

Introducing spatial availability, a singly-constrained competitive-access accessibility measure

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Abstract

Accessibility measures are widely used in transportation, urban, and healthcare planning, among other applications. These measures are weighted sums of the opportunities that can be reached given the cost of movement and are interpreted to represent the potential for spatial interaction. Though useful to understanding spatial structure, recent research on balanced floating catchment areas (BFCA) and competitive measures of accessibility raises questions about their interpretability. In this paper, we propose a new measure of *spatial availability* which is calculated by imposing a single constraint on gravity-based accessibility. Similar to the gravity model from which spatial availability is derived, a single constraint ensures that a single set of marginals are met and thus the number of opportunities are preserved. Through examples, we detail the formulation of the proposed measure. Further, we use data from the 2016 Transportation Tomorrow Survey of the Greater Golden Horseshoe area in southern Ontario, Canada, to contrast how the conventional accessibility measure tends to overestimate and underestimate the number of jobs *available* to workers. We conclude with some discussion on the possible uses of spatial availability and argue that, compared to conventional measures of accessibility, it can offer a more meaningful and interpretable measure of opportunity access. All data and code used in this research are openly available.

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Introduction

The concept of accessibility is a relatively simple one whose appeal derives from combining the spatial distribution of opportunities and the cost of reaching them (Hansen, 1959). Numerous methods for calculating accessibility have been proposed that can be broadly organized into infrastructure-, place-, person-, and utility-based measures (Geurs and van Wee, 2004). Of these, the place-based family of measures is arguably the most common, capturing the number of opportunities reachable from an origin using the transportation network. A common type of place-based measure is the gravity measure of accessibility that captures the potential for interaction; since it was first developed by Hansen (1959) it has been widely adopted by literature in many forms (e.g., Cervero et al., 2002; Geurs and van Wee, 2004; Handy and Niemeier, 1997; Levinson, 1998; Paez, 2004).

Accessibility analysis is employed in transportation, geography, public health, and many other areas, particularly as mobility-based planning is de-emphasized in favor of access-oriented planning (Deboosere et al., 2018; Handy, 2020; Proffitt et al., 2017; Yan, 2021). However, while measures of accessibility are excellent indicators of the intersection between urban structure and transportation infrastructure, their interpretability has been criticized in the past. Previous research has highlighted how the weighting of opportunities using an impedance function can make gravity measures more difficult for planners and policymakers to interpret compared to simpler cumulative opportunity measures (Geurs and van Wee, 2004; Miller, 2018). Moreover, because place-based measures are sensitive to the number of opportunities and the size of the opportunity-seeking population (e.g., a large city has more nearby jobs and more job-seekers than a smaller city), raw values cannot be easily compared across study areas (Allen and Farber, 2019).

For this reason, place-based intra- and inter-regional comparisons of accessibility are challenging to interpret. While gravity-based accessibility indicators are spatially smoothed estimates of the total number of opportunities, the meaning of their magnitudes is unclear. This is evident when we consider the “total accessibility” in the region, a quantity that is not particularly meaningful since it is not constrained to resemble, let alone match, the number of opportunities available. Furthermore, while accessibility depends on the number of opportunities weighted by the travel costs associated with reaching them, the calculated accessibilities are not sensitive to the demand for those opportunities at the origins.

Put another way, traditional measures of place-based accessibility do not capture the competition for opportunities. This shortcoming (Geurs and van Wee, 2004) is particularly acute when opportunities are “non-divisible” in the sense that, once taken they are no longer available to other members of the population. Examples of these types of opportunities include jobs (when a person takes up a job, the same job cannot be taken by anyone else) and placements at schools (once a student takes a seat at a school, that particular opportunity is no longer available for another student). From a different perspective, employers

may see workers as opportunities, so when a worker takes a job, this particular individual is no longer in the available pool of candidates for hiring.

To remedy these issues, researchers have proposed several different approaches for calculating competitive accessibility values. On the one hand, this includes several approaches that first normalize the number of opportunities available at a destination by the demand for them from the origin zones and, second, sum the demand-corrected opportunities which can be reached from the origins (e.g. Joseph and Bantock, 1984; Shen, 1998). These advances were popularized in the family of two-step floating catchment area (FCA) methods (Luo and Wang, 2003) that have found widespread adoption for calculating competitive accessibility to a variety of opportunities such as healthcare, education, and food access (B. Y. Chen et al., 2020; Chen, 2019; Z. Chen et al., 2020; Yang et al., 2006; Ye et al., 2018). In principle, floating catchments purport to account for competition/congestion effects, although in practice several researchers (e.g., Delamater, 2013; Wan et al., 2012) have found that they tend to over-estimate the level of demand and/or service. The underlying issue, as demonstrated by Paez et al. (2019), is the multiple counting of both population and level of service, which can lead to biased estimates if not corrected.

A second approach is to impose constraints on the gravity model to ensure flows between zones are equal to the observed totals. Based on Wilson's (1971) entropy-derived gravity model, researchers can incorporate constraints to ensure that the modeled flows match some known quantities in the data inputs. In this way, models can be singly-constrained to match the row- or column-marginals (the trips produced or attracted, respectively), whereas a doubly-constrained model is designed to match both marginals. Allen and Farber (2019) recently incorporated a version of the doubly-constrained gravity model within the floating catchment area approach to calculate competitive accessibility to employment using transit across eight cities in Canada. But while such a model can account for competition, the mutual dependence of the balancing factors in a doubly-constrained model means they must be iteratively calculated which makes them more computationally-intensive. Furthermore, the double constraint means that the sum of opportunity-seekers and the sum of opportunities must match, which is not necessarily true in every potential use case (e.g., there might be more people searching for work than jobs exist in a region).

In this paper we propose an alternative approach to measuring competitive accessibility. We call it a measure of **spatial availability**, and it aims to capture the number of opportunities that are not only *accessible* but also *available* to the opportunity-seeking population, in the sense that they have not been claimed by a competing seekers of the opportunity. As we will show, spatial availability is a singly-constrained measure of accessibility. By allocating opportunities in a proportional way based on demand and distance, this method avoids the issues that result from multiple counting of opportunities in conventional accessibility analysis. The method returns meaningful accessibility estimates that correspond to the rate of available opportunities per opportunity-seeking population. Moreover, the method also returns a benchmark value for the region under study against which results for individual origins can be compared both

inter- and intra-regionally.

In the following sections we will describe and illustrate the proposed measure using a synthetic example and an empirical example. First, we will describe the analytical framework of the measure. Second, we calculate the spatial availability using data from the Transportation Tomorrow Survey (TTS) home-to-work commute in 2016 for the Greater Golden Horse (GGH) area in Ontario, Canada, and discuss differences with conventional unconstrained accessibility analysis. Third, we return to the synthetic example and calculate spatial availability for two additional use-cases: one use case for jobs from the perspective of the population considering catchment restrictions and another use case for workers from the perspective of employers. Finally, we conclude by discussing the advantages of the spatial availability measure and the breadth of potential uses.

In the spirit of openness of research in the spatial sciences (Brunsdon and Comber, 2021; Páez, 2021) this paper has a companion open data product (Arribas-Bel et al., 2021), and all code will be available for replicability and reproducibility purposes.

Background

Most accessibility measures (excluding utility-based measures) are derived from the gravity model and follow the formulation shown in Equation (1). The limitations associated with this conventional and widely used measure, namely issues in interpretation and spatial bias, are the motivation for the proposed *spatial availability* measure. We begin this section by conceptually demonstrating the issues associated with the conventional accessibility measure using a simple synthetic example. We introduce the analytical framework of spatial availability and highlight the differences between the measures to demonstrate how the proposed method improves the interpretability of opportunity access.

$$A_i = \sum_{j=1}^J O_j f(c_{ij}) \quad (1)$$

where:

- A is accessibility.
- i is a set of origin locations.
- j is a set of destination locations.
- O_j is the number of opportunities at location j . These are opportunities for activity and add some sort of *supply* to the area;
- c_{ij} is a measure of the cost of moving between i and j
- $f(\cdot)$ is an impedance function of c_{ij} ; it can take the form of any monotonically decreasing function chosen based on positive or normative criteria (Paez et al., 2012).

As formally defined, accessibility A_i is the weighted sum of opportunities that can be reached from location i , given the cost of travel c_{ij} . Summing the

Table 1: Description of synthetic example

ID	Number	Location Type
E1	750	jobs
E2	2250	jobs
E3	1500	jobs
P1	260	population
P2	255	population
P3	510	population
P4	495	population
P5	1020	population
P6	490	population
P7	980	population
P8	260	population
P9	255	population

opportunities in the neighborhood of i , as determined by the impedance function $f(\cdot)$, provides estimates of the number of opportunities that can be reached from i at a certain cost. The type of accessibility can be modified depending on the impedance function; for example, the measure could be cumulative opportunities (if $f(\cdot)$ is a binary or indicator function e.g., El-Geneidy et al., 2016; Geurs and van Wee, 2004; Qi et al., 2018; Rosik et al., 2021) or a gravity measure using an impedance function modeled after any monotonically decreasing function [e.g., Gaussian, inverse power, negative exponential, or log-normal, among others; see, *inter alia*, Kwan (1998); Vale and Pereira (2017); Reggiani et al. (2011); Li et al. (2020)]. In practice, the accessibility measures derived from many cumulative and gravity formulations tend to be highly correlated with one another (Higgins, 2019; Santana Palacios and El-geneidy, 2022).

Synthetic example

The setup for our synthetic example is a system with three employment centers and nine population centers, as summarized in Table 1. Accessibility to jobs at each population center is calculated using the accessibility measure A_i in Equation (1). In this simple example, we use the straight line distance between the population and jobs for c_{ij} and a negative exponential function with $\beta = 0.0015$. As noted, A_i represents the number of jobs (i.e., opportunities) that can be reached from each population center given the estimated cost as depicted in Figure 1.

Figure 1 shows the locations of the three employment centers (black circles), where the size of the symbol is in proportion to the number of jobs at each location. We also see nine population centers (triangles), where the size of the symbol is proportional to the accessibility (A_i) to jobs. The accessibility values illustrates the following:

- Population centers (triangles) in the middle of the plot are relatively close to all three employment centers and thus have the highest levels of job

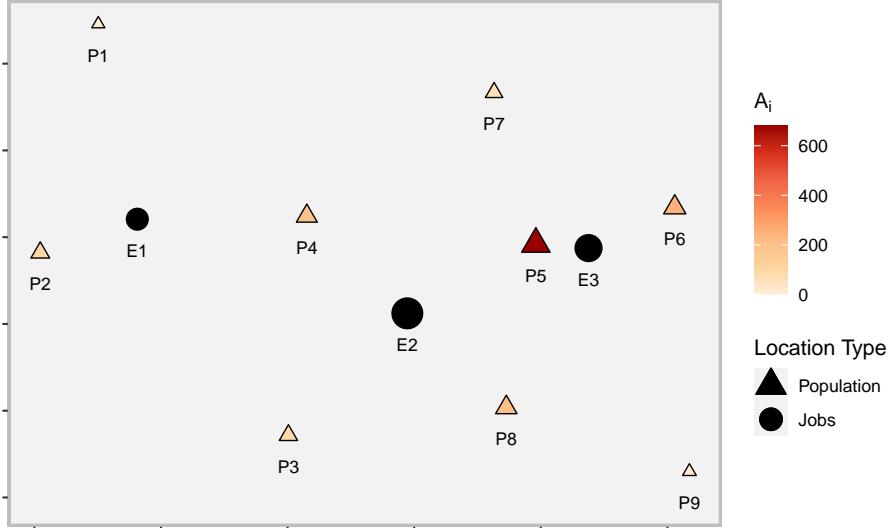


Figure 1: Accessibility of jobs from population centers for the simple synthetic example

accessibility. Population center P5 is relatively central and close to all employment centers, and it is the closest population to the second largest employment center in the region. Unsurprisingly, this population center has the highest accessibility (680.64);

- Population centers (triangles) near the left edge of the map (only in proximity to the small employment center) have the lowest levels of job accessibility. Population center P1 is quite peripheral and the closest employment center is also the smallest one. Consequently, it has the lowest accessibility with $A_i = 17.12$);

The effect of competition for opportunities

Accessibility measures are excellent indicators of the intersection between urban structure and transportation infrastructure (Kwan, 1998; Reggiani et al., 2011; Shi et al., 2020). However, beyond enabling comparisons of relative values they are not highly interpretable on their own (Miller, 2018). For instance, from Figure 1, P1 has lower accessibility than P5 but despite the accessibility value for P1 being relatively low it is still better than zero. To address this interpretability issue, previous research has aimed to index and normalize values on a per demand-population basis (e.g., Barboza et al., 2021; Pereira et al., 2019; Wang et al., 2021).

However, as recent research on accessibility discusses (see for instance Allen and Farber, 2019; Paez et al., 2019), these steps do not address the bias introduced

through the uneven multiple-counting of opportunities which are unconstrained by demand-side competition. This is similar to the congestion effect that floating catchment area methods aim to address, although they do not necessarily solve the issue completely (see Paez et al., 2019). The underlying issue arises as a result of the underlying assumption that for conventional accessibility A_i all opportunities for all origins $i = 1, \dots, n$ are *available* to any one who can reach them: in other words, they are assumed to be divisible and non-competitive. This results in every opportunity entering the weighted sum once for every origin i that can reach it. Put another way, if a densely populated population center pops up next to P5 this center too will have a high accessibility score since A_i does not consider competition of opportunities from neighbouring population centers. Neglecting to constrain opportunity counts (i.e., single-constraint) obscures the interpretability of accessibility which can bias results in two ways:

- 1) Demand centers in the less dense outer limits of the urban core may be assigned disproportionately *high* accessibility values. These periphery areas are traditionally located in proximity to more dense urban demand centers and large urban opportunity centers and thus may have low travel cost to these large opportunity centers. Accessibility A_i does not consider opportunity-constraints and, as such, these periphery demand centers benefit from the high accessibility to opportunities without competition considerations from their more dense and more centrally located neighbours.
- 2) Remote areas which are still within the region of the analysis and have regionally-relative low demand centers, opportunity centers, and travel costs to opportunity centers, are assigned disproportionately *low* accessibility values. These more remote areas may be sufficiently supplied with opportunities proportionate to their demand but this relationship is obscured by the artificially high accessibility awarded to demand- and opportunity-rich areas in which competition disproportionately occurs.

The spatially uneven multiple-counting of opportunities (i.e., the competition effect) leave decision makers unclear on how to interpret resulting accessibility estimates. All recent accessibility measures which seek to improve interpretability are either vulnerable to this impact or require potentially unrealistic assumptions. As previously mentioned, the floating catchment areas (FCA) method increases interpretability by purporting to account for competition, however, as discussed by Paez et al. (2019), FCA methods are vulnerable to a similar multiple-counting effect. On this same note, the doubly-constrained gravity model proposed by Allen and Farber (2019) which is based on the FCA method, accounts for competition, but requires that the magnitude of demand matches the opportunities or be re-scaled to match. As already noted, this assumption is not always realistic for many opportunity types such as in the case of job seekers and jobs.

To address the competition effect and introduce a more realistic assumption regarding non-divisible opportunities, we propose a singly-constrained gravity measure called **spatial availability**. This measure seeks to answer the following questions for an individual at a specific demand center: “*many opportunities*

are accessible, but the same opportunities are also accessible to my (possibly) numerous neighbours... what does a high accessibility actually mean to me?" and "*a few opportunities are accessible to me but I am located in a remote area with proportionally few neighbours relative to the region... what does low accessibility mean to me?*". Beyond the individual, spatial availability, can also be used as-is to evaluate the *spatial mismatch* of accessible opportunities and demand-seeking population within regions and between regions.

Analytical framework

Formally, spatial availability V_{ij} is defined by opportunities O which are proportionally allocated based on a population allocation factor F_{ij}^p and cost of travel allocation factor F_{ij}^c for all origins i to all destinations j as detailed in Equation (2). In line with the tradition of gravity modeling, the proposed framework distinguishes between opportunities at a destination and demand for opportunities at the origin.

$$V_{ij} = O_j \frac{F_{ij}^p \cdot F_{ij}^c}{\sum_{i=1}^K F_{ij}^p \cdot F_{ij}^c} \quad (2)$$

where:

- V_{ij} is spatial availability.
- i is a set of origin locations in the region K .
- j is a set of destination locations in the region K .
- O_j is the number of opportunities at location j in the region K .
- F_{ij}^p is the proportional allocation factor of the population in i relative to the population in region K .
- F_{ij}^c is the proportion allocation factor of travel cost for i relative to the travel cost in region K ; it is a product of a monotonically decreasing (i.e., impedance) function associated with the cost of travel between i and j .

Since spatial availability V_{ij} consists of these two allocation factors, we detail the role of population allocation factor F_{ij}^p in producing V_{ij}^p , the role of the travel cost allocation factor F_{ij}^c in producing V_{ij}^c , and finally how both allocation factors in the final general form of spatial availability V_{ij} are combined. The calculation of spatial availability is introduced with a step-by-step example for two population centers (P_2 and P_3) in the role of demand (i.e., the number of individuals in the labour market who 'demand' employment) and one employment center (O_1) in the role of opportunities.

Population and travel cost allocation factors

We begin with allocation based on demand; consider an employment center j with O_j^r jobs of type r . In the general case where there are K population centers in the region, the following factor can be defined in Equation (3).

$$F_{ij}^p = \frac{P_{i \in r}^\alpha}{\sum_{i=1}^K P_{i \in r}^\alpha} \quad (3)$$

The population allocation factor F_{ij}^p corresponds to the proportion of the population in origin i relative to the rest of the region's population centres K . On the right hand side of the equation, the numerator $P_{i \in r}$ is the population at origin i that is eligible and 'demand' jobs of type r (e.g., those with a certain level of training or in a designated age group, etc.). The summation in the denominator is over $i = 1, \dots, K$, the number of population at all origins i in the region K . To modulate the effect of the size in from this factor we also add an empirical parameter α (i.e., $\alpha < 1$ places greater weight on smaller centres relative to larger ones while $\alpha > 1$ achieves the opposite effect). This population allocation factor F_{ij}^p can now be used to proportionally allocate a share of the jobs at a destination j to all origin pairs.

More broadly, since the factor F_{ij}^p is a proportion, when it is summed over $i = 1, \dots, K$ it always equals to 1 (i.e., $\sum_i^K F_{ij}^p = 1$). This is notable since the share of jobs (the spatial availability based on population V_{ij}^p) at each destination j allocated to (i.e., available to) each origin is equal to $V_{ij}^p = O_j \cdot F_{ij}^p$ and since the sum of F_{ij}^p is equal to 1 it follows that $\sum_{i=1}^I V_{ij} = O_j$. In other words, the number of jobs across the region is preserved. The result is a proportional allocation of jobs (opportunities) to origins based on population demand; this factor does not consider travel cost, that is defined in the travel cost allocation factor F_{ij}^c which is introduced shortly.

To illustrate the population allocation factor, consider an employment center has 300 jobs ($O_1 = 300$) in a region with two population centers which have 240 and 120 people, respectively ($P_2 = 240$ and $P_3 = 120$). This example is different than the synthetic example presented above. For simplicity, assume that all the population in the region is eligible for these jobs, that is, that the entirety of the population is included in the set r . Also assume that $\alpha = 1$ meaning the only impact on value is the population size for each center. The population allocation factors F_{ij}^p for the jobs at O_1 for each population center P_2 and P_3 would be defined as shown in Equation (4).

$$\begin{aligned} F_{2,1}^p &= \frac{P_2^\alpha}{P_2^\alpha + P_3^\alpha} = \frac{240}{240+120} = \frac{240}{360} \\ F_{3,1}^p &= \frac{P_3^\alpha}{P_2^\alpha + P_3^\alpha} = \frac{120}{240+120} = \frac{120}{360} \end{aligned} \quad (4)$$

The F_{ij}^p values can be used to find a *partial* spatial availability of jobs which is only defined by the relative population demanding jobs; this partial spatial availability V_{ij}^p for each population center is calculated as follows in Equation (5).

$$\begin{aligned} V_{2,1}^p &= O_1 \cdot F_{2,1}^p = 300 \cdot \frac{240}{360} = 200 \\ V_{3,1}^p &= O_1 \cdot F_{3,1}^p = 300 \cdot \frac{120}{360} = 100 \end{aligned} \quad (5)$$

When using only the proportional allocation factor F_{ij}^p to calculate spatial availability (differentiated here by being defined as V_{ij}^p instead of V_{ij}), propor-

tionally more jobs are allocated to the bigger population center (i.e., 2 times more jobs as it is 2 times larger in population). We can also see that the sum of spatial availability for all population centers is equal to the sum of jobs, i.e., total opportunities are preserved. However, as mentioned, using only the proportional allocation factor F_{ij}^p to calculate spatial availability does not account for how far population centers P_2 or P_3 are from employment center O_1 . To account for this effect, we introduce a second allocation factor F_{ij}^c based on distance to the employment centers defined in Equation (6).

$$F_{ij}^c = \frac{f(c_{ij})}{\sum_{i=1}^K f(c_{ij})} \quad (6)$$

where c_{ij} is the cost (e.g., the distance, travel time, etc.) from population center i to employment center j , and $f(\cdot)$ is an impedance function that is a monotonically decreasing function of cost (c_{ij}); in other words, the travel cost allocation factor F_{ij}^c serves to proportionally allocate more jobs to closer locations through an impedance function. To continue illustrating, assume that the impedance function is a negative exponential function. Next, assume the parameter β modulates the steepness of the impedance effect and is empirically determined in the case of positive accessibility, or set by the analyst to meet a preset condition in the case of normative accessibility (Paez et al., 2012). For the sake of the example, we set a value of 1. Also suppose that the distance from population center P_2 to employment center O_1 is 0.6 km, and the distance from population center P_3 to employment center O_1 is 0.3 km. The proportional allocation factor F_{ij}^p for the jobs at O_1 for both population centers P_2 and P_3 is defined as follows in Equation (7).

$$\begin{aligned} F_{2,1}^c &= \frac{\exp(-\beta \cdot D_{2,1})}{\exp(-\beta \cdot D_{2,1}) + \exp(-\beta \cdot D_{3,1})} = \frac{\exp(-0.6)}{\exp(-0.6) + \exp(-0.3)} = 0.426 \\ F_{3,1}^c &= \frac{\exp(-\beta \cdot D_{3,1})}{\exp(-\beta \cdot D_{2,1}) + \exp(-\beta \cdot D_{3,1})} = \frac{\exp(-0.3)}{\exp(-0.6) + \exp(-0.3)} = 0.574 \end{aligned} \quad (7)$$

We can see that the proportional allocation factor for P_3 is larger than P_2 since the cost (i.e., distance) to O_1 is shorter. Using the travel cost proportional allocation factors F_{ij}^c as defined in Equation (7), we can now calculate the spatial availability of jobs for each population center based only on F_{ij}^c and the jobs available O_1 to these two competing population centers (note: V_{ij}^c not the complete V_{ij}) as follows in Equation (8).

$$\begin{aligned} V_{2,1}^c &= O_1 \cdot F_{2,1}^c = 300 \times 0.426 = 127.8 \\ V_{3,1}^c &= O_1 \cdot F_{3,1}^c = 300 \times 0.574 = 172.2 \end{aligned} \quad (8)$$

As shown, the spatial availability defined by F_{ij}^c (i.e., V_{ij}^c) allocates P_3 a larger share of jobs since the population center is closer to O_1 . However, as previously discussed, P_3 has a smaller population than P_2 , so P_2 receives a larger share of jobs when spatial availability when it is defined by F_{ij}^p (i.e., V_{ij}^p). It is necessary to combine population and travel cost components into spatial interaction models to better reflect demand. These two components are in line with how demand is

conventionally modelled in accessibility calculations, namely, by re-scaling on a per demand-population basis or considering competition effects (e.g., Allen and Farber, 2019; Barboza et al., 2021; Yang et al., 2006). Fortunately, since both F_{ij}^c and F_{ij}^p preserve the total number of opportunities (jobs) as they independently sum to 1, they can be combined multiplicatively to calculate the proposed spatial availability (V_{ij}) which considers demand to be based on both population and travel cost.

Putting spatial availability together

We can combine the proportional allocation factors by population F_{ij}^p and travel cost F_{ij}^c and calculate spatial availability V_{ij} as introduced in Equation (2) and repeated below:

$$V_{ij} = O_j \frac{F_{ij}^p \cdot F_{ij}^c}{\sum_{i=1}^K F_{ij}^p \cdot F_{ij}^c}$$

To complete the illustrative example of employment center O_1 and population centers P_2 and P_3 , the resulting spatial availability V_{ij} is calculated for both population centers is calculated in Equation (9).

$$\begin{aligned} V_{2,1} &= O_1 \cdot \frac{F_{2,1}^p \cdot F_{2,1}^c}{F_{2,1}^p \cdot F_{2,1}^c + F_{3,1}^p \cdot F_{3,1}^c} = 300 \frac{\left(\frac{2}{3}\right)\left(0.426\right)}{\left(\frac{2}{3}\right)\left(0.426\right) + \left(\frac{1}{3}\right)\left(0.574\right)} = 179.4 \\ V_{3,1} &= O_1 \cdot \frac{F_{3,1}^p \cdot F_{3,1}^c}{F_{2,1}^p \cdot F_{2,1}^c + F_{3,1}^p \cdot F_{3,1}^c} = 300 \frac{\left(\frac{1}{3}\right)\left(0.574\right)}{\left(\frac{2}{3}\right)\left(0.426\right) + \left(\frac{1}{3}\right)\left(0.574\right)} = 120.6 \end{aligned} \quad (9)$$

From the resulting values we can see, fewer jobs are allocated to population center P_2 compared to the allocation by population only, to account for the higher cost of reaching the employment center. On the other hand, distance alone allocated more jobs to the closest population center (i.e., P_3), but since it is smaller, it also gets a smaller share of the jobs overall. To reiterate, the sum of jobs at employment center O_1 that are allocated to population centers P_2 and P_3 simultaneously based on *population-* and *travel cost* allocation factors are preserved (i.e., $V_{2,1} + V_{3,1} = O_1$).

In the common case that population centers have multiple destination opportunities j , spatial availability is simply the sum of Equation (2) for all opportunities J (i.e., $V_i = \sum_{j=1}^J V_{ij}$). The resulting value of V_i represents opportunities (e.g., jobs) that can be accessed from origin i and that are *not* allocated to any other competing origin: V_i is thus the weighted sum of available opportunities and is the *opportunity access* for that origin i considering constrained opportunity availability. When comparing V_i to the singly-constrained gravity model (see Wilson (1971)), V_i is the result of constraining A_i to match one of the marginals in the origin-destination table, the known total of opportunities.

Since the sum of opportunities is preserved in the procedures above, it is possible to calculate a highly interpretable measure of spatial availability per capita (lower-case v_i) as follows in Equation (10).

$$v_i = \frac{V_i}{P_i} \quad (10)$$

To complete the illustrative example, the per capita spatial availability of jobs would be calculated as follows in Equation (11).

$$\begin{aligned} v_{2,1} &= \frac{V_{2,1}}{P_2} = \frac{179.4}{240} = 0.8 \\ v_{3,1} &= \frac{V_{3,1}}{P_3} = \frac{120.6}{120} = 1.0 \end{aligned} \quad (11)$$

From the resulting values we can see that since P_3 is closer to O_1 and has less competition (as it has a smaller population than P_2), P_3 benefits with a higher spatial availability of jobs per job-seeking population. We can also compare these values to the overall ratio of jobs-to-population in this region of one job center and two population centers is $300/(240 + 120) = 0.83$.

Empirical data set: measuring spatial availability and accessibility of jobs in the GGH

Two scales of analysis using an empirical data set of home-based work trips is used in this section. The first example demonstrates how accessibility broadly overestimates *job access* (relative to spatial availability) and particularly overestimates job access for areas in the less dense outer limits of the urban core. The second example demonstrates how accessibility underestimates job access for areas in the urban periphery. We first introduce the data used, then calibrate the impedance function, and finally visualize the two scales of analysis

Data

The home-based work trips from the 2016 Transportation Tomorrow Survey (TTS) area is retained; the TTS collects representative urban travel information from 20 municipalities contained within the GGH area in the southern part of Ontario, Canada (see Figure 2) (Data Management Group, 2018). These home-based work trips include origins and employment destinations defined by centroids of Traffic Analysis Zones (TAZ) ($n=3,764$), the number of jobs ($n=3,081,885$) and workers ($n=3,446,957$) at each origin and destination, and the number trips from origin to destination for the morning home-to-work commute ($n=3,446,957$). The TTS data is based on a representative sample of between 3% to 5% of households in the GGH and is weighted to reflect the population covering the study area has a whole (Data Management Group, 2018).

To generate the travel cost for these trips, travel times between origins and destinations are calculated for car travel using the R package {r5r} (Rafael H. M. Pereira et al., 2021) with a street network retrieved from OpenStreetMap for the GGH area. Travel times based on car travel alone are unrealistic, since we know a significant proportion of trips are taken by non-car modes. Moreover, this method does not account for traffic congestion. Though modal split and travel times can be estimated through other methods (e.g., Allen and Farber,

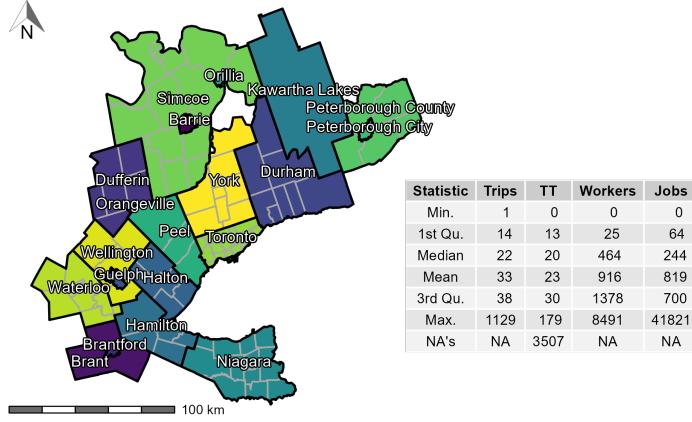


Figure 2: TTS 2016 study area within the GGH in Ontario, Canada along with the descriptive statistics of the trips, calculated origin-destination car travel time (TT), workers per TAZ, and jobs per TAZ. Contains 20 regions (black boundaries) and sub-regions (dark gray boundaries).

2021; Higgins et al., 2021), for simplicity, we carry on with the assumption that all trips are taken by car in uncongested travel conditions.

All data and data preparation steps can be freely explored in companion open data product {TTS2016R}.

Calibrating an impedance function

In the synthetic example introduced in a preceding section, an arbitrary negative exponential function describing travel cost (as a function of distance) was used as the impedance function. In this TTS work commute example, an impedance function is calibrated based on the trip length distribution (TLD). For background, a TLD is the representation of the likelihood that a proportion of trips are taken at a specific travel cost (e.g., travel time); this distribution is commonly used to derive impedance functions in accessibility research (Batista et al., 2019; Horbachov and Svichynskyi, 2018).

The empirical and theoretical TLD for this data set are represented in the top-left panel of Figure 3. Maximum likelihood estimation and the Nelder-Mead method for direct optimization available within the {fitdistrplus} package (Delignette-Muller and Dutang, 2015) were used. Based on goodness-of-fit criteria and diagnostics seen in Figure 3, the gamma distribution was selected (also see Figure 11 in the Appendix).

The gamma distribution-based impedance function takes the following general form where the estimated ‘shape’ is $\alpha = 2.019$, the estimated ‘rate’ is $\beta = 0.094$, and $\Gamma(\alpha)$ is defined in Equation (12).

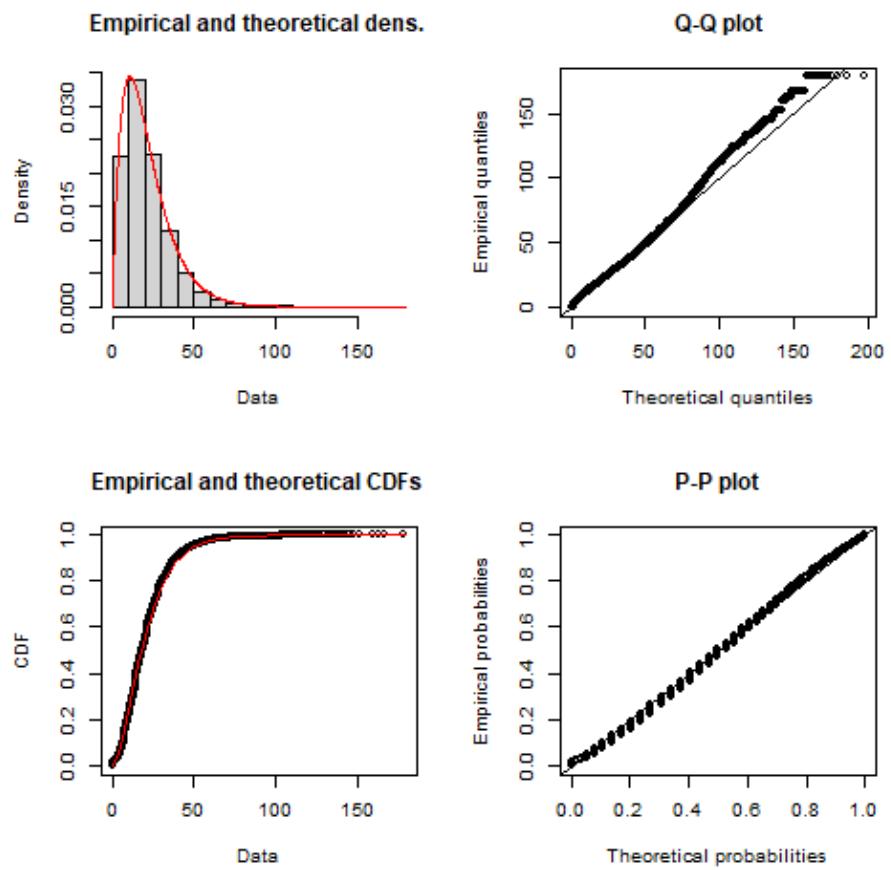


Figure 3: Empirical TTS 2016 home-based car trip length distribution (black points) and calibrated gamma distribution impedance function (red line) with associated Q-Q and P-P plots

$$f(x, \alpha, \beta) = \frac{x^{\alpha-1} e^{-\frac{x}{\beta}}}{\beta^\alpha \Gamma(\alpha)} \quad \text{for } 0 \leq x \leq \infty$$

$$\Gamma(\alpha) = \int_0^\infty x^{\alpha-1} e^{-x} dx$$
(12)

Measuring access to jobs in the GGH

Toronto is the largest city in the GGH and represents a significant subset of workers and jobs in the GGH; 51% of workers in the GGH travel to jobs in Toronto and 73% of jobs are located within Toronto. As will be discussed, when accessibility and spatial availability values are compared, this significant subset of jobs in Toronto contributes to both issues associated with the competition effect. Specifically, since accessibility does not include the single-opportunity constraint like spatial availability does, accessibility *overestimates* job access for most TAZs in proximity to Toronto (i.e., GTA) and contributes to the *underestimation* of job access for TAZs in the periphery of the GGH.

Figure 4 presents the accessibility and spatial availability for the full TTS data set. Within the accessibility plot, job access values follow a radial trend where a few TAZ with a high values are strictly located within the boundaries of Toronto and values radially decrease further from the boundaries of Toronto. This general trend is echoed in qualitative studies which find the further from Toronto, the longer the employment commute (Axisa et al., 2012) and the closer to core of Toronto, the more opportunities are accessible (for some to certain types of jobs: Páez et al. (2013)).

Conversely, competitive job access is calculated using the spatial availability measure and is presented alongside the accessibility plot in Figure 4. Similar to the accessibility plot, the higher the value, the more access that TAZ has to jobs in the GGH. Since spatial availability constrains the total number of opportunities, higher values of spatial availability can be interpreted as higher access to *available* jobs (i.e., competitive job access). We can observe which TAZs have spatial availability values that are above or below the regional average of 642. It is worth noting that the spatial availability and accessibility plots do not follow the same spatial distribution. Within the spatial availability plot, job access appears more evenly assigned throughout the GGH. Particularly, job access values, as measured by spatial availability, are higher around the north east and south west periphery TAZs and more moderate in and around Toronto than compared to accessibility.

Note that in Figure 4 it can be observed that a few TAZ are greyed out; this corresponds to a null accessibility and spatial availability. Overall, 22% of TAZ are greyed out as a result of containing zero home-to-work GGH trips and as such are allocated a null accessibility and spatial availability. The majority of these no-trip TAZ because they contain no worker population, specifically, 95% have zero workers while only 18% of these TAZ have zero jobs (17% have both zero workers and jobs).

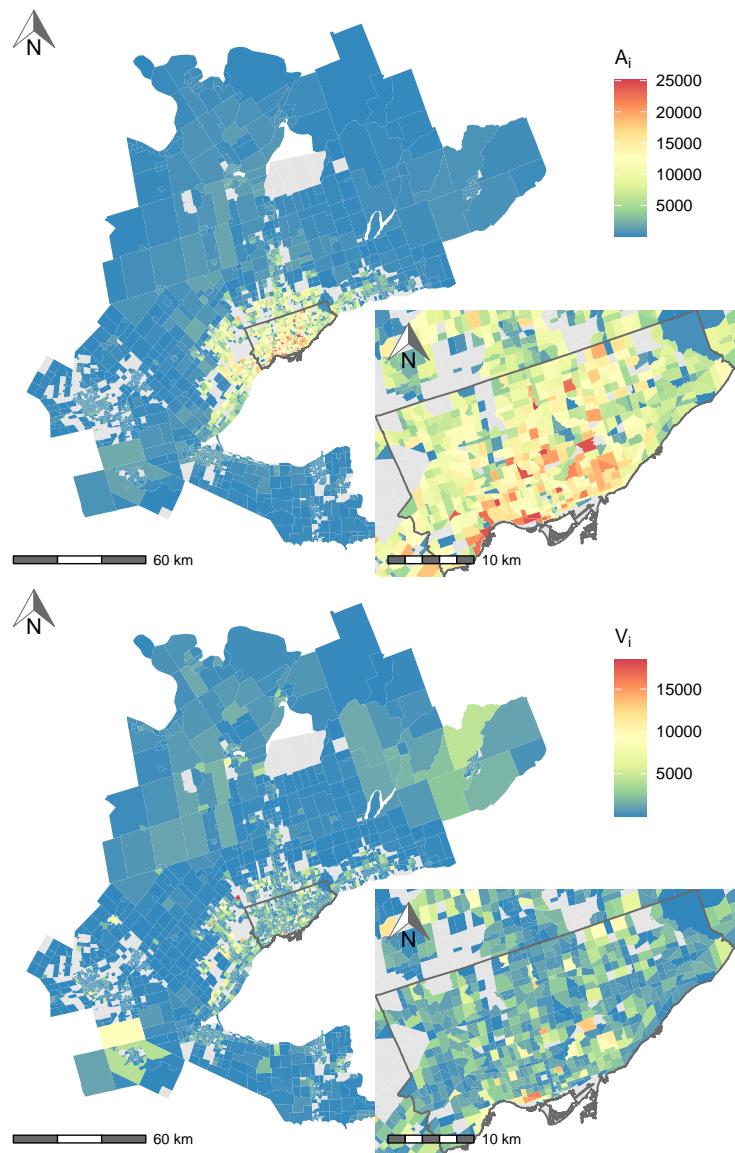


Figure 4: Calculated accessibility (top) and spatial availability (bottom) of employment from origins in the GGH to destinations in the GGH. Greyed out TAZs represent null accessibility and spatial availability values .

To enhance the interpretability of spatial availability, the measure can be normalized to provide more meaningful insight into how many jobs are *available* on average for each TAZ. This normalization, shown in Figure 5, demonstrates which TAZ have above (reds) and below (blue) the average (available jobs per worker in the GGH). Similar to the spatial availability plot of the GGH jobs in Figure 4, we can see that many average or above average jobs per worker TAZ (whites and reds) are present in southern Peel and Halton (south-west of Toronto), Waterloo and Brantford (even more south-west of Toronto), and Hamilton and Niagara (south of Toronto), however, the distribution is uneven and many TAZ within these areas do have below average values (blues).

Interestingly, when considering *competitive* job access, many areas outside of Toronto have similar jobs per worker values as TAZ in Toronto. This is contrary to the notion that since Toronto has high job access it has a significant density of employment opportunities in the GGH. Not all jobs in Toronto are *available* since Toronto has a high density of *competition* in addition to density of jobs opportunities. For instance, urban centers outside of Toronto such as those found in Brantford, Guelph, southern Peel, Halton, and Niagara have TAZ which are far above the the TTS average jobs per worker and higher than TAZ within Toronto. High job access is not seen in the accessibility plot which suggests that these less densely populated urban centers may have sufficient employment opportunities for their populations; This finding is obscured when only considering the accessibility measure for job access as will be later discussed.

It is also worth noting that there is almost two times more jobs per worker in the GGH jobs spatial availability results than the GGH Toronto spatial availability results. This suggests that all GGH people who work in the city of Toronto, on average, face more competition for jobs than all GGH people who work anywhere in the GGH .

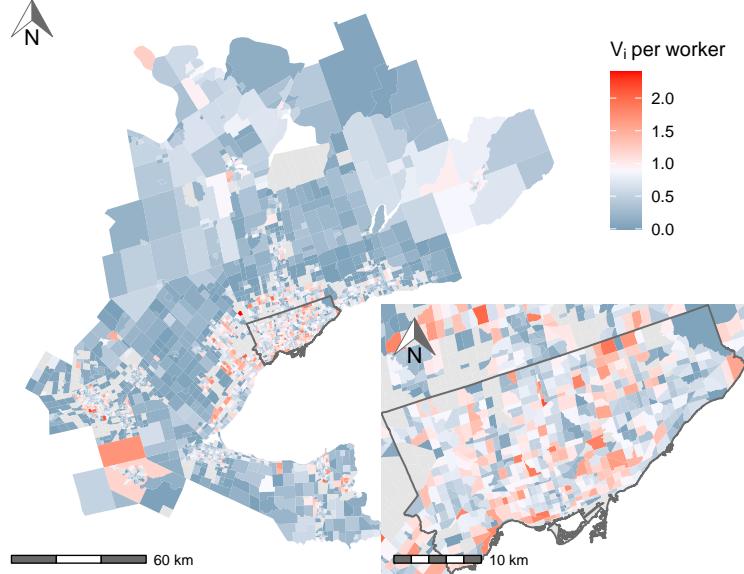


Figure 5: Spatial availability per worker, from origins to job opportunities in the GGH.

Discussion

In the preceding section we used both accessibility and spatial availability to explore the job access landscape in the GGH. To build on the findings, we return to the two issues associated with the accessibility A_i measure. As we described, accessibility has the tendency to overestimate job access for areas which may experience high competition (issue 1) and underestimate job access for areas with low competition (issue 2).

To compare both accessibility and spatial availability, we calculate their relative magnitudes by re-scaling both measures from 0 to 100 where each value of the measure is divided by the maximum value as described in Equation 13 by A_{ij}^I and V_{ij}^I . Re-scaling is repeated for both measures and the proportional difference between the measures is calculated as described in Equation 14. This difference represents how many times over- or under- estimated job access is for a TAZ when measured by the re-scaled accessibility relative to the re-scaled spatial availability (e.g., accessibility is X times *larger* than spatial availability thus job access is *overestimated* when using the accessibility measure compared to the spatial availability measure).

$$\begin{aligned} A_{ij}^I &= \frac{A_{ij}}{\max(A_{ij})} \cdot 100 \\ V_{ij}^I &= \frac{V_{ij}}{\max(V_{ij})} \cdot 100 \end{aligned} \quad (13)$$

$$Dif_{ij} = \frac{A_{ij}^I}{V_{ij}^I} \quad (14)$$

Accessibility's role in overestimating and underestimating jobs access

Here we demonstrate the difference between the two job access values for the full data set, namely, all jobs within the GGH and all workers within the GGH. While the majority of TAZ have difference values which correspond to accessibility being overestimated relative to spatial availability, 83% of TAZ are underestimated.

The overestimated TAZ have a median difference of 4.43 which indicates that the median accessibility value over-estimates the median spatial availability by 4.43 times. The overestimate difference ranges between 1 to 1889 with an upper quartile value (75%) of 10.54. It should be noted that these TAZ with an upper 95% of difference values (69 to 1889) are a result of high competition and/or high multiple-counting of opportunities; They contain exceptionally low spatial availability values and relatively high accessibility values.

Conversely, a few TAZ are underestimated and are plotted in Figure 6 alongside the overestimated TAZ for comparison. Of the underestimated TAZ, the median spatial availability value is 0.605 indicating that the median accessibility is 0.605 the spatial availability value. The difference values ranges between 0.006 to 0.995.

As observed from the top plot in Figure 6, the TAZ with overestimated job access are coloured in varying shades of red. TAZ with the highest degree of overestimation (darkest reds) are concentrated within Toronto and the periphery of the GTA. Differences between the number of workers and travel time partially explain the overestimation, with TAZs that have a lower number of workers and higher travel time having a larger overestimation. Specifically, the correlations between workers and overestimation, and travel time and overestimation is -0.17 and 0.13 respectively.

Nonetheless, the TAZ-specific density of workers and travel time does not fully explain the variation in overestimation; the number of opportunities and the value of these variables in neighbouring TAZ also factor into the calculation for both measures. From the perspective of accessibility, since opportunity-constraints are not considered, the *overestimated* TAZ (relative to spatial availability) are awarded higher values since they are more centrally located to opportunities (i.e., low travel cost) and are not discounted from being in proximity to highly competitive TAZ (i.e., high density of workers). On the other hand, spatial availability considers this competition by proportionally allocating jobs to TAZ relative to their travel cost and worker population. In other words, TAZ appears *overestimated* when the impact of travel cost alone outpaces the impact of both travel cost and workers thus the proportional allocation of opportunity results in a significantly smaller job access than the resulting value for accessibility. This may explain why TAZ which are exceptionally overestimated (dark reds) are on the periphery of more densely populated urban cities. These TAZ are located far enough away from workers in densely populated TAZ but still relatively close enough to jobs in Toronto. As such, their high accessibility value is a result of counting many more opportunities than the single-constrained spatial availability proportionally allocates.

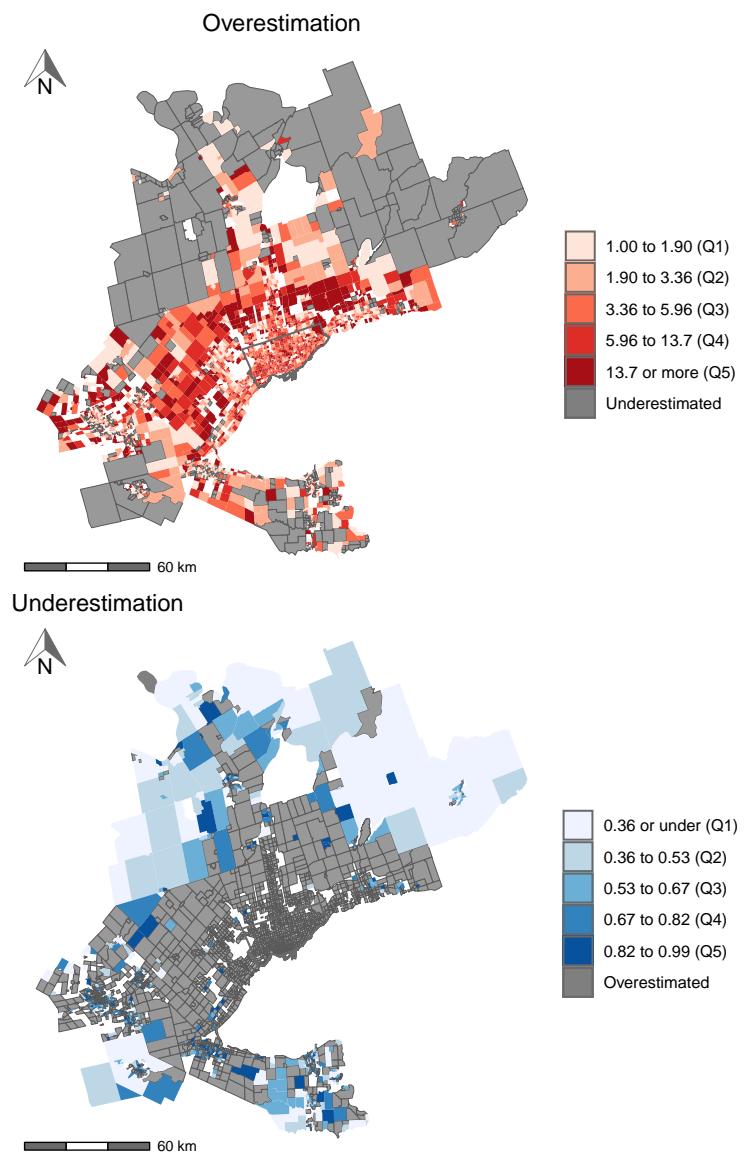


Figure 6: Overestimated (top) and underestimated (bottom) differences between the re-scaled accessibility and spatial availability job access measures in the context of employment from all origins and destinations in the GGH. Values are expressed in five quantile ranges. Greyed TAZs have values which are underestimated in the top plot and are overestimated in the bottom plot. TAZs with no trips and thus no spatial availability or accessibility values are not drawn.

Since both measures account for values contained in neighbouring TAZ differently (i.e., unconstrained or competition-constraint), correlations between TAZ-specific variables evidently cannot fully explain differences between variables. As such, the exploration of ways in which the number of workers, opportunities, and travel times in neighboring TAZ as well as within TAZs impact the two measures is out of scope for this paper and will be detailed in future analysis. However, within the scope of this paper, it can be stated that TAZs that are overestimated have relatively high job access when calculated using accessibility as a result of result of unconstrained multiple-counting of jobs and have relatively low job access as measured by spatial availability due to worker competition.

Turning to the bottom plot in Figure 6, TAZ with underestimated job access (i.e., re-scaled accessibility values are smaller than re-scaled spatial availability values) are located on the periphery of the GGH area. The majority of these underestimated TAZ are not within the center of the GGH where the GTA is located but are in proximity to other, smaller, employment areas within smaller municipalities. It can be understood that the underestimation of TAZ is a result of both high spatial availability as a result of low job competition and low accessibility scores that are a by-product of the job multiple-counting occurring within more densely job-populated TAZ in the GTA. Accessibility's multiple-counting effectively deflates the job access in these peripheral TAZ since their accessibility values are significantly lower compared to their multiple-counted GTA TAZ neighbours. The impact of this multiple-counting is starkly apparent when compared to the re-scaled spatial availability measure since spatial availability allocates jobs proportionally based on workers and travel cost, TAZ do not multiple-count of jobs and TAZ which are not in the position to multiple-count are not deflated as a consequence. This is supported by viewing the spatial availability of jobs per worker (Figure 5) where we can see that commercial areas throughout the GGH area have similar job access values as within some commercial areas in the GTA; this is not the case for the accessibility measure (see trends in Figure 4).

Comparing differences in job access when only considering Toronto jobs in the GGH

Next, we present two final difference plots in Figure 7 as a point of comparison; included is a consolidated plot of those included in Figure 7 and another plot calculated only using the subset of jobs in Toronto (i.e., all workers in the GGH who travel to work in a Toronto-located job). This subset of jobs is significant but are concentrated in Toronto, which is spatially a small portion of the whole GGH. Specifically, 51% of workers in the GGH travel to jobs in Toronto and 73% of jobs are located within Toronto. It can be observed, that when subsetting the analysis to *only* include Toronto jobs, almost all TAZ are overestimated (i.e., accessibility is larger than spatial availability). Notably, we can see virtually all *underestimation* disappears (blues) and the TAZs in the GGH periphery are now all overestimated (reds).

When inspecting the results for the subset of jobs in Toronto and comparing it to the results of the GGH periphery TAZ within the full GGH analysis, the effect

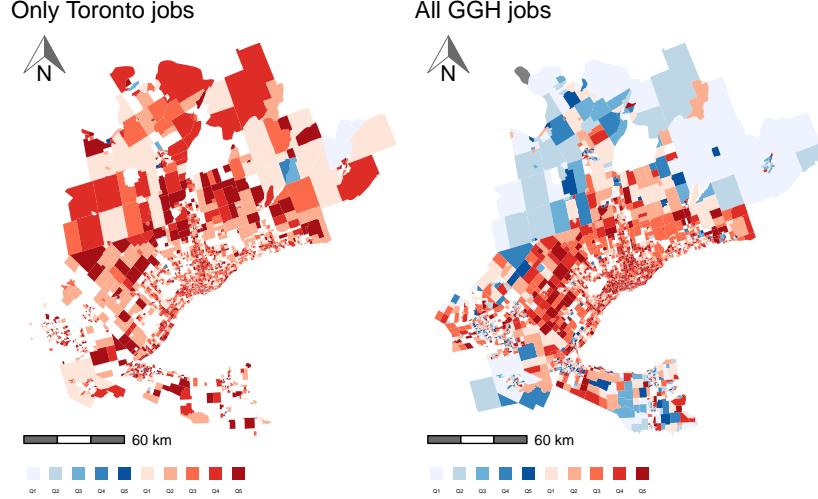


Figure 7: Overestimated and underestimated difference quantiles between the re-scaled accessibility and spatial availability for Toronto only jobs (left) and all GGH jobs (right). Red represent overestimated differences (i.e., accessibility larger than spatial availability) and blue represents underestimated differences (i.e., spatial availability larger than accessibility). TAZs with no trips and thus no spatial availability or accessibility values are not drawn.

of the single-constraint of the spatial availability measure is evident. Looking at the GGH peripheral TAZ in the left plot (Figure 6), these TAZ have relatively low spatial availability as they experience moderately high job competition since they have relatively high travel times to jobs in Toronto and have a moderately low worker population. Similarly, these peripheral TAZ also have relatively low accessibility (compared to the region) as a result of the multiple-counting which occurs within and around the high density of jobs in Toronto. However, when spatial availability and accessibility are compared, accessibility is still *higher* than spatial availability thus the difference appears *overestimated* (red).

Interestingly, the difference in the two measures flips when the workers who work in areas outside of Toronto are re-introduced to these peripheral TAZ as represented in right plot (Figure 6). Since more workers (more competition) and more jobs with lower travel costs (less competition) are introduced, it can be inferred that these peripheral TAZ experience moderately higher job access as measured with spatial availability. Conversely, for the accessibility measure, the introduction of additional workers does not meter the accessibility gained by the introduction of additional jobs and as such, the re-scaled accessibility values are *higher* than the spatial availability resulting in underestimated TAZ.

As such, we see that when including all the jobs in the region back into the analysis - these periphery TAZ are much less *job deprived* when measured using spatial availability than when measuring using accessibility. Overall, within the full set of jobs in the GGH, the first and second issue associated with accessibility's

competition effect are observed.

Other use cases of spatial availability

In addition to measuring access to jobs for workers, spatial availability can be used to measure many other opportunity types and scenarios. In this section we demonstrate two additional ways in which spatial availability can be applied. Since spatial availability singly-constraints opportunities which are allocated to the demand seeking population, opportunities or demand seeking populations can be subset while the resulting access measure does not lose any interpretability. As such, we firstly present a practical application is calculating job access for a specialized subset of population to specialized employment centers. We then present an application where the roles of workers and employers are reversed and employers are the demand seeking population. These two additional use cases are non-exhaustive and applications outside of employment are tenable and warranted.

To illustrate these two additional examples, we return to the synthetic example initially introduced in Background section.

Specialized employment opportunities

Suppose that population centers P1 through P8 are not all eligible for employment at the three employment centers E1, E2, and E3. This can be due to education attainment or more simply a geographic barrier (i.e., river without a road) making it impossible for certain populations to be employed at certain employment centers. In this synthetic example, we consider that only population center P1 and P2 are eligible for employment at employment center E1. Next assume that jobs in employment center E2 can be taken by individuals in population centers P3, P4, P5, P7, and P8. Lastly, jobs in employment center E3 require qualifications available only among individuals in population centers P5, P6, P8, and P9. In essence, eligibility criteria create catchments which can be easily considered within the spatial availability measure and this specialized job access is presented in Figure 8.

For higher interpretability, we can view Figure 9 which demonstrates a plot of spatial availability per capita considering catchments and also another plot which assumes the same number of employment center opportunities and population but no catchments.

In the bottom plot of Figure 9, we see that population center P5 has the highest level of spatial availability, due to being a large population center that is more relatively close to jobs. We also see population centers which are further from employment centers have low spatial availability (P1, P3, P6, P7, P9) and population centers which are more central have, evidently, higher job access. We can also discern that the regional spatial availability per capita is 0.908. In contrast, when catchments are introduced, as shown in the top plot of Figure 9, we see that the job access for population centers in the blue catchment decreases as job competition increases. However, we also observe that access marginally

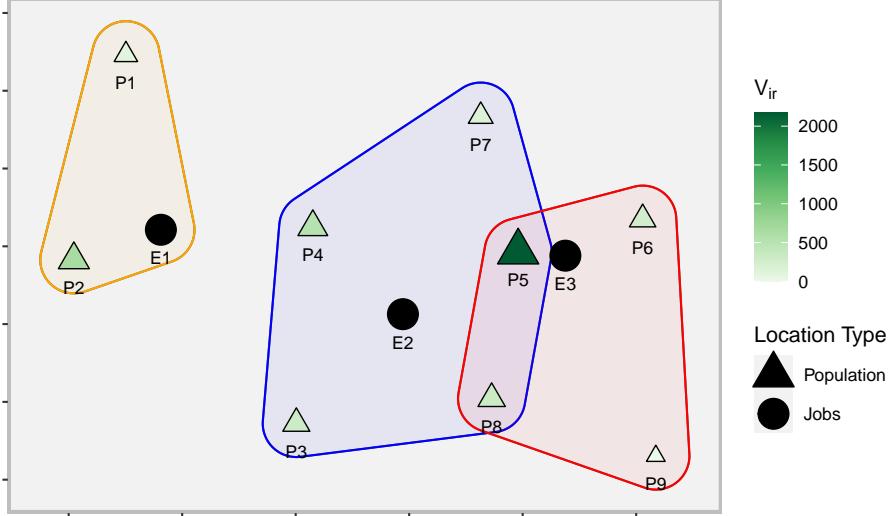


Figure 8: Spatial availability of jobs from population centers assuming catchment restrictions (r) for the simple synthetic example

increases for the population centers in the yellow catchment and the regional spatial availability per capita increases slightly to 0.964.

Spatial availability of labor pool

In this use case, we remove the catchments and switch the demand and opportunity roles of the employment centers and population centers. In this way, the spatial availability measure reflects *worker access* by proportionally allocating *workers* to employment centers based on travel cost (i.e., distance) and population (i.e., jobs at each employment center). Figure 10 presents spatial availability generally and per capita for this use case.

As shown in Figure 10, the top plot demonstrates the spatial availability which measures *worker access* for the three employment centers. As with all spatial availability calculations, the number of all opportunities (in this case *workers*) are proportionally allocated to each employment center so employment center E3, E2 and E1 have access to 2205.19, 1709.52, and 610.29 workers respectively. Again, this totals to 4500 workers in the area. In the bottom plot, these spatial availability values are normalized per job (i.e. the ‘population’ of the employment centers) and we can see that employment center E3 has an above average worker access of 1.47 workers per job while E2 and E1 have 0.76 and 0.81 workers per job respectively.

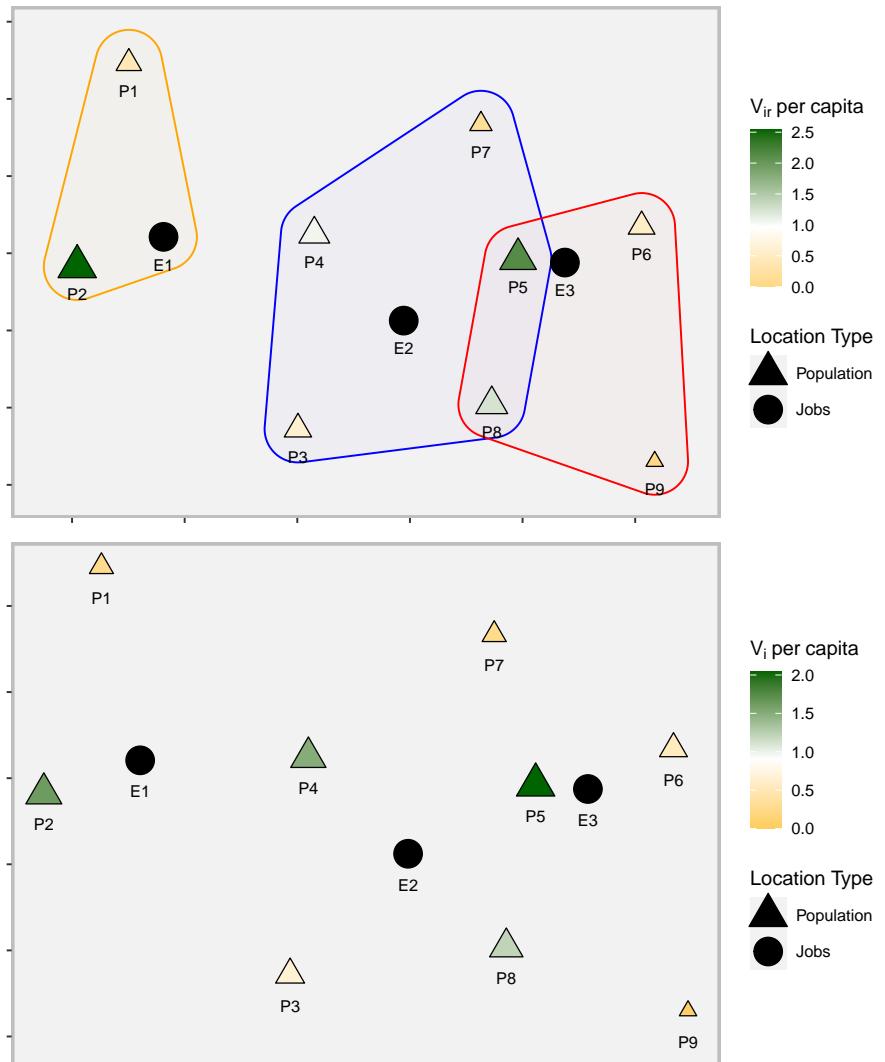


Figure 9: Spatial availability of jobs per capita for each population centers with catchment restrictions (r) (top) and without catchment restrictions (bottom) for the synthetic example

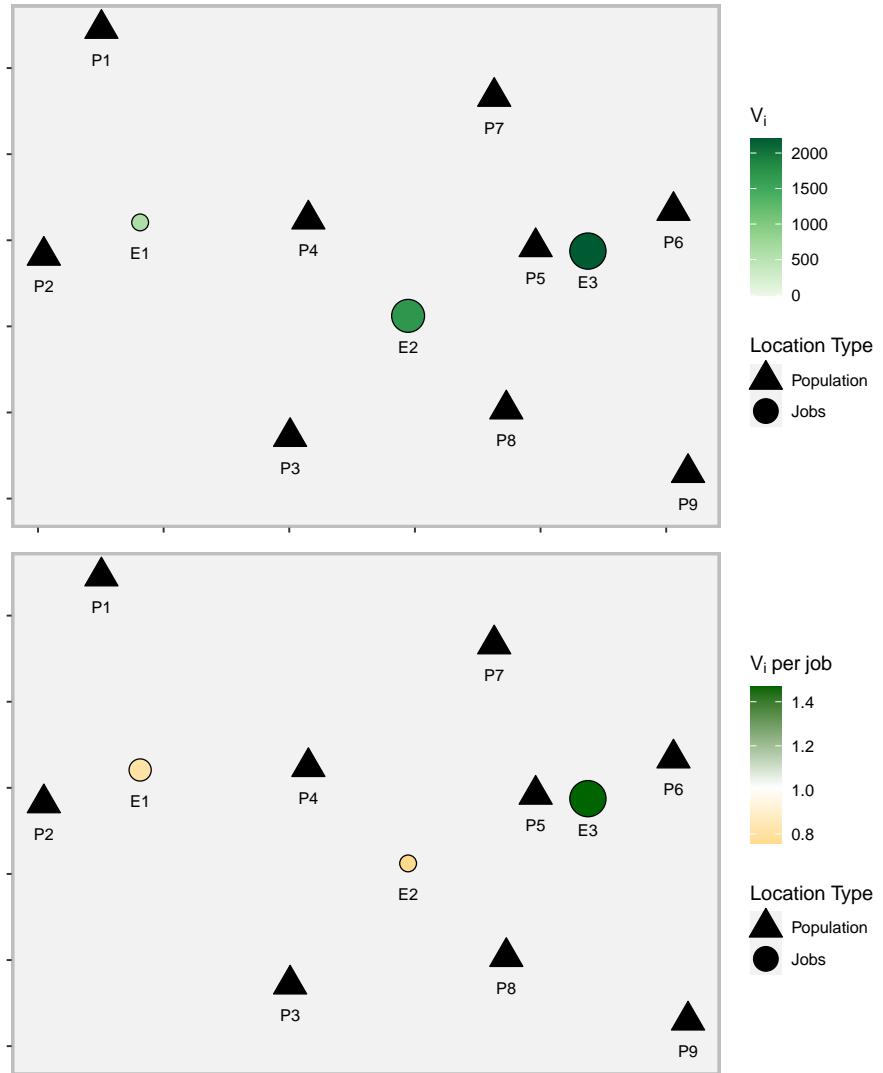


Figure 10: Spatial availability of workers for each employment center (top) and the spatial availability of workers per job for each employment center (bottom) for the simple synthetic example

Concluding remarks and future applications

In this paper, we propose *spatial availability* as an alternative to conventional accessibility which measures opportunity access which addressed the *competition effect* and thus produces a meaningful opportunity access measure which can be normalized per demand population and used to compare access across regions. As a reminder, the competition effect results in the over- and under- estimation of opportunity access, under specific conditions, due to the multiple-counting of opportunities which is embedded in accessibility's method and thus makes comparing accessibility across regions potentially biased . Spatial availability, however, proportionally allocates opportunities based on the demand population and travel cost thus constraining the number of opportunities allocated across the measured region to the number of opportunities available. This single-sided opportunity constraint can be said to only consider opportunity competition for any magnitude of demand population (i.e., when measuring job access per worker the number of workers (demanding population) does not need to match the number of jobs (opportunities)). We demonstrate the use of this measure and how it compares with accessibility in an empirical example of workers and jobs in the GGH. We also demonstrate two additional employment use cases for this versatile measure in a hypothetical synthetic example. These data sets and examples highlight how intuitive the per demand population access values are and captures some of the extent to which accessibility overestimates and underestimates access.

We acknowledge recent work to address limitations associated with the accessibility measure; in this light, we propose that spatial availability be seen as a type of spatial mismatch and an evolution of the BFCA approach. Historically, literature has iteratively improved measures assessing access to opportunities. In the context of employment and healthcare opportunities, simple container counting solutions such as the population-to-provider ratio (PPR) for healthcare services and jobs to housing ratio were implemented. This approach, while straight forward, is highly susceptible to the modifiable unit area problem (MUAP). Recognizing this and harnessing the computation power and access to finer resolution data as it became available, scholars proposed the next evolution, namely the accessibility measure which is widely used today and we implemented in our examples for comparison. It partially addresses the MUAP by considering opportunities outside of the conventional ‘containers’ which represented opportunities in a census areas/neighbourhoods by counting opportunities informed by an impedance function based on travel cost. Our measure, spatial availability, iterates on the accessibility measure by proportionally allocating travel cost and population (workers) of origins to opportunities at destinations. This single-constrained approach ensures that the population is mutually exclusive in essence replicating the properties of the self-contained unit which is *not* limited to a zoning system proposed; the pros of accessibility solution in using the impedance function and pros of the container solutions.

Fundamentally, accessibility measure's methodology results in the overestimation or underestimation of opportunity access as a result of the competition

effect. Accessibility does not include factors to bound the summation so origins, hypothetically, can have infinite opportunity access. Spatial availability includes a single-sided opportunity constraint so it can be used to calculate access to any opportunity type, whether competitive or non-competitive in nature. In this paper, we only examined access to employment (or access to workers from the perspective of employment centers), but any opportunities which are competitive (i.e., a finite number of seats or capacity is available at any given time) such as schools, hospitals, and other essential services can be measured. Additionally, opportunities which are non-competitive in the sense that they have always larger capacities than population can still benefit from this measure as access will not be over or underestimated as a result of the competition effect seen in accessibility; non-competitive opportunities can include large natural parks and beaches. As such, all access values measured for all opportunities can benefit from spatial availability measure through the reduction in competition effect (from accessibility) and a meaningful per demand population benchmark.

Appendix

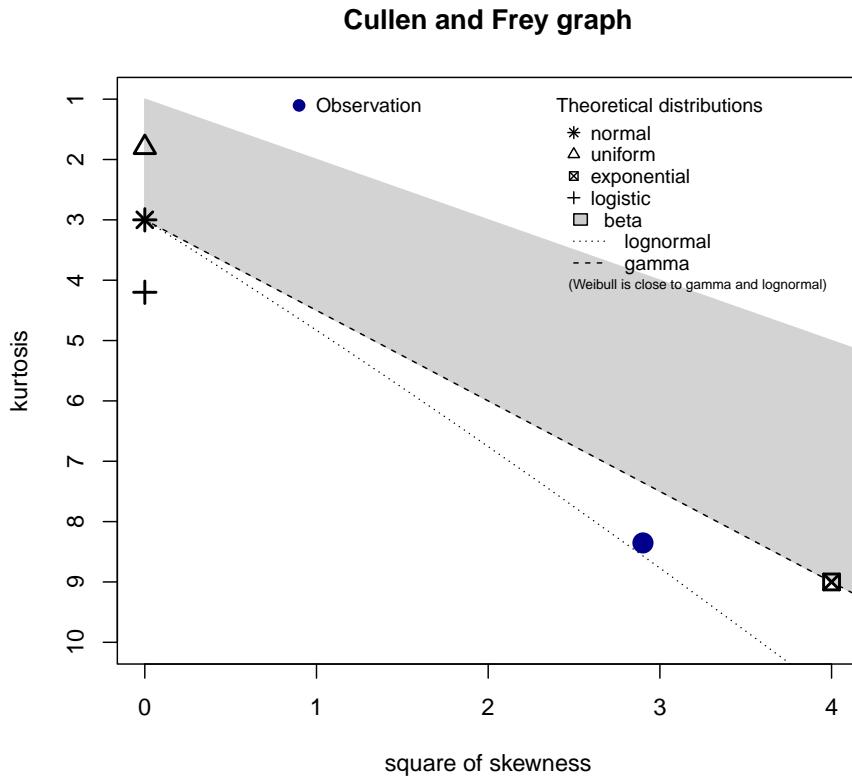


Figure 11: Cullen and frey graphy for the 2016 TTS calculated travel times.

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