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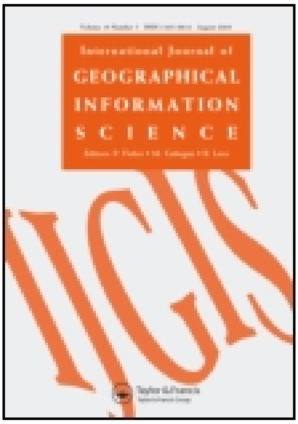

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A three-step floating catchment area method for analyzing spatial access to health services

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A three-step floating catchment area method for analyzing spatial access to health services

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Gravity-based spatial access models have been widely used to estimate spatial access to healthcare services in an attempt to capture the interaction of various factors. However, these models are inadequate in informing health resource allocation work due to their inappropriate assumption of healthcare demand. For the purpose of effective healthcare resource planning, this article proposes a three-step floating catchment area (3SFCA) method to minimize the healthcare-demand overestimation problem. Specifically, a spatial impedance-based competition scheme is incorporated into the enhanced two-step floating catchment area (E2SFCA) method to account for a reasonable model of healthcare supply and demand. A case study of spatial access to primary care physicians along the Austin–San Antonio corridor area in central Texas showed that the proposed method effectively minimizes the overestimation of healthcare demand and reflects a more balanced geographic pattern of spatial access than E2SFCA. In addition, by using an adjusted spatial access index, the 3SFCA method indicates strong potential for identifying health professional shortage areas. The study concludes that 3SFCA is a promising method to provide health professionals and decision makers with useful healthcare accessibility information.

Keywords: spatial access; health professional shortage area; health service; GIS; E2SFCA; Gravity model

1. Introduction

Promoting fair access to medical services across all population groups is a long-standing priority for health professionals in the United States. Ensuring this goal requires that all sectors of society have equal and adequate access to basic healthcare services (e.g., primary care, health screening facilities), regardless of personal, socio-economic, or geographic factors. This is key to improving public health, reducing health disparities, and minimizing disease risk (Lee 1991, Weissman *et al*. 1991, U.S. General Accounting Office (GAO) 1995, Andrulis 1998). To reasonably allocate medical services, health planners first need to identify social groups and areas that have poor access to services. Spatial characteristics and population demand factors, including access, type, and nature of medical services

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(Aday and Anderson 1974, Meade *et al*. 1988), provide important criteria for identifying medically underserved regions and population groups (Ricketts *et al*. 2007).

Generally, three factors are critical for measuring spatial access to health care: healthcare capacity, population demand, and geographic impedance (Kleinman and Makuc 1983, Wing and Reynolds 1988, GAO 1995, Luo 2004). Healthcare capacity refers to the amount of supply in terms of healthcare services. It can be represented by the number of hospital beds, physicians, or specific facilities. Population demand is the number of people who potentially need the service. Geographic impedance refers to the extent to which the 'distance' between population demand and service location would influence access. Common criteria in defining the spatial distance include terrain complexity, transportation mode, road network, traffic volume, time of incidence, and any other factors that may represent 'frictional surface'. In general, larger healthcare capacity, smaller population demand, and weaker geographic impedance imply higher spatial access to health care.

Numerous methods have been proposed to estimate spatial access to medical services. 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 *et al*. 2010). The regional availability method compares 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 calculates medical supply and demand using a kernel function, is superior to the regional availability measure in estimating spatial access to health care because it considers both the distance decay effect and the cross-boundary healthcare-seeking behaviors (Guagliardo 2004). However, the kernel function is problematic for estimating medical service areas and population density (Yang *et al*. 2006). Gravity-based spatial access models assume 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 are conceptually more complete and more flexible to realize than the above-mentioned two models (Luo and Qi 2009).

The primary purpose of this article is to propose an improved approach which can reveal a more reasonable spatial access and effectively identify healthcare shortage areas. Specifically, it introduces a competition scheme to overcome the overestimation problem of the enhanced two-step floating catchment area (E2SFCA) method, a recent development of the gravity model. Then, this improved method is evaluated by estimating spatial access to primary care physicians (PCPs) and identifying shortage areas in the Austin–San Antonio corridor area of Texas. This article has significant implications for spatial access modeling and healthcare service planning in the United States and internationally.

2. Reviews of gravity models

2.1. The basic gravity model

Gravity models, based on Newton's law of gravitation, have been used to analyze spatial access to health care since the 1980s (Joseph and Bantock 1982). The basic gravity model can be expressed as

$$A_i = \sum_{j=1}^{n} \frac{S_j f\,[\mathrm{Dist}(i,j)]}{\sum_{k=1}^{m} P_k f\,[\mathrm{Dist}(k,j)]} \tag{1}$$

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where A_i is the gravity-based spatial access for location i, S_j is the supply capacity of medical site j, P_k is the population size of location k, and Dist (i,j) is the travel cost from i to j. n and m are the total numbers of supply site and location, respectively. The geographic impedance function, $f(d)$, determines how travel distance influences the accessibility. According to Kwan (1998), the three most common forms of $f(d)$ are the inverse-power function ($f(d) = d^{-\beta}$), the exponential function ($f(d) = \mathrm{e}^{-\beta d}$), and the Gaussian function ($f(d) = \mathrm{e}^{-d^2/\beta}$), where β is the impedance coefficient indicating the extent of distance decay.

The basic gravity model assumes that a population's spatial access to medical services is equal to the sum of impedance-weighted physician-to-population ratios of all nearby medical sites. This model is conceptually more complete than the previous methods, but is not intuitive to interpret (Luo and Qi 2009).

2.2. The floating catchment area methods

An improvement of the basic gravity model is 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 basic 2SFCA model works in two steps. The first step is to generate a driving time zone (or catchment) with a threshold travel time (d_0) for each service site j, searching all population locations within the catchment and computing the physician-to-population ratio, R_j, by

$$R_j = \frac{S_j}{\sum\limits_{k \in \{\mathrm{Dist}(k,j) \le d_0\}} P_k} \tag{2}$$

where P_k is the population of any area unit k within the catchment, S_j is the medical capacity of j, and Dist(k,j) is the travel time between k and j. The second step is to generate a catchment with d_0 as the threshold travel time for each population location i, searching all service sites that fall within the catchment, and sum up the physician-to-population ratios of these service sites as the spatial access index (SPAI) of i:

$$A_i^F = \sum_{j \in \{\mathrm{Dist}(i,j) \le d_0\}} R_j \tag{3}$$

where A_i^F is the SPAI of i, R_j is the physician-to-population ratio of any service site j within the catchment of i, and Dist (i,j) is the travel time between i and j.

The 2SFCA method stems from the basic gravity model but expresses the model in a more intuitive way. It first estimates the demand for each medical site and calculates the physician-to-population ratio according to its medical capacity and local demand. The second step sums up the physician-to-population ratios of nearby medical sites for each population. Both steps are easy to interpret and implement in a Geographic Information System (GIS) environment. The 2SFCA method has been employed to estimate spatial access to healthcare services in a number of studies (Guagliardo 2004, Albert and Butar 2005, Langford and Higgs 2006, Yang *et al*. 2006, Wang 2007, Cervigni *et al*. 2008, Wang *et al*. 2008). However, it is 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).

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The most recent version of 2SFCA (Luo and Qi 2009), or the E2SFCA method, was designed to overcome the limitation of the basic 2SFCA method. E2SFCA also works in two steps. The first step is to generate a 30-minute catchment area for each service site, dividing the catchment into three sub-zones based on 10- and 20-minute intervals and calculating the physician-to-population ratio, R_j, for the medical site according to

$$\begin{aligned} R_j &= \frac{S_j}{\sum\limits_{r=1,2,3} \sum\limits_{k \in D_r} P_k W_r} \\ &= \frac{S_j}{\sum\limits_{k \in D_1} P_k W_1 + \sum\limits_{k \in D_2} P_k W_2 + \sum\limits_{k \in D_3} P_k W_3} \end{aligned} \tag{4}$$

where S_j is the supply of medical site j, P_k is the population of any location k within the rth sub-zone D_r, and W_r is a predefined Gaussian weight for D_r. The second step calculates the SPAI of location i as the sum of weighted physician-to-population ratios of all medical service sites within the catchment of i:

$$\begin{aligned} A_i^F &= \sum_{r=1,2,3} \sum_{j \in D_r} R_j W_r \\ &= \sum_{j \in D_1} R_j W_1 + \sum_{j \in D_2} R_j W_2 + \sum_{j \in D_3} R_j W_3 \end{aligned} \tag{5}$$

where A_i^F is the SPAI of population site i, R_j is the physician-to-population ratio of site j that falls within the catchment of i, and W_r is the Gaussian weight for D_r. In E2SFCA, people's access to a medical site decreases with an increase in travel time. This is an improvement because it considers the distance impedance within the catchment.

Based on the 2SFCA method, McGrail and Humphreys (2009a, 2009c) proposed an integrated approach to characterize spatial access to primary care services in rural areas of Victoria, Australia. Specifically, they used an impedance function to overcome the equal access problem within the catchment and adopted service 'caps' (i.e., number of service sites), instead of traveling time thresholds, to delineate the catchment size for different steps. This integrated approach represents a more reasonable implementation of the basic 2SFCA method.

2.3. The modified gravity model

In a study on spatial access to primary healthcare (PHC) physicians in Nova Scotia, Canada, Schuurman *et al*. (2010) proposed a modified gravity model in which two modifications were made to the basic gravity model. First, they use travel time, instead of travel distance, to represent the travel cost. Second, the distance impedance is captured by a segmented inverse-power function which can be expressed by

$$f(t_{ij}) = \begin{cases} 1, t_{ij} < 10 \\ 10/t_{ij}, 10 < t_{ij} < 120 \\ 0, t_{ij} > 120 \end{cases} \tag{6}$$

where t_{ij} (minutes) is the travel time between service site i and location j. The modified gravity model works in a similar way to the 2SFCA method. The only difference is that the

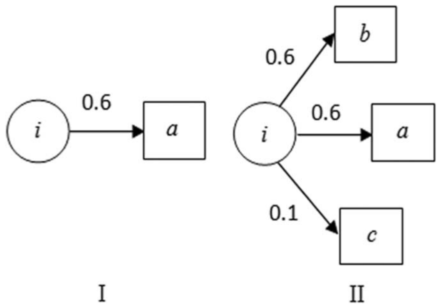

Figure 1. Different scenarios of healthcare demand. Scenario I: only one medical facility (*a*) is accessible to population at site *i*. Scenario II: multiple medical facilities (*a*, *b*, and *c*) are accessible to population at site *i*.

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former uses a continuous, inverse-power impedance function but the latter uses discretized Gaussian weights. Discretized weights have been considered more suitable for representing the distance impedance in healthcare studies because people do not mind the time difference of a few minutes when driving for healthcare services (Luo and Qi 2009).

While the 2SFCA method and the modified gravity model are more complete than previous models, they have their limitations. First, it is likely that both methods may overestimate the demand for some service sites. This limitation can be illustrated by the two scenarios shown in Figure 1. Suppose *i* is a population location and *a*, *b*, and *c* are medical sites. The numbers above the arrow represent the distance impedances (i.e., W_r in 2SFCA or $f(t_{ij})$ in the modified gravity model) between *i* and service sites. In scenario I, there is only one medical site (i.e., site *a*) near *i*. In scenario II, three medical sites (i.e., *a*, *b*, and *c*) are available for *i*. According to 2SFCA and the modified gravity model, the demand of *i* on *a* equals 0.6 times the population of *i* (i.e., P_i). This demand amount is constant for both the scenarios. This is false, however, because people's demand on one service site can get lower when other sites are available at the same time. In other words, the demand of *i* on *a* is overestimated in scenario II. The overestimation effect becomes greater when there are more service sites around *i* (e.g., in urban areas where medical sites are densely concentrated). Overestimating demand will lead to unreliable results of spatial access to health service.

The second limitation of both the 2SFCA method and the modified gravity model stems from the impedance coefficient. Researchers have used arbitrarily determined impedance coefficients in previous studies but seldom assessed the influence of this coefficient. Wan *et al*. (2012) proposed a relative spatial access presentation approach to overcome the uncertainty problem of the E2SFCA method. Specifically, they used a spatial access ratio (SPAR), instead of the SPAI calculated in Equation (5), to present the result of the E2SFCA method. The SPAR of a census tract was calculated as the ratio between that census tract's SPAI and the mean SPAI of all census tracts. Their study shows that, although the results of SPAI varied greatly with the change of the impedance, the SPAR remains stable to the change of the impedance.

3. Development of a three-step floating catchment area method

To minimize the demand overestimation problem of gravity-based spatial access models mentioned above, we proposed a three-step floating catchment area (3SFCA) method in this study. The model is based on a more reasonable assumption of healthcare demand

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for medical services. Conceptually, it assumes that a population's healthcare demand for a medical site is influenced by the availability of other nearby medical sites. Practically, it assigns a travel-time-based competition weight for each pair of population-medical sites in addition to the methodology outlined in E2SFCA. This weight is then used in the calculation of the demand of services sites, thereby minimizing the overestimation. The method is implemented in three steps:

Step 1: Determine the catchment of a population location i based on a 60-minute driving zone. Then, divide the catchment into four sub-zones with the breaks at 10, 20, and 30 minutes. Search all service sites within the catchment, assign a Gaussian weight to each service site based on the sub-zone in which the site lies (e.g., if a service site is located within the third sub-zone, the Gaussian weight (i.e., W_3) of the sub-zone is assigned to the service site), and calculate a selection weight between each service site and i by

$$G_{ij} = \frac{T_{ij}}{\sum\limits_{k \in \{\mathrm{Dist}(i,k) < d_0\}} T_{ik}} \tag{7}$$

where G_{ij} is the selection weight between location i and service site 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 60 minutes in this study). T_{ij} and T_{ik} are the assigned Gaussian weights for j and k, respectively. The computation of the Gaussian weights will be discussed in the next section.

Step 2: Determine the 60-minute catchment area of each service site j and divide the catchment into four sub-zones by using the same procedure of step 1. Search all locations within the catchment and compute the physician-to-population ratio (R) of j by

$$\begin{aligned} R_j &= \frac{S_j}{\sum\limits_{r=1,2,3,4} \sum\limits_{k \in D_r} G_{kj} P_k W_r} \\ &= \frac{S_j}{\sum\limits_{k \in D_1} G_{kj} P_k W_1 + \sum\limits_{k \in D_2} G_{kj} P_k W_2 + \sum\limits_{k \in D_3} G_{kj} P_k W_3 + \sum\limits_{k \in D_4} G_{kj} P_k W_4} \end{aligned} \tag{8}$$

where S_j is the medical capacity of j, W_r is the impedance of the rth sub-zone D_r, G_{kj} is the selection weight between j and population site k, and P_k is the population size of k.

Step 3: Compute the spatial access of population site i by

$$\begin{aligned} A_i^F &= \sum_{r=1,2,3,4} \sum_{j \in D_r} G_{ij} R_j W_r \\ &= \sum_{j \in D_1} G_{ij} R_j W_1 + \sum_{j \in D_2} G_{ij} R_j W_2 + \sum_{j \in D_3} G_{ij} R_j W_3 + \sum_{j \in D_4} G_{ij} R_j W_4 \end{aligned} \tag{9}$$

where R_j is the physician-to-population ratio of j within the catchment, G_{ij} is the selection weight between i and j, and W_r is the Gaussian weight of the rth sub-zone D_r.

Thirty minutes has been suggested an appropriate catchment size for analyzing spatial access to health care (Lee 1991, Luo and Wang 2003). This study extends the catchment size to 60 minutes so that isolated rural regions can be included in the computation (McGrail *et al*. 2009b, Wan *et al*. 2012). The fourth sub-zone (30–60 minutes) represents the extended region.

The 3SFCA assumes that a local population's demand at a nearby service site is affected by the population's travel cost to that site as well as its travel costs to adjacent service sites. In reality, this is a logical assumption because people's demand for a medical site will decrease when adjacent sites are also available. The selection weight, G_{ij}, reflects this change. G_{ij} equals 1 when only one medical site is available for a population site but decreases with increasing number of available alternatives. The multiplication of G_{ij}, P_i, and W_{ij} represents the adjusted population demand of location i on medical site j. For example, for the two scenarios in Figure 1, the 3SFCA will estimate the demand of i on a to $G_{ia} \times W_{ia} \times P_i = (0.6/0.6) \times 0.6 \times P_i = 0.6P_i$ for scenario I but will adjust the demand to $G_{ia} \times W_{ia} \times P_i = (0.6/(0.6 + 0.6 + 0.1)) \times 0.6 \times P_i = 0.28P_i$ for scenario II.

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4. Evaluation procedures of 3SFCA

4.1. Case study area and data

The study evaluated the 3SFCA method by analyzing spatial access to PCPs in the Austin–San Antonio corridor in central Texas (Figure 2). The corridor area contains nine counties along the Interstate 35 freeway. The area is composed of both metropolitan areas (e.g., Austin and San Antonio) with highly concentrated PCP sites and rural areas (e.g., Wilson and Caldwell counties) where PCP sites are few. The total population of the corridor area in 2000 was 2,842,146. To account for the 'edge effect', a 60-minute buffer zone was identified for the borders of the study area. Both the buffer zone and the corridor area were incorporated in the computation, but only the results of the corridor area are presented.

Primary care is an important medical resource because it is a patient's point of contact with the healthcare system (Gualiardo 2004). Access to PCPs has proved critical for disease prevention and reducing medical costs (Lee 1995, Luo 2004, Wang *et al*. 2008). Ensuring adequate access to primary care for all population groups is an ongoing goal for US health departments.

The PCP data of Texas in 2000 were obtained from the Center for Health Statistics, Texas Department of State Health Services. The PCPs include family physicians, general practice physicians, general internists, pediatrics, and obstetrician-gynecologists (Cooper 1994). PCP data include the name, specialization, practicing and mailing addresses, and practicing facility name of each PCP. The data were address-matched to geographic points according to the practicing addresses. If the practicing address is a PO Box or missing, the mailing address was used instead. The address matching was conducted in ArcGIS 9.3 with the Census 2000 street map as the reference file. A total of 2042 out of the 2094 PCPs were successfully geocoded into 855 PCP sites. The average number of physicians per PCP site is 2.4.

Population data at the census tract and census block levels were derived from the Texas Census 2000 Summary File 1 (US Bureau of the Census 2001a). The geographic boundaries of census tracts and census blocks were obtained from the Census 2000 Topologically Integrated Geographic Encoding and Referencing (TIGER)/Line dataset (US Bureau of the Census 2001b).

4.2. Evaluation procedure

The entire evaluation procedure was composed of three steps. First, the sensitivity of SPAR as compared to SPAI was assessed for the 3SFCA method. Second, spatial access results calculated by 3SFCA and E2SFCA were compared. The third step compared the

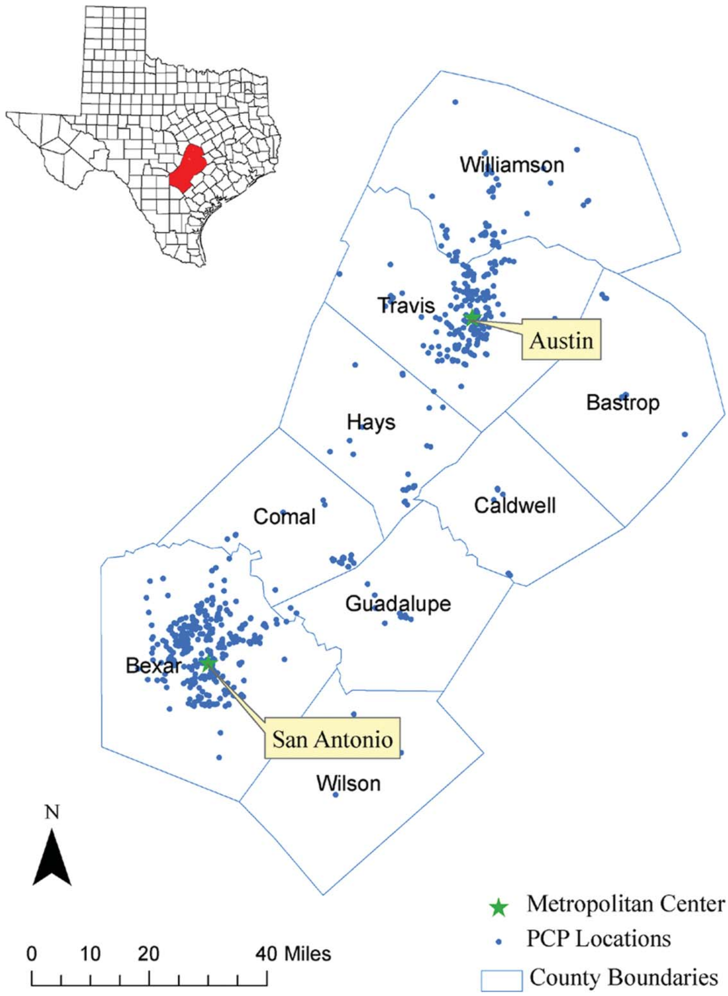

Figure 2. Study area and PCP locations. The study area is composed of the nine counties of the Austin–San Antonio corridor in central Texas.

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geographic patterns of the spatial access results and the detected shortage areas derived by the two methods. The specific implementations of the two methods and the comparison procedure are described as follows.

For each census tract, a population-weighted centroid was calculated based on the population distributions of its census blocks (Hwang and Rollow 2000). This weighted centroid was then used to represent the location of demand population for the census tract. Travel time was used to represent the travel cost because it has been proved a better indicator than other measures such as straight-line distance or network distance (Wang and Minor 2002). Travel time between census tract centroids and PCP sites were computed using the Origin–Destination Cost Matrix function of ArcGIS 9.3 (Environmental Systems Research Institute 2008) in this process. Using a road network and a set of origin and destination points as inputs, this function creates a matrix showing the travel time between all origin and destination pairs within a travel-time threshold. The computation considers the speed limit of the road network as well as some general driving conventions, such as

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one-way streets. The road network and the corresponding speed limit information were derived from the US 2000 street map.

4.2.1. *Sensitivity assessment of SPAR and SPAI*

Since the 3SFCA method has incorporated a competition scheme, it may not be considered a 'full' gravity model. Therefore, it is necessary to conduct a sensitivity assessment to compare the stability of SPAI and SPAR in presenting the results of 3SFCA. The Gaussian function was used to calculate the distance impedance coefficient because it reveals a better 'distance decay' effect than other types of weight functions (Wang 2007). The mean travel time for each sub-zone (5, 15, 25, and 45 minutes for the four sub-zones, respectively) was used as d in the computation of Gaussian weights. Seven impedance coefficients, which range from 440 to 1040 with an increment of 100, were used to evaluate the stabilities of SPAI and SPAR. The minimum value was set to 440 so that the Gaussian weight for the fourth zone is always greater than 0.01, a critical value for the Gaussian function approaching 0 (Kwan 1998). The maximum value was set to 1040 because the curve is relatively 'flat' at this point (Wan *et al*. 2012). The impedance coefficients and the corresponding Gaussian weights are listed in Table 1.

4.2.2. *Quantitative comparison between 3SFCA and E2SFCA*

As indicated in Section 2, the overestimation of demand for health care by E2SFCA may be more evident in areas where medical sites are densely distributed. Since the density of PCP sites is higher in urban areas than in non-urban areas, the analysis was implemented for urban and non-urban census tracts, respectively. The urban statuses of census tracts were assigned by the 2000 Rural Urban Commuting Area (RUCA) scheme (Hart 2006) which utilizes the standard Bureau of Census Urbanized Area and Urban Cluster definitions in conjunction with work commuting data to characterize the urban or rural status of census tracts. According to the RUCA definition, there were 536 (93.5%) urban and 37 (6.5%) non-urban census tracts in the corridor area. For each of the rural/urban setting, we compared the quantitative differences of spatial access results between 3SFCA and E2SFCA.

4.2.3. *Identifying shortage areas*

SPAR has been suggested inappropriate for identifying PCP shortage areas because it does not quantitatively reveal a supply-to-demand ratio of PCP for an area unit (Wan *et al*. 2012).

Table 1. Distance impedance coefficients and the corresponding Gaussian weights for sub-zones.

Distance impedance coefficient (β)	Sub-zone 1	Sub-zone 2	Sub-zone 3	Sub-zone 4
440	0.945	0.600	0.242	0.010
540	0.955	0.659	0.314	0.024
640	0.962	0.704	0.377	0.042
740	0.967	0.738	0.430	0.065
840	0.971	0.765	0.475	0.090
940	0.974	0.787	0.514	0.116
1040	0.976	0.805	0.548	0.143

However, since SPAR reflects a type of stable and relative comparison of different population locations, it has the potential to identify shortage areas. In this study, we designed an extension of SPAR for the purpose of detecting PCP shortage areas. Specifically, the adjusted spatial access (ASPA) of a census tract i within the study area is calculated as

$$\mathrm{ASPA}_i = \frac{\mathrm{sum}(S) \times \dfrac{\mathrm{SPAR}_i \times P_i}{\sum \mathrm{SPAR}_k \times P_k}}{P_i} = \frac{\mathrm{sum}(S) \times \mathrm{SPAR}_i}{\sum \mathrm{SPAR}_k \times P_k} \tag{10}$$

where sum(S) represents the amount of medical supply for the entire area (i.e., the total number of PCPs of the corridor area in this study), SPAR_i is the spatial access ratio of i, and P_i is the population size of i.

In Equation (10), $\mathrm{sum}(S) \times \left(\mathrm{SPAR}_i \times P_i / \sum \mathrm{SPAR}_k \times P_k\right)$ denotes the medical supply for census tract i based on the supplier competition. ASPA, therefore, reflects the real supply-to-demand ratio for i. Consequently, given a threshold value of supply-to-demand ratio, the shortage areas can be identified as those whose ASPA values are below the threshold.

5. Results

5.1. Results of the sensitivity assessment

Table 2 shows the mean value and normalized standard deviations of SPAIs and SPARs for the seven impedance coefficients. As revealed in Table 2, the mean value of SPAI remained almost unchanged (i.e., 0.000737 vs. 0.000738) between the first two impedance coefficients but rapidly increased thereafter, reaching 0.00439 at the last impedance coefficient. This indicates that SPAIs calculated by the 3SFCA method are very unstable to the change of the impedance coefficient. However, as expected, the mean values of SPAR are always equal to one. On the other hand, the normalized standard deviations of both SPAI and SPAR decreased with the increase of the impedance coefficient. This suggests that increased distance impedance leads to a less extent of variance of the spatial access, thus imposing a smoothing effect on the results.

The geographic patterns of SPAI and SPAR for different extents of distance impedance are shown in Figure 3. As shown in Figure 3a, the geographic pattern of SPAI changed

Table 2. Means and normalized standard deviations of SPAI and SPAR calculated by the 3SFCA method with different impedance coefficients.

	Mean		Normalized standard deviation	
Distance impedance coefficient (β)	SPAI	SPAR	SPAI	SPAR
440	0.000737	1.000	0.280	0.280
540	0.000738	1.000	0.262	0.262
640	0.001470	1.000	0.256	0.256
740	0.002202	1.000	0.251	0.251
840	0.002934	1.000	0.247	0.247
940	0.003663	1.000	0.243	0.243
1040	0.004390	1.000	0.240	0.240

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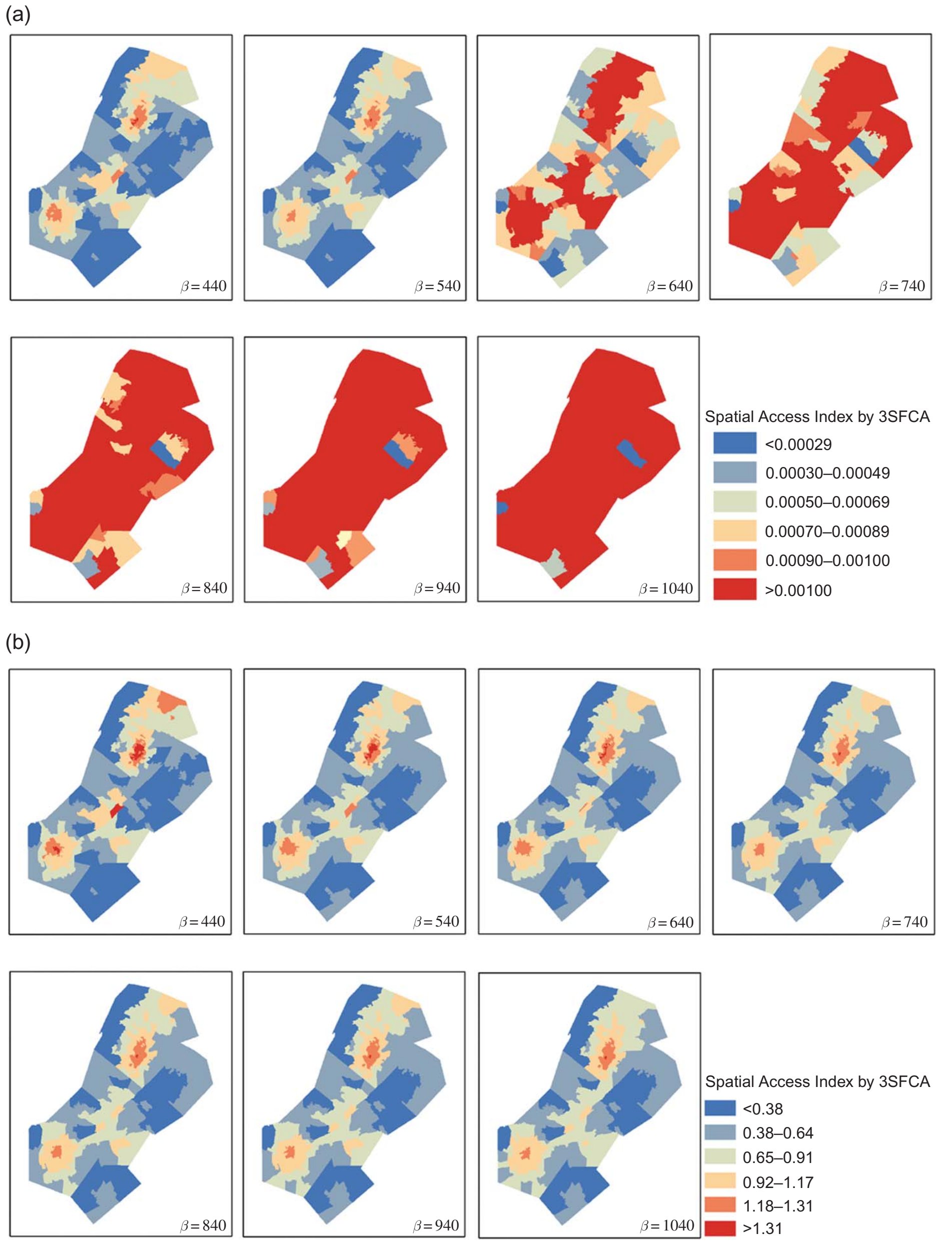

Figure 3. Geographic patterns of SPAI (a) and SPAR (b) calculated by 3SFCA at different extents of distance impedance. Note: β is the distance impedance coefficient of the impedance function.

greatly with the change of the impedance coefficient. For example, less than six census tracts had SPAI values greater than 0.001 when the impedance coefficient was 440 or 540. However, almost all census tracts were characterized with large SPAIs (e.g., SPAI > 0.001) when the impedance coefficient was greater than 740. On the other hand, the geographic pattern of SPAR remained almost unchanged (Figure 3b). This contrasting difference, along with the results mentioned in the last paragraph, indicates that SPAR is better than SPAI in presenting the result of the 3SFCA method. Therefore, SPAR would be adopted in subsequent analyses.

5.2. Performance of 3SFCA validated by 2SFCA

Figure 4 presents the plot of SPARs of the 3SFCA method and the E2SFCA method for urban and non-urban census tracts. Differences between the two methods were mixed. For urban census tracts, 3SFCA SPARs tended to be larger than E2SFCA SPARs for most

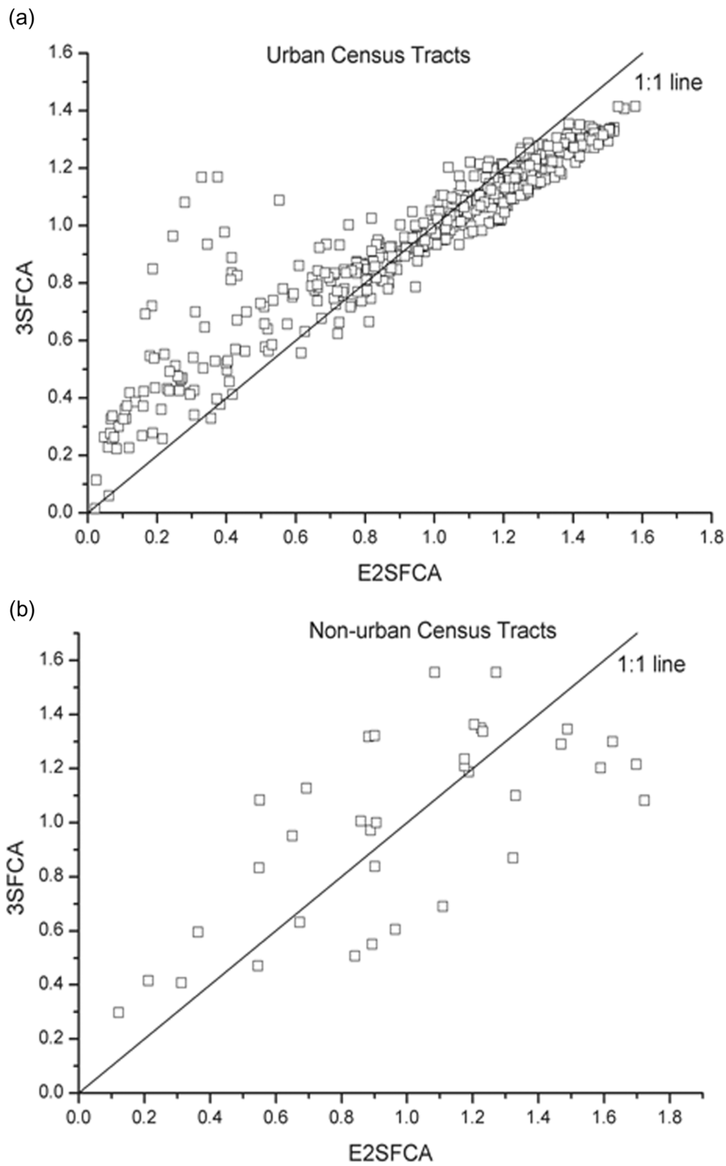

Figure 4. A comparison of spatial access ratios between E2SFCA and 3SFCA: (a) urban census tracts and (b) non-urban census tracts.

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values less than 1.0. For values greater than 1.0 an opposite trend was observed as the 3SFCA SPARs tended to be smaller than E2SFCA SPARs (Figure 4a). For non-urban census tracts, the 3SFCA method predicts higher SPARs than the E2SFCA method for low-access census tracts (SPAR < 0.4) (Figure 4b) but not for median- or high-SPAR census tracts. It appears that 3SFCA had a moderating effect, especially among the urban census tracts where the density of healthcare supply and the demanding population are higher, in determining spatial access.

5.3. Geographic patterns of spatial access to PCPs

The geographic patterns of SPAR computed by the 3SFCA and E2SFCA methods are shown in Figure 5. For the purpose of comparison, we categorized census tracts into the same intervals (i.e., 0–0.38, 0.39–0.64, 0.65–0.91, 0.92–1.17 and >1.17) for both methods.

As shown in Figure 5, 3SFCA and E2SFCA derived similar geographic patterns of SPAR, showing the major metropolitan areas have high access ratios (>1.17) while rural areas have low access ratios (<0.38). However, the 3SFCA method generated more medium SPARs than E2SFCA. Specifically, the peripherals of metropolitan areas were characterized with medium SPARs by 3SFCA but very low SPARs by E2SFCA. The new method modeled a reasonable surface of spatial access because it has a smooth transition from very high access metropolitan areas to very low access rural areas. On the other hand, the E2SFCA method identified a large proportion of the Austin–San Antonio corridor as very low access area, making the two major metropolitan areas 'isolated' from the surrounding rural areas.

We used 1:3500, the national threshold value for designating health professional shortage areas (HPSAs), to identify PCP shortage areas (Ricketts *et al*. 2007). As shown in Figure 5a, E2SFCA detected 21 census tracts as PCP shortage areas. Some of these census tracts were located in small town areas near the Austin metropolitan center. This may be false because these areas encompass a reasonable supply of PCPs and are close to nearby

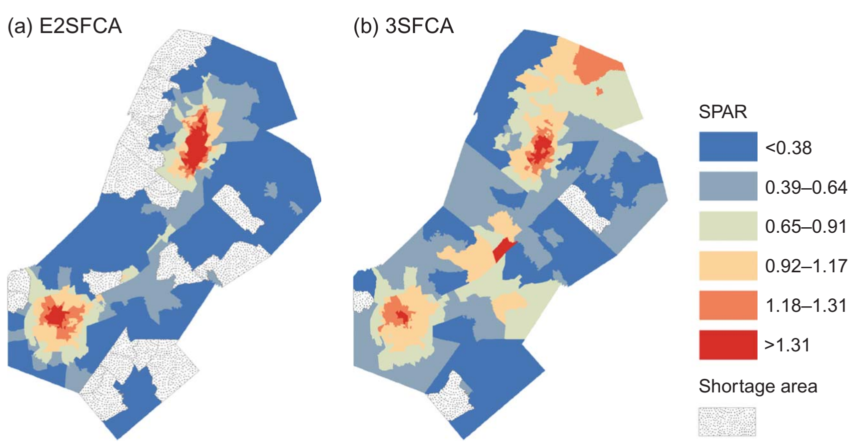

Figure 5. Geographic patterns of spatial access ratio determined by the E2SFCA method (a) and the 3SFCA method (b).

Note: The shortage areas were determined as areas whose adjusted spatial access is smaller than 1/3500.

PCP sites. In contrast, 3SFCA only detected three PCP shortage census tracts which either were far away from the metropolitan centers or had zero PCP sites within (Figure 5b). Compared to E2SFCA, 3SFCA suggested a more rational distribution of PCP shortage areas.

6. Discussion and conclusion

This article proposes a 3SFCA method to overcome the demand overestimating problem of previous gravity-based spatial access models. As indicated by the case study in the Austin–San Antonio corridor area of central Texas, the 3SFCA method can effectively minimize the overestimation problem. In addition, it presents a more reasonable geographic pattern of spatial access to primary care than the E2SFCA method. Study findings document the potential of the 3SFCA method to identify healthcare shortage areas.

The major advantage of the 3SFCA method over previous models lies in its more reasonable assumption of competition of medical sites. Using a travel-time-based competition scheme, the 3SFCA method reveals a lower demand for medical sites, thus minimizing the overestimation problem. The change of the demand also leads to a more smoothed geographic pattern of spatial access to medical services and derives more reasonable healthcare shortage areas.

The moderating effect of 3SFCA may result from its service competition scheme. For example, since the selection weight 'allocates' a smaller portion of services for metropolitan areas where PCPs are densely distributed, more service capacity will be 'assigned' to peripheral and isolated areas. Therefore, the reallocated service supply increased the spatial access for non-metropolitan areas. In other words, with service competition, the waiting lists of metropolitan PCPs are actually shorter than estimated by E2SFCA, thus allowing people from peripheral areas to visit these PCPs more conveniently. This also explains why the spatial access of some non-urban areas (e.g., the northwestern part of the corridor area in Figure 5) 'jumped' from low values (blue color) with E2SFCA to high values (orange color) with 3SFCA.

Two census tracts (i.e., the two with red color in Figure 5b) in the middle of the corridor area were characterized with very high spatial access by 3SFCA but with very low access by E2SFCA. This difference may be explained by their geographic locations. These two tracts lie approximately at the middle of the Interstate 35 freeway which connects the Austin and the San Antonio metropolitan areas. This location advantage gives them access to almost all medical sites of the corridor area. As a result, the 'service reallocation' of 3SFCA leads to much higher access for these two census tracts than does E2SFCA. In addition, the Central Texas Medical Center, which hosts 17 PCPs (compared to 2.4, the average number of PCPs per site of the entire study area), is located within one of the two census tracts. This may also lead to elevated spatial access within this area.

Though the 3SFCA method has 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. This study used 60-minute driving time to define the catchments of both locations of population in demand and PCP sites. However, as claimed by previous studies (Yang *et al*. 2006, McGrail *et al*. 2009a, 2009c), the catchment size could vary according to neighborhood characteristics and the specific type of medical service in demand. For example, larger catchment sizes should be used for rural than urban areas and for cancer treatment services rather than

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for screening services. A possible way to determine the optimal size is to incrementally increase the catchment until the population demand or the service capacity reaches a predefined threshold (Tiwari and Rushton 2005, McGrail *et al*. 2009c). In addition, the catchment sizes do not have to be constant at different steps. For urban physicians, the catchment size of the second step of 3SFCA should be larger because they may serve a large area including nearby small towns. For access computation of urban populations (step 3 of 3SFCA), however, the catchment size could be smaller because urban residents are less likely to seek health care in suburban or rural areas (Luo and Qi 2009, McGrail *et al*. 2009c).

A second question is which sub-zone intervals can best reflect PCP-seeking behaviors. This study divides the catchment into four sub-zones with 10, 20, and 30 minutes as the breaks, with the last sub-zone (30–60 minutes) used to include more rural census tracts in the analysis. However, the actual intervals may vary according to the characteristics of a specific study area (e.g., urban vs. rural) and the spatial resolution (e.g., county level vs. census tract level; grid level vs. vector level) needed. Therefore, the Gaussian weights and the second lines of Equations (4), (5), and (8) could vary with these characteristics.

In the broader field of spatial accessibility research, gravity-based models have been considered a major branch of spatial interaction models which simulate the interactions or 'flows' among origin locations (or regions) and destination locations (or regions) as a function of location characteristics and friction of distance (Fortheringham and O'Kelly 1989). The 3SFCA method represents a special case of 'spatial interaction' because it models the mutual interactions of medical supply and demand. The difference between 3SFCA and other spatial interaction methods is that it uses a simple, travel-time-based weight to describe the competition effect. Obviously, this scheme cannot reflect the complex interactions between populations and medical service sites. People's knowledge of local PCP sites, health insurance status, and the quality of service provision can also impact people's choice of visiting physicians. We did not intend to incorporate the complex interactions of these factors in this study because data about how people balance these factors when visiting physicians are difficult to obtain. However, integrating existing competition methods (e.g., those used in job accessibility studies) and patient survey and hospital admission data would greatly enhance the applicability of the 3SFCA method.

As this is a spatial access study, we did not consider socio-demographic factors such as poverty rate, infant mortality rate, and percentage of older people, which are the important variables for government designation of HPSAs and medically underserved populations. Therefore, it is not meaningful or relevant to compare our results with government-designated HPSAs in Texas. However, 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, Luo and Qi 2009). This is a logical extension of the work described in this article and will be an important contribution to improved healthcare access in central Texas.

In conclusion, this article proposes an important improvement to gravity-based spatial access models. This proposed method revealed better results of spatial access than the most recent gravity model and showed great potential in health resource allocation works.

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