice that the NHAIM can be applied to different levels of health services, including primary care, secondary care, and tertiary care, depending on research interests. In the following case study, we demonstrate the application of NHAIM using hospital data in Hillsborough County, Florida. Note that hospitals generally incorporate different levels of health care, which provides a good estimate for the overall local health resources.

3.2 STUDY AREA AND DATA

To test the NHAIM, we selected Hillsborough County in Florida as the study area. Hillsborough County is located on the west coast of Florida in the Tampa-St. Petersburg metropolitan area. It is the largest county by metropolitan area and the fourth largest county in the state. Hillsborough County has a relatively even and flat landscape, which decreases the effect of geographic barriers. As shown in Figure 4, this county comprises

several major cities, including Tampa, Temple Terrace, Lutz, Plant City, Brandon, Apollo Beach, Ruskin, and Sun City Center. Noticeably, many hospitals are clustered in those cities along major highways. The population data was extracted from the 2010 Census Summary File (US Bureau of Census 2010). In this case study, we used ZIP code areas as the basic spatial unit to apply the NHAIM. Population-weighted centroid was used to represent aggregated demand location, which is considered to be a more accurate representation than simple geographic centroid (Hwang and Rollow 2000). The population centroids for ZIP code areas were generated based on Census Tract level population data in a GIS environment. ZIP code areas are aggregated to develop Primary Care Service Areas (PCSAs) by the U.S. Department of Health and Human Services (DHHS), which are the basic spatial units used to identify Medically Underserved Areas/Populations (MUA/Ps) and Health Professional Shortage Areas (HPSAs). Fifty-five ZIP code areas were identified in the study area with a total population of 1,229,226 (as of 2010). The network distance between any pair of population centroids and health facility locations was measured based on the road networks for travel-time distance estimation using the 2010 Census TIGER/Line files.

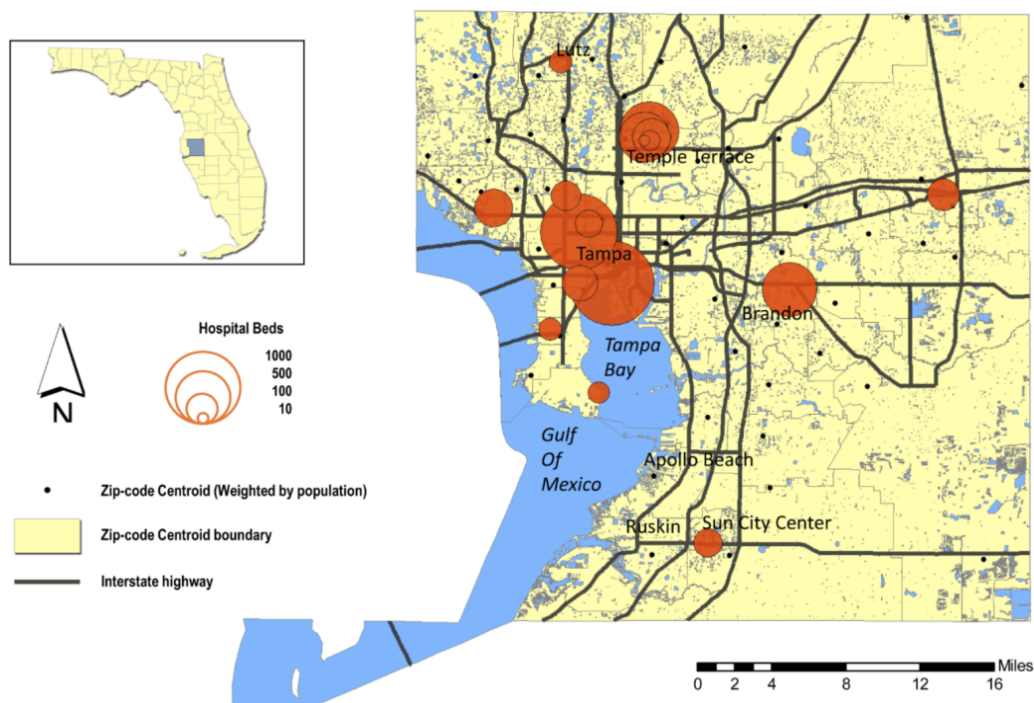


Figure 4. The study area: distribution of Hospitals in Hillsborough County, FL.

The hospital data for Hillsborough County was downloaded and extracted from the Florida Geographic Data Library Documentation. The original dataset includes the addresses and capacity information of hospitals in Florida in 2010. The hospital locations were geo-coded using ArcGIS 10.1. To apply the NHAIM, we needed to define two key parameters – the travel time threshold and health care facility capacity. In the previous

literature, a 30 minute travel time threshold for primary road conditions is suggested (Lee 1991). The 30 minute threshold is also used for defining rational service area and capturing HPSAs by DHHS (Wang and Luo 2005). In this case, we used both 30 minute and 10 minute travel zones for comparison. By applying different thresholds, we were able to evaluate how travel distances influence spatial accessibility. Since the information on number of physicians is lacking, we used the number of hospital beds as a measurement for facility capacity.

4. RESULTS

Figure 5 shows the NHA-SI indexes for both 10 minute and 30 minute thresholds. 75% of the ZIP code areas are identified with zero number of hospitals ($S_i=0$), and most of them are rural areas. In contrast, the NHA-SI obtains highest values within and around Tampa, followed by Brandon and Temple Terrace, which are urban areas with high population densities. The NHA-SI decreases as the threshold increases from 10 minute to 30 minute. As the travel time increases, the service range of a hospital increases. The hospital becomes less 'available' for it is serving a larger population while the capacity is fixed. The NHA-SI becomes smaller as the denominator – the number of population gets larger.

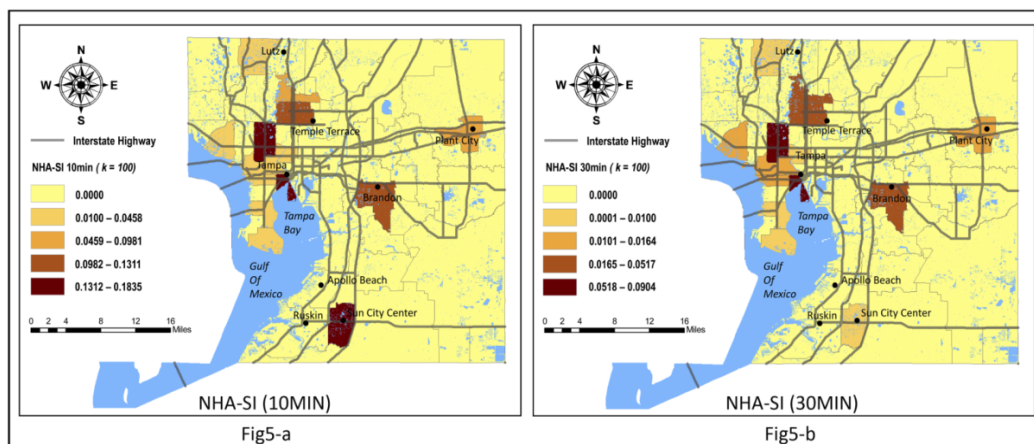


Figure 5. Spatial pattern by the NHA-SI, 10 (5-a) and 30 minutes time zone buffer (5-b).

Compared to Figure 5, Figure 6 highlights the spatial heterogeneity of the NHA-DI. First, the highest values are observed in Tampa (West and South, in particular) and Temple Terrace, while most rural areas obtain much lower values. The high values of NHA-DI indicate the satisfaction for the demand-side. The population residing in urban areas with high NHA-DI values benefit from accessibility to local hospitals with large capacities. Second, NHA-DI is highly dependent on the threshold. As the threshold increases from 10 (Figure 6-a) to 30 minutes (Figure 6-b), more spatial units obtain higher NHA-DI values. Hospitals further away from the population centroid will become accessible when the threshold increases, which improves the overall level of accessibility.

The NHA-DP evaluates the interaction between both dimensions of accessibility and

availability. Figure 7 shows that ZIP code areas are categorized into groups based on NHA-DP. We calculate the Means – the average values for both NHA-SI and NHA-DI, respectively to determine area's positionality among quadrants. The availability level of a ZIP code area is *High Availability* (HAv) if the NHA-SI value is above the Mean and *Low Availability* (LAv) if it's below the Mean. Similarly, the accessibility level of a ZIP code area is classified as *High Accessibility* (HAc) if the NHA-DI is above the Mean and as *Low Accessibility* (LAc) if the index value is below the Mean. According to the results, four quadrants of NHA-DP are identified.

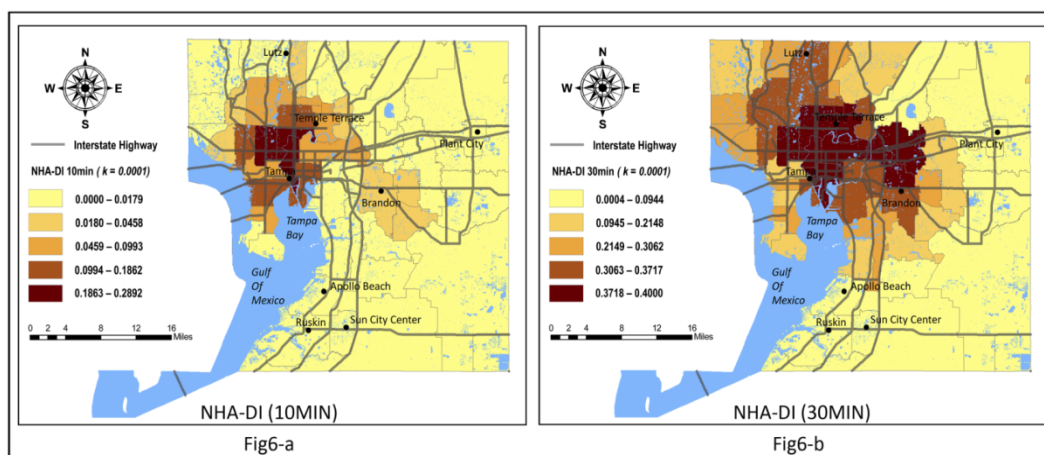


Figure 6. Spatial pattern by the NHA-DI, 10 (6-a) and 30 minutes time zone buffer (6-b).

- 1Q: the west and north areas of Tampa benefits from both HAv & HAc, which is considered as being ideal in terms of balance between health care demand and supply. There are two possible reasons behind this pattern. First, areas identified with HAv & HAc are recognized as being the core of the Tampa metropolitan area. It consists of a fast-growing population area called New Tampa, and the Tampa downtown area, where most hospitals are located. Second, the Tampa downtown area is the center of Hillsborough and the well-developed transportation network ensures great accessibility.
- 2Q: Several pockets with HAc & LAv are captured around Tampa and Temple Terrace. These ZIP code areas contain either none or very few hospitals, but the local population is able to access other facilities in neighboring areas. Since the level of accessibility is high, this case is considered as being acceptable.
- 3Q: The spatial mismatch between health supply and demand is captured in areas identified with LAc & HAv, such as Plant City, Brandon, and Sun City Center. Although the hospitals are considered as being 'available' with satisfactory capacities, the local population somehow do not obtain a high level of accessibility. This could be the result of either a low percentage of population covered by service areas or poor transportation networks. The LAc & HAv areas can potentially evolve into an ideal level, HAc & HAv. For example, when the threshold increases from 10 minute to 30 minute, Brandon is re-classified as a HAc & HAv area. Further research is needed to explore the cause of this spatial mismatch and improve the accessibility level from a

health planning perspective.

- 4Q: Most rural areas in Hillsborough County are identified as having both LAc & LAV. Those areas are considered as health service shortage areas. As the threshold increases, the level of spatial accessibility in some areas improve from LAc & LAV to HAc & LAV, since population become able to access hospitals further away. Still, LAc & LAV areas require extra attentions when allocating health resources in the future.

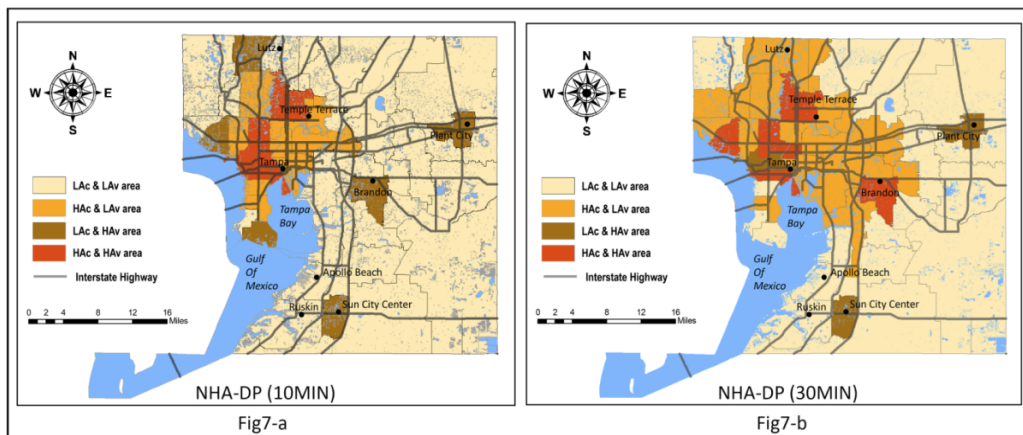


Figure 7. Spatial disparity by the NHA-DP, 10 (7-a) and 30 minutes time zone buffer (7-b).

5. CONCLUDING REMARKS

This paper aims to propose an alternative set of methodology – the NHAIM to measure spatial disparity in the health care delivery system. We demonstrate the application of the NHAIM in a case study of Hillsborough County, Florida. The NHAIM applies network distance rather than Euclidean distance, which improves accuracy in capturing distance decay. The greatest strength of the NHAIM is in measuring and representing both dimensions of accessibility and availability, respectively. Instead of using one single index to represent the overall level of spatial accessibility, the NHAIM evaluates the interaction between both dimensions of accessibility and availability, and examines the potential access to health care facilities located in neighboring spatial units. In the end, spatial units are categorized in four groups. Areas with HAc & HAv or HAc & LAV are considered as being acceptable, while areas with LAc & HAv and LAc & LAV need further investigation and improvement. The results are straightforward for health professionals and policy makers to interpret. Since applying network distances and generating population centroids can be easily achieved in GIS, the application of the NHAIM should not be intimidating for most professionals.

This research has several limitations that need to be further explored in the future. First, we only applied hospital data as a general estimate of health care resources for our analysis. The NHAIM is supposed to be applicable for different levels of health services in theory. Since the major focus of this paper is methodology, we didn't demonstrate how NHAIM can also be applied to other levels of health care such as primary care services.

We would like to expand the application of NHAIM to other levels of health care in future studies. Second, there are smaller spatial units than ZIP code areas that can be applied in the future research. Using smaller spatial units can reduce aggregation errors when applying accessibility measures. Third, we didn't include aspatial factors in this study. People with low socioeconomic status might still have no desirable access to health care despite that they are residing in areas identified with high levels of spatial accessibility. Thus, the results of the NHAIM can be complemented by qualitative analysis. Fourth, further improvement of the NHAIM can be made by applying different thresholds for urban and rural areas, as well as taking into account of multiple transportation modes. For example, network travel distances might be smaller in urban areas when the travel time is fixed considering traffic congestion.

In summary, this paper demonstrates the application of the proposed method – the NHAIM by measuring spatial accessibility to hospitals in Hillsborough County, Florida. Some areas are identified as having a spatial mismatch between health care demand and supply, or simply being short of supply. The results provide a direct and straightforward reference for future health planning in the study area.

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