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Spatial accessibility in suboptimally configured health care systems: A modified two-step floating catchment area (M2SFCA) metric

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ABSTRACT

The floating catchment area (FCA) family of metrics employ principles from gravity-based models to incorporate supply, demand, and distance in their characterization of the spatial accessibility of health care resources. Unlike traditional gravity models, the FCA metrics provide an output in highly interpretable container-like units (e.g., physicians per person). This work explores two significant issues related to FCA metrics. First, the Three Step Floating Catchment Area is critically examined. Next, the research shows that *all* FCA metrics contain an underlying assumption that supply locations are optimally configured to meet the needs of the population within the system. Because truly optimal configurations are highly unlikely in real-world health care systems, a modified two-step floating catchment area (M2SFCA) metric is offered to address this issue. The M2SFCA is built upon previous FCA metrics, but allows for spatial accessibility to be discounted as a result of the suboptimal configuration of health care facilities within the system. The utility of the new metric is demonstrated through simulated data examples and a case study exploring acute care hospitals in Michigan.

1. Introduction

Characterizing the opportunities available to populations or groups of people has been a longstanding goal in health services and health geographic research. Populations are distributed nearly continuously throughout a region, yet are served by a facility or set of facilities located at discrete point locations (Joseph and Phillips, 1984). Inequalities in the availability and accessibility of resources are an inevitable outcome of this configuration. Regional availability measures attempt to characterize these differences, allowing researchers to explore relationships between population-based health outcomes or behaviors and the spatial organization of the health care delivery system.

Regional availability can be defined as the number of opportunities available to a population as moderated by distance. In this, the supply of resources and the potential demand (availability) and the separation between the population and supply (accessibility) must both be considered for a comprehensive characterization. Previous research has identified availability and accessibility as the spatial components of a population's overall access (Khan, 1992). The combination or fusion of accessibility and availability has more recently been referred to as “spatial accessibility” (Guagliardo, 2004).

The floating catchment area (FCA) family of metrics are based on gravity models, incorporating the interaction among supply, potential demand, and travel cost in their characterization of spatial accessibility. These metrics offer a substantial theoretical advantage over traditional container-based regional availability measures. Specifically, the shortcomings of container-based measures (e.g., travel across unit boundaries is not considered) are overcome by allowing the containers to “float” as travel buffers or catchments based on distance or travel time from the facility and population locations. Unlike general gravity models, the FCA metrics provide an output in a highly interpretable supply to population ratio. The most popular of the FCA metrics are the two-step floating catchment area (2SFCA, Radke and Mu, 2000; Luo and Wang, 2003) and the Enhanced 2SFCA (E2SFCA, Luo and Qi, 2009). The E2SFCA represents a significant advance in spatial accessibility characterization and has been implemented in a number of studies (e.g., see McGrail and Humphreys, 2009a; Dai, 2010; Wan et al., 2011).

Recently, Wan et al. (2012) and Bell et al. (2013) proposed modified versions of the E2SFCA, both called the three-step floating catchment area (3SFCA). Although these two metrics share a name, the content of the “3rd” step in each is dissimilar. In Bell et al. (2013), the 3rd step of the 3SFCA is an aggregation of E2SFCA values into larger population units. No modifications are made to

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the underlying calculation of E2SFCA values for the smaller population units; therefore, this metric remains solidly grounded in the two-step framework. The 3SFCA provided by Wan et al. (2012) varies more dramatically from its predecessors. The 3rd step incorporates the potential for competition among facilities when more than a single facility falls within the catchment area of a population location. In this, the 3SFCA assumes that the potential population demand at a single facility will be discounted by the presence of other nearby facilities. The integration of competition into an FCA metric appears reasonable on a theoretical level and novel in the applied model; however, this work illustrates that the 3SFCA from Wan et al. (2012) overestimates the role of competition in an applied setting, leading to both over and underestimation of spatial accessibility for population units within the system.[1]

Luo and Wang (2003) and Luo and Qi (2009) point out that FCA metrics represent a special case of a supply to population ratio, integrating distance decay to overcome the limitations of treating regions as simple “containers”. The weighted average of FCA values for the individual population units has been shown to equal the supply to population ratio of the overall study area (Shen, 1998; Luo and Wang, 2003; Wang, 2012). This perceived strength of the FCA metrics also doubles as a major limitation – through this property, the overall study area is considered a single, large “container”. All supply opportunities are assumed available to the population, regardless of the configuration of people and supply locations within the study area. Thus, current FCA metrics carry the inherent assumption that the configuration of supply locations is *optimal* – (1) all supply is fully allocated to the population regardless of how the opportunities are arranged within the larger study area and (2) any reconfiguration of the supply locations will affect spatial accessibility of the individual population units, but will have no effect on the overall spatial accessibility of the study area. This is troubling given that no delivery system is truly optimal and any attempts to reconfigure existing supply locations will not be reflected in the spatial accessibility of the overall system as reported by the current FCA metrics.

As a result of this property, spatial accessibility calculated with current FCA metrics may accurately describe the availability of resources, but does not simultaneously integrate both accessibility and availability. The assumption of an optimal population/provider configuration will necessarily result in an overestimation of spatial accessibility throughout the system. The specific effects of this assumption are difficult to observe in large, complex systems of providers and populations, providing the likely explanation for why this problem has not been addressed in the previous literature.

This work presents the modified two-step floating catchment area (M2SFCA) metric. By accounting for suboptimal configuration of health care locations, the M2SFCA provides two major advances in characterizing spatial accessibility. First, accessibility and availability are integrated simultaneously and coherently into a single metric, allowing for the measured output to better resemble the underlying theory of spatial accessibility. Second, the M2SFCA can be used to describe the overall “efficiency” of spatial accessibility within the health care system. As a result, large-scale health care systems (e.g., states or regions) can be compared quantitatively. Additionally, the M2SFCA output offers the ability to evaluate the overall impacts of local changes in the health care system (e.g., opening, closing, or relocation of facilities) and provides a metric that can be employed in health care planning applications.

The remainder of this paper is divided into five main sections. First, a short background on the evolution of the FCA family of metrics is provided and the limitations in the newly proposed 3SFCA are highlighted. The second section demonstrates the manner in which the current FCA metrics contain the assumption of an optimal population/provider configuration. Next, the M2SFCA is detailed, while also exploring the implications associated with assuming a suboptimal configuration. Fourth, to illustrate the applied differences in outputs among FCA metrics, the outputs of the M2SFCA, 3SFCA, and E2SFCA are compared in case study of the spatial accessibility of hospital beds in Michigan. The final section includes a discussion of the advantages provided by the M2SFCA and suggests directions for future research.

2. Background

Early research exploring the spatial components of population access to health care services often separated accessibility and availability characterization or only considered one or the other. The limitations of non-integrated measures can be highlighted simply by considering the differences in the available opportunities for two populations of equal size – one near a small, local hospital and the other near a major teaching or research hospital. Although the distance between each population and its respective hospital would be similar, the availability of resources would clearly be much different for the populations. As a result, only considering accessibility would inadequately capture the opportunities available to each population.

Another method often employed to characterize regional availability is to employ a container-based, availability metric. To calculate these metrics, the opportunities available within predetermined areal units (the containers) are summed, then divided by the population of the areal unit. Often, existing administrative boundaries (e.g., counties or Zip Codes) are chosen for this task. Container-based metrics are easy to implement and interpret; however, they are limited in their underlying assumption that facilities outside the predefined areal unit are inaccessible and that those within the unit are equally accessible to all people within the areal unit. This limitation is particularly significant for populations residing near the border of the areal unit or when the population units represent large geographic areas. Although both supply and potential demand is incorporated in container-based measures, the actual separation among people and facilities is not considered.

Gravity models allow supply, demand, and distance to be incorporated simultaneously to estimate spatial accessibility (Weibull, 1976). A gravity model takes the general form

$$A_i^G = \sum_{j=1}^{m} \frac{S_j f(d_{i,j})}{D_j} \tag{1}$$

where

$$D_j = \sum_{i=1}^{k} P_i f(d_{i,j}). \tag{2}$$

In the model, A_i^G is the measure of “attraction”, S_j is the supply of services at location j, P_i is the population of i, D_j is the potential demand at location j, m is the set of all hospitals, k is the set of all population units, and $f(d_{i,j})$ is a distance decay function based on the distance between i and j. Unfortunately, the units of the output values (A^G) in gravity models are not intuitively comprehensible (Joseph and Phillips, 1984). Therefore, although gravity models offer a more complete theoretical model of spatial accessibility, their output units limit their general applicability towards health care resources evaluation and planning and/or health care policy concerns.

[1] For the remainder of this paper, any further mention of the 3SFCA refers to Wan et al. (2012).

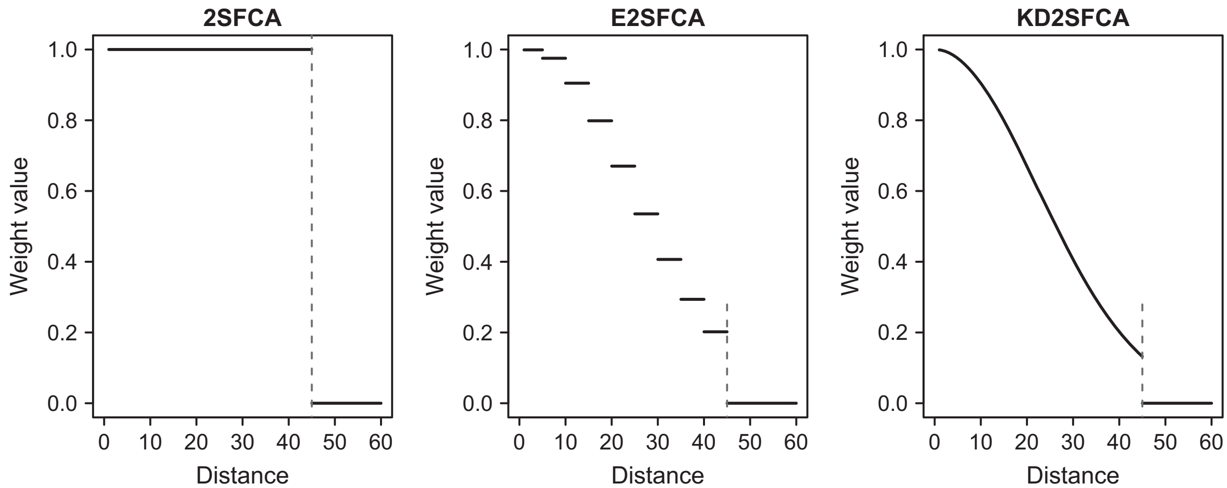

Fig. 1. Examples of accessibility characterization in FCA metrics. In each example, d is equal to 45. For the 2SFCA, all values less than d have a weight of 1 and all greater than d are 0. In the E2SFCA, the tiered weight values are based on 5 min travel rings and the Gaussian decay function. In the KD2SFCA, the weights are based on the Gaussian function. For both the E2SFCA and KD2SFCA, the Gaussian function takes the form, $f(d) = e^{d^2/1000}$.

The FCA family of spatial accessibility metrics are built upon theoretical underpinnings of gravity models, but provide output units expressed in container-like values (i.e., opportunities per person). As a result, these metrics overcome the difficulty in interpreting the gravity-based output units; the ease of interpretation offered by container-based metrics is wedded to the more advanced underlying theory of spatial accessibility in the gravity model.

2.1. 2SFCA

The initial FCA metric, the 2SFCA, allows the catchment (or container) area for both population and facility locations to float based on the location. Network-based travel time or travel distance buffers are generated in a GIS for each population and facility location. These travel buffers or drivesheds are used as the catchments, thereby overcoming the fixed-boundary limitation of container-based measures. The first step in the 2SFCA is to calculate the supply to demand ratio (D) at each facility (j) by dividing the number of opportunities or supply (S) by the sum of the number of people (P) that are inside their respective catchments, as defined by some threshold distance (d):

$$D_j = \frac{S_j}{\sum_{i \in [d_{i,j} < d]} P_i}. \tag{3}$$

In the 2SFCA, the opportunities can be singular in nature, such as a single physician at a particular geographic location, or they can represent collections of opportunities in one place, such as the number of beds in a hospital or the number of physicians practicing at a single clinic. The second step in the 2SFCA is to sum the supply to demand ratio D for all facilities falling within d of each population location (i):

$$A_i = \sum_{j \in [d_{i,j} < d]} D_j. \tag{4}$$

Because A is the sum of each supply to demand ratio falling within the catchment, the output unit of the 2SFCA is opportunities per person.

2.2. E2SFCA and KD2SFCA

In the 2SFCA, all distances less than d are considered to be similarly accessible; any distance greater than d is considered inaccessible. This dichotomous characterization of distance in the 2SFCA was augmented by incorporating distance decay within the catchments in the E2SFCA (Luo and Qi, 2009). In the E2SFCA, rather than identifying a single catchment, distance rings are created, emanating from each facility and population location. To incorporate distance decay, weight values are assigned to each distance ring tier such that the likelihood of travel is diminished as distance increases. The integration of distance decay in the E2SFCA was further advanced in the Kernel Density 2SFCA (KD2SFCA, Dai and Wang, 2011) by assigning weights based on a continuous decay function, an advancement also offered by Langford et al. (2012). In lieu of creating discrete travel rings, the pairwise distance between each population and opportunity location is measured. A weight value is then assigned to each pair using the measured distance and the distance decay function. The most popular distance decay functions are the Gaussian, Inverse power, and Exponential (Kwan, 1998). Fig. 1 illustrates the progression of accessibility characterization in the FCA family of metrics.

After weight values are assigned for each population and facility pairing, the initial step in the E2SFCA and KD2SFCA is to modify Eq. (3) such that

$$D_j = \frac{S_j}{\sum_{i \in [d_{i,j} < d]} P_i W_{i,j}} \tag{5}$$

where $W_{i,j}$ is the weight value corresponding to which distance ring $d_{i,j}$ the population unit falls in or the weight value provided by the distance decay function. The second step in the E2SFCA and KD2SFCA also incorporates the weight values:

$$A_i = \sum_j D_j W_{i,j}. \tag{6}$$

Because the only difference between the E2SFCA and the KD2SFCA is the specific method used to assign weight values, we consider these metrics to be of the same "class". Both metrics are based on the two-step format and integrate distance decay within the catchments. For the remainder of the paper, the term "E2SFCA" will be used to represent this class of metrics.

2.3. 3SFCA

In the 3SFCA metric, Wan et al. (2012) modify the E2SFCA by incorporating the potential for competition among facilities. The authors state (p. 7)

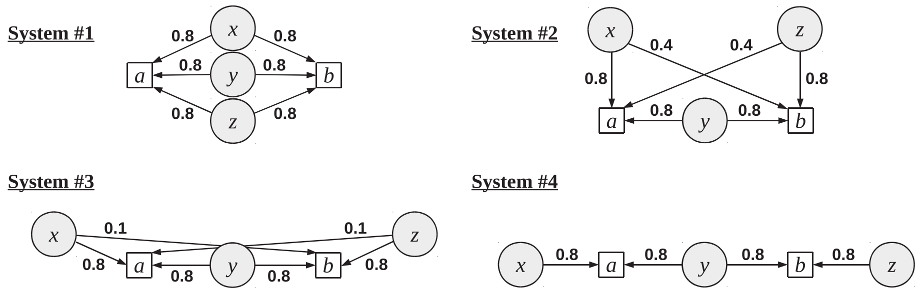

Fig. 2. Example systems with simulated data. In each example system, populations units *x, y, z* have 100 people and hospitals *a, b* have 10 beds. Travel distances are represented by "weight" values and are not to scale.

Table 1
Results from example Systems #1–4. The output units are in beds per person.

System	E2SFCA			3SFCA		
	x	*y*	*z*	*x*	*y*	*a*
1	0.067	0.067	0.067	0.067	0.067	0.067
2	0.06	0.08	0.06	0.063	0.075	0.063
3	0.053	0.094	0.053	0.064	0.071	0.064
4	0.05	0.1	0.05	0.067	0.067	0.067

> *The 3SFCA assumes that a local population demand at a nearby service site is affected by the population travel cost to that site as well as its travel costs to adjacent service sites.*

The authors also suggest that, by failing to include the potential for competition, the 2SFCA and E2SFCA overestimate the potential population demand in cases where multiple facilities are accessible to a population location. To correct for this, the 3SFCA includes an initial step to calculate a selection weight (G) for all population and facility pairings. To determine the G value for a population unit i and facility j pairing, their specific pairwise weight value $W_{i,j}$ is divided by the sum of all the W values for facilities falling within d of population unit i. This can be represented as

$$G_{i,j} = \frac{W_{i,j}}{\sum_{j \in [d_{i,j} < d]} W_j}. \tag{7}$$

Steps two and three of the 3SFCA then incorporate the G values into Eqs. (5) and (6) from the E2SFCA formula:

$$D_j = \frac{S_j}{\sum_{i \in [d_{i,j} < d]} P_i W_{i,j} G_{i,j}} \tag{8}$$

and

$$A_i = \sum_j \ D_j W_{i,j} G_{i,j}. \tag{9}$$

2.3.1. Competition in the 3SFCA

To illustrate the implications associated with the incorporation of the selection weights in the 3SFCA, the output of the metric is examined in four simulated systems of population units and facilities (see Fig. 2). These systems illustrate the mechanisms by which the potential for competition affects spatial accessibility in the 3SFCA. The four systems have simple spatial configurations that include three population units (x, y, z) and two hospitals (a, b). In all of the examples, the population of each unit is 100 people and the number of beds at each hospital is 10. Therefore, the overall population of each system is 300 people having 20 available hospital beds for a system-wide rate of 0.067 beds per person. Some changes among the example systems are the spatial configuration of the population units x and z, which, from System #1 to #4, are moved progressively further away from population unit y at the center of the system. The distances among the population units and hospitals are represented by weight values (W), rather than actual measured distances.

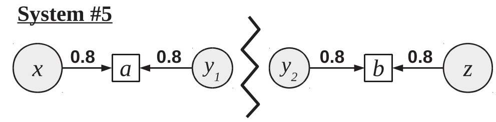

Fig. 3. Example System #5.

The E2SFCA and 3SFCA outputs for the example systems are found in Table 1. An example calculation is provided below (for System #2):

E2SFCA

1. $D_a = \frac{10}{100\times0.8+100\times0.8+100\times0.4} = \frac{10}{200} = 0.05$
   $D_b = \frac{10}{100\times0.4+100\times0.8+100\times0.8} = \frac{10}{200} = 0.05$
2. $A_x = 0.05 \times 0.8 + 0.05 \times 0.4 = 0.06$
   $A_y = 0.05 \times 0.8 + 0.05 \times 0.8 \times 0.08$
   $A_z = 0.05 \times 0.4 + 0.05 \times 0.8 = 0.06$

3SFCA

1. $G_{x,a} = \frac{0.8}{0.8+0.4} = 0.667$
   $G_{x,b} = \frac{0.4}{0.8+0.4} = 0.333$
   $G_{y,a} = \frac{0.8}{0.8+0.8} = 0.5$
   $G_{y,b} = \frac{0.8}{0.8+0.8} = 0.5$
   $G_{z,a} = \frac{0.4}{0.4+0.8} = 0.333$
   $G_{z,b} = \frac{0.8}{0.4+0.8} = 0.667$
2. $D_a = \frac{10}{100\times0.8\times0.667+100\times0.8\times0.5+100\times0.4\times0.333} = \frac{10}{106.67} = 0.094$
   $D_b = \frac{10}{100\times0.4\times0.333+100\times0.8\times0.5+100\times0.8\times0.667} = \frac{10}{106.67} = 0.094$
3. $A_x = 0.094 \times 0.8 \times 0.667 + 0.094 \times 0.4 \times 0.333 = 0.063$
   $A_y = 0.094 \times 0.8 \times 0.5 + 0.094 \times 0.8 \times 0.5 = 0.075$
   $A_z = 0.094 \times 0.4 \times 0.333 + 0.094 \times 0.8 \times 0.667 = 0.063$

Both metrics provide similar results for System #1; each population unit has the exact same level of spatial accessibility. In System #2, as population units x and z are moved away from the center, their spatial accessibility decreases in both metrics. However, when units x and z are moved progressively further from the center in Systems #3 and #4, the spatial accessibility provided by the 3SFCA for these units increases. In the E2SFCA, spatial accessibility for units x and z decreases throughout this progression. Although these results cause concern, the most striking result of the simulated data experiment is that the 3SFCA provides similar values for each population unit in Systems #1 and #4, even though these systems clearly present dissimilar levels of spatial accessibility among the population units.

To further illustrate the output of the 3SFCA, a fifth example system is provided in Fig. 3. This system is a slight modification of System #4 such that population unit y is split evenly into two separate units of 50 people each (y_1 and y_2) with an impassable barrier placed between the leftmost and rightmost population units and hospitals. The population of units *x* and *z* and supply at hospitals *a* and *b* are unchanged in System #5.

Because there is no "competition" in System #5, the E2SFCA and 3SFCA provide the exact same results; the output values are 0.067 beds per person for each population unit. The most important result of this hypothetical scenario is that the 3SFCA produces the exact same values for *x* and *z* in both Systems #4 and #5. However, the spatial configurations of Systems #4 and #5 would clearly provide dissimilar levels of accessibility for all three population units, given the split of *y*'s population and barrier. The main implication of the demand correction provided by the 3SFCA is that, by using the added *G* weight term to allocate potential demand, the metric essentially "splits" population units into separate pieces as if an impassable barrier was placed between them. In this specific example, the *G* term in the 3SFCA mathematically "creates" System #5 when System #4 is being evaluated. As a result, the 3SFCA does not consider all opportunities available to population unit *y* in System #4.

Spatial accessibility measures describe the availability of opportunities as moderated by distance. Here, a hard distinction between realized and potential access is necessary. Realized access is based on actual utilization of services, while potential access is based on the ability or potential to access services (Aday and Andersen, 1974; Joseph and Phillips, 1984). Because the FCA metrics are *not* based on actual use of services, they should only aim to capture the "potential" of the system with respect to the specific arrangement of people and facilities within the system. Given this conceptualization of potential spatial accessibility, the shortcoming of the 3SFCA becomes apparent when considering the results provided by Systems #4. Although population *y* has twice the opportunities available in comparison to units *x* and *z*, the 3SFCA considers their spatial accessibility equivalent. In Systems #2–4, spatial accessibility, as calculated by the 3SFCA, is both underestimated (*y*) and overestimated (*x*,*z*).

The limitations of the 3SFCA can be further observed using another basic test. In this test, the location of a population unit within an example system is moved in a series of steps (see Fig. 4). The initial state of the system is the same as System #4. In a series of steps, the location of population unit *z* is moved toward the center of the system, ending with a weight value of 0.8 in the final step. The weight value between unit *z* and hospital *b* remains unchanged throughout this progression. However, the distance between unit *z* and hospital *a* decreases, thus the weight value increases. The configuration of all other system components is not changed as unit *z* is moved.

Using rudimentary logic, the resulting effects on spatial accessibility are considered for each unit. For unit *x*, spatial accessibility should decrease throughout this progression. This is due to the increased potential demand on hospital *a* as unit *z* is moved nearer to it. The spatial accessibility for unit *z* should increase as it moves near the center of the system – its relationship with hospital *b* does not change, but hospital *a* is more accessible. Finally, the spatial accessibility for unit *y* should decrease throughout the progression. Although the relationships among units *y, z* and hospital *b* are unchanged, as unit *z* moves toward hospital *a*, the availability of hospital *a*'s resources for *y* is diminished due to the increased demand from *z*.

To test these relationships, the E2SFCA and 3SFCA were calculated using steadily increasing weight values ranging from 0 to 0.8 for population unit *z* and hospital *a*, while holding all other relationships constant. Fig. 5 confirms that the E2SFCA provides empirical values matching the expected logic-based outcomes, while the 3SFCA does not. Specifically, spatial accessibility decreases for units *x* and *y* and increases for unit *z* in the E2SFCA. In the 3SFCA, spatial accessibility decreases for unit *x*. Although the values generally increase for unit *z*, there is a small initial decrease. Interestingly, the 3SFCA shows a steady increase for unit *y*. In addition, as Fig. 5 shows, the 3SFCA underestimates spatial accessibility for unit *y*, overestimates it for unit *x*, and both over and underestimates it for unit *z* as it moves nearer to the center of the system.

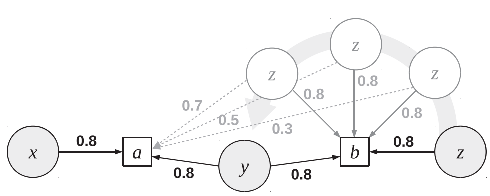

Fig. 4. System #4 with progressive movement of population unit *z*.

3. Optimally configured health care systems and the FCA metrics

As previously mentioned, the weighted average of the FCA values in a system will equal the supply/population rate of the overall system. Multiplying the FCA values of the individual population units by their population and summing those results

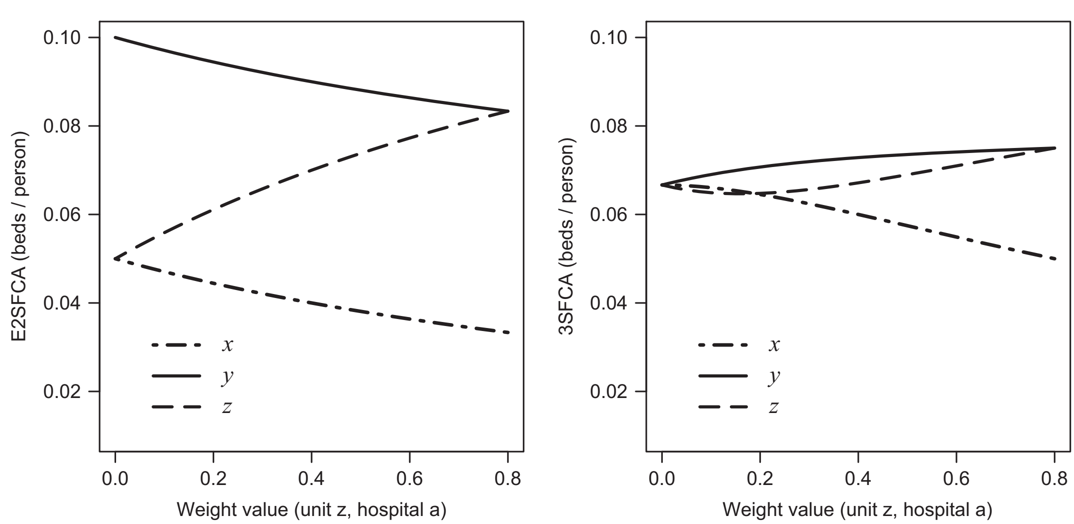

Fig. 5. E2SFCA (left) and 3SFCA (right) values corresponding to Fig. 4.

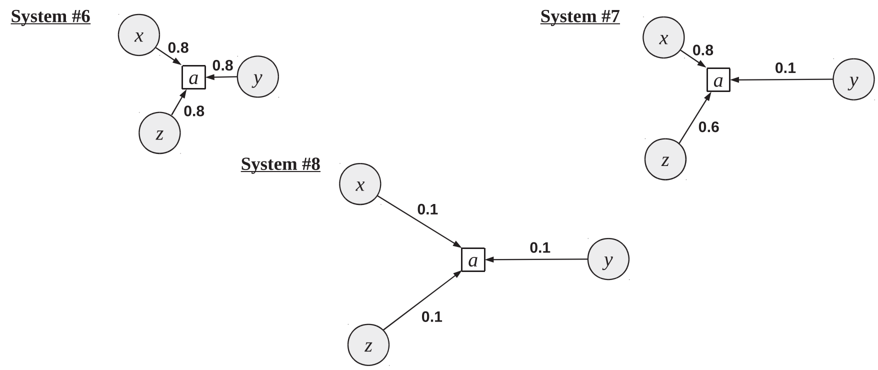

Fig. 6. Additional example systems with simulated data. In all example systems, units *x*, *y*, and *z* each have a population of 100 and hospital *a* has 20 beds. Travel distances are represented by "weight" values and are not to scale.

Table 2
Results from example Systems #6–8. The output units are in beds per person.

System	E2SFCA			3SFCA		
	x	*y*	*z*	*x*	*y*	*z*
6	0.067	0.067	0.067	0.067	0.067	0.067
7	0.107	0.013	0.08	0.107	0.013	0.08
8	0.067	0.067	0.067	0.067	0.067	0.067

Table 3
Results from example Systems #6–8. The output units are in total opportunities, calculated by multiplying the opportunities per person (the output of the FCA metrics) by the population of each unit.

System	E2SFCA				3SFCA			
	x	*y*	*z*	*Total*	*x*	*y*	*z*	*Total*
6	6.67	6.67	6.67	20	6.67	6.67	6.67	20
7	10.67	1.33	8	20	10.67	1.33	8	20
8	6.67	6.67	6.67	20	6.67	6.67	6.67	20

will return the total number of opportunities in the system. In the previous example systems, the overall system comprises 300 people distributed evenly among 3 population units with 20 total opportunities available at 2 facilities (e.g., hospital beds or physicians). The FCA metrics distribute all 20 opportunities among the 300 people as moderated by their particular configuration in relation to the facilities. In the example systems, this can manifest as any combination of 20 opportunities for 300 people (e.g., the results in Table 1).

In the second step of the 2-step methods and third step of the 3-step method, all opportunities are fully allocated to the population units falling within the predetermined distance radius (d), regardless of the actual distance separating populations and providers. Although Eqs. (6) (in the E2SFCA) and (9) (in the 3SFCA) appear to moderate the availability of opportunities with distance by multiplying the supply ratios by their weight values, these steps only function to *balance* the results of the previous steps; they do not discount *availability* due to the *accessibility* of the supply locations.

Although a balanced outcome may seem to be trivial, or even necessary for estimating spatial accessibility in a system of population and providers, it is an important component in the evaluation of the E2SFCA and 3SFCA and the development of the M2SFCA. Through this property of balance, the current FCA metrics consider the overall system as a single container, continuing to be subject to the limitations of container-based measures. Further, the FCA metrics do not account for the suboptimal character of real-world facility configuration. Specifically, because all opportunities are fully allocated, no possible reconfiguration of the opportunities within the system will provide any change in the overall output of the system. Every opportunity is treated as both fully accessible and available, regardless of their location within the study area container – the main problem with container-based measures. In the FCA metrics, a reconfiguration of opportunities may redistribute the spatial accessibility values of the individual population units; however, the overall spatial accessibility of the system will remain unchanged.

This property of the current FCA metrics and the resulting implications for spatial accessibility characterization can be illustrated in an additional set of example systems (see Fig. 6). In this set of systems, only a single hospital with 20 beds is present; again, there are three population units having 100 people each. The only differences among systems are the distances (and therefore, weight values) among the population units and hospital serving them.

The results for the E2SFCA and 3SFCA can be found in Table 2. The results show that, regardless of the distances among population units and hospitals, the weights only function as a *relative* distribution mechanism. This can easily be observed in the differences in the results of the systems. In Systems #6 and #8, the opportunities are evenly distributed due to equivalent weights among population locations. System #7 shows that the rates are distributed according to the proportion of the summed weights.

The property of balance in the FCA metrics results in the allocation of all opportunities, regardless of the absolute distance that must be overcome to access those opportunities.[2] The *absolute* distance separating the population units and hospital is not considered in either FCA metric. Most notably, Systems #6 and #8 provide equivalent results (see Table 3), even though these two configurations would provide very different spatial accessibility scenarios for their respective populations.

This outcome can be understood by revisiting the initial gravity model (Eqs. (1) and (2)) from which the FCA metrics are constructed. For a system having a single supply location and single population unit, the gravity-based formula produces

$$A_i^G = \frac{S_j f(d_{i,j})}{P_i f(d_{i,j})}, \tag{10}$$

[2] Opportunities are allocated to all population units falling within the threshold distance, d, of any supply location.

which is equivalent to

$$A_i^G = \frac{S_j}{P_i} \times \frac{f(d_{i,j})}{f(d_{i,j})}. \tag{11}$$

Because the $f(d_{i,j})$ term is found in both the numerator and denominator, it will always equal one for any possible value and can be represented as ω

$$A_i^G = \frac{S_j}{P_i} \times \omega \tag{12}$$

where

$$\omega = 1. \tag{13}$$

The implications of this re-examination of the gravity model are evident – it will always provide the exact same value, regardless of the distance separating the supply and demand location; any reduction in supply will be perfectly offset by a decrease in potential demand, providing the same spatial accessibility value. The distance decay terms effectively cancel each other out. Interestingly, this relationship holds true even in systems having multiple supply and demand locations, as evidenced by comparing the FCA output from Systems #6 and #8.

It is through this property of the gravity model that the FCA metrics carry the inherent assumption that the location of the providers are *optimal* and their services are both fully accessible and available to the entire population. In the 2SFCA, E2SFCA, and 3SFCA, the ω value for every system is assumed to *always* equal one. This assumption does not acknowledge the true suboptimal nature of actual delivery systems (where $\omega < 1$). As a result, these measures do not capture the true "potential" spatial accessibility of the supply configuration. Further, this limitation in the FCA metrics does not allow for the overall system effect of alternate configurations of opportunities to be evaluated (as illustrated in the example systems).

Although the example systems detailed here are primitive models and do not resemble the complex provider and population configurations likely found in real-world systems, they do serve as sufficient generalizations. The use of simulated systems exposes the theoretical limitations of the optimal configuration assumption by illustrating the outcomes of extreme conditions. Most importantly, these results highlight the potential that exists for overestimation of spatial accessibility in real-world applications using the FCA metrics as currently constructed. Although the effect of this assumption may be more subtle and difficult to detect in real-world health care systems, it does raise concerns regarding the robustness of the FCA metrics. Perhaps the greatest concern is the potential to overestimate spatial accessibility for populations that are truly disadvantaged.

Table 4
M2SFCA results from example Systems #1–4 and #6–8. The output units are in beds per person.

System	E2SFCA			M2SFCA		
	x	*y*	*z*	*x*	*y*	*z*
1	0.067	0.067	0.067	0.053	0.053	0.053
2	0.06	0.08	0.06	0.04	0.064	0.04
3	0.053	0.094	0.053	0.038	0.075	0.038
4	0.05	0.1	0.05	0.04	0.08	0.04
6	0.067	0.067	0.067	0.053	0.053	0.053
7	0.107	0.013	0.08	0.085	0.001	0.048
8	0.067	0.067	0.067	0.007	0.007	0.007

Table 5
M2SFCA results from example Systems #1–4 and #6–8. The output units are in total opportunities, calculated by multiplying the opportunities per person (the output of the FCA metrics) by the population of each unit.

System	E2SFCA				M2SFCA			
	x	*y*	*z*	*Total*	*x*	*y*	*z*	*Total*
1	6.67	6.67	6.67	20	5.33	5.33	5.33	16
2	6	8	6	20	4	6.4	4	14.4
3	5.29	9.41	5.29	20	3.82	7.53	3.82	15.18
4	5	10	5	20	4	8	4	16
6	6.67	6.67	6.67	20	5.33	5.33	5.33	16
7	10.67	1.33	8	20	8.53	0.13	4.8	13.47
8	6.67	6.67	6.67	20	0.67	0.67	0.67	2

4. The modified two step floating catchment area

The M2SFCA incorporates the potential for *sub*optimal health care system configurations by allowing ω to vary based on the configuration of supply and demand. To accomplish this, the M2SFCA is built upon a modified gravity model that considers both the relative *and* absolute distances among population units and supply locations by including an additional $f(d)$ variable such that

$$\alpha_i^G = \sum_{j=1}^{m} \frac{S_j f(d_{i,j}) f(d_{i,j})}{\sum_{i=1}^{k} P_i f(d_{i,j})}. \tag{14}$$

Using this model, the only case where all opportunities would be considered completely accessible and available is when a

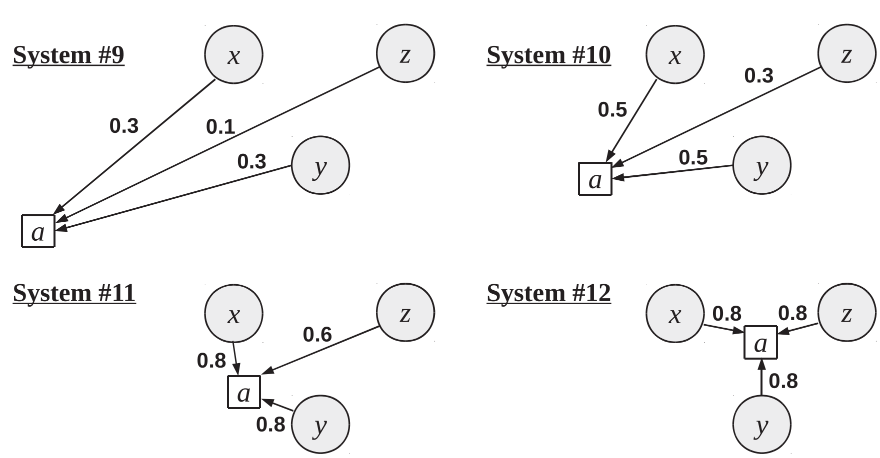

Fig. 7. Additional example systems showing suboptimal configurations of a supply location. In all example systems, each unit *x*, *y*, *z* has a population of 100 and hospital *a* has 20 beds. Travel distances are represented by "weight" values and are not to scale.

perfectly optimal system is assessed – one where there is no separation between population and supply locations. In this situation, $f(d)$ is equal to one and Eq. (14) reduces to the original gravity model. In all other cases, $0<\omega<1$, dependent upon the overall configuration of supply locations.

The applied calculation of the M2SFCA is quite similar to that of the E2SFCA. After the travel distances are converted to weight values (using either travel time bands or a distance function), the initial step is to calculate supply ratios. In the M2SFCA, a specific supply ratio is constructed for each population unit and hospital pair ($D_{i,j}$) for all pairs where the distance separating i and j is less than d:

$$D_{i,j}=\frac{S_j W_{i,j}}{\sum_{i\in[d_{i,j}<d]} P_i W_{i,j}} \tag{15}$$

The significant difference between the supply ratio step in the M2SFCA and the corresponding step in previous FCA metrics is that *specific pairwise* supply ratios ($D_{i,j}$) are calculated for each hospital and population unit pairing. Previous FCA metrics employ a single supply ratio (D_j) for each hospital. This slight modification essentially moderates the overall supply ratio of each hospital in accordance with the *absolute* distance separating the hospital and the population units, while also considering the potential demand as calculated in the E2SFCA.

The second step in the M2SFCA is the same as the E2SFCA. For each population unit, the hospitals falling within d are located. The pairwise supply ratio of each hospital is multiplied by the pairwise weight value and summed:

$$A_i=\sum_j D_{i,j} W_{i,j}. \tag{16}$$

Like the other FCA metrics, the M2SFCA produces a provider to the population ratio. In all FCA metrics, the W values are essentially "unitless" as they only serve as moderators of S and P values (through distance decay). Including an additional $W_{i,j}$ term in the M2SFCA formulation only moderates the numeric value of S_j, not the unit of measure. Thus, the M2SFCA upholds the previously acknowledged strength of the FCA metrics – easily interpretable output units.

By incorporating a modified gravity model, the overall measure of spatial accessibility (A) provided by the M2SFCA describes the availability of opportunities as moderated by relative and absolute distance simultaneously. In well-configured or nearly optimal provider and population systems, this modification will only lead to minor variations from the E2SFCA results; specifically, most opportunities are both available and accessible in systems approaching an optimal configuration. However, in highly *sub*-optimal systems, the M2SFCA output values have the potential to deviate greatly from E2SFCA results. In these systems, the effects of the absolute distance separating populations and providers will be captured in the M2SFCA output.

Table 6
Results showing effects of suboptimal configuration in the M2SFCA. The output units are in total opportunities, calculated by multiplying the opportunities per person (the output of the FCA metrics) by the total population.

System	E2SFCA				M2SFCA			
	x	*y*	*z*	*Total*	*x*	*y*	*z*	*Total*
9	8.57	8.57	2.86	20	2.57	2.57	0.29	5.43
10	7.69	7.69	4.62	20	3.85	3.85	1.38	9.08
11	7.27	7.27	5.45	20	5.82	5.82	3.27	14.91
12	6.67	6.67	6.67	20	5.33	5.33	5.33	16

4.1. M2SFCA results from example systems

A comparison of the M2SFCA and E2SFCA output for example Systems #1–4 and #6–8 is found in Table 4. These results show that the M2SFCA does not dramatically alter the spatial accessibility characterization in Systems #1–6. In these systems, the M2SFCA values are discounted due to distance, but the E2SFCA and M2SFCA report relatively similar levels of spatial accessibility. In System #7, the effects of absolute distance become more apparent when unit y is located at the periphery of the system and units x and z are located relatively near the supply location. In this scenario, the spatial accessibility for unit y is heavily discounted.

When all population locations are located far from the supply location in System #8, the M2SFCA accounts for this separation and reports low spatial accessibility values for each unit. It is important to note that in Systems #7 and #8, the W_y values are equal, yet y has a higher M2SFCA value in System #8; like the E2SFCA, the M2SFCA incorporates the configuration of population locations near to each supply location. In this case, the potential demand on hospital a is moderated through the proximity of all population locations.

To illustrate how the M2SFCA can be used to describe the overall efficiency of the configuration of supply locations, Table 5 shows the number of beds allocated to each population unit in example Systems #1–4 and #6–8. As noted previously, the E2SFCA

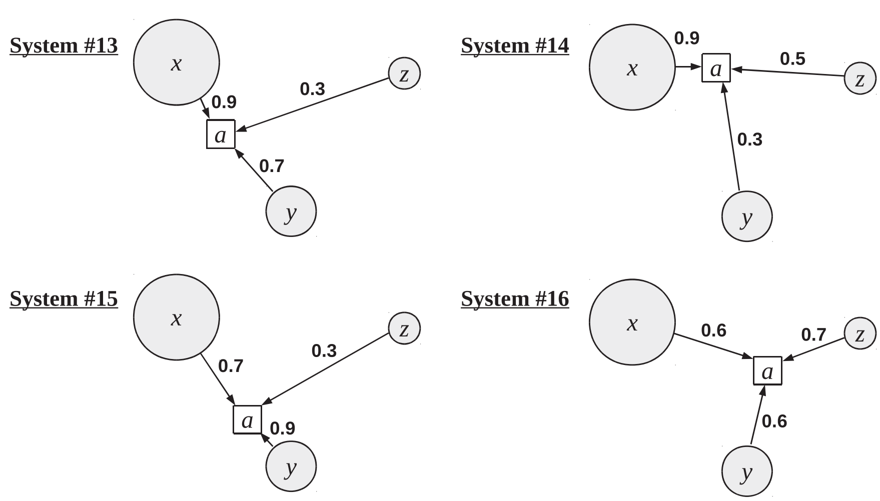

Fig. 8. Additional example systems showing suboptimal configurations of a supply location. In all example systems, units x, y, z have populations of 200, 75, and 25 respectively and hospital a has 20 beds. Travel distances are represented by "weight" values and are not to scale.

allocates all 20 beds, regardless of the absolute distances among the population units and supply location(s). The M2SFCA, on the other hand, does not allocate all of the opportunities in any of the systems; the suboptimal configuration (all W values are less than one) of providers and populations is acknowledged. This effect is most noticeable in System #8, where only 2 of the 20 hospital beds are allocated to the population units.

To further explore how the location of a supply location influences the output from the M2SFCA, an additional set of example systems is provided in Fig. 7. This set of systems contains a static group of population locations. Progressively, the location of a hospital is moved toward the "center" of the population locations. Given that each population location has an equal number of people, the most optimal supply location to serve the overall system is a central location among all units (where $W_x = W_y = W_z$). Table 6 shows that the M2SFCA indeed captures the suboptimal configuration of Systems #9–11 (see *total* column), showing an increase in the number of beds available as the hospital is moved toward the central location of the system.

A final set of example systems is found in Fig. 8. These systems illustrate how the M2SFCA can be used to understand the efficiency of supply locations when considering populations with dissimilar sizes. This example set functions as a surrogate for real-world configurations of cities and hospitals. Like the previous set of systems, the population locations are static throughout each and the location of the hospital is modified, allowing the output of the M2SFCA to be understood in terms of describing the overall spatial accessibility provided within the system.

The results for Systems #13–16 can be found in Table 7. Noticeably, when the supply location is located nearest to the largest population unit (x), the overall spatial accessibility of hospital beds for the entire system is maximized. As System #16 shows, unlike previous examples in which the population of each unit was equal, the most optimal hospital location is not near the center of the system. Again, comparing the results of the M2SFCA to those from the E2SFCA shows that, in the E2SFCA, all opportunities within the system are considered both available and fully accessible, regardless of the distance separating them from the population units.

Table 7
Results showing effects of suboptimal configuration in the M2SFCA. The output units are in total opportunities, calculated by multiplying the opportunities per person (the output of the FCA metrics) by the total population.

System	E2SFCA				M2SFCA			
	x	*y*	*z*	*Total*	*x*	*y*	*z*	*Total*
13	15	4.38	0.63	20	13.5	3.06	0.19	16.75
14	16.74	2.09	1.16	20	15.07	0.63	0.58	16.28
15	13.02	6.28	0.7	20	9.12	5.65	0.21	14.98
16	13.15	4.93	1.92	20	7.89	2.96	1.34	12.19

5. Case study

The simulated data systems illustrate the behavior of the FCA metrics in basic configurations of populations and providers. To understand how the differences among the M2SFCA, E2SFCA, and 3SFCA manifest in real-world applications, a case study is conducted in a large and complex system of people and hospitals. The spatial accessibility of acute care hospitals is explored in the state of Michigan. Michigan has a population of nearly 10 million residents (United States Census Bureau, 2010) served by 169 hospitals having 26,180 licensed inpatient hospital beds. As Fig. 9 shows, the state has a large breadth of urban and rural regions offering varying degrees of spatial accessibility of hospital beds.

Given the state's bi-peninsular physical structure, Euclidean distance measurements are not suitable for measuring the separation among locations. A custom-built road network database was used to estimate vehicular travel time within the state (Delamater et al., 2012). Zip Code population data were employed as the underlying population units due to their oft-used status in health-related research (Berke and Shi, 2009). Population counts were assigned by overlaying the 2010 census block population centroids with the Zip Code polygons. The population weighted centroid of each Zip Code was calculated using the spatially joined block population data. Travel time estimates were calculated from the population-weighted centroid of each Zip Code to hospital locations using the custom-built network database.

The E2SFCA, 3SFCA, and M2SFCA values were calculated for each Zip Code in Michigan. The downward log-logistic distance decay function was used to assign weight values according to travel time estimates (de Vries et al., 2009). This function was selected as it has been shown to accurately represent the observed travel patterns for inpatient hospitalizations in Michigan (Delamater et al., 2013). The threshold distance (d) was set to 60 min in all FCA metrics. Although past research has suggested setting d equal to 30 min, recent research suggests increasing this value to 60 min to include highly rural populations in the FCA calculation (McGrail and Humphreys, 2009a). Of the 908 Zip Codes in Michigan, 899 are located within 60 min travel time from a

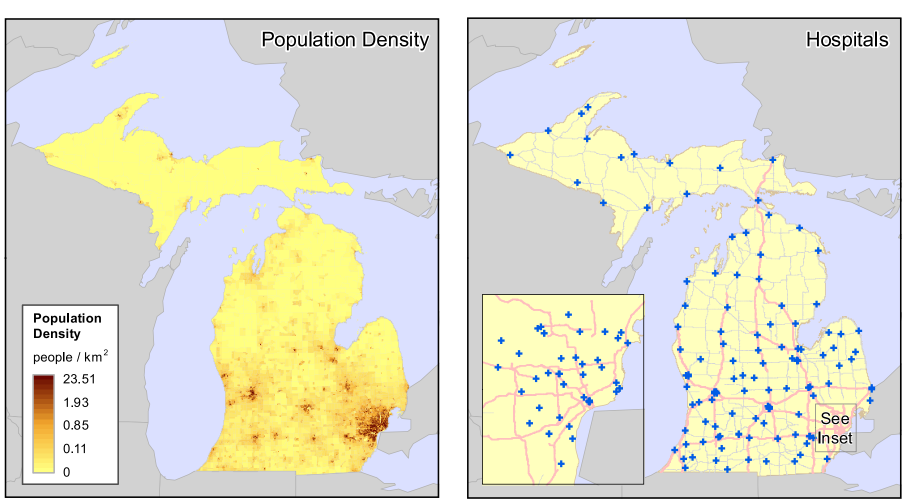

Fig. 9. Michigan population distribution and hospital locations.

hospital. As a result, the nine Zip Codes outside of a 60 min drive had a spatial accessibility of 0 in all FCA metrics. These Zip Codes and their population were removed from the subsequent analysis.

5.1. Results

The overall 2010 population is 9,858,295 people in the 899 Zip Codes under consideration. Given the 26,180 licensed beds available at Michigan hospitals, this produces an overall state-wide rate of 2.66 beds per 1000 state residents. Summary statistics for the FCA metrics are found in Table 8. By multiplying the FCAs' beds per person rates by the population of each Zip Code and summing, the total number of allocated beds in the state are 26,180 for the E2SFCA and 3SFCA and 10,241.43 for the M2SFCA. As a result of the suboptimal configuration of hospitals detected by the M2SFCA, the effective overall state-wide rate is 1.04 beds per 1000 state residents.

Maps of the FCA results are found in Figs. 10 (rates) and 11 (allocated beds). As measured by both the M2SFCA and the E2SFCA, the geographic patterns of spatial accessibility appear to be somewhat similar throughout the state. High regions of spatial accessibility are generally found in and near urban regions (where hospitals are located). In the less populated northern Lower Peninsula and Upper Peninsula, pockets of high spatial accessibility are found near to large, "regional" hospitals.

Fig. 11(D) highlights locations where the results of the M2SFCA and E2SFCA deviate. The most apparent differences in the total

Table 8
FCA results for Michigan. The output units are in hospital beds per 1000 residents.

Metric	Minimum	Maximum	Mean	St. deviation
M2SFCA	0.017	5.541	0.686	0.683
E2SFCA	0.213	6.585	1.991	1.027
3SFCA	0.252	8.192	1.907	1.181

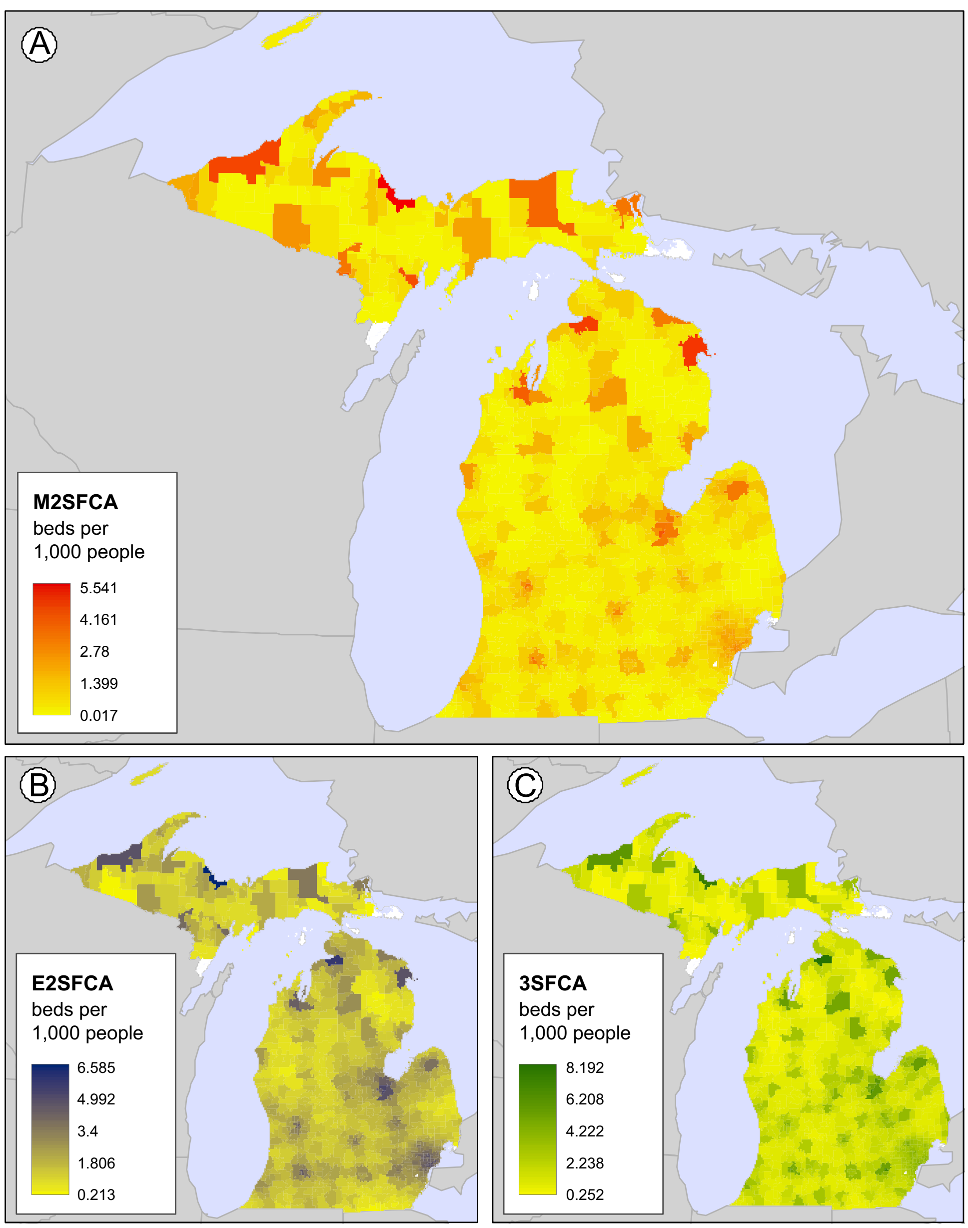

Fig. 10. FCA results. (A) M2SFCA, (B) E2SFCA, and (C) 3SFCA.

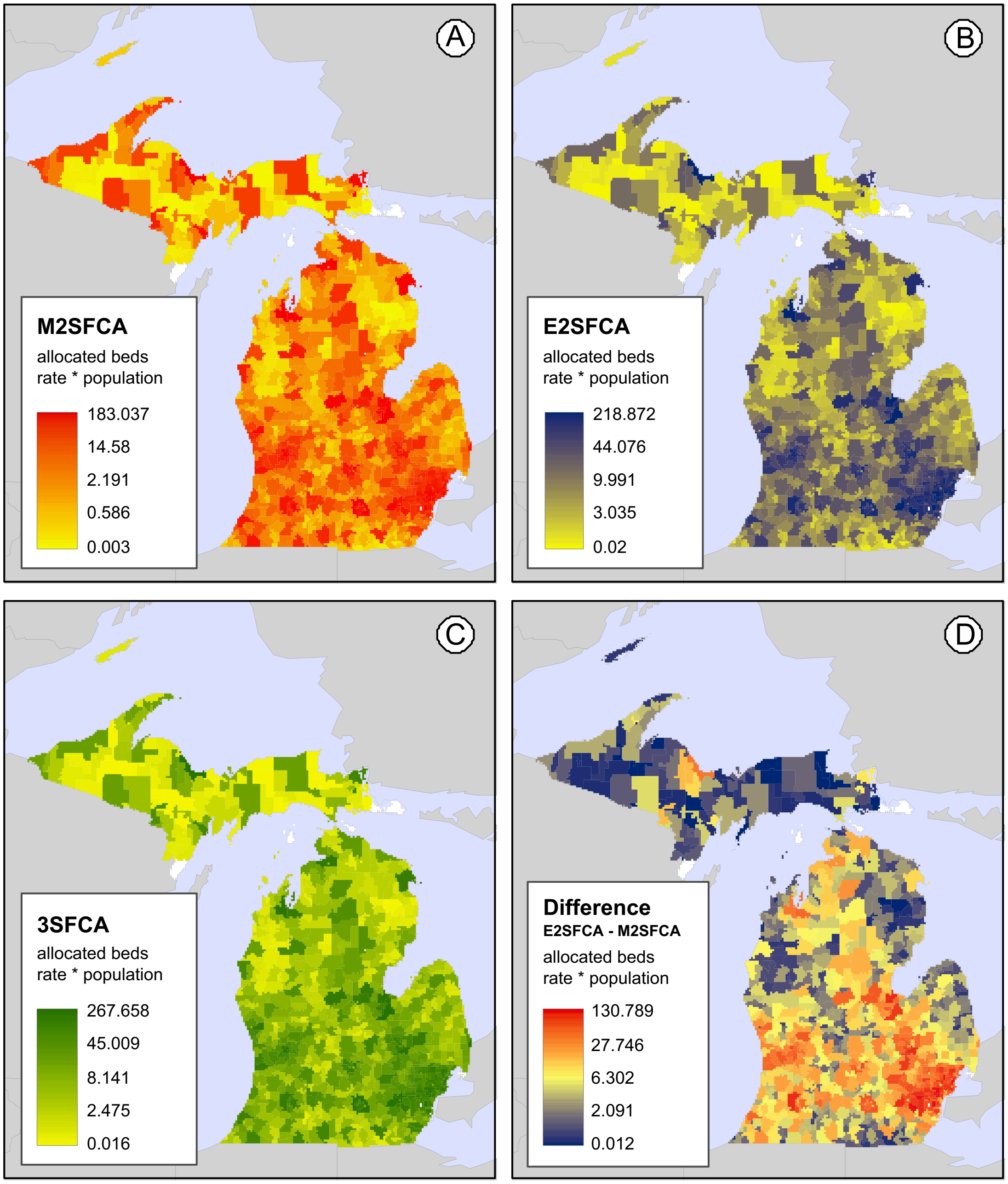

Fig. 11. FCA hospital bed allocation results. Allocated beds are calculated by multiplying the beds per person rate by the total population of each Zip Code. (A) M2SFCA, (B) E2SFCA, (C) 3SFCA, (D) difference between E2SFCA and M2SFCA.

number of beds allocated to population units can be found in the southeast and east portion of the Lower Peninsula (near the Detroit Metro region and near Bay City) with small pockets in the southwest and northern Lower Peninsula. The regions where the M2SFCA and E2SFCA results are most similar are generally found in less-populated regions of the state.

Fig. 12 plots the 3SFCA output compared to the E2SFCA. As noted in the simulated data examples, the 3SFCA has the potential to both over and underestimate spatial accessibility (when compared with the E2SFCA) due to the metric's incorporation of the competition-based weight values (G). In the complex health care system of Michigan, this outcome is confirmed as points fall both above and underneath the 1:1 line in Fig. 12.

To illustrate the overestimation of spatial accessibility present in the E2SFCA and 3SFCA, their results have been plotted against the M2SFCA values in Fig. 13. The relative locations of the point clouds with regard to the 1:1 line highlight similar magnitudes of overestimation present in the E2SFCA and 3SFCA.

Wan et al. (2011) propose the spatial access ratio (SPAR), a rescaling of raw E2SFCA output values. Although the authors developed this approach to test the results of modifications to the distance decay parameter in the E2SFCA, this normalization procedure provides an opportunity to further compare the FCA output. To calculate the SPAR, the output values of the FCA are divided by the overall mean value. The SPAR was calculated independently for the M2SFCA, E2SFCA, and 3SFCA. The E2SFCA and 3SFCA SPAR values are plotted against the M2SFCA SPAR values in Fig. 14. These results show that a small number of values fall underneath the 1:1 line in the E2SFCA and slightly more in the 3SFCA; however, overestimation of spatial accessibility remains systemic in both the E2SFCA and 3SFCA as nearly all of their SPAR values are greater than the M2SFCA SPAR values.

6. Discussion

By incorporating both relative and absolute distances separating populations and health care opportunities, the M2SFCA marginalizes the contribution of more distant supply locations to the overall spatial accessibility of a population unit. The main implication of this property can be observed in the results of Table 8, where the minimum value in the M2SFCA output is an order of magnitude lower than that of the E2SFCA and 3SFCA. Additionally, this effect is also likely the cause for the regional differences near Detroit and Bay City in the southeastern and eastern Lower Peninsula (Fig. 10(D)). These areas have a large number of hospitals falling within the 60 min travel time constraint of many of the population units. The individual contributions of these hospitals may each be small; however, when those contributions are summed over all the hospitals in the region, the effect appears to be significant in the E2SFCA and 3SFCA. Because distant contributions are marginalized in the M2SFCA, these regions appear to have a substantially lower spatial accessibility.

Density plots of the FCA results (and SPAR values) for Michigan are found in Fig. 15. The plot shows that the distributions of each metric have a unique character. Compared with the output of the E2SFCA and 3SFCA, the M2SFCA's peak value is much nearer to 0 in both plots. This result reflects the dampening of spatial accessibility values in the M2SFCA due to the consideration of both relative and absolute distances. In general, the M2SFCA reports lower spatial accessibility values throughout the range of data, as the overall number of beds allocated is nearly 16,000 less for the entire state. Although this effect is not as substantial in the SPAR values, the M2SFCA values remain concentrated toward lesser values. The distribution of the E2SFCA and 3SFCA values is similar for both the raw and SPAR FCA values.

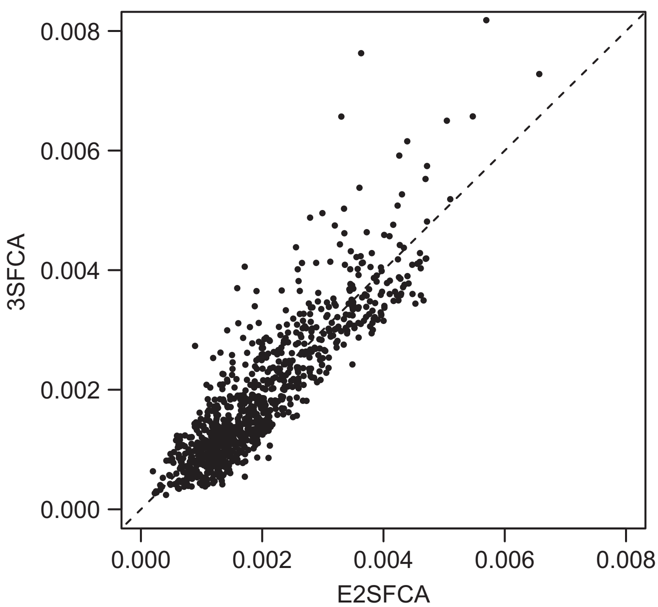

Fig. 12. 3SFCA and E2SFCA comparison. Values are plotted along with a dashed 1:1 line for reference.

Much of the applied research cited in this paper focuses on identifying population-level disparities in spatial accessibility to health care services. Although this work is undoubtedly important, the next reasonable step is to move past identification and towards the ability to suggest pathways that would result in improving spatial accessibility. Herein lies the significant limitation in the current FCA metrics. Alterations to the configuration of health care supply locations may be detected in the E2SFCA or 3SFCA values of the individual population units; however, the overall effectiveness of any system change cannot be evaluated. Because all opportunities are fully allocated, the effective spatial accessibility of the system remains static.

This limitation also affects the ability to evaluate scenarios in which a supply location is added or removed from the system. In these cases, because all the opportunities are fully allocated, regardless of the *absolute* distance separating the facility location and population units. The following theoretical example of this scenario provides an illustration of how this property of the FCA metrics could manifest in misleading results. In the example, consider the potential ramifications of a 200 bed hospital being placed in a remote region of a study region (e.g., the National Forest area in Michigan's northwest lower peninsula). If this facility was to fall within the threshold distance of *any* population unit or units, the E2SFCA and 3SFCA would fully allocate all 200 beds. In this case, although the added facility would be largely inaccessible, the E2SFCA and 3SFCA would report a 200 bed improvement in spatial accessibility for the state. In this case, the M2SFCA would properly discount the gain in spatial accessibility by incorporating the absolute distance separating the new, remotely located facility and the population units. Placing a hospital in a highly inaccessible region is extremely unlikely. Yet, the example again highlights the potential for overestimation of spatial accessibility in the E2SFCA and 3SFCA metrics.

The M2SFCA provides a measure of the *effective* availability of resources within a given system; for Michigan, the effective number of hospital beds available was less than half of the total number of beds (10,241.43 and 26,180 respectively). As a result, the M2SFCA provides the ability to detect whether local changes in

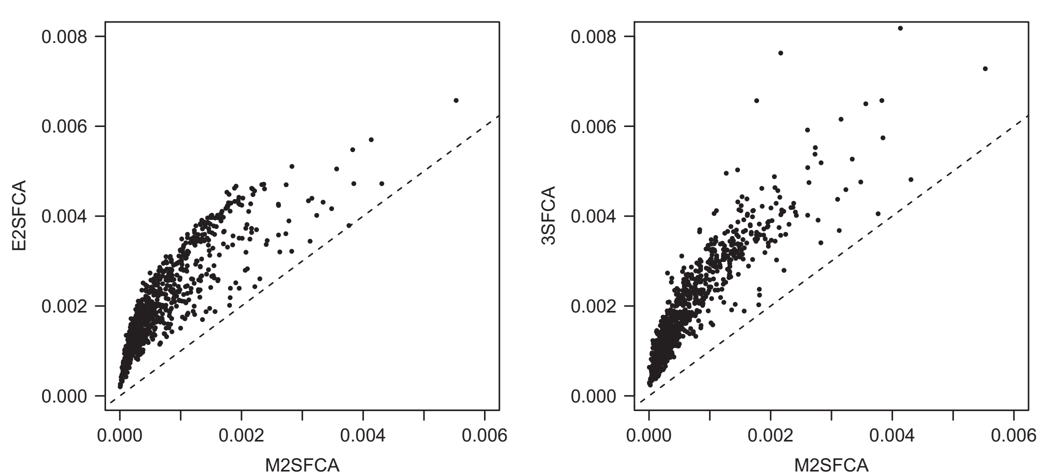

Fig. 13. 3SFCA and E2SFCA compared to M2SFCA. Values are plotted along with a dashed 1:1 line for reference.

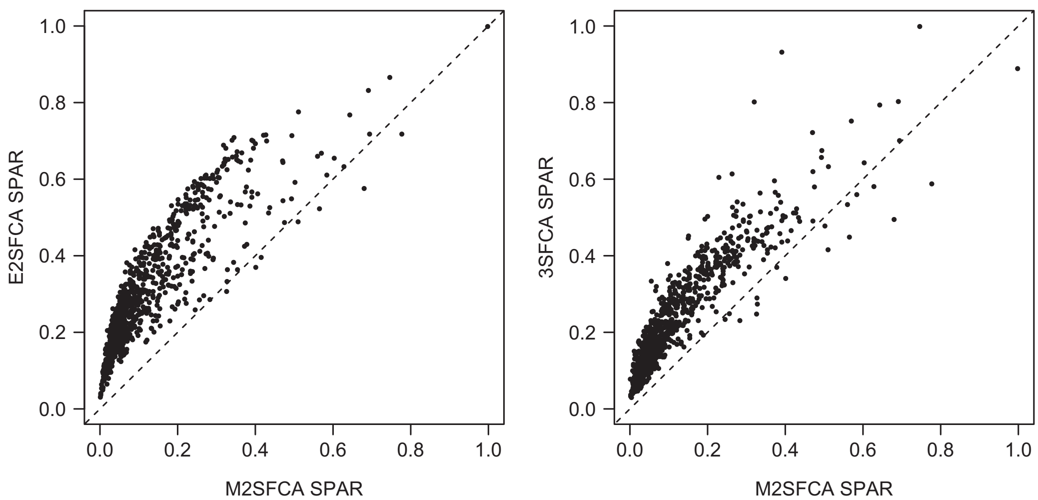

Fig. 14. SPAR values of 3SFCA and E2SFCA compared to M2SFCA. Values are plotted along with a dashed 1:1 line for reference.

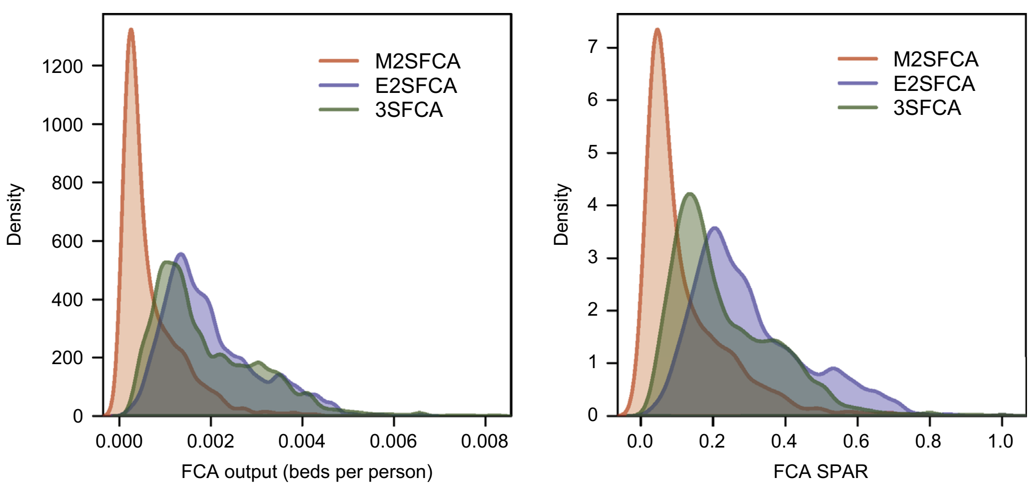

Fig. 15. Density plots of FCA output for Michigan. (Left) The raw FCA output values and (Right) the SPAI values.

resources or potential demand have an effect on the spatial accessibility of the overall system. The E2SFCA and 3SFCA do not provide additional information beyond what could be calculated by dividing the total number of beds by the study area population, thus providing no information about the efficacy of the configuration of supply locations within the system. By accounting for absolute distance among populations and facilities, the M2SFCA offers a richer characterization of system-wide spatial accessibility.

Furthermore, the M2SFCA can be employed to compare the effective availability of resources among independent health care systems. To compare independent health care systems, the overall rates of spatial accessibility can be employed or the ratios of effective availability vs. total availability (e.g., in Michigan, this ratio would equal 39.12%). Any system-to-system comparison would necessarily need to account for the distribution of the underlying population, as an optimal configuration is more difficult to achieve for highly dispersed populations. Yet, the M2SFCA provides an initial step towards understanding differences among health care systems.

The ability of the M2SFCA to characterize the overall efficacy of spatial accessibility in a health care system has further ramifications. The M2SFCA output has the potential to be incorporated into location-allocation models. Location-allocation models locate new facility (or facilities) by attempting to *optimize* a particular function, model parameter, or system output (Fotheringham et al., 1995; Cromley and McLafferty, 2002; Messina et al., 2006). Hypothetically, a location-allocation model could be developed such that the spatial accessibility of the overall health care system, as measured by the M2SFCA, functions as the parameter to be optimized. Although this integration would likely be computationally expensive, the output could potentially identify regions for new facilities not previously considered in population- or distance-based models.

This work does not consider other recently proposed modifications of the E2SFCA metric. McGrail and Humphreys (2009b) and Ngui and Apparicio (2011) implement a demand model that accounts for the potential users of the healthcare services, rather than simple population counts. This approach could be incorporated into the M2SFCA and may prove highly useful for study areas having population units with highly divergent health care needs. Another modification, proposed by Luo and Whippo (2012), is the use of variable catchment sizes in the demand estimation step of the E2SFCA. In this method, the travel time or distance used to define the catchment area is allowed to vary according to the number of opportunities at the facility; the main assumption being that large facilities will draw patients from longer distances than small facilities. This research did not examine the effects of variable catchment sizes; therefore, future work is necessary to evaluate the implications of this modification as they relate to the issues identified in the current study.

7. Conclusions

This research has aimed to (1) critically examine the 3SFCA, (2) expose the "optimal" assumption in the current FCA metrics, and (3) provide a new FCA metric that considers the suboptimal distribution of health care resources. Through simulated data examples, I illustrated the theoretical limitations of both the 3SFCA and E2SFCA. I detailed the M2SFCA, a new FCA metric that incorporates both absolute and relative distance in characterizing spatial accessibility. The applied outcomes of this metric were considered in simulated data examples and a case study of Michigan's hospitals, a complex health care system. Compared to the E2SFCA and 3SFCA, I show that the M2SFCA provides an improved characterization of the spatial accessibility of health care resources and also has the potential to inform future planning opportunities.

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References

Aday, L.A., Andersen, R., 1974. A framework for the study of access to medical care. Health Services Research 9, 208–220.
Bell, S., Wilson, K., Bissonnette, L., Shah, T., 2013. Access to primary health care: does neighborhood of residence matter?. Annals of the Association of American Geographers 103, 85–105.
Berke, E., Shi, X., 2009. Computing travel time when the exact address is unknown: a comparison of point and polygon ZIP code approximation methods. International Journal of Health Geographics 8, 1–9.
Cromley, E.K., McLafferty, S., 2002. GIS and Public Health. Guilford Press, New York.
Dai, D., 2010. Black residential segregation, disparities in spatial access to health care facilities, and late-stage breast cancer diagnosis in metropolitan Detroit. Health & Place 16, 1038–1052.
Dai, D., Wang, F., 2011. Geographic disparities in accessibility to food stores in southwest Mississippi. Environment and Planning B: Planning and Design 38, 659–677.
de Vries, J.J., Nijkamp, P., Rietveld, P., 2009. Exponential or power distance-decay for commuting? An alternative specification. Environment and Planning A 41, 461–480.
Delamater, P.L., Messina, J.P., Grady, S.C., WinklerPrins, V., Shortridge, A.M., 2013. Do more hospital beds lead to higher hospitalization rates? A spatial examination of Roemer's law. PLoS ONE 8, e54900.
Delamater, P.L., Messina, J.P., Shortridge, A.M., Grady, S.C., 2012. Measuring geographic access to health care: raster and network-based methods. International Journal of Health Geographics 11, 1–18.
Fotheringham, A.S., Densham, P.J., Curtis, A., 1995. The zone definition problem in location-allocation modeling. Geographical Analysis 27, 60–77.
Guagliardo, M., 2004. Spatial accessibility of primary care: concepts, methods and challenges. International Journal of Health Geographics 3, 1–13.
Joseph, A.E., Phillips, D.R., 1984. Accessibility and Utilization: Geographical Perspectives on Health Care Delivery. Harper & Row Ltd., London.
Khan, A.A., 1992. An integrated approach to measuring potential spatial access to health care services. Socio-Economic Planning Sciences 26, 275–287.
Kwan, M.P., 1998. Space–time and integral measures of individual accessibility: a comparative analysis using a point-based framework. Geographical Analysis 30, 191–216.
Langford, M., Fry, R., Higgs, G., 2012. Measuring transit system accessibility using a modified two-step floating catchment technique. International Journal of Geographical Information Science 26, 193–214.
Luo, W., Qi, Y., 2009. An enhanced two-step floating catchment area (E2SFCA) method for measuring spatial accessibility to primary care physicians. Health & Place 15, 1100–1107.
Luo, W., Wang, F., 2003. Measures of spatial accessibility to health care in a GIS environment: synthesis and a case study in the Chicago region. Environment and Planning B: Planning and Design 30, 865–884.
Luo, W., Whippo, T., 2012. Variable catchment sizes for the two-step floating catchment area (2SFCA) method. Health & Place 18, 789–795.
McGrail, M.R., Humphreys, J.S., 2009a. Measuring spatial accessibility to primary care in rural areas: improving the effectiveness of the two-step floating catchment area method. Applied Geography 29, 533–541.
McGrail, M.R., Humphreys, J.S., 2009b. A new index of access to primary care services in rural areas. Australian and New Zealand Journal of Public Health 33, 418–423.
Messina, J., Shortridge, A.M., Groop, R.E., Varnakovida, P., Finn, M.J., 2006. Evaluating Michigan's community hospital access: spatial methods for decision support. International Journal of Health Geographics 5, 1–18.
Ngui, A., Apparicio, P., 2011. Optimizing the two-step floating catchment area method for measuring spatial accessibility to medical clinics in Montreal. BMC Health Services Research 11, 1–12.
Radke, J., Mu, L., 2000. Spatial decompositions, modeling and mapping service regions to predict access to social programs. Annals of GIS 6, 105–112.
Shen, Q., 1998. Location characteristics of inner-city neighborhoods and employment accessibility of low-wage workers. Environment and Planning B: Planning and Design 25, 345–365.
United States Census Bureau, 2010. 2010 Census Data. 〈http://2010.census.gov/2010census/data/〉.
Wan, N., Zhan, F.B., Zou, B., Chow, E., 2011. A relative spatial access assessment approach for analyzing potential spatial access to colorectal cancer services in Texas. Applied Geography 32, 291–299.
Wan, N., Zou, B., Sternberg, T., 2012. A three-step floating catchment area method for analyzing spatial access to health services. International Journal of Geographical Information Science 26, 1073–1089.
Wang, F., 2012. Measurement, optimization, and impact of health care accessibility: a methodological review. Annals of the Association of American Geographers 102, 1104–1112.
Weibull, J.W., 1976. An axiomatic approach to the measurement of accessibility. Regional Science and Urban Economics 6, 357–379.