Examination of spatial accessibility at micro- and macro-levels using the enhanced two-step floating catchment area (E2SFCA) method

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ABSTRACT
Floating catchment area (FCA) metrics are a family of measures used to quantify spatial accessibility. Spatial accessibility fuses the concepts of accessibility and availability to describe the relationship between the supply and demand of resources. FCA metrics have been applied to measure accessibility of numerous amenities including health services, public transportation, and recreation areas. Macro-level data such as census tracts and census blocks are often used to represent population locations in the calculation of FCA metrics. This approach is susceptible to masking geographic variability that may exist at less aggregated levels, such as at the individual level. This research explores how level of data aggregation can impact the measurement and interpretation of FCA based metrics. Our case study uses the E2SFCA method to measure and compare the spatial accessibility of public parks using micro- and macro-level population representations. Our analysis shows a general agreement in the FCA results among various levels of data aggregation. As expected, error in the FCA measurements generally increased as larger areal units were used; however, our results also show a somewhat nuanced picture, as particularities arising from the Modifiable Areal Unit Problem and the gravity-based calculation of the E2SFCA appear to affect the resulting differences among FCA values. Because obtaining and using individual based data can be challenging for researchers, macro-level data are often the only reliable alternative. Our findings provide insight into the limitations associated with using macro-level data to measure and interpret spatial accessibility.

Introduction

In an ideal scenario, regardless of where people lived, they would have equal access to resources such as primary health care, healthy food options, or recreation opportunities. However, given that these resources are only available at finite locations, their distribution inevitably leads to geographic disparities within the populations they serve (Joseph and Phillips 1984), which leaves certain portions of the population with superior access and availability compared to others. Geographic disparities in access have been observed for numerous amenities such as primary health care, healthy food options, and public transit (Langford, Higgs, and Fry 2012; Shah, Bell, and Wilson 2016; Smith et al. 2010). Understanding how these disparities manifest and their effects on the population is often an issue of concern for public officials, as equity of access and availability are an important priority.

Measuring geographic disparities in access to services requires identifying both the accessibility and availability of resources. Measures of accessibility capture the distance people must overcome to access the resource, while measures of availability consider the amount or volume of services available, often in relation to the number of people that must be served. The integration of accessibility and availability into a single measure has been deemed, ‘spatial accessibility’ (Guagliardo 2004) and provides a richer evaluation of access, rather than measuring the two components separately. Floating catchment area (FCA) metrics are a family of measures used to quantify spatial accessibility and are built upon a modified gravity model that integrates accessibility and availability simultaneously. As a result, FCA metrics depict spatial accessibility as supply-to-population ratios, which are more easily interpretable than standard gravity model results (Delamater 2013) and provide detailed insights into the geographic distribution of spatial accessibility.

The data required to calculate spatial accessibility using most FCA metrics are population locations, resource or facility locations, and a measure of the distance separating people and resources. Frequently, population locations are represented using macro-level geographies such as US Census tracts, block groups, or...
blocks. This approach is generally necessary due to the limited availability of finer population data. However, the use of macro-level data to represent an entire group of people masks the variability of their positions within these geographic units, potentially distorting the spatial accessibility for some members of the population.

This research explores variation of spatial accessibility, as measured using FCA metrics, between and among micro-level and traditional macro-levels of population aggregation. Through this examination, we assess the impacts of data resolution on the calculation and interpretation of FCA based metrics. An array of distance, container, and coverage based accessibility measures have been evaluated in prior research; however, little to no research to our knowledge has examined aggregation error for FCA based metrics. We performed a case study applying the E2SFCA method to measure the spatial accessibility of parks within the City of Alexandria, Virginia.

**Background**

FCA-based metrics were created to address limitations in how geographic access was characterized, wherein accessibility and availability often were treated as distinct entities. Distance-based measures, such as distance to the nearest facility, capture separation, but are not able to incorporate differences in availability among facilities. Container-based regional availability measures, such as the identification of Health Professional Shortage Areas (HPSAs) and Medically Underserved Areas or Populations (MUAs/MUPs) produce physician-to-population ratios for defined service areas (i.e. county, group of counties, or portions of a county). This approach produces easy to interpret availability ratios, but distance is not accounted for within the ‘container’ and potential to access to services outside the container is not considered.

To address these limitations, Luo and Wang (2003) developed the initial FCA metric called the two-step floating catchment area (2SFCA). As the name suggests, the calculation of the 2SFCA consists of two steps. **Step 1** creates service areas (catchments) for each of the facilities (j) based on a certain distance threshold (d). For each catchment, a supply-to-demand ratio (R) is calculated by summing the population demand (P) for locations (i) that falls within the distance threshold (dij ≤ d):

\[ R_j = \frac{\sum_{i \in \{d_{ij} < d\}} P_i}{C_j} \]  

**Step 2** in the 2SFCA is similar to the first. A catchment is created for each population demand location (i), based on the same distance threshold (d) from Step 1. For each population location, the supply-to-demand ratios (Rj) for supply facilities located within the catchment are summed to obtain the final accessibility score (Ak):

\[ A_k = \sum_{j \in \{d_{kj} < d\}} R_j \]  

There are several benefits in using the 2SFCA approach. First, the 2SFCA incorporates the concepts of availability and accessibility simultaneously into metric with an output that is easy to interpret (e.g. opportunities per person). Second, calculation of this metric is straightforward using a Geographic Information System (GIS). Third, the floating catchment areas alleviate the issues associated with treating predefined areal units as containers. While the 2SFCA was a breakthrough in spatial accessibility characterization, it has shortcomings. Most notably, all people located within a catchment area are considered to have equal access and any located outside a catchment area have no access.

The Enhanced 2SFCA (E2SFCA) provided by Luo and Qi (2009) and the Kernel Density 2SFCA (KD2SFCA) provided by Dai and Wang (2011) integrate a distance decay function within the supply and demand catchments, which accounts for variations in accessibility within the catchments as a function of distance. Weights determined from the distance decay function are applied to each supply and demand pair, such that that closer pairs are more likely to interact than those further apart. The basic two steps for the E2SFCA and KD2SFCA are similar to the 2SFCA with the addition of the weight values. The first step is formulated as:

\[ R_j = \frac{S_j}{\sum_{i \in \{d_{ij} < d\}} P_i W_{ij}} \]  

where \( W_{ij} \) is the weight value provided by the distance decay function. The second step also integrates the weight values:

\[ A_k = \sum_{j} R_j W_{kj} \]  

Additional advancements and modification of FCA metrics include the Modified 2SFCA (M2SFCA) by Delamater (2013) and the 3 Step FCA (3SFCA) by Wan, Zou, and Sternberg (2012b). Zhuolin and Yang (2016) review recent FCA metrics and highlight the recent additions to the family of FCA metrics, while McGrail (2012) compares results generated from various FCA methods.

The application of FCA metrics has largely been for health care services, such as primary care (Bauer and Gronenberg, 2016; McGrail 2012; McGrail and Humphreys 2014; Cheng, Wang, and Rosenberg 2012) and tertiary care (Wan et al. 2012a). However, spatial accessibility of numerous non-health related applications have also been
evaluated using FCA metrics, such as libraries (Higgs, Langford, and Fry 2013), public transportation (Langford, Higgs, and Fry 2012), day care centres (Fransen et al. 2015), and recreation areas (e.g. Dony, Delmelle, and Delmelle 2015; Langford, Higgs, and Radcliffe 2017; Ye et al. 2014). This diversity in application underscores the robustness and usefulness of the FCA metrics to understand spatial accessibility across a variety of applications.

While much of the recent FCA-related research has gravitated towards the mechanics and applications of the metrics themselves, less has focused on the effects of the data used to calculate spatial accessibility using the metrics. Data collection costs and privacy concerns make the availability of high resolution (e.g. individual-level) population data scarce. In FCA calculations, macro-level areal units such as census tracts, census block groups or census blocks usually serve as the population units. This representation simplifies underlying spatial distribution of individuals and introduces the potential for spatial data aggregation errors, which is a longstanding challenge associated with spatial analysis in general. Particularly, the modifiable areal unit problem (Wong 2004, 2009) arises due to the data partitioning scheme, which can produce varying results with changes in resolution (scale effect) and the arrangement of the boundaries used in the partitioning scheme (zone effect). Exploring and understanding the consequences of the MAUP within spatial analysis is popular among researchers (Cheong and Park 2015; Louvet et al. 2015; Malczewski and Rinner 2015; Swift, Liu, and Uber 2014).

Some researchers have explored the extent of spatial data aggregation error as it relates to access. Omer (2006) used house-level population data and neighbourhood areal units to evaluate accessibility to parks and found accessibility measures at the neighbourhood level failed to capture individual variations of access within neighbourhoods. Mizen et al. (2015) used individual addresses, centroids of postal codes, and three UK census geographies to measure accessibility based on minimum distance using network and Euclidean distances; they suggest that network distance and the smallest unit of aggregation, preferably individual level data, should be used for more accurate accessibility measurements. Apparicio et al. (2008) used residential areas and a collection of health care facilities to evaluate aggregation and distance errors in measuring geographic accessibility and recommends using the smallest area unit possible to minimize aggregation errors. This analysis adds to this body of knowledge by specifically focusing on how the MAUP affects spatial accessibility as measured by the E2SFCA.

**Materials and methods**

**Study area**

The case study was performed for the city of Alexandria, VA, an independent city of approximately 150,000 people located within the Washington D.C. metro area (US Census Bureau 2017). Alexandria sits on the banks of the Potomac River with Fairfax and Arlington counties as neighbouring jurisdictions. Despite its small geographic size of 38.9 square kilometres, the city is dense in terms of population with 4,114 people per square kilometer compared to 1,134 in nearby Fairfax and 3,493 in Arlington Counties (US Census Bureau 2017). A diverse mix of residential, commercial and mixed use development permeates this predominantly urban area.

**Data**

The spatial data used in this analysis include buildings, sidewalks, parks, and US census unit boundaries (tracts, block groups, and blocks). All non-census data was downloaded from the City of Alexandria open data portal (http://cityofalexandria-alexgis.opendata.arcgis.com/); census-related data products were downloaded from the American Factfinder (https://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml).

The building database contains polygon representations of all buildings located within the City of Alexandria (n = 33,632) and attributes describing various characteristics of each building, such as use (residential, commercial, industrial etc.), number of residential units, and ownership information.

The census tracts, block groups and blocks data are a set of polygons representing the areal extent of each unit. Of the three geographies, blocks are the smallest (typically the size of a 2–3 city blocks) and tracts are the largest (the size of a large neighborhood). Block groups are intermediate in size, falling between blocks and tracts. These three geographies form a nested hierarchy, such that block groups are a collection of blocks and tracts are a collection of block groups. In Alexandria, there are 38 tracts, 106 block groups, and 1,287 blocks. Average household size (2010 census) was downloaded in tabular format for use in calculating population estimates and joined to the spatial features (blocks).

The parks database contains polygons that depict the areal extent of all the publicly accessible parks within Alexandria. In total, there are 141 parks of varying classifications (citywide, neighborhood, and pocket) and sizes. Citywide parks (n = 26) are the largest and range in size from 10–60 acres (4–24 ha). Neighborhood parks (n = 47) are medium sized, ranging from 2–10 acres (0.8–4 ha).
while pocket parks (n = 68) are the smallest park type and have a range of 0.1–2 acres (0.04–0.8 ha).

The sidewalk database is a polyline representation of all sidewalk centerlines within Alexandria, including those in residential neighborhoods, commercial areas, public areas (such as schools and parks), and recreation trails. The collection of sidewalks creates an interconnected walking travel network that covers the extent of Alexandria. In total, there are over 76,000 sidewalk segments in the database, totaling over 800 miles (1,287 km) in length.

Data preprocessing

Several data pre-processing tasks were performed to prepare the data for the FCA calculations and analysis. All tasks were performed using ArcGIS v10.6.

The buildings database was subset to include only residential buildings via an attribute query. The polygon features (of the building footprint) were converted into point features representing the geographic centroid and number of residential units of each building. The resulting residential building points were spatially joined to the census block data containing the average household size information. Estimates of the number of people residing in each residential building were generated by multiplying the residential units in each building by the average household size of the census block each was located within. For example, a residential building containing 2 residential units located in a census block with an average household size of 2.23 people would equal 4.46 people for that building. This dataset was used as the micro-level population data.

Macro-level population data were created for the three different census geographies by aggregating the micro-level population data (buildings) located in each areal unit. This approach ensured consistent population counts across each of the analysis scales. The macro-level data were then subset to include only units having non-zero populations, resulting in 961 blocks, 106 block groups, and 38 tracts. For each census geography layer, population weighted centroids were calculated for each areal unit using the residential buildings layer (and corresponding residential population) to enable distance calculations.

The park polygons also required conversion to a point representation for distance calculations. However, the approach of converting the park polygons to geographic centroids creates complications related to access; specifically, this approach assumes that only one point of access exist for each park, which is especially problematic for larger parks with many potential points of entry. To better reflect the reality of park access, a point layer of park entrances was created by manually placing (via heads up digitizing) points along the edges of the park boundary using a combination of satellite imagery and the sidewalk centreline data for reference. The use of aerial imagery and the sidewalk network as a digitization guide provided a representation of park entrances that better reflected real-world park entry opportunities by accounting for natural and physical obstacles. For example, if one border of a park has a tall fence that prohibits entry, no park entrance points were added along that border. Further, for parks with long borders that span several blocks, a park entrance point was placed roughly at every street block, such that there was an even coverage of park entrance points across all accessible sides of a park. Once all park entrance points were created, the original park attribute information was transferred back to the points through a spatial join. This resulted in a park entrance point layer in which each feature contained park characteristics such as name, size, and a park identifier. This point dataset represented the resource locations used in the analysis.

The sidewalk centreline database represents an interconnected travel network that can be used to model walking distances. The sidewalk line feature data were converted to a network dataset to enable network-based distance calculations. Topology checks were performed on the sidewalk network data to resolve connectivity issues. Additional sidewalk segments were manually added to residential areas, parking lots of large apartment complexes, alleys, and common pedestrian paths to ensure that all residential buildings were connected to the sidewalk network.

Travel distance calculation

An essential measurement required in the E2SFCA calculation is the distance separating the demand and supply locations. To obtain these distances, an origin-destination (OD) matrix of walking travel distances was generated within ArcGIS using the population points as origins, park entrances as destinations, and the sidewalk network as the network connecting origins and destinations. This process was completed for the micro-population dataset using the residential building locations for the origins and the park entrances for the destinations. For the three macro-population datasets, the population weighted centroids were used as the origin locations and the park entrances as the destinations. Because some parks had multiple entrances, we assigned the minimum distance separating each population and park pair under the assumption people would use the nearest entrance.

E2SFCA calculation

The E2SFCA was calculated to measure the spatial accessibility of populations to parks in Alexandria. In the E2SFCA
calculation, the population datasets were used to represent the demand locations, park entrances were used as the supply locations, and walking distances as the measure of separation among supply and demand locations.

Previous research suggests that an acceptable walking distance ranges from ¼ mile (402 m) to just over 1-mile (1,609 m) (Ayvalik and Jotin Khisty 2002; Biba, Curtin, and Manca 2010; Buehler et al. 2011; Pucher et al. 2011; Yang and Diez-Roux 2012). A distance threshold (d) of 1-mile was used in the E2SFCA calculation based on studies related to park accessibility (Maroko et al. 2009; Moore et al. 2008; Tarrant and Cordell 1999). Walking distances among supply and demand locations that were 1-mile or less were converted into weight values (W) using a Gaussian decay function, similar to those applied in other studies (Kwan 1998; Langford, Higgs, and Fry 2012) and manually adjusted (α = 3960²) such that weight values begin a steep decline at ¼ mile:

\[ W_{ij} = e^{-\frac{d_{ij}^2}{2\alpha}} \]  

(5)

The E2SFCA calculation was performed using population counts to represent potential demand (P) and park size (in acres) as the supply (S). Thus, the output unit of the E2SFCA calculation was acres per person. The calculations were performed using the micro- and macro-level population datasets, producing four distinct outputs.

**Comparison of E2SFCA output**

The comparison analysis consisted of several measurements used to evaluate how the level of data aggregation affected the results of the E2SFCA values.

To enable comparison, the micro-level E2SFCA values were aggregated to their corresponding macro-level areal unit. For each polygon in the three macro-level geography layers, the weighted-average of the E2SFCA values was calculated based on the micro-level points located within its boundaries, using the population size as the weights. The weighted average was considered as the ‘true’ measure of spatial accessibility for each of the macro-level geographies. To characterize the variability within the macro-level areal units, the standard deviation of all micro-level points falling in each unit was calculated (for each macro-level geography). The aim of this measure is to quantify the magnitude of individual variability lost when aggregating to macro-level geographies.

Pearson’s r was used to compare the similarity in the E2SFCA values across scales by comparing the output of the macro-level calculation to the ‘true’ values from the micro-level calculation. For example, at the tract level, two sets of 38 E2SFCA values were evaluated, in which one set was based on the population weighted centroid of each tract and the other used the weighted average of micro-level scores within each tract.

To further evaluate the measurement error between the E2SFCA outputs at the micro- and macro-levels, we subtracted the macro-level E2SFCA output from the weighted-average micro-level output (for each geography). This difference calculation provides insight into the accuracy of the macro-level E2SFCA measurements.

**Results**

Descriptive statistics of the E2SFCA values for each level of geography are presented in Table 1. The lowest minimum accessibility value was found at the micro- and block levels, whereas the highest minimum accessibility value was found at the census tract. The widest range of output values occurred in the block group and the narrowest range in the tracts. The block groups had the highest maximum accessibility value, while the tracts had the lowest. Overall, the variability and central tendency measures of the block group and tract values differ from the micro-level values, while the block values appear quite similar.

The E2SFCA outputs are mapped in Figure 1, demonstrating the variation in spatial accessibility within Alexandria and how that variation is captured at the different geographies. From a citywide perspective, each of the maps shows a similar overarching pattern of spatial accessibility to parks across the city. Pockets of high accessibility can be found at the eastern border, centre of the city, and parts of the southwest. Low accessibility areas are located near the northwest border and east of the city’s geographic centre. Visually comparing the results across the levels of geography, the spatial accessibility of some regions varies depending on the level of data aggregation, notably in the southwest, and central parts of Alexandria.

The Pearson’s r results comparing the macro-level E2SFCA output to the weighted average micro-level values are as follows: block r = 0.992 (p < 0.001), block group r = 0.886 (p < 0.001), and tract r = 0.8796 (p < 0.001). The magnitude and direction of the correlation results confirm the intuitive hypothesis that units with a higher resolution would be more similar to the micro-level results than units with a coarser resolution.

Table 2 and Figure 2 show results from the standard deviation calculation (standard deviation of the FCA values)

| Geography   | Mean     | Min   | Max     | Range   | Standard Dev |
|-------------|----------|-------|---------|---------|--------------|
| Micro-level | 0.006828 | 0.0   | 0.031793| 0.031793| 0.004897     |
| Blocks      | 0.008079 | 0.0   | 0.033582| 0.033582| 0.005236     |
| Block Groups| 0.007167 | 0.000067| 0.042612| 0.042045| 0.005591     |
| Tracts      | 0.006343 | 0.000696| 0.016431| 0.015735| 0.004239     |
Overall, the standard deviation of spatial accessibility within the areal units is low throughout much of Alexandria. However, as the size of the polygons increase, larger standard deviation values are noticeable; specifically, at the block group and tract levels, several polygons have high standard deviations such as those in the central, eastern and south eastern parts of the city. Table 2 indicates that the block-level areas contain the least amount of variation compared to the block-group and tract areas, which seems logical when considering their relative sizes. However, a surprising result is that the block group level data have the highest standard deviation values, which may suggest a central tendency leveling effect occurring at the tract level.

The results of the measurement error calculation are provided in Table 3 and Figure 3. Negative values represent areas where the macro-level geography underestimated accessibility and positive values show areas of overestimation. As Figure 3 shows, each of the macro-level geographies contain high values of both under- and overestimation. Table 3 indicates that the block group level contains the areal unit with the single largest measurement error at 0.022624. As expected, the block geography has the lowest average measurement error (0.00019) out of the three macro-level geographies, while the tract has the highest (−0.000436).

Measurement error within this context, whether overestimated or underestimated, has a direct impact on how...
the results of an FCA analysis are interpreted. Using the classification bins in Figure 3 as reference, the number of people who would have their spatial accessibility misrepresented (either over- or underestimation) was approximated for each geography. The middle bin (−0.002499–0.002500) represents a relatively small error and is where the much of the population fell for all three geographies; the exact values were blocks: 159,829 people (98.1% of the total population), block groups: 137,552 people (84.4%), and tracts: 145,754 (89.5%). When examining the largest magnitude of error including both underestimates (less than −0.005) and overestimates (greater than 0.005), the block group geography had the highest number of affected persons at 13,582 (8.3% of total population), blocks had the fewest at 966 (0.6%), while the tract geography had 6,263 people (3.8% of the total geography). Interestingly, in the study area, the block group level of aggregation often produced worse results than the tract level.

**Discussion**

Due to limitations in data availability, most applications of FCA methods use polygon centroids to represent population locations for distance calculations. Our analysis demonstrated that the centroid-based macro-level calculations were generally in agreement with the micro-level calculations; however, we did identify areas in which the centroid-based approach is susceptible to the miscalculation, and therefore misinterpretation, of spatial accessibility using FCA metrics.

While the potential for the MAUP exists when performing any spatial analysis using aggregated observations, it is likely exacerbated by the gravity-based formulation of the E2SFCA. For example, in Figure 3, some polygons are quite similar in size and shape at the block group and tract level but their margin of error either decreases (see mid-northwest, eastern areas) or increases (mid-western area) between these scales. The centroid locations of these polygons only change slightly. However, the centroids of their neighbouring
polygons change between levels of aggregation. Due to the gravity-based formulation of the E2SFCA, a change to one polygon will influence the spatial accessibility calculations for all polygons in that area.

Because FCA methods rely on distance measurements, the expectation would be that distances measured from the centroids of larger aggregation units would lead to larger errors. Further, we would expect less variation in the E2SFCA output as the level of aggregation increased due to central tendency levelling. While our findings show that these expectations generally hold for the E2SFCA results in this study area, we did observe deviations at the block group level (i.e. highest range of E2SFCA output values and largest single-observation measurement error value). Factors such as the distribution of the population within the units, the shape of the units, and peculiarities of the road network within the units (e.g. if the centroid happens to fall in a region with poor connectivity to main roads) can also impact the resulting E2SFCA values. We suspect that the block group deviations are specific to the study area and are not a meaningful finding; however, this does present an opportunity for future research.

One obvious solution to the problems associated with data aggregation is to restrict analysis to only consider individual or other high-resolution data when measuring spatial accessibility. Individual data allows for a more realistic depiction of access compared to the macro-level scales, as revealed by this research and others such as Omer (2006) and Mizen et al. (2015). However, there are challenges associated with individual data. Privacy concerns and data collection costs are significant barriers to the availability of individual data. For some regions, grid-based population data estimates (e.g. Landscan or SEDAC) may offer a higher resolution alternative to data tied to administrative units or census-based collection units; however, for urbanized study areas in developed countries (such as our study area), the administrative data are likely available at a finer resolution than grid-based alternatives. Furthermore, if researchers do obtain individual or extremely high resolution data (e.g. all residential buildings in a US state or an entire country), the FCA calculation would require additional computational power and processing time. These limitations often leave macro-level population datasets as the only viable option, and our research highlights the potential ramifications of using these data.

The pitfalls associated with using macro-level data to calculate FCA metrics are critical for researchers and public officials to understand because policy decisions based on the results may fail to address the intended populations or problems. FCA metrics are often used to
highlight or identify regions with low spatial accessibility; interestingly, our findings suggest that measurement error and variability are smaller for regions with relatively lower spatial accessibility. As such, the potential effects of aggregation error may be dampened in the regions that are often the focus of the analysis.

There are limitations with this analysis. Hewko, Smoyer-Tomic, and Hodgson (2002) suggest that spatial aggregation error in spatial accessibility studies is dependent on study area and the spatial properties of the amenity being examined. To that point, our case study only examined a single study area and access to parks, so the results may not be generalizable across study areas or services; future studies are warranted to evaluate whether similar results are found in different settings and for different services.

An additional limitation of our analysis is the use of a single distance decay function and set of parameters in the E2SFCA calculations. The decision to use one function and set of parameters allowed for a more in-depth analysis on the effects of data aggregation on E2SFCA results, but also did not allow us to evaluate potential sensitivity of our findings to changes in the distance decay function. While converting the E2SFCA output to normalized metrics such as the Spatial Accessibility Index (SPAI) or Ratio (SPAR) reduces sensitivity to changes in the decay function (Wan et al. 2012a; Lin et al. 2018), this option was not appropriate for this analysis because we were concerned with evaluating the absolute differences in the E2SFCA output between levels of aggregation. Future research could extend our work to consider how variations in the distance decay function or parameter settings interacts with the MAUP effects or whether SPAI and SPAR values are less sensitive to MAUP effects.

This research explored how data aggregation and scale can impact the measurement and interpretation of spatial accessibility as measured using the E2SFCA. We found that the level of aggregation can affect the analysis and the resulting identification of regions having high and low spatial accessibility. While macro-level population datasets are more accessible than individual data, they introduce errors in measuring spatial accessibility, which can result in potentially misleading information regarding a population’s access to a resource. These results are important for researchers to understand and acknowledge if using FCA metrics.

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Data availability

The data used in the analysis are publicly available online. Links have been provided in the manuscript text.

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