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

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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).

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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 place-based healthcare accessibility. 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. While 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:

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

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 population centres to clinics. The general form of this function is as follows:

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

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
- R_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:

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

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

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

$$\sum_{i\in I}\sum_{j\in J} T_{ij} R_j = \bar{R}T$$

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
- $\bar{R}$ 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:

$$C_j = \omega Z_j$$

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

Solving this set of equations yields the following:

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

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

$$P_{ij} = \frac{e^{\beta_1 t_{ij} + \beta_{K+2} log \omega Z_j + \beta_{K+3} R_j}}{\sum_{j\prime} e^{\beta_1 t_{ij\prime} + \beta_{K+2} log \omega Z_{j\prime} + \beta_{K+3} R_{j\prime}}}$$

Ideally, the β_1, β_{K+2}, and β_{K+3} parameters would be estimated iteratively in order to meet the outlined constraints. However, due to a lack of observed data on trips to doctors, 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 and to align with the 2SFCA and B2SFCA approaches above
- Random utility theory requires β_{K+2} to lie between 0 to 1 in value. It is set equal to 1 in this case to maximize the attractiveness of larger clinics.
- No theory is currently available to guide the choice of the β_{K+3} parameter and so -0.5 is chosen as a "first guess" at a parameter 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, and increased capacity at clinic j increases the probability.

In order to ensure that $\bar{R}$ 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. Since R_j is a function of T_{ij} and vice-versa, an iterative approach is taken to estimate the R_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 and those closer to the origins attract more trips.

Utility-based Accessibility

As shown by Anas (1983), multinomial logit (MNL) models are equivalent to gravity models. Following Ben-Akiva and Lerman (1985), accessibility can be defined within random utility theory as the expected maximum utility for a trip. For the MNL model, it can be shown that this is the natural logarithm of the denominator of the logit model (the so-called "logsum" or "inclusive value" term), yielding for this model the following accessibility measure:

$$a_i = log(\sum_{j'} e^{\beta_1 t_{ij'} + \beta_{K+2} log \omega Z_{j'} + \beta_{K+3} R_{j'}})$$

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, the smallest geographic unit in the census, 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.

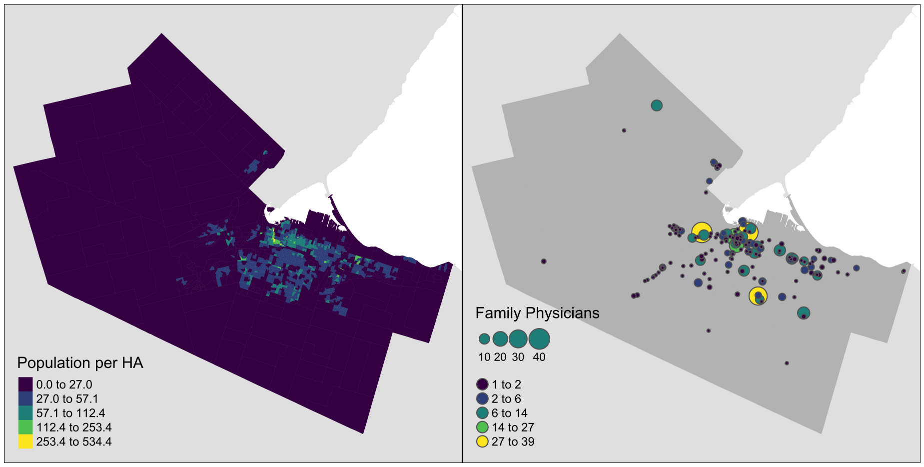

Figure 1: Population Density and Physician Locations

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 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

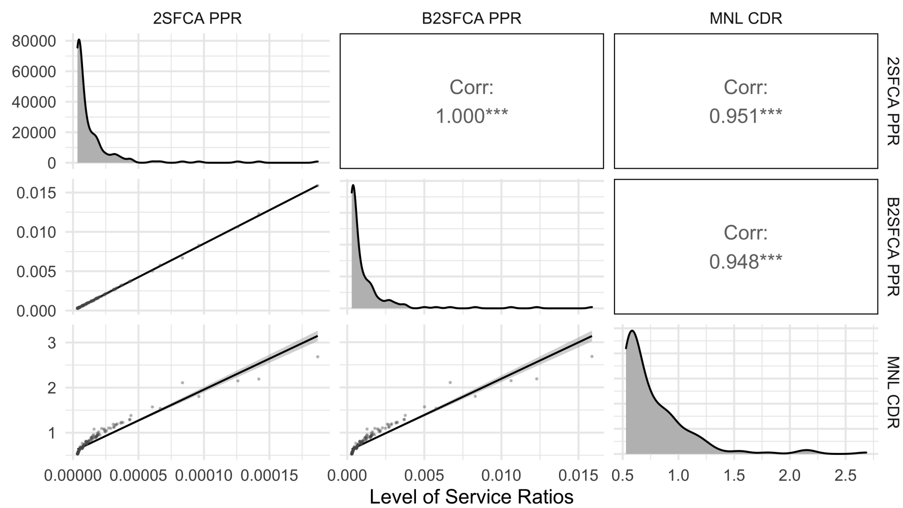

Figure 2: Comparing Accessibility Distributions

(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 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.

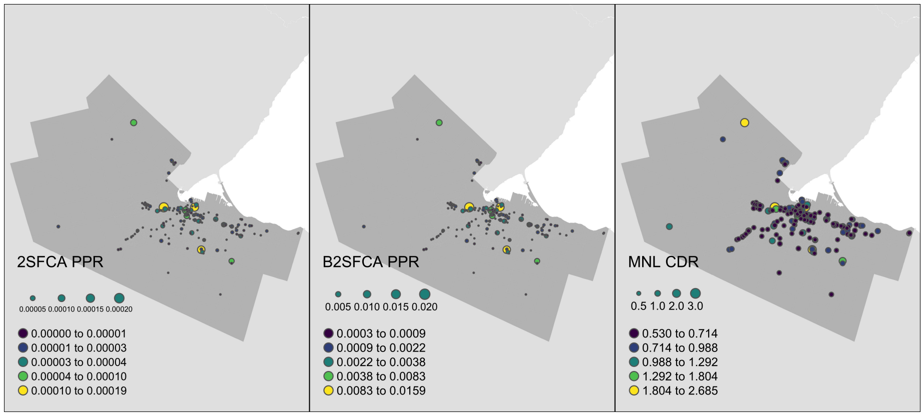

Figure 3: Comparing Accessibility Distributions

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 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

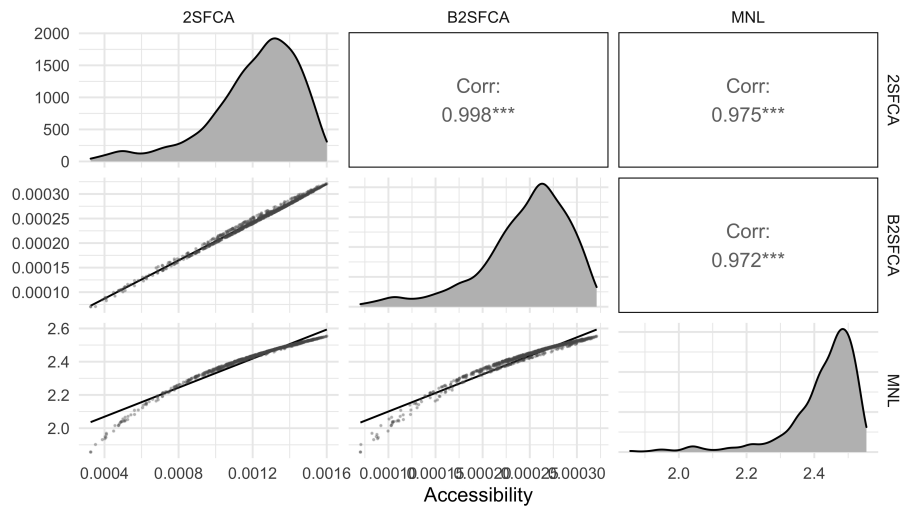

Figure 4: Comparing Accessibility Distributions

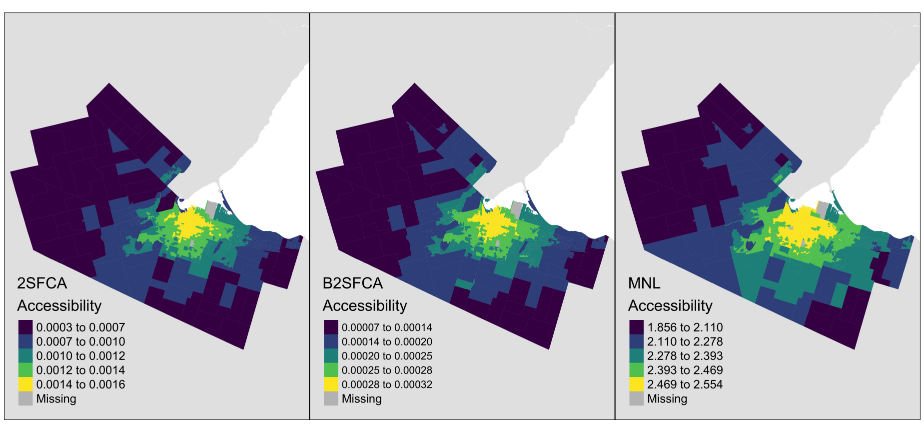

Figure 5: Accessibility Results

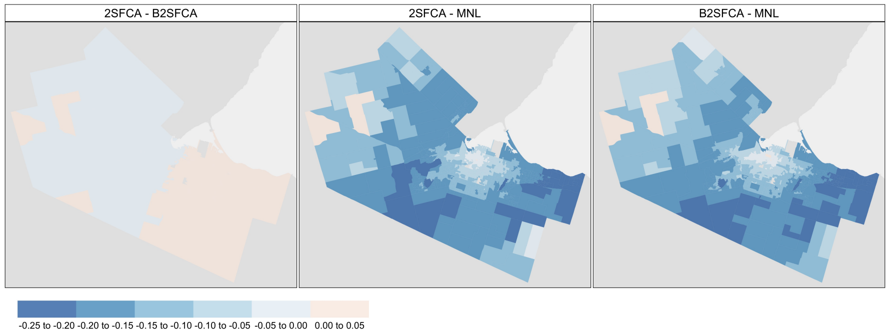

Figure 6: Accessibility Differences

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 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 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

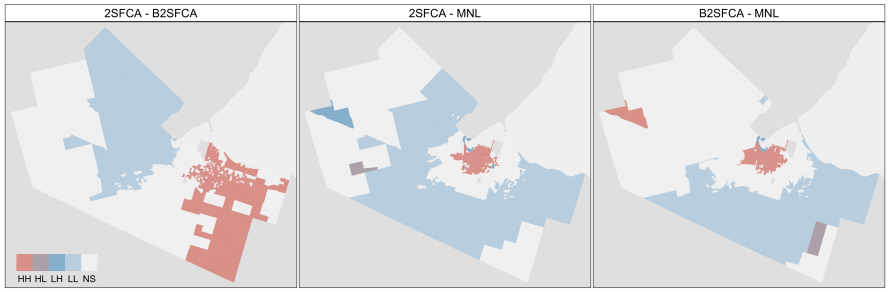

Figure 7: Accessibility Difference Hot Spots

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.

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 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 no doubt sensitive to the several 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.

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