Accessibility to Primary Care Physicians: Comparing Floating Catchments with a Utility-based Approach

Author One[a], Author One[*,a], Author One[a], Author One[a]

[a] *Address*

Abstract

Floating Catchment Area (FCA) methods are a popular choice for modelling accessibility to healthcare services because of their ability to consider both supply and demand. However, FCA methods do not fully consider aspects of travel and choicemaking behaviour as the only behavioural component is the impedance function. FCA approaches also tend to assign population demand to clinics and levels-of-service to population zones in an overlapping manner that has been shown to bias results by inflating/deflating supply and demand. While the adjustments proposed in the recent "Balanced FCA" method can rectify this, it apportions population and levels of service in a fractional manner. In response, this research proposes a utility-based measure of healthcare accessibility based on a multinomial logit (MNL) destination choice model that avoids the multiple-counting issue in FCA methods and considers several additional behavioural aspects that define the appeal of clinics in addition to the travel time required to reach them, including their capacity and level of crowding. Comparisons of the MNL approach with the original and balanced FCA models using data for the City of Hamilton, Canada, suggests that while the accessibility patterns produced by each method are broadly similar, some key differences exist in the calculated accessibilities and their spatial patterns. The MNL model in particular estimates higher accessibilities in suburban and rural areas. Based on these findings, we argue that both the Balanced FCA and MNL approaches offer merit for planning and policy.

Key words: healthcare accessibility place-based accessibility utility-based accessibility destination choice model accessibility analysis

Introduction

The global COVID-19 pandemic has emphasized the importance of healthcare accessibility, particularly access to primary care physicians, who provide the first point of contact between patients and the healthcare system. In Canada, the Canada Health Act states that all residents should have "reasonable access" to healthcare. However, the 2017 Canadian Community Health Survey revealed that 15.3% of Canadians aged 12 or over did not have a primary care physician, of whom 17.2% stated that there is no physician accessible within their area (StatsCan, 2019).

*Corresponding Author

Email addresses: `Some Email` (Author One), `Some Email` (Author One), `Some Email` (Author One), `Some Email` (Author One)

Accessibility to healthcare services is defined by both spatial and aspatial components (Joseph and Bantock, 1982). Aspatial factors include the cost and quality of healthcare services and the socioeconomic, demographic, and mobility profile of potential users (Joseph and Bantock, 1982). The second component considers geographic accessibility, which can be defined as the potential to interact with a given set of opportunities, such as healthcare facilities or primary care physicians, from a given location using the transportation network (Hansen, 1959). Accessibility to healthcare can therefore be improved through either an increase in the number of available opportunities or through improvements to the transportation network.

In general, four approaches for calculating accessibility exist: infrastructure-based, which focuses on the capacity of transportation infrastructure; location-based, which focuses on spatial distributions of opportunities; person-based, which focuses on accessibility on an individual level; and utility-based, which focuses on the utility derived from interacting with the opportunity or participating in an activity (Geurs and van Wee, 2004). Place-based measures are the most common in the literature and, of these, the family of "floating catchment area" (FCA) methods is one of the most popular approaches for calculating measures of place-based healthcare accessibility that takes the competition for opportunities into account. Because healthcare access is sensitive to demand and supply, Luo and Wang (Luo and Wang, 2003) (drawing on Radke and Mu (2000)) introduced the Two-step Floating Catchment Area (2SFCA) method that first estimates the demand for healthcare at service locations from population zones and then allocates the level of service back to the population zones using a binary measure of travel impedance.

Since then, various improvements have been made to the 2SFCA approach including adjustments to better capture the friction of distance (Apparicio et al., 2017). The original 2SFCA has also been criticized for over-estimating demand and under-estimating levels of service in the estimation of accessibilities due to the multiple-counting of populations that arises from the overlapping catchments in a study area. In response, researchers have proposed solutions such as the Three-step Floating Catchment Area (3SFCA) (Wan et al., 2012), Modified 2SFCA (M2SFCA) (Delamater, 2013), and Balanced 2SFCA (B2SFCA) (Paez et al., 2019) methods. Of these, the B2SFCA is the only approach that preserves the original population and resulting levels of service in calculating floating catchment accessibilities.

However, despite these innovations, FCA methods remain limited in several ways. First, FCA approaches often inflate or deflate demand and supply in the calculation of healthcare access. While the B2SFCA remedies this, it does so by assigning fractions of populations to clinics and service ratios to population zones. Although the parameters of the balanced method sum to the original zonal populations and provider-to-population ratios, this fractional approach does not reflect the ways in which individuals choose to visit facilities. Second, the appeal of any given healthcare facility from the perspective of the population is based solely on its distance or travel time from the origin zone using the transportation network.

In response, this research utilizes a random utility-based formulation for modelling accessibility to healthcare services. Utility-based measures of access are flexible and allow the analyst to include any information that corresponds to the expected value or attractiveness of travel alternatives. While commonly used in alternatives appraisals for transport infrastructure (de Jong et al., 2007), utility-based measures of accessibility have not been as widely applied to capture other types of access. However, they appear to be gaining some traction with recent applications considering transit accessibility (Nassir et al., 2016), first/last mile access to transit (Hasnine et al., 2019), regional accessibility by income class (Jang and Lee, 2020), and accessibility to parks (Macfarlane et al., 2020). To the best of our knowledge, utility-based methods have not yet been applied to the problem of healthcare access. In contrast to FCA approaches, each patient is, on average, assigned to a single clinic, avoiding the issue of double-counting and inflation/deflation of the demand and levels-of-service respectively in the 2SFCA methods and the assignment of fractional individuals to clinics in the B2SFCA method. Beyond travel time, this specification also allows the analyst to include additional characteristics of the facilities that affect their appeal, such as competition or crowding at the facility.

To illustrate the potential of the MNL approach, we compare it against the use of the 2SFCA and B2SFCA, both using a continuous decay function. To facilitate open and reproducible research in the spatial sciences (Brunsdon and Comber, 2020; Páez, 2021), all data and code for this analysis are contained within computational notebooks available at (self-citation; .zip of files for review available anonymously via Google Drive link).

Methodology

Floating Catchment Methods

The 2SFCA method, developed by Luo and Wang (2003), calculates accessibility to healthcare using catchment areas based on a travel time threshold. The first step of this method is calculating the physician-to-population ratio, R_j, for each clinic at location j:

$$R_j = \frac{S_j}{\sum_i P_i W_{ij}}$$

Where S_j is the number of physicians at clinic j and P_i is the population of zone i weighted by some function of the travel time W_{ij} between zones i and j. In the original 2SFCA, Luo and Wang (2003) utilize a binary impedance function:

$$W_{ij} = f(t_{ij}) = \begin{cases} 1 & t_{ij} \le t_0 \\ 0 & t_{ij} > t_0 \end{cases}$$

where the weight equals 1 for populations within the travel time threshold t_0 and zero beyond. In this case, Luo and Wang (2003) set $t_0 = 15$ minutes. The second step calculates accessibility A_i for the population centres as the sum of the physician-to-population ratios R_j weighted by the impedance function:

$$A_i = \sum_j R_j W_{ij}$$

While the 2SFCA approach is a special case of a gravity-based accessibility measure, the binary impedance function used by Luo and Wang (2003) does not consider the effects of competition and travel impedance within a given catchment area. All clinics within a population centre's catchment area are considered equally accessible, regardless of distance, size, wait times, or any other measures of attractiveness. Moreover, all clinics outside of a population centre's catchment area are considered completely inaccessible. To remedy this, Luo and Qi (2009) propose the Enhanced 2-step Floating Catchment Area (E2SFCA) method that introduces categorical weights for different travel time thresholds to account for travel impedance. Others have improved on the 2SFCA and E2SFCA by using variable catchment sizes (McGrail and Humphreys, 2009), continuous travel time decay functions (Dai, 2010), and adaptive approaches (Bauer and Groneberg, 2016) to better reflect travel time costs and the greater appeal of more proximate opportunities.

Researchers have also sought to improve the ways in which supply and demand are modeled in floating catchment approaches. Previous research has shown that both demand and supply can be inflated/deflated in FCA methods (Delamater, 2013; Paez et al., 2019; Wan et al., 2012). This is a consequence of the overlapping floating catchments that cause the populations in zones i to be counted multiple times in the calculation of the provider-to-population ratio R_j. These levels-of-service are, in turn, counted multiple times when allocated back to the population zones in the calculation of A_i. In response, Wan et al. (2012)] propose the use of additional Gaussian weights to modify the binary impedance function used by Luo and Wang (2003). Delamater's (2013) M2SFCA modifies the second step of the 2SFCA approach by squaring the impedance function to increase the rate of decay on the level of service. This is done to reflect the increased friction population centres may experience when accessing healthcare facilities in sub-optimally configured urban systems.

However, neither of these approaches fully resolves the issue of demand and supply inflation/deflation. To that end, the B2SFCA approach from Páez et al. (2019) replaces the impedance functions with row-standardized weights W_{ij}^i in the first step:

$$R_j = \frac{S_j}{\sum_i P_i W_{ij}^i}$$

$$W_{ij}^i = \frac{W_{ij}}{\sum_j W_{ij}}$$

and with column-standardized weights W_{ij}^j in the second step:

$$A_i = \sum_j R_j W_{ij}^j$$

$$W_{ij}^j = \frac{W_{ij}}{\sum_i W_{ij}}$$

In this formulation, the travel-time weighted populations sum to the original population values and do not deflate the level-of-service at the clinics. By extension, the levels of service available at the population centres are not inflated through multiple counting. Nevertheless, despite offering balance across both stages of the FCA approach, the B2SFCA also results in fractional apportionment of the population and levels-of-service between the population zones and clinics.

For this research, we employ both the 2SFCA and B2SFCA approaches with a negative exponential impedance function:

$$W_{ij} = e^{-\beta t_{ij}}$$

where β is a parameter that determines the decay of the function and t_{ij} is the travel time between clinic j and population centre i. The β parameter is set to 0.05 as this is in the range of typical auto travel time parameters in logit mode choice models calibrated in the Greater Toronto and Hamilton Area. Travel times are calculated based on car travel using a street network from OpenStreetMap and the `r5r` routing tool (Pereira et al., 2021).

Utility-based Method

To address the limitations of existing methods, a novel methodology for deriving utility-based accessibility is developed which assigns trips from households in population centres to clinics. The general form of this function is as follows:

$$T_{ij} = f(H_i, Z_j, D_j, t_{ij}, \beta)$$

where:

- T_{ij} is the number of trips from zone i to clinic j
- H_i is the number of households in zone i
- Z_j is the number of doctors at clinic j
- D_j is the demand-to-capacity ratio at clinic j (note this is inverted from the physician-to-population ratios used in previous FCA approaches)
- t_{ij} is the travel time between zones i and j, and β is a row vector of parameters to be estimated.

To estimate these parameters, information minimization is used as this approach allows for the least-biased parameter estimation and has been proven to be identical to utility maximization (Anas, 1983). Based on information minimization theory, the probability that a household in zone i will visit clinic j can be estimated as follows:

$$MAX_{T_{ij}} E = -\sum_{j \in J} \sum_{i \in I} T_{ij} log(T_{ij})$$

Subject to the following constraints:

$$\sum_{j \in J} T_{ij} = \alpha H_i \forall i \in I$$

$$\sum_{i \in I} \sum_{j \in J} T_{ij} t_{ij} = \bar{t} T$$

$$\sum_{i \in I} \sum_{j \in J} T_{ij} log(C_j) = \sum_{i \in I} \sum_{j \in J} T_{ij} log \omega Z_j = \bar{C} T$$

$$\sum_{i \in I} \sum_{j \in J} T_{ij} D_j = \bar{D} T$$

where:

- I is the set of all residential zones
- J is the set of all clinics
- α is the average number of visits to the doctor per household
- $\bar{t}$ is the average observed travel time for home-based trips to clinics
- T is the total number of daily trips to clinics
- C_j is the nominal service capacity at clinic j
- ω is the average number of patients served by a doctor per day
- $\bar{C}$ is the average observed nominal service capacity
- $\bar{D}$ is the average observed demand-to-capacity ratio
- H is the total number of households
- Z is the total number of primary care physicians

The service capacities and demand-to-capacity ratios are calculated as follows:

$$C_j = \omega Z_j$$

$$D_j = \frac{\sum_{i \in I} T_{ij}}{C_j} = \frac{\sum_{i \in I} T_{ij}}{\omega Z_j}$$

Solving this set of equations yields the following:

$$T_{ij} = \alpha H_i Pr_{ij}$$

This is a singly-constrained gravity model where the probability that a household in zone i will visit clinic j is as follows:

$$Pr_{ij} = \frac{e^{\beta_1 t_{ij} + \beta_{K+2} log \omega Z_j + \beta_{K+3} D_j}}{\sum_{j'} e^{\beta_1 t_{ij'} + \beta_{K+2} log \omega Z_{j'} + \beta_{K+3} D_{j'}}}$$

Ideally, the three β parameters would be estimated iteratively in order to meet the outlined constraints. However, due to a lack of observed data on trips to doctors in the study area, these parameters are instead chosen based on the following considerations:

- The β_1 travel time impedance parameter is set to -0.05 based on previous choice models in the region (Kasraian et al., 2020) and to align with the 2SFCA and B2SFCA approaches above.
- Random utility theory requires the β_{K+2} capacity attractiveness parameter to lie between 0 to 1 in value. It is set equal to 1 in this case to maximize the attractiveness of larger clinics with more physicians.
- No theory is currently available to guide the choice of the β_{K+3} parameter that influences sensitivity to overcrowding when trip demand exceeds the capacity to see patients at a clinic. In this case, -0.5 is chosen as a "first guess" value that would produce a reasonable sensitivity to clinic over-crowding, but not prevent over-crowding from occurring.

These values ensure that increased travel times and demand-to-capacity ratios reduce the probability that a household in zone i will visit clinic j, while increased capacity at clinic j increases the probability.

In order to ensure that the average observed demand-to-capacity ratio $\bar{D}$ is approximately equal to 1, the α and ω parameters are assumed to be 0.065 visits to the doctor per household and 22 patients seen by a doctor per day, on average, respectively. The patients per day number is derived from the Canadian Institute for Health Information who reports that the median number of patients seen by primary care physicians during a typical work week in Ontario was 100 in 2019 (CIHI, 2020). At an assumed 20 patients per day over a 5-day work week and 50 weeks in a typical year after holidays, this results in an estimated patient capacity of approximately 3.2 million patients per year across the 631 primary care physicians in the data, or 5.9 visits per person per year. On the other hand, Vogel (2017) reports a Canada-wide average of 7.6 visits per person per year in 2016, which would result in demand for more than 4 million visits per year from the population residing in the City of Hamilton. Taking into consideration that Hamilton is part of the larger Greater Golden Horseshoe region, meaning not all trips and visits are bounded by the study area, and the uncertainties surrounding the estimated visits per year and physician practices, we slightly increased the number of patients seen per physician per day to 110 for a capacity of 6.46 visits per person per year and a total of 13,882 trips generated per day. Dividing the total estimated number of daily trips by the number of households yields a household trip generation rate of approximately 0.065 trips per household per day.

Since D_j is a function of T_{ij} and vice-versa, an iterative approach is taken to estimate the D_j values. The multinomial logit destination choice model ensures that demand at clinics is not over-estimated, as each patient on average is assigned to a single clinic and is not double counted, as occurs in the 2SFCA method. The end result is an approach that involves location choice modelling by maximizing utility for patients, with clinics with higher demand and longer travel times attracting fewer trips while larger clinics that are uncongested and those closer to the origins attract more trips.

Utility-based Accessibility

While the probability of visiting a particular clinic is based on its utility relative to the utility of others available within the choice set, following Ben-Akiva and Lerman (1985), the expected maximum utility from all destination choices available to a household can be understood as a random utility theory-based measure of accessibility. For the multinomial logit (MNL) model, it can be shown that this is the logarithm of the denominator (the so-called "logsum" or "inclusive value" term), yielding for this model the following accessibility measure:

$$A_i = log(\sum_{j\prime} e^{\beta_1 t_{ij\prime} + \beta_{K+2} log \omega Z_{j\prime} + \beta_{K+3} D_{j\prime}})$$

where accessibility is based not only on the utility of the clinic with the greatest probability of visitation, but the utility of all clinics available to a household considering travel impedance, clinic size and capacity, trip-based household demand for primary care physicians, and congestion or crowding.

Study Area

The study area for this research is the City of Hamilton in Ontario, Canada. Based on data from the 2016 Canadian Census of Population, the population of Hamilton is 536,917 living in 211,596 households. Based on the assumed $\omega = 0.065$ visits to the doctor per household, this results in 13,753.74 trips to the doctor entering the MNL model. The left panel of Figure 1 plots population densities in the Dissemination Areas (DAs) in the City of Hamilton, highlighting that the higher-density urban core is surrounded by lower-density suburbs that extend into land that is largely rural in character. DAs are the smallest geographic unit in the census for which socioeconomic and demographic data are publicly available.

Information on the count and location of primary care physicians was obtained using the College of Physicians and Surgeons of Ontario's online registration database. Clinic locations were geocoded based on their address and records were aggregated to count the number of physicians practicing at each unique location. The data for this paper have been used previously by Páez et al. (2019), although in this case we consider only clinics that are within the spatial extent of the City of Hamilton. While this does introduce edge effects in the calculation of accessibility, limiting the study extent to a closed system permits calculation of the multinomial logit model's congestion effects and utility-based accessibilities. In total, there are 631 primary care physicians available at clinics in the City of Hamilton in our data. Note that this is not strictly the number of physicians, as some physicians offer services at more than one clinic. Rather, it reflects the availability of physicians at given locations. The right panel of Figure 1 plots the location and total number of available physicians at the clinic locations. This total produces a city-wide average provider-to-population ratio of 117.52 primary care doctors available per 100,000 people. Based on our assumption

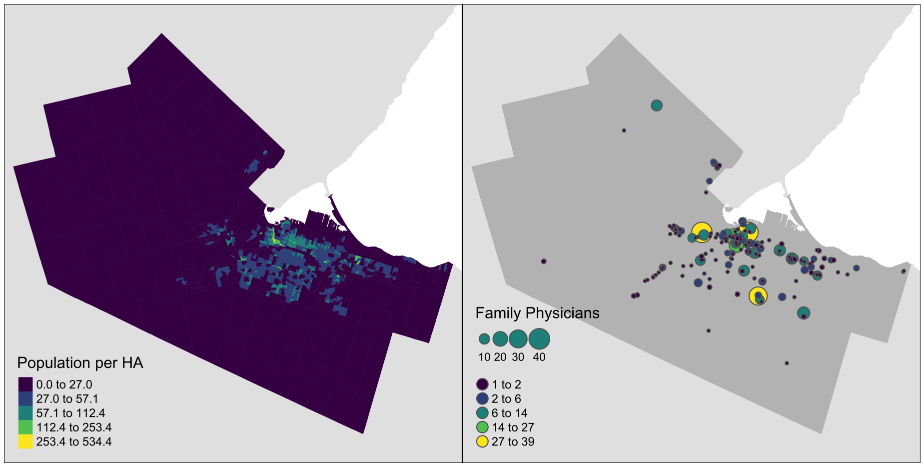

Figure 1: Population Density and Physician Locations

of $\alpha = 22$ patients seen per doctor every day, this results in a total capacity of 13,882 patient visits per day in the MNL model formulation.

Results

Demand and Clinic Level of Service

To compare the three methods, we focus first on the results associated with how each of the methods calculates demand and levels of service at the clinic locations. The level of service for the FCA approaches is the local provider-to-population ratio (PPR) for each clinic while the MNL model calculates trip demand-to-patient capacity ratios (DCR). To make this comparable, we first take the inverse of the MNL ratios to reflect patient capacity-to-trip demand ratio (CDR). Figure 2 displays a pair plot of the density of each level-of-service statistic and their relationship and correlations with one another. The plot highlights how the 2SFCA and B2SFCA methods are fundamentally similar in the ways in which they allocate demand to the clinics with only a few clinics above or below the scatterplot trend line. Likewise, it is interesting to note the relatively high correlations between the PPRs at the clinics in the FCA methods and the capacity-to-demand ratios in the MNL model with the scatterplot revealing some non-linearity in this relationship across the methods.

Figure 3 displays the levels of service for the clinic locations. In general, more urban clinics tend to exhibit higher levels of demand and lower levels of service across all three models. However, the PPR values for the individual clinics in the 2SFCA are extremely small compared to results from the B2SFCA model, highlighting how the original method's multiple counting tends to inflate the (travel time weighted) population numbers in each clinic's catchment and deflate the level of service available at the clinics. In contrast, the PPRs in the B2SFCA method are readily interpretable as the local ratio of doctors per person for a

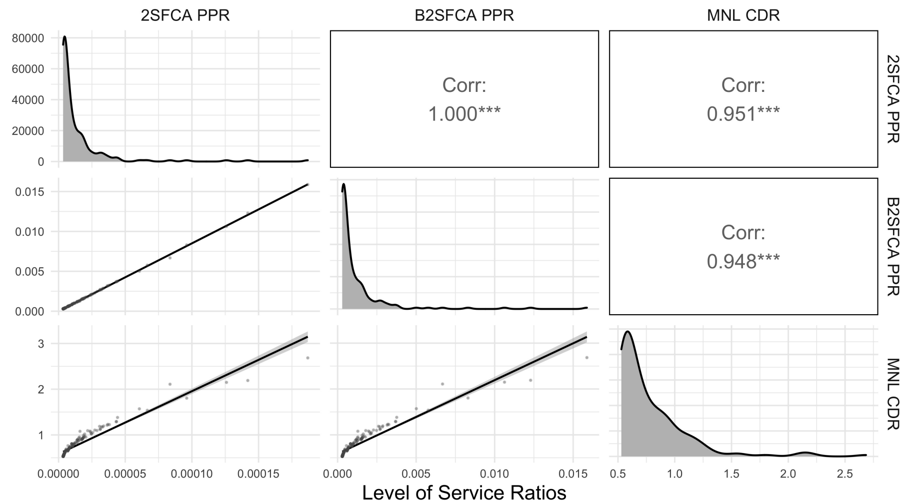

Figure 2: Comparing Level of Service Distributions

given clinic considering the (travel-time weighted and apportioned) populations within its catchment. Similarly, the MNL CDRs reflect the relationship between the trip demand and patient capacity based on the assumed rates. In terms of spatial trends, results from the 2SFCA and MNL models suggest both calculate higher levels of service at larger clinics in the urban core as well as at a larger clinic in the city's rural north-west. In contrast, the B2SFCA method generally produces higher levels of service in an east-to-west direction. This could reflect boundary effects in the study area that omit the large populations present in the rest of the Greater Toronto Area on the northern side of Lake Ontario that may also have access to these clinics by driving.

Healthcare Accessibility

With the levels of service calculated above, the three models then calculate accessibility to healthcare services in Hamilton. Distributions, relationships, and correlations for the accessibility results are shown in Figure 4. In this case, all three models are highly correlated. The 2SFCA and B2SFCA produce nearly identical distributions of results, although in the case of the balanced method, the accessibilities correspond to the sum of travel time weighted and apportioned provider-to-population ratios available in the population zones free of the inflation and deflation that occurs in the 2SFCA. In contrast, the scatterplots of the MNL results again highlight some non-linearity in the way the utility-based accessibilities are calculated compared to the FCA methods. The thinner tail of the MNL distribution suggests the method also results in fewer population zones with lower accessibility compared to the FCA methods.

The general spatial trends are similar across all three models (Figure 5). The absolute accessibility values differ in accordance with the ways each method

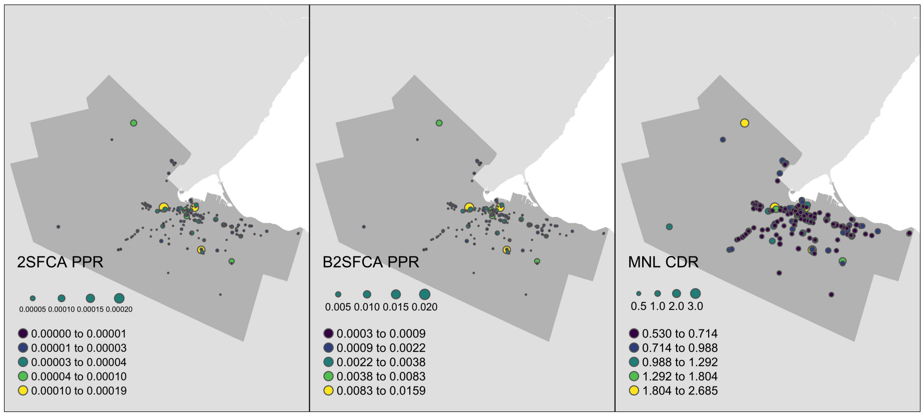

Figure 3: Calculated Clinic Levels of Service

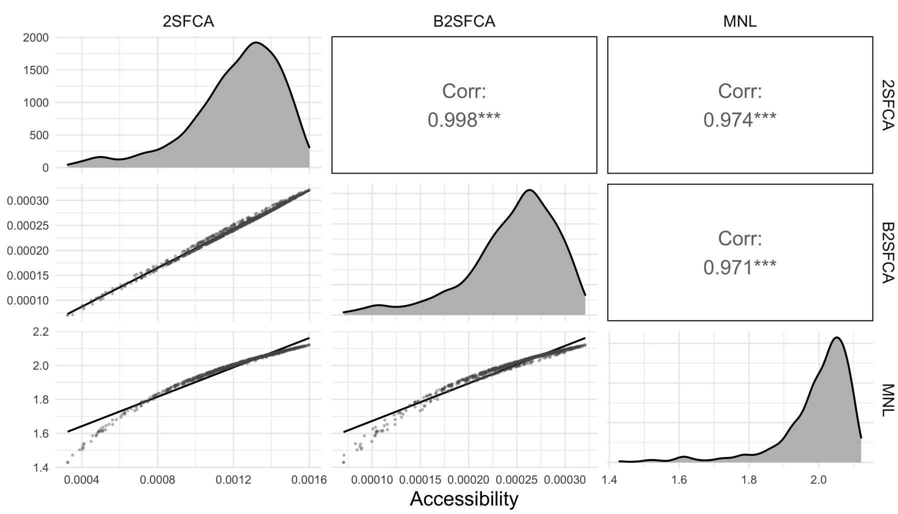

Figure 4: Comparing Accessibility Distributions

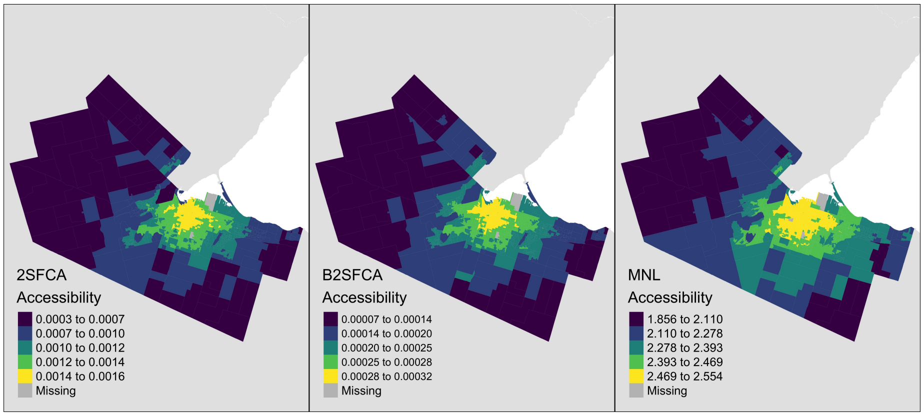

Figure 5: Accessibility Results

calculates its accessibility results. The FCA methods define accessibility based on the physician-to-population ratios of clinics, resulting in smaller values. In contrast, the MNL method defines accessibilities as the logsum of the multinomial logit model, resulting in larger values that have no direct interpretation. In general, the highest accessibilities to primary care physicians correspond to the downtown area of Hamilton, where a large number of clinics are concentrated. Accessibility to physicians generally decreases with increased distance from the downtown area.

To better highlight significant differences in the spatial patterns of accessibility produced by each method, Figure 6 displays the absolute differences in the normalized accessibilities across models. To make the values comparable, we first normalize each accessibility vector between 0-1 and take the differences of the normalized values across each approach. In general, the MNL method tends to produce higher accessibilities for most zones compared to the FCA methods. In line with the distributions above, the 2SFCA and B2SFCA models appear to be most similar, with only slight absolute differences in the calculated accessibility values.

To examine whether there are any spatial patterns in these differences, Figure 7 plots the results of Local Moran's I tests. The Local Moran's I is calculated on the differences using queen-style contiguity weights, a critical significance level of $p = 0.05$, and without correcting for multiple testing. The resulting maps reveal some interesting patterns of spatial clustering in the calculated normalized differences, particularly across the two FCA models compared to the MNL model. Here, differences in accessibility are greatest between the FCA and MNL methods in the low-low (LL) cluster in the ring of outer suburbs that surround the city where the MNL model tends to estimate higher accessibilities. In contrast, the calculated accessibilities are more consistent across the methods in the high-high (HH) cluster in the central part of the city. Differences in the remaining zones are generally not significant (NS) aside from a very small

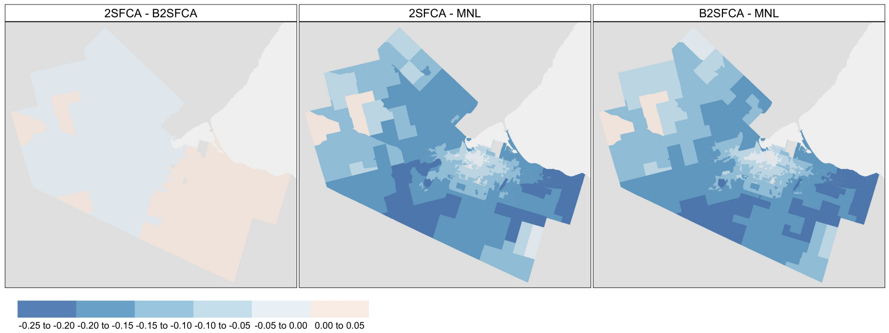

Figure 6: Normalized Accessibility Differences

number of high-low (HL) and low-high (LH) outliers.

This overall pattern is likely due to the way the MNL approach handles clinic choices with populations tending to select their nearest clinics. On the one hand, the greater accessibilities in more suburban and rural zones is likely derived from these populations accessing their closest facility. On the other hand, this also means that fewer individuals from more urban locations are competing for healthcare resources in these more suburban and rural areas, leading to higher levels of service at these suburban and rural clinics. In contrast, the FCA methods allocate populations to all clinics within their catchment area using weights derived from the impedance function. While this produces a smoothing of the accessibilities, it can result in lower levels of service and accessibility for clinics that populations may not actually use. This effect seems to be minimized in more urban locations featuring higher population densities and a greater number of clinics with available physicians. Comparing the normalized results from the 2SFCA and the B2SFCA models, the patterns of spatial clustering in the differences appears to be less associated with the city's urban-suburban-rural urban structure. While the B2SFCA method generally calculates slightly higher accessibilities across the western half of the city, the methods are most dissimilar in the south-east rural area.

Sensitivity Analysis

In order to assess the impact of the β_{K+2} and β_{K+3} parameters on the results generated by the MNL method, a sensitivity analysis was undertaken. The β_{K+2} parameter that influences the attractiveness of higher-capacity clinics was gradually increased from 0.1 to 1 and the β_{K+3} parameter that influences sensitivity to congestion or crowding at the clinics was gradually increased from -1 to -0.1. Increments of 0.1 are used for each variable. Results are summarized by calculating average CDRs and accessibilities across the clinics and DAs

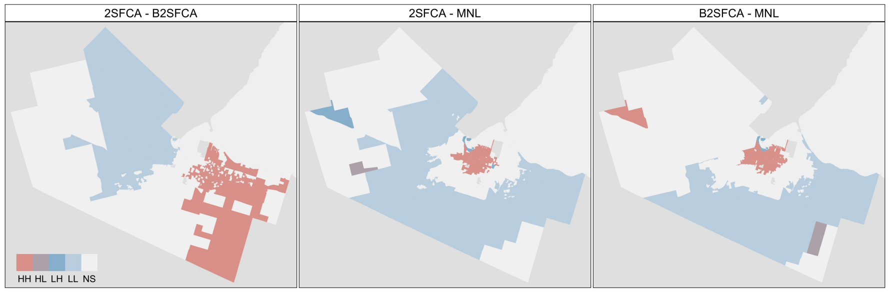

Figure 7: Accessibility Difference Hot Spots

respectively in each of the 100 scenarios (Figure 8). Two example scenarios are also created for illustration. In Scenario 1, the β_{K+2} parameter was decreased from 1 to 0.5 relative to the original calculations while the β_{K+3} parameter was decreased from -0.5 to -1 in Scenario 2.

For the CDRs in the left panel of Figure 8, the sensitivity analysis reveals that decreasing sensitivity to the attractiveness of capacity (as β_{K+2} approaches 0.1) and decreasing sensitivity to overcrowding (as β_{K+3} approaches -0.1) combine to produce more balance between the supply of physician capacities and patient demand, on average. Examining the clinic data in greater detail, this weighting results in more trips being made to smaller and more congested clinics relative to larger ones where there is more supply relative to demand. Greater weight placed on facility capacity (as β_{K+2} approaches 1) and high sensitivity to overcrowding (as β_{K+3} approaches -1) also results in more balanced CDRs, but in this case, more trips are made to larger clinics that become more congested versus smaller ones that are less congested. Scenarios along the diagonal exhibit relatively less balance, on average, across the clinics.

In terms of accessibilities, average accessibilities are, in general, more sensitive to changes in the β_{K+2} parameter than β_{K+3}. Comparing the original results against Scenario 1, average accessibilities increase by around 22% when β_{K+2} increases from 0.5 to 1. In contrast, access increases by about 11% across Scenario 2 and the original calculations as the β_{K+3} sensitivity to overcrowding parameter decreases in weight from -1 to -0.5. The greatest average accessibilities in 8 result from high attractiveness to clinic capacity and low weight on overcrowding ($\beta_{K+2} = 1$ and $\beta_{K+3} = -0.1$), leading to more trips made to smaller overcrowded clinics that are more evenly distributed around the city and likely closer to the origins in terms of travel time relative to some of the larger clinics that are more centrally-located.

To examine whether the sensitivity analysis impacts the spatial distributions of calculated accessibilities, Figure 9 plots normalized accessibility results from

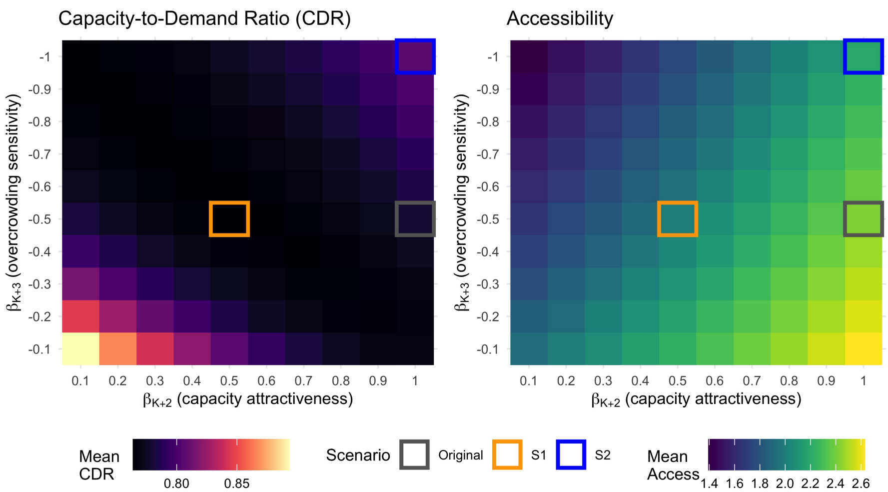

Figure 8: Sensitivity Analysis Results

the original and two sensitivity scenarios. Although both adjustments to the parameters result in decreased absolute accessibilities in Figure 8, comparisons of the normalized values suggest there are no distinct spatial trends associated with changes in β_{K+2} and β_{K+3} across the sensitivity scenarios.

As shown in the above figure, the accessibilities have decreased across the City of Hamilton in both sensitivity analysis scenarios. However, reducing the β_{K+2} parameter has a larger effect as compared to reducing the β_{K+3} parameter, with more dissemination areas being in the lowest category of accessibilities. The model is therefore more sensitive to the β_{K+2} parameter, however, adjusting the β_{K+3} parameter also has a large effect on the results produced by the MNL method. It is therefore important to calibrate the model's parameters in order to match observed trip distributions in the City of Hamilton.

Discussion and Conclusions

Since the 2SFCA was proposed by Luo and Wang (2003), the floating catchment area approach has been a popular one for calculating place-based accessibility to healthcare services that considers both the supply and demand components and several key innovations have been made to FCA methods since. However, FCA methods are still limited in two important ways. First, FCA methods do not fully consider aspects of travel and choicemaking behaviour. Like many of the other place-based accessibility measures, the only behavioural component of FCA methods is the impedance function that is used to weight the value of opportunities by the distance or travel time required to reach them. Second, FCA approaches also tend to assign population demand and levels-of-service to facilities or population zones in an overlapping manner, using the impedance

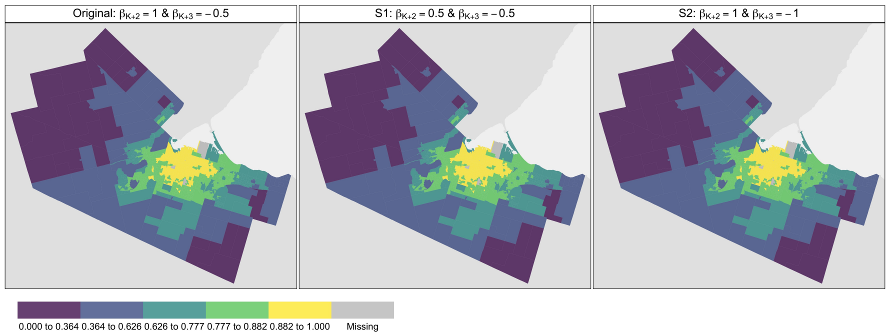

Figure 9: Sensitivity Scenario Maps

function (and other adjustments) to weight each value within a catchment area. Crucially, this use of overlapping catchment areas in previous FCA approaches has been shown to bias results by inflating/deflating supply and demand. While the B2SFCA proposed by Páez et al. (Paez et al., 2019) rectifies this, it does so by apportioning fractions of populations and levels-of-service through adjustments to the impedance function.

To respond to these issues, this research developed a multinomial logit destination choice model for calculating utility-based transportation accessibility to primary care physicians. While FCA approaches consider accessibility in terms of provider-to-population ratios weighted by distance or travel time, the MNL approach reframes the measurement of health accessibility into individual trips to visit primary care physicians and the utility-bearing aspects of clinics. With its basis in random utility theory, the MNL model considers several additional aspects that define the appeal of clinics in addition to the travel time required to reach them, including the number of physicians available at the clinic and the level of crowding. The destination choice model also avoids multiple-counting as the iterative fitting procedure results in the assignment of each patient trip to a single clinic on average.

Comparisons of the MNL approach with 2SFCA and B2SFCA models using data for the City of Hamilton suggests that the accessibility patterns produced by each method are broadly similar, with the highest accessibilities in the central core of the city where many clinics and physicians are located. However, further analysis of the distributions, correlations, and spatial clustering of accessibility differences reveals that the MNL method produces generally higher accessibilities throughout much of Hamilton with the greatest differences seen in the ring of suburban and rural zones that surround the city. It seems likely that these results arise from the MNL model assigning trips based on the most proximate clinic for these residents while more urban residents are being drawn to more urban clinics. In contrast, the FCA approaches assign population values to all clinics within their catchment area and all population zones share the levels-of-service of accessible clinics, likely leading to higher demand and lower available supply at these rural and suburban clinics.

For planning and policy, our analysis suggests that both the B2SFCA and MNL approaches offer merit. While the 2SFCA is generally straightforward to calculate with limited data requirements, it has been shown to return biased results as a consequence of double counting that makes the interpretation of provider-to-population ratios and accessibility scores problematic. The B2SFCA, on the other hand, requires the same data as the 2SFCA method but improves on it by preserving the population being serviced and the level of service. Both the levels-of-service and accessibilities calculated in the B2SFCA method are readily interpretable as population-to-provider ratios. However, the only travel behaviour component in both the 2SFCA and B2SFCA approaches is the impedance function. While it does tend to result in the greatest weight placed on the nearest locations in practice, it still results in a spreading or smoothing of demand and supply. In contrast, the MNL model's utility-based approach has a stronger behavioral foundation and considers more aspects that define the appeal of particular clinics. It also appears to produce what are arguably more realistic results in suburban and rural areas. However, the MNL approach is more data-hungry and its results are highly sensitive to the parameter assumptions that were made on the part of the research team. Moreover, the accessibility scores have no direct healthcare interpretation.

All methods in our comparative study are limited due to the imposition of boundary effects that likely over-estimate levels-of-service at the edges of the city and the consideration of only car travel. Further research should also be taken to ascertain the sensitivity of the MNL model results to the parameter assumptions. Moreover, we only focus on the spatial component of accessibility and do not consider the aspatial components that also play a significant role in defining an individual's potential to reach and utilize healthcare services (Joseph and Bantock, 1982). In this regard, future research should utilize the B2SFCA and MNL approaches for welfare analysis to measure place- and utility-based accessibility to primary healthcare services for different socioeconomic, demographic, and mobility profiles.

References

Anas, A., 1983. Discrete choice theory, information theory and the multinomial logit and gravity models. Transportation Research Part B: Methodological 17, 13–23. doi:10.1016/0191-2615(83)90023-1

Apparicio, P., Gelb, J., Dubé, A.-S., Kingham, S., Gauvin, L., Robitaille, É., 2017. The approaches to measuring the potential spatial access to urban health services revisited: distance types and aggregation-error issues. International Journal of Health Geographics 16. doi:10.1186/s12942-017-0105-9

Bauer, J., Groneberg, D.A., 2016. Measuring Spatial Accessibility of Health Care Providers Introduction of a Variable Distance Decay Function within the Floating Catchment Area (FCA) Method. PLOS ONE 11, e0159148. doi:10.1371/journal.pone.0159148

Ben-Akiva, M., Lerman, S.R., 1985. Discrete choice analysis: Theory and application to travel demand. MIT Press.

Brunsdon, C., Comber, A., 2020. Opening practice: supporting reproducibility and critical spatial data science. Journal of Geographical Systems 23, 477–496. doi:10.1007/s10109-020-00334-2

CIHI, 2020. How canada compares: Results from the commonwealth fund's 2019 international health policy survey of primary care physicians. Canadian Institute for Health Information.

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. doi:10.1016/j.healthplace.2010.06.012

de Jong, G., Daly, A., Pieters, M., van der Hoorn, T., 2007. The logsum as an evaluation measure: Review of the literature and new results. Transportation Research Part A: Policy and Practice 41, 874–889. doi:10.1016/j.tra.2006.10.002

Delamater, P.L., 2013. Spatial accessibility in suboptimally configured health care systems: A modified two-step floating catchment area (M2SFCA) metric. Health & Place 24, 30–43. doi:10.1016/j.healthplace.2013.07.012

Geurs, K.T., van Wee, B., 2004. Accessibility evaluation of land-use and transport strategies: review and research directions. Journal of Transport Geography 12, 127–140. doi:10.1016/j.jtrangeo.2003.10.005

Hansen, W.G., 1959. How Accessibility Shapes Land Use. Journal of the American Institute of Planners 25, 73–76. doi:10.1080/01944365908978307

Hasnine, M.S., Graovac, A., Camargo, F., Habib, K.N., 2019. A random utility maximization (RUM) based measure of accessibility to transit: Accurate capturing of the first-mile issue in urban transit. Journal of Transport Geography 74, 313–320. doi:10.1016/j.jtrangeo.2018.12.007

Jang, S., Lee, S., 2020. Study of the regional accessibility calculation by income class based on utility-based accessibility. Journal of Transport Geography 84, 102697. doi:10.1016/j.jtrangeo.2020.102697

Joseph, A.E., Bantock, P.R., 1982. Measuring potential physical accessibility to general practitioners in rural areas: A method and case study. Social Science & Medicine 16, 85–90. doi:10.1016/0277-9536(82)90428-2

Kasraian, D., Raghav, S., Miller, E.J., 2020. A multi-decade longitudinal analysis of transportation and land use co-evolution in the Greater Toronto-Hamilton Area. Journal of Transport Geography 84, 102696. doi:10.1016/j.jtrangeo.2020.102696

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. doi:10.1016/j.healthplace.2009.06.002

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. doi:10.1068/b29120

Macfarlane, G.S., Boyd, N., Taylor, J.E., Watkins, K., 2020. Modeling the impacts of park access on health outcomes: A utility-based accessibility

approach. Environment and Planning B: Urban Analytics and City Science 48, 2289–2306. doi:10.1177/2399808320974027
McGrail, M.R., Humphreys, J.S., 2009. 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. doi:10.1016/j.apgeog.2008.12.003
Nassir, N., Hickman, M., Malekzadeh, A., Irannezhad, E., 2016. A utility-based travel impedance measure for public transit network accessibility. Transportation Research Part A: Policy and Practice 88, 26–39. doi:10.1016/j.tra.2016.03.007
Paez, A., Higgins, C.D., Vivona, S.F., 2019. Demand and level of service inflation in Floating Catchment Area (FCA) methods. PLOS ONE 14, e0218773. doi:10.1371/journal.pone.0218773
Páez, A., 2021. Open spatial sciences: an introduction. Journal of Geographical Systems 23, 467–476. doi:10.1007/s10109-021-00364-4
Pereira, R.H.M., Saraiva, M., Herszenhut, D., Braga, C.K.V., Conway, M.W., 2021. r5r: Rapid Realistic Routing on Multimodal Transport Networks with R5 in R. Findings. doi:10.32866/001c.21262
Radke, J., Mu, L., 2000. Spatial Decompositions, Modeling and Mapping Service Regions to Predict Access to Social Programs. Annals of GIS 6, 105–112. doi:10.1080/10824000009480538
StatsCan, 2019. Primary health care providers, 2017. Statistics Canada.
Vogel, L., 2017. Canadians still waiting for timely access to care. Canadian Medical Association Journal 189, E375–E376. doi:10.1503/cmaj.1095400
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. doi:10.1080/13658816.2011.624987