A comparative analysis of accessibility measures by the two-step floating catchment area (2SFCA) method

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ABSTRACT
The recent decade has witnessed a new wave of development in the place-based accessibility theory, revolving around the two-step floating catchment area (2SFCA) method. The 2SFCA method, initially serving to evaluate the spatial inequity of health care services, has been further applied to other urban planning and facility access issues. Among these applications, different distance decay functions have been incorporated in the thread of model development, but their applicability and limitations have not been thoroughly examined. To this end, the paper has employed a place-based accessibility framework to compare the performance of twenty-four 2SFCA models in a comprehensive manner. Two important conclusions are drawn from this analysis: on a small analysis scale (e.g., community level), the catchment size is the most critical model component; on a large analysis scale (e.g., statewide), the distance decay function is of elevated importance. In sum, this comparative analysis provides the theoretical support necessary to the choice of the catchment size and the distance decay function in the 2SFCA method. Justification of model parameters through empirical evidence (e.g., field surveys about local travel activities) and model validation through sensitivity analysis are needed in future 2SFCA applications for various urban planning, service delivery, and spatial equity scenarios.

1. Introduction

‘Everything is related to everything else, but near things are more related than distant things (Tobler 1970).’ Tobler’s first law of geography has established the theoretical foundation of spatial interaction (SI) models in the analysis of spatial associations between geographic entities (Miller 2004). Modeling accessibility to urban facilities, as a proxy for the potential of space for interaction, has been widely explored for two evaluative purposes: a planning purpose evaluating if land use or transportation systems can cater to the need of urban population (Geurs and Wee 2004) and a corroborative purpose identifying if the inequity of patronizing opportunities exists among different social groups (Kwan et al. 2003). Central to the discussion is how opportunities could be
articulated and how the spatial separation could be quantified to better capture the complexities of urban forms and individual mobilities (Kwan 2010).

The origin of accessibility studies can be traced back to Hansen’s (1959) empirical model for land use planning, considering place-based accessibility as an integrated assessment of urban opportunities (e.g., employment, shopping opportunities, residential activity). The placed-based accessibility measures, mainly including cumulative-opportunity models and gravity-type models (Kwan 2010), evaluate the degree of accessibility for a reference location (i.e., the demand location, such as a community center) according to the density of or the proximity to surrounding facilities (Talen and Anselin 1998, Neutens et al. 2010). The other thread of research has shifted the focus to individual-based accessibility measures, relying on the construct of the space-time prism in time geography (Hägerström 1970). Time-geographic accessibility metrics (i.e., number of opportunities within the prism, utilities gained from the travel) have been proposed to represent individuals’ capabilities in reaching opportunities given their motility constraints (Miller 2010, Neutens et al. 2010). Despite the proliferating examples of place-based and individual-based accessibility measurements for evaluating urban service delivery or justifying issues of social inequities (Kwan et al. 2003, Neutens et al. 2010), the recent decade has witnessed a new wave of development in the place-based accessibility theory, revolving around the two-step floating catchment area (2SFCA) method (Luo and Wang 2003). The 2SFCA method, as a special form of the gravity model (i.e., the major type of SI models), considers accessibility to be mediated by not only the distance decay (“transferability in the parlance of SI theory) but also the interactions between supply and demand (“complementarity”; Haynes and Fotheringham 1984). It overcomes the caveat of traditional place-based accessibility measures where the demand for service is largely overlooked. The 2SFCA method, initially serving to evaluate the spatial inequity of health care services (Wang 2012), has been further applied to other urban planning and facility access issues, including green space (Dai 2011, Xing et al. 2018), job opportunities (Dai et al. 2018), food stores (Dai and Wang 2011, Chen 2017, 2019), and emergency shelters (Zhu et al. 2018). In addition, the formation of the 2SFCA model has been further modified to accommodate other service scenarios, such as measuring the crowdedness of the facility usage (Wang 2017).

The 2SFCA method as a prototype model has been further developed to capture the complexities of real-world travel environments, travel behaviors, and diverse service needs. The thread of development primarily concerns three distinct facets of the method: the catchment size, the regional competition, and the distance decay (as reviewed in the next section). Specifically, various forms of the distance decay function, such as the negative linear function (Schuurman et al. 2010), the inverse power function (Schuurman et al. 2010), the exponential function (Jamtsho et al. 2015), the Gaussian function (Wan et al. 2012a), and the kernel density function (Dai and Wang 2011), have been incorporated to improve the 2SFCA method. Although there have been studies testing the sensitivity of the method, primarily about the distance weight (McGrail 2012) and the distance impedance coefficient (Luo and Wang 2003, Wan et al. 2012a), to date, there has been no comprehensive evaluation of the different distance decay functions in the 2SFCA family. Furthermore, the discussion on the applicability and limitations of different 2SFCA models has yet to be initiated. This research gap poses a considerable challenge to the overarching understanding of the method.
To this end, the paper fills the gap by performing the sensitivity analysis of typical models in the 2SFCA family. First, we have conceptualized the analytic framework that includes twenty-four 2SFCA models based on the place-based accessibility theory. Second, we have thoroughly compared and contrasted these 2SFCA models by state-of-the-art statistical measures. Lastly, based on the analysis results, we have offered suggestions for the choice of the model parameters. This comparative analysis is the first to provide a comprehensive discussion on different 2SFCA models and could corroborate the state of equity measures by the 2SFCA method in various planning scenarios.

2. Development of the 2SFCA method

The 2SFCA method, originated from a gravity model (Joseph and Bantock 1982) and further inspired by a spatial decomposition method (Radke and Mu 2000), aims to evaluate the physical accessibility to health care services based on the spatial interaction between the supply and demand (Luo and Wang 2003). The operation of the 2SFCA method is a two-step search procedure. The first step evaluates the supply-to-demand ratio \( R_j \) by dividing the capacity of a facility \( S_j \) (the supply) to all population \( P_k \) (the demand) within a threshold distance \( d_0 \) (the catchment size), as shown in Equation (1). This step characterizes the capability of the supply in fulfilling the needs of all population in its service radius. The second step calculates the accessibility index \( A_i \) for the demand point \( i \) as a summation of the \( R_j \) derived from the first step, as shown in Equation (2). The summation is based on all the service providers within the catchment, which conceptualizes the activity space of population living at location \( i \). The 2SFCA method contributes to the formation of the spatial interaction in previous place-based accessibility measures, which have invariably overlooked the demand side of the spatial interaction.

\[
R_j = \frac{S_j}{\sum_{k \in \{d_k \leq d_0\}} P_k}
\]

(1)

\[
A_i = \sum_{j \in \{d_j \leq d_0\}} R_j = \sum_{j \in \{d_j \leq d_0\}} \frac{S_j}{\sum_{k \in \{d_k \leq d_0\}} P_k}
\]

(2)

The original 2SFCA method has been further extended to capture the complex ways in which the spatial interaction between the supply and demand is mediated. These improvements are primarily towards three distinct but cohesive directions: the catchment size, the regional competition, and distance decay functions. The thread of development, extended from a review article (Tao and Cheng 2016), is summarized below.

The first aspect of improvements considers the variation of the catchment size as a better approximation of the maximum ‘transferability.’ The foundation of the 2SFCA method, rooted in the SI economic theory, assumes that the benefit derived from the spatial interaction must outweigh the cost of travel between the supply and demand. Thus, the catchment size in the 2SFCA method represents a threshold distance, beyond which the interaction cannot be established. In the original 2SFCA model, the search procedure in the first and the second steps is based on an arbitrarily defined catchment size. In reality, the catchment size is beyond a simple delineation of the service area and
is mostly dependent on the utilization pattern of the service and the activity space of the consumer (Yang et al. 2006, Wang 2012). On the one hand, comparing to metropolitan areas, empirical evidence revealed that people living in rural areas are more willing to travel long distances for services, in cases such as health care utilization (Arcury et al. 2005, McGrail and Humphreys 2009) and food procurement (Mceachern and Warnaby 2006). In this regard, the dynamic 2SFCA (D2SFCA) method was proposed to differentiate the catchment size in areas with different population densities (McGrail and Humphreys 2014). On the other hand, the service capacity of facilities varies and may be unable to fulfill the need of all the demand within a predefined distance buffer. To address the issue, two separate modifications were implemented, referred to as the variable 2SFCA (V2SFCA) method and the nearest-neighbor modified 2SFCA (NN-M2SFCA) method. The V2SFCA method considers that the supply catchment increases until the capacity is exhausted by the population under coverage; similarly, the second step of the search is terminated when the maximum supply-to-demand ratio ($R_j$) within the demand catchment is met (Luo and Whippo 2012). The NN-M2SFCA method considers that people are more likely to seek services from their nearest facilities, so the supply and the demand catchments should only include the nearest few points (Jamtsho et al. 2015). The V2SFCA and the NN-M2SFCA methods were implemented beyond the health care system, in cases where the capacity of facility largely dictates the service quality and planning outcomes, such as the emergency shelter planning (Zhu et al. 2018). In addition, a spatial disaggregation method was proposed to better estimate the catchment size (Bell et al. 2013). This method uses a smaller geographic unit to measure the accessibility and then aggregates the accessibility index to a larger geographic unit which contains the smaller units.

The second aspect of improvements considers the regional competition among comparable service providers, a facet analogous to the concept of ‘intervening opportunities’ in the SI theory (Haynes and Fotheringham 1984). In reality, consumers are more likely to patronize a facility in their immediate proximity in lieu of equalizing the visit possibility within an arbitrary distance. Thus, the 3-step floating catchment area (3SFCA) method was developed by introducing a selection weight that represents the probability of the demand point patronizing its nearby supply points (Wan et al. 2012b). The generation of the selection weight in the 3SFCA method, however, is purely based on the relative spatial proximity. In reality, the preference for service locations could be determined by not only the proximity to but also the attractiveness of a facility. Thus, the Huff model (one type of SI models) was incorporated in developing the selection weight in the 3SFCA method (Luo 2014). In a similar vein, a facility might not be fully utilized because of the lack of functionality or the limited demand in its proximity. Then, the modified 2SFCA (M2SFCA) method was proposed to consider the suboptimal configuration of the supply (Delamater 2013). Although the 3SFCA method and its extensions add another tier of consideration to estimate the facility utilization pattern, they have been criticized for causing unnecessary complications in the model formation and therefore, posing considerable technical challenges to the model implementation (Wang 2017).

The third aspect of improvements considers the form of the distance decay that intervenes in the supply-demand interaction. To better represent the complex form of ‘transferability,’ the distance decay function $f(d)$ (i.e., $f(d_{ij})$ and $f(d_{kj})$) is added to
Equations (1) and (2), respectively, representing the travel friction that contributes to the formation of $R_j$ in the first step and subsequently $A_i$ in the second step, as shown in Equations (3) and (4), respectively. The distance decay function in the 2SFCA method primarily takes three different forms: the binary decay, the continuous decay, and the hybrid decay, as shown in Figure 1 (adapted from Wang 2012). The binary decay function (Figure 1(a)), primarily the original 2SFCA method (Luo and Wang 2003), is a constant within the catchment and is zero beyond. This dichotomous approach may cause the edge effect, referring to the statistical bias that including or excluding points near the boundary would significantly affect the outcome (Van Meter et al. 2010, Chen 2017). The continuous decay (Figure 1(b)), such as the Gaussian form (Dai 2010) and the kernel density form (Dai and Wang 2011), is under the premise that the function value is or converges to zero when approaching the boundary. This form could alleviate the bias caused by the uncertainty of the catchment size. The hybrid decay (Figure 1(c)) is derived from the context that there is a sharp distinction between urban and rural travel environments, because of the disaggregated settlement and service patterns in rural regions (Arcury et al. 2005). For this reason, the enhanced 2SFCA (E2SFCA) method was proposed by introducing a zone-based discrete distance weight $W_r$ that estimates the distance decay in different sub-zones (Luo and Qi 2009). Moreover, the hybrid decay could take the form of a piecewise function composed of both binary and continuous decays, such as combining the binary form with a negative linear form (Schuurman et al. 2010). To date, there has been no consensus about the best formulation of the distance decay effect due to the lack of observation on the real-world travel and service utilization patterns (Wang 2012).

\begin{equation}
R_j = \sum_{k \in \{d_{k} \leq d_{b}\}} \frac{S_j}{P_k f(d_{kj})}
\end{equation}

\begin{equation}
A_i = \sum_{j \in \{d_{j} \leq d_{b}\}} R_j f(d_{ij}) = \sum_{j \in \{d_{j} \leq d_{b}\}} \frac{S_j f(d_{ij})}{\sum_{k \in \{d_{k} \leq d_{b}\}} P_k f(d_{kj})}
\end{equation}

Figure 1. Three different forms of the distance decay function in the 2SFCA method: a) binary decay, b) continuous decay, and 3) hybrid decay.

Although the 2SFCA family is originated from the SI models, the effect of the distance decay as the foundation of the SI theory has not been thoroughly examined. There was
a limited scope of work testing the sensitivity of the 2SFCA method to the distance decay effect; and most of the discussion revolved around the distance weight $W_r$ (McGrail 2012) or the distance impedance coefficient $\beta$ (Luo and Qi 2009, Luo and Wang 2003, Wan et al. 2012a) by a selected 2SFCA model. To date, no existing research has scrutinized the full range of the distance decay functions in the 2SFCA family, eventually posing considerable difficulty to the justification of the state of spatial equity in various planning scenarios.

3. Data collection

The research chooses the Supplemental Nutrition Assistance Program (SNAP) authorized food retailers in the state of Arkansas, United States, as the subject of study. Although the 2SFCA method is primarily designed for evaluating the accessibility to health care services, the paper chooses food retailers for the following reasons: (1) comparing to health care centers, food retailers have a larger quantity, a wider spatial distribution, and fewer spatial gaps, especially in the rural areas. This consistency in the spatial pattern facilitates systematically testing different 2SFCA models; (2) the United States Department of Agriculture (USDA) has published the Food Access Research Atlas that includes distance standards for defining efficient food accessibility (USDA 2017), which can guide the evaluation of the catchment size.

The SNAP food retailer data in the fiscal year of 2017 was collected from the Center on Budget and Policy Priorities (CBPP 2017). This dataset includes food retailers ($n = 2808$) participating in the SNAP program (formerly known as ‘food stamps,’ a nutrition improvement program for low-income populations in the United States). The supply weight ($S_j$) of the store was estimated by the distribution of SNAP redemptions in dollar value by store type (USDA 2018). The definition of $S_j$ is further articulated in the supplemental data.

The demand weight ($P_k$) in the study was derived from the estimated SNAP recipient data (total households received SNAP in the past 12 months) sourced from the United States Census Bureau (USCB) 2012–2016 American Community Survey 5-year estimates at the block group level as the most refined unit (USCB 2016). The centroid of the block group was generated for deriving the accessibility index for the block group. The store data, overlapped with the block groups ($n = 2147$), was geocoded in Esri ArcGIS 10.4, as shown in Figure 2.

4. Analytic framework

The comparative evaluation of the 2SFCA method is situated in the framework of place-based accessibility measures (Kwan 2010). Based on past examples in the 2SFCA applications, we have proposed an analytic framework that includes six distance decay functions: the rectangular cumulative-opportunity (CUMR), negative-linear cumulative-opportunity (CUML), inverse-power gravity-type (POW), exponential gravity-type (EXP), and Gaussian gravity-type (GAUSS), and kernel density (KD) models, generating a total of twenty-four measures, as shown in Table 1. These functions represent $f(d_{ij})$ and $f(d_{kj})$ in Equations (3) and (4). Examples drawn from these six models are illustrated in Figure 3.

Several notes about Table 1 should be mentioned:

(1) The binary decay in the original 2SFCA method can be regarded as the cumulative-opportunity model (rectangular form) in the place-based accessibility measure
(Kwan 2010), because the demand/supply points within the catchment are fully counted and those beyond are completely overlooked (i.e., \( f(d) = 1, \) if \( d \leq d_0; f(d) = 0, \) if \( d > d_0 \)).

2. The kernel density function as an additional place-based proximity measure is introduced into the analytic framework. The kernel function includes a bandwidth, which is equivalent to the concept of the catchment size in the 2SFCA method (Dai and Wang 2011). The kernel density function can be represented in different forms, such as Exponential, Gaussian, Quartic, Epanechnikov, Polynomial of Order 5, and Constant. The Epanechnikov form, the shape of which shares a similarity with the normal distribution (Gibin et al. 2007), is tested in this study.

3. Although there are different forms of spatial separation (e.g., distance, time, monetary cost) and health service access usually adopts travel time, this study employs the travel distance in terms of the shortest path distance (in miles) based on the USDA’s standards for efficient food access using distance measures. Specifically, USDA defines thresholds of efficient food access as half a mile and one mile in urban areas and ten miles and twenty miles in rural areas (USDA 2017).

4. The evaluation only includes the binary decay (CUMR) and the continuous decay (CUML, POW, EXP, GAUSS, and KD). In cases of the continuous decay, the distance decay function yields a value of 0 (CUML and KD) or 0.01 (POW, EXP, and GAUSS) at the
boundary, where the distance impedance coefficient $\beta$ in each model is determined by $d_0$, correspondingly. The choice of 0.01 is based on Wan et al. (2012a): 0.01 is considered a critical value when the distance decay function converges to 0. The hybrid decay is not discussed because it is a combination of the binary decay and/or continuous decay. Exploration of the hybrid decay can be found in McGrail (2012) and Apparicio et al. (2017), where the fast-step decay, the slow-step decay, and the continuous decay are compared.

5. Results

To implement the proposed analytic framework, we first generated the shortest path O-D cost matrix between demand points and supply points using the Network Analysis

| Table 1. The analytic framework consisting of twenty-four distance decay functions in the 2SFCA method. |
| f(d) | $d_0$ | $\beta$ | Examples |
|------------------|------------------|------------------|------------------|
| Cumulative-opportunity, rectangular (CUMR) | f(d) = 1 | 0.5 | N/A | Bell et al. 2013, |
| CUMR05 | f(d) = 1 | 0.5 | N/A | Ngui and Apparicio 2011, |
| CUMR10 | f(d) = 1 | 10 | N/A | Luo and Wang 2003 |
| CUMR20 | f(d) = 1 | 20 | N/A | |
| Cumulative-opportunity, negative linear (CUML) | f(d) = 1 - $d/d_0$ | 0.5 | N/A | Schuurman et al. 2010 |
| CUML05 | f(d) = 1 - $d/0.5$ | N/A | Bell et al. 2013, |
| CUML10 | f(d) = 1 - $d/10$ | 10 | N/A | |
| CUML20 | f(d) = 1 - $d/20$ | 20 | N/A | |
| Gravity-type inverse-power (POW) | f(d) = $d^{-\beta}$ | $\beta = \frac{\log_2 1.01}{\log_2 d_0}$ | 0.5 | 2.0 | Yao et al. 2013 |
| POW05 | f(d) = $d^{-2}$ | 0.5 | 2.0 | 2.0 |
| POW1 | f(d) = $d^{-2}$ | 1 | 2.0 |
| POW10 | f(d) = $d^{-2}$ | 10 | 2.0 |
| Gravity-type Exponential (EXP) | f(d) = $e^{-0.2d}$ | $\beta = \frac{\log_2 1.01}{\log_2 d_0}$ | 0.5 | 9.2 | Jamtsho et al. 2015 |
| EXP05 | f(d) = $e^{-9.2d}$ | 0.5 | 9.2 |
| EXP1 | f(d) = $e^{-4.6d}$ | 1 | 4.6 |
| EXP10 | f(d) = $e^{-0.5d}$ | 10 | 0.5 |
| Gravity-type Gaussian (GAUSS) | f(d) = $e^{-d^2/\beta}$ | $\beta = \frac{\log_2 1.01}{\log_2 d_0}$ | 0.5 | 0.05 | Dai 2010, |
| GAUSS05 | f(d) = $e^{-d^2/0.05}$ | 0.5 | 0.05 | |
| GAUSS1 | f(d) = $e^{-d^2/0.2}$ | 1 | 0.2 |
| GAUSS10 | f(d) = $e^{-d^2/21.7}$ | 10 | 21.7 |
| GAUSS20 | f(d) = $e^{-d^2/86.9}$ | 20 | 86.9 |
| Kernel density (KD) | f(d) = $0.75 - \left(\frac{1 - (d/d_0)^2}{0.5}\right)$ | 0.5 | NA | Dai and Wang 2011 |
| KD05 | f(d) = $0.75 - \left(\frac{1 - (d/0.5)^2}{0.5}\right)$ | 0.5 | NA |
| KD1 | f(d) = $0.75 - \left(\frac{1 - d^2}{0.5}\right)$ | 1 |
| KD10 | f(d) = $0.75 - \left(\frac{1 - (d/10)^2}{0.5}\right)$ | 10 |
| KD20 | f(d) = $0.75 - \left(\frac{1 - (d/20)^2}{0.5}\right)$ | 20 |

*If $d_0$ is too small, the $\beta$ in POW will be extremely large and will thus deviate from the realistic interpretation of the travel friction (Guy 1983, Kwan 2010). Thus, $\beta = 2.0$ is designated for POW05 and POW1.
module in ArcGIS 10.4. Then we calculated the accessibility indices based on the twenty-four 2SFCA models with customized Python scripts. Lastly, we visualized twenty-four sets of accessibility indices on the block group scale. The mapping results are included in an online data repository (Chen and Jia 2019).

5.1 Statistical correlations between models

In order to identify the difference in the evaluation outcome between models, we performed Pearson’s correlation analysis between every two of these twenty-four accessibility measures, as shown in Table 2. All correlation coefficients \(r\) are significant at the level of 0.01.

The most remarkable effect is that the correlations between models with the same distance decay function but different \(d_0\) remain significantly low, as can be seen from grey cells in Table 2. On the other hand, the majority of high correlations \((r \geq 0.80)\) exist between models with the same \(d_0\), as can be seen from the bold numbers in Table 2. The highest correlation \((r \geq 0.98)\) is found between CUML and KD with the same \(d_0\). This consistency is very likely the result of their similarity in the mathematical formulation, where CUML is a first-degree polynomial and KD is a second-degree polynomial. Other groups of high correlations \((r \geq 0.97)\) exist between EXP and POW at \(d_0 = 0.5\) and 1 and between GAUSS and EXP at \(d_0 = 10\) and 20. In addition, the models are ranked by the average of the correlation coefficients with other models in descending order, as shown in Table 3. It can be seen from the table that, POW20 is the highest in the average \(r\) \((\bar{r} = 0.57)\), and in contrast, the original model CUMR20 is relatively low \((\bar{r} = 0.34)\). In general, the average correlations are higher for models at \(d_0 = 10\) and 20 than those at \(d_0 = 0.5\) and 1.
Table 2. Pearson’s correlation coefficient ($r$) between the 2SFCA models. Correlation between models with the same distance decay function is in grey shading; high correlation ($r \geq 0.80$) is in bold text.

|        | CUMR05 | CUMR1 | CUMR10 | CUMR20 | CUML05 | CUML1 | CUML10 | CUML20 | POW05 | POW1 | POW10 | POW20 |
|--------|--------|-------|--------|--------|--------|-------|--------|--------|-------|------|-------|--------|
| CUMR05 | 1.00   | 1.00  |        |        |        |       |        |        |       |      |       |        |
| CUMR1 | 0.27   | 1.00  | 0.20   | 0.12   | 0.01  | 0.25  | 0.15   | 0.25   | 0.17  | 0.17 | 0.35  | 1.00   |
| CUMR10 | 0.14   | 0.20  | 1.00   | 0.55   | 0.05  | 0.25  | 0.15   | 0.25   | 0.78  | 1.00 | 0.88  | 1.00   |
| CUMR20 | 0.13   | 0.16  | 0.55   | 1.00   | 0.20  | 0.05  | 0.15   | 0.25   | 1.00  | 0.88 | 1.00  | 1.00   |
| CUML05 | 0.80   | 0.20  | 0.20   | 1.00   | 0.80  | 0.80  | 0.80   | 0.80   | 0.80  | 0.80 | 0.80  | 0.80   |
| CUML1 | 0.33   | 0.93  | 0.20   | 0.15   | 0.25  | 0.25  | 0.25   | 0.25   | 0.25  | 0.25 | 0.25  | 0.25   |
| CUML10 | 0.18   | 0.25  | 0.85   | 0.46   | 0.15  | 0.25  | 0.25   | 0.25   | 0.25  | 0.25 | 0.25  | 0.25   |
| CUML20 | 0.18   | 0.23  | 0.83   | 0.80   | 0.15  | 0.25  | 0.25   | 0.25   | 0.25  | 0.25 | 0.25  | 0.25   |
| POW05  | 0.95   | 0.24  | 0.13   | 0.11   | 0.88  | 0.88  | 0.88   | 0.88   | 0.88  | 0.88 | 0.88  | 0.88   |
| POW1   | 0.34   | 0.92  | 0.20   | 0.15   | 0.29  | 0.97  | 0.25   | 0.25   | 0.25  | 0.25 | 0.25  | 0.25   |
| POW10  | 0.35   | 0.41  | 0.41   | 0.23   | 0.31  | 0.66  | 0.55   | 0.55   | 0.55  | 0.55 | 0.55  | 0.55   |
| POW20  | 0.43   | 0.45  | 0.58   | 0.40   | 0.36  | 0.72  | 0.65   | 0.65   | 0.65  | 0.65 | 0.65  | 0.65   |
| EXP05  | 0.92   | 0.24  | 0.13   | 0.11   | 0.93  | 0.92  | 0.92   | 0.92   | 0.92  | 0.92 | 0.92  | 0.92   |
| EXP1   | 0.33   | 0.86  | 0.19   | 0.14   | 0.26  | 0.96  | 0.68   | 0.68   | 0.68  | 0.68 | 0.68  | 0.68   |
| EXP10  | 0.34   | 0.86  | 0.20   | 0.15   | 0.29  | 0.97  | 0.68   | 0.68   | 0.68  | 0.68 | 0.68  | 0.68   |
| EXP20  | 0.22   | 0.29  | 0.84   | 0.62   | 0.28  | 0.92  | 0.65   | 0.65   | 0.65  | 0.65 | 0.65  | 0.65   |
| GAUSS05 | 0.71  | 0.18  | 0.09   | 0.09   | 0.93  | 0.93  | 0.93   | 0.93   | 0.93  | 0.93 | 0.93  | 0.93   |
| GAUSS1 | 0.25   | 0.69  | 0.15   | 0.11   | 0.20  | 0.85  | 0.46   | 0.46   | 0.46  | 0.46 | 0.46  | 0.46   |
| GAUSS10 | 0.18  | 0.26  | 0.73   | 0.39   | 0.14  | 0.96  | 0.84   | 0.84   | 0.84  | 0.84 | 0.84  | 0.84   |
| GAUSS20 | 0.19  | 0.25  | 0.90   | 0.65   | 0.16  | 0.90  | 0.68   | 0.68   | 0.68  | 0.68 | 0.68  | 0.68   |
| KD05   | 0.85   | 0.21  | 0.12   | 0.10   | 1.00  | 1.00  | 1.00   | 1.00   | 1.00  | 1.00 | 1.00  | 1.00   |
| KD1    | 0.32   | 0.95  | 0.20   | 0.15   | 1.00  | 1.00  | 1.00   | 1.00   | 1.00  | 1.00 | 1.00  | 1.00   |
| KD10   | 0.16   | 0.23  | 0.90   | 0.48   | 0.13  | 0.99  | 0.80   | 0.80   | 0.80  | 0.80 | 0.80  | 0.80   |
| KD20   | 0.16   | 0.21  | 0.78   | 0.87   | 0.13  | 0.68  | 0.98   | 0.98   | 0.98  | 0.98 | 0.98  | 0.98   |

(Continued)
Table 2. (Continued).

|        | EXP05 | EXP1  | EXP10 | EXP20 | GAUSS05 | GAUSS1 | GAUSS10 | GAUSS20 | KD05  | KD1   | KD10  | KD20  |
|--------|-------|-------|-------|-------|---------|--------|---------|---------|-------|-------|-------|-------|
| EXP05  | 1.00  |       |       |       |         |        |         |         |       |       |       |       |
| EXP1   | 0.30  | 1.00  |       |       |         |        |         |         |       |       |       |       |
| EXP10  | 0.21  | 0.32  | 1.00  |       |         |        |         |         |       |       |       |       |
| EXP20  | 0.21  | 0.26  | 0.84  | 1.00  |         |        |         |         |       |       |       |       |
| GAUSS05| 0.89  | 0.23  | 0.16  | 0.17  | 1.00    |        |         |         |       |       |       |       |
| GAUSS1 | 0.23  | 0.94  | 0.27  | 0.20  | 0.18    | 1.00   |         |         |       |       |       |       |
| GAUSS10| 0.16  | 0.24  | 0.97  | 0.86  | 0.13    | 0.20   | 1.00    |         |       |       |       |       |
| GAUSS20| 0.18  | 0.22  | 0.76  | 0.98  | 0.14    | 0.18   | 0.81    | 1.00    |       |       |       |       |
| KD05   | 0.95  | 0.28  | 0.19  | 0.19  | 0.91    | 0.21   | 0.15    | 0.16    | 1.00  |       |       |       |
| KD1    | 0.28  | 0.94  | 0.33  | 0.28  | 0.21    | 0.81   | 0.26    | 0.24    | 0.26  | 1.00  |       |       |
| KD10   | 0.15  | 0.21  | 0.86  | 0.91  | 0.12    | 0.17   | 0.92    | 0.92    | 0.14  | 0.23  | 1.00  |       |
| KD20   | 0.15  | 0.18  | 0.55  | 0.85  | 0.12    | 0.14   | 0.59    | 0.90    | 0.14  | 0.20  | 0.71  | 1.00  |
Accessibility by urban-rural status

The evaluation of place-based accessibility concerns the travel environment where the service is delivered. This consideration stems from the distinction between urban and rural landscapes. In rural areas, because health-related service facilities are limited in both quantity and density, rural residents have a higher tolerance for long trips (Arcury et al. 2005, McGrail et al. 2015). The same observation applies to food procurement (Mceachern and Warnaby 2006); and for this reason, USDA (2017) has designated different criteria for efficient food access: urban access is defined under 0.5 miles or 1 mile; rural access is defined under 10 miles or 20 miles. Similar to a comparative study that evaluated accessibility indices by population size (McGrail 2012), we evaluated the 2SFCA models by urban-rural status and drew attention to their regional applicability.

Census block groups and urban-rural areas are two sets of administrative units, and their delineations are not overlapped. Thus, we first categorized the block groups into urban and rural units by a reclassification method employed by the USDA (2017): A block group is labeled as urban if its geographic centroid is within the USCB urbanized areas (with population of 50,000 or more) or urban clusters (with population between 2,500 and 50,000); all other block groups are considered rural.

We then evaluated the results in urban and rural block groups, respectively. First, we selected urban block groups and derived the average accessibility index for each urban unit \( i \) by the twelve models with \( d_0 = 0.5 \) and 1. Similarly, we selected rural block groups and derived the average for each rural unit \( i \) by the other twelve models with \( d_0 = 10 \) and 20. These two average accessibility indices \( \bar{A_i} \) served as the reference accessibility for urban and rural areas, respectively. We then employed the Root Mean Square Error (RMSE)
to evaluate the goodness of the fit between $A_i$ and the modeling results, as shown in Equation (5) and Table 4.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (A_i - \bar{A}_i)^2}{n}} \quad (5)$$

In urban areas, the POW1 has the best performance (RMSE = 0.47), followed by the CUML05 (RMSE = 0.34). In rural areas, GAUSS10 (RMSE = 0.84) performs significantly better than other models. In contrast, CUMR1 and CUMR20 have the least level of correspondence with $A_i$ in urban and rural areas, respectively.

### Table 4. The evaluation of the 2SFCA modeling results by urban-rural status.

The RMSE was derived between the average urban/rural accessibility ($\bar{A}_i$) and each 2SFCA model applied to urban or rural areas, respectively.

| Urban areas | RMSE with urban $\bar{A}_i$ | Rural areas | RMSE with rural $\bar{A}_i$ |
|-------------|-----------------------------|-------------|-----------------------------|
| POW1        | 0.47                        | GAUSS10     | 0.84                        |
| CUML05      | 0.34                        | EXP10       | 0.54                        |
| GAUSS05     | 0.33                        | CUML10      | 0.49                        |
| KD05        | 0.33                        | POW10       | 0.46                        |
| EXP05       | 0.32                        | KD10        | 0.46                        |
| POW05       | 0.31                        | CUMR10      | 0.41                        |
| CUMR05      | 0.27                        | POW20       | 0.16                        |
| EXP1        | 0.20                        | EXP20       | 0.11                        |
| GAUSS1      | 0.17                        | GAUSS20     | 0.10                        |
| CUML1       | 0.14                        | CUML20      | 0.09                        |
| KD1         | 0.14                        | KD20        | 0.08                        |
| CUMR1       | 0.12                        | CUMR20      | 0.08                        |

### 5.3 Variability analysis of the catchment size

The catchment size $d_0$ dictates the modeling results to a great extent, in that a high correlation exists between models with the same $d_0$ (Section 5.1) and that different $d_0$ should be applied to urban and rural areas (Section 5.2). In existing studies, $d_0$ is selected in a relatively arbitrary manner because the lack of observation on the service area of the supply or the activity data of the demand. In this regard, we would like to explore the effect of $d_0$ in the 2SFCA method.

Coefficient of variation ($CV$), defined as the division of the standard deviation to the mean, is explored in this study as the variability metric, as shown in Equation (6). The coefficient of variation was originally a measure of price volatility in economic studies (Shiue 2002). It was also employed to test the variability of landscape pattern in research on urbanization (Luck and Wu 2002). The spatial pattern becomes consistent when $CV$ becomes convergent. Thus, we examined if the spatial inequity interpreted by the 2SFCA method could be relatively consistent as the $d_0$ increases. Specifically, $CV$ was calculated for each model with a specific distance decay function. We then derived a series of $CV$ by changing the $d_0$ of the model.
\[ C_v = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n-1}} \]

where \( x_i \) is the accessibility index for a block group, \( \bar{x} \) is the average accessibility index for all block groups, and \( n \) is the total number of block groups (i.e., \( n = 2147 \)).

We conducted our experiments based on a binary decay function (CUMR20) and five continuous decay functions (i.e., CUML20, POW20, EXP20, GAUSS20, and KD20, as illustrated in Figure 3). Specifically, the distance decay function remains uniform in each set of analysis, while the inclusion-exclusion criteria differ by \( d_0 \). Figure 4 is the results of \( C_v \) yielded by these six 2SFCA models with different \( d_0 \) (ranging from 0.5 to 20 at an increment of 0.5). As Figure 4 illustrates, all models have a large degree of variability with a small \( d_0 \); when \( d_0 \) increases to a certain threshold (i.e., \( d_0 \geq 9.5 \)), \( C_v \) becomes relatively convergent. It is also observed that POW20 has a different convergence pattern than other functions.

6. Discussion

The comparative analysis of twenty-four 2SFCA models provides useful information for understanding the intricacy of the model components in the 2SFCA family. Based on the different facets of statistical analyses, we would like to offer suggestions for the choice of model parameters.

First, the catchment size \( d_0 \) plays the most significant role in the assessment of accessibility. As revealed by the correlation analysis in Table 2, there is a relatively high correlation between models with the same \( d_0 \), indicating that the accessibility

![Figure 4](image-url)
pattern is relatively consistent across different models with the same $d_0$. This result further reveals that the change of $d_0$ in the 2SFCA model may significantly affect the evaluation outcome. The variability analysis in Figure 4 further extends the observation: a small $d_0$ could largely polarize the spatial pattern and introduces a considerable degree of uncertainty; a large $d_0$, on the contrary, may smooth the spatial pattern but may conceal local clusters of extreme values. This paper confirms that this spatial smoothing effect (Luo and Wang 2003) exists in all types of 2SFCA models regardless of the distance decay.

These results necessitate the careful selection of the catchment size in 2SFCA applications. Specifically, on a small scale (e.g., community level), $d_0$ must be carefully scrutinized because of the high variability of the accessibility index. On a large scale (e.g., statewide), $d_0$ must be set beyond a certain threshold to derive a consistent spatial pattern (and this study suggests > 9.5 miles on the state scale). In most 2SFCA models, the catchment size $d_0$ and the distance impedance coefficient $\beta$ are mathematically dependent; a small catchment size $d_0$ corresponds to a large $\beta$, signifying a high level of travel friction that deters the spatial interaction (Luo and Wang 2003). Therefore, when $d_0$ is determined, $\beta$ must be adjusted accordingly.

However, the methodological discussion about $d_0$ is only based on the premise that the travel behaviors are unknown. In reality, the catchment size represents the acceptable distance that people are willing to travel (Luo and Wang 2003). Not only does the difference in the acceptable travel distance exist across travel modes but also it differs by individuals. The specification of the catchment size, thus, relies heavily on the evaluation of individuals’ activity space, which is fundamentally rooted in people’s social discourses and identities, in aspects of income, car ownership, familiarity with the neighborhood, and perception of safety (Chen and Kwan 2015). Although it is impossible to generalize these sets of knowledge in the 2SFCA method as a place-based measurement, we recommend corroborating the selection of the catchment size with field observations on people’s expected activity space. For example, McGrail et al. (2015) conducted structured surveys to investigate the maximum time that people are willing to travel to visit a doctor. Milakis et al. (2015) employed in-depth interviews to examine the acceptable time for daily commuting. These empirical investigations can be deployed in a local study for retrieving the realistic catchment size. When such observations are not available, we recommend using distance thresholds in the literature (Allan 2014), federal definitions of efficient service areas (USDA 2017), and criteria in urban planning guidelines (Chen et al. 2013).

Second, the distance decay function in the 2SFCA method affects the level of accessibility to a certain degree and is non-negligible under a large $d_0$. One noticeable result is that CUMR20 has the lowest average correlation with other models (Table 3). Also, CUMR 1 and CUMR 20 have the poorest model performance in urban and rural areas, respectively (Table 4). Under the context that a high level of correlation is the ground truth, this finding indicates that the binary decay 2SFCA model with a large $d_0$ may be relatively ineffective for accessibility evaluation. However, when a distance decay function is incorporated, the correlation with other models becomes distinctly higher. Specifically, POW20, EXP20, and GAUSS20 are the top three models in the correlation analysis (Table 3). We therefore recommend EXP20 and GAUSS20 functions for assessments in areas with a mixed service landscape. We do not recommend POW20 as it
shows a different variability pattern than other models (Figure 4). Also, we recommend GAUSS10 for rural areas, as it performs significantly better than other functions (Table 4).

The distance decay function may not be uniform: it could be weighted as different binary decays in sub-zones (Luo and Qi 2009) or could be a hybrid form combining both the binary and continuous decays (Schuurman et al. 2010). As the 2SFCA is a special case of the gravity model, the precise quantification of the distance decay should resort to the long-standing tradition of calibrating the distance decay parameters in SI models; and a thorough understanding of the interaction data and the spatial structure becomes a necessity (Fotheringham 1981). Also, the travel between origin and destination is beyond a simple movement along road networks and is confounded by travel behaviors and transport systems. Some recent 2SFCA models have attempted to incorporate these real-world complexities, using trip-chaining (Fransen et al. 2015), public transit (Langford et al. 2012), and modal split (Mao and Nekorchuk 2013, Lin et al. 2018). Improvements on the model calibration and behavioral formulation to demystify the effect of distance decay are still needed in future work.

Third, the last aspect of discussion is model validation. The majority of the 2SFCA model development has resorted to the comparison with existing models for validation, primarily the ‘milestone’ models, such as 2SFCA (Luo and Wang 2003), E2SFCA (Luo and Qi 2009), and 3SFCA (Wan et al. 2012b). Some studies have attempted to validate the 2SFCA results by comparing with existing accessibility metrics published by federal agencies, such as the USDA Food Access Research Altas (Chen 2017, 2019). The limited scope of validation efforts is very likely due to the lack of generally accepted classifications on the accessibility index, especially for health-related services in small-area estimation (McGrail et al. 2015). In the absence of a universal standard for accessibility assessment, we urge alternative means to evaluate the robustness of the 2SFCA method: testing the sensitivity of the model to different modeling parameters (Wan et al. 2012a) or different aggregation methods (Apparicio et al. 2017) to ensure the consistency of the spatial pattern and identify sources of measurement uncertainties. Only if the methodological validation is undertaken can the evaluative role of the 2SFCA method for urban planning and equity measures be justified.

7. Conclusions

The paper has employed a place-based accessibility framework to compare the performance of twenty-four 2SFCA models in a comprehensive manner. This comparison provides the theoretical support necessary to the choice of model parameters in the 2SFCA’s applications for various urban planning, service delivery, and spatial equity issues. Two important conclusions are drawn from this paper. On the one hand, on a small analysis scale, the catchment size is the most critical model component: variation in the catchment size can introduce a high degree of measurement uncertainties; under this context, justification and sensitivity analysis of the catchment size become a necessity. On the other hand, on a large analysis scale, the distance decay function is of elevated importance; using the binary decay under a large catchment size will likely overestimate the supply-demand interaction and thus obfuscate the inequity pattern of physical accessibility. Because these facets are scale-dependent, we urge caution on the selections of analysis scale, aggregation method, and the proximity measure between...
supply and demand (see Apparicio et al. 2017 for further discussion). Also, the fundamental spatial structure of the data can influence the performance of the 2SFCA method to a meaningful extent; thus, we suggest refining the statistical unit (e.g., Bell et al. 2013, Chen 2019) in future model implementation.

This exploratory study also has limitations. First, the comparison of 2SFCA models is based on the topical issue of food accessibility. The conclusions drawn from the study may not apply to other service types, scales, or regions, because of the heterogeneity of the landscape across different study areas. Second, the assessment of the accessibility by the 2SFCA method is purely place-based without accounting for individual travel behaviors or mobilities. How to leverage the supply-demand interaction articulated by the 2SFCA method for interpreting the level of accessibility actually experienced by individuals on a daily basis, and reciprocally, using the empirical evidence to corroborate the place-based accessibility metrics would be an important direction in future work.

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Data availability statement

The data that support the findings of this study are available in Github [https://github.com/peterbest52/2SFCA-Comparison]. These data were derived from the following resources available in the public domain: SNAP retailers database https://www.cbpp.org/snap-retailers-database and TIGER/Line with selected demographic and economic data https://www.census.gov/geo/maps-data/data/tiger-data.html

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