Estimating spatial availability/mismatch using singly constrained accessibility measures

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Abstract

Accessibility measures are widely used in transportation, urban, and health care planning, among other applications. By giving a weighted sum of the opportunities that can be reached given the cost of movement and are interpreted as the potential for spatial interaction. While these measures are useful to understand spatial structure there are issues in interpretability and spatial biasis which have been partially addressed in recently introduced measures such as the balanced floating catchment areas (BFCA) and competitive measures of accessibility. In following this spirit, we propose a new measure of *spatial availability* which is calculated by imposing a single constraint on the conventional accessibility measure. Similar to the gravity model from which it is derived, a single constraint ensures that the marginals at the origin and destination are met and thus the number of opportunities are preserved. In this paper, we detail the formulation of the proposed spatial availability measure, use-cases of the measure using a simple toy data set, and contrast how the access to jobs changes between spatial availability and conventional accessibility measure using empirical 2016 travel survey data in the City of Toronto, Canada. We show that measure of spatial availability should be used for opportunities which are individible. . . . the values are more interpretable, less baisised than conventional accessibility measure. All data presented and original manuscript 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. This type of measure is also referred to as a gravity-based measure of accessibility that captures the potential for interaction.

What accessibility measures is sometimes referred to as *opportunity access* and the analysis of opportunity access is widely employed in transportation, geography, public health, and many other areas, and there is increasing emphasis on a shift from mobility-oriented to access-oriented planning (Deboosere et al., 2018; Handy, 2020; Proffitt et al., 2017; Yan, 2021). However, while these types of opportunity access measures are excellent indicators of the intersection between urban structure and transportation infrastructure, they have been criticized in the past for not being highly interpretable. 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 characteristics of the transportation network, raw values cannot be easily compared across study areas (Allen and Farber, 2019).

Intra- and inter-regional comparisons are challenging because gravity-based accessibility indicators are spatially smoothed estimates of the total number of opportunities, however, 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 supply of destination 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 theoretical shortcoming (Geurs and van Wee, 2004) is particularly problematic when those opportunities are "non-divisible" in the sense that, once they have been taken by someone, are no longer available to other members of the population. Examples of indivisible opportunities include jobs (when a person takes up a job, the same job cannot be taken by someone else) and placements at schools (once a student takes a seat at a school, that particular opportunity is no longer there 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 methods (Luo and Wang, 2003) that have found widespread adoption for calculating competitive accessibility to healthcare and other uses. In principle floating catchment areas 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 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** (SA), and it aims to capture the number of indivisible 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 seeker 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 of conglomeration that result from multiple counting of opportunities in traditional accessibility measures. The method returns meaningful accessibilities that correspond to the rate of available opportunities per person. Moreover, the method also returns a benchmark value for the region under study against which results for individual origins can be compared.

In the following sections we will describe and illustrate this new measure using simple toy data sets. First, we will describe the measure. Second, we will calculate the SA using a simple hypothetical population and employment centers data set for three use-cases: one of jobs from the perspective of the population, another considering catchment restrictions, and another of workers from the perspective of employers. Thirdly, we calculate the SA using real world data for the Transportation Tomorrow Survey (TTS) home-to-work commute in 2016 for the Greater Golden Horseshoe (GGH) area in Ontario, Canada. Finally, we discuss the differences between accessibility estimates to the proposed measure of SA and the potential range of uses of the SA measure.

Background

Most accessibility measures (excluding utility-based measures) are derived from the gravity model and follow the widely used formulation in (1). A thorough explanation of this conventional accessibility measure through a toy data set and its limitations are detailed in this section. The limitations of the conventional accessibility measure, namely issues in interpretation and basis, are the motivation for the *spatial availability* measure which we propose and describe in the following sections.

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

where:

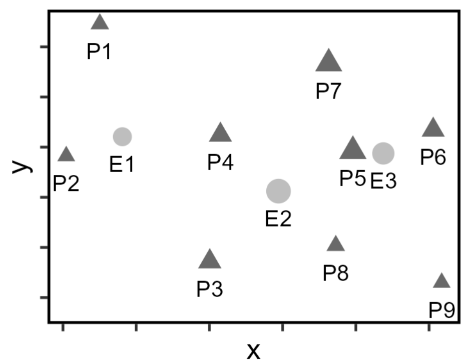
- A is accessibility.
- i is a set of origin locations.
- j is a set of destination locations.
- O_j is the number of opportunities at location j. These are opportunities for activity and add some sort of *supply* to the area;
- c_{ij} is a measure of the cost of moving between i and j
- $f(\cdot)$ is an impedance function of c_{ij}; it can take the form of any monotonically decreasing function (e.g., negative exponential distribution) .

The accessibility value A_i is the weighted sum of opportunities that can be reached from location i, given the cost of travel c_{ij} determined by the impedance function $f(\cdot)$. Summing the opportunities in the neighborhood of i (the neighborhood is defined by the impedance function) estimates of the total number of opportunities that can be reached from i at a certain cost. The type of accessibility value A_i can be changed depending on the impedance function, the measure could be cumulative opportunities (if $f(\cdot)$ is a binary or indicator function e.g., [XX]) or a more traditional gravity measure (e.g., a Gaussian impedance function [XX], inverse cost impedance function [XX], ..). .

We use a simple toy data set to introduce the key concepts, and we will use the usual accessibility measure for comparison. In this way, we aim to show the differences between accessibility and spatial availability, which helps to explain how spatial availability can improve interpretability in the analysis of spatially dispersed opportunities.

Table 1: toy data set

id	number	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



Numerical Accessibility Example

The setup for the simple toy data set is a system with three employment centers and nine population centers, as summarized in Table 1. The access to jobs for each population center is calculated using the conventional accessibility measure A_i (1). In this toy data set 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 depicts three employment centers locations (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 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 $A_i = 17.12$);

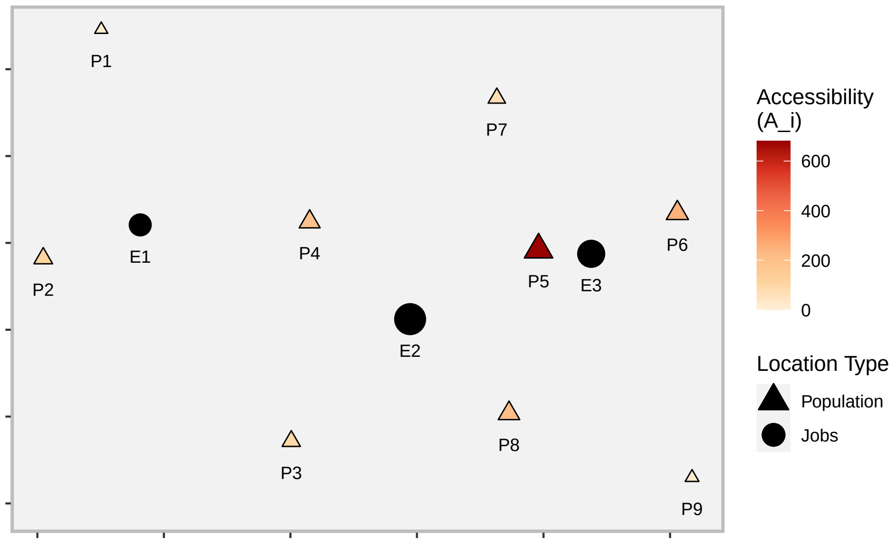


Figure 1: Accessibility of jobs from population centers for the simple toy data set

Issues With the Conventional Accessibility Measure

Accessibility measures are excellent indicators of the intersection between urban structure and transportation infrastructure . However, beyond enabling comparisons of relative values they are not highly interpretable on their own. 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 index and normalize values on a per-capita basis . However, as recent critical research on accessibility discusses (see for instance Paez, Higgins, Vivona (2019) and Allen and Farber (2019)), these steps do not address the bias introduced through the uneven multiple-counting of opportunities which are unconstrainted by demand-side competition. We call this issue the 'conglomeration effect' and it arises as a result of the underlying mathematical assumption that for conventional accessibility A_i all opportunities for all origins $i = 1, \cdots, n$ are 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 demand centers. This neglect to constraint opportunity counts (i.e., single-constraint) obscures the interpretability of accessibility which may manifests in the following two ways of biased estimation:

1) Demand centers in the less dense outer limits of the urban core may be assigned disproportionately *high* accessibility values. These periphery ar-

eas 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/isolated areas which are still within the region of the analysis and have regionally-relative low demand centers, opportunity centers, and travel cost to opportunity centers, are assigned disproportionately *low* accessibility values. These remote/isolated areas may be sufficiently supplied with opportunities proportionate to their demand but is obscured by the artificially high accessibility awarded to periphery/other areas in which conglomeration disproportionately occurs.

The spatially uneven multiple-counting of opportunities (i.e., the conglomeration effect) leave decision makers unclear on how to interpret resulting access values and all recent accessibility measures which seek to improve interpretability are either vulnerable to this impact or require potentially unrealistic assumptions . For instance, the floating catchment areas (FCA) method increases interpretability by purporting to account for competition, however, as discussed by Paez, Higgins, and Vivona (2019), FCA methods are vulnerable to conglomeration 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. As already mentioned, this assumption is not always realistic for many opportunity types such as in the case of job seekers and jobs.

To address the conglomeration effect and introduce a more realistic assumption for opportunities, we propose a singly-constrained gravity measure called **spatial availability**. This measure fundamentally seeks to answer for a individual at a specific population center the following questions: *"many jobs are accessible, but the same jobs are also accessible to my (possibly) numerous neighborus… what does a high accessibility actually mean to me?"* and *"few jobs are accessible but I am located in a remote area with proportionally few neighbours… what does low accessibility mean to me?"*.

The Analytical Framework of Spatial Availability

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

$$V_{ij} = O_j \frac{F^p_{ij} \cdot F^c_{ij}}{\sum_{i=1}^{K} F^p_{ij} \cdot F^c_{ij}} \tag{2}$$

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^p_{ij} is the proportional allocation factor of the population in i relative to the population in region K.
- F^c_{ij} 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.

To explain the analytical framework, the calculation of *job access* is illustrated with a simple 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.

Additionally, since spatial availability V_{ij} consists of these two allocation factors, we detail first how the role of population allocation factor F^p_{ij} in producing V^p_{ij}, next the role of the travel cost allocation factor F^c_{ij} in producing V^c_{ij}, and finally how both allocation factors in the final general form of spatial availability V_{ij} are combined.

Population and Travel Cost Allocation Factors

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

$$F^p_{ij} = \frac{P^\alpha_{i\in r}}{\sum_{i=1}^K P^\alpha_{i\in r}} \tag{3}$$

The population allocation factor F^p_{ij} 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 (maybe those with a certain level of training or in a designated age group). The summation in the denominator is over $i = 1, \cdots, K$, 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^p_{ij} 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^p_{ij} is a proportion, when it is summed over $i = 1, \cdots, K$ it always equals to 1 (i.e., $\sum_i^K F^p_{ij} = 1$). This is notable since the share of jobs (the spatial availability based on population V^p_{ij}) at each destination j allocated to (i.e., available to) each origin is equal to $V^p_{ij} = O_j \cdot F^p_{ij}$ and since the sum of F^p_{ij} 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 $P_3 = 120$). 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 (4).

$$\begin{array}{c} F_{2,1}^{p} = \frac{P_2^{\alpha}}{P_2^{\alpha}+P_3^{\alpha}} = \frac{240}{240+120} = \frac{240}{360} \\ F_{3,1}^{p} = \frac{P_3^{\alpha}}{P_2^{\alpha}+P_3^{\alpha}} = \frac{120}{240+120} = \frac{120}{360} \end{array} \tag{4}$$

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 would be calculated as follows in (5).

$$\begin{array}{c} V_{2,1}^{p} = O_1 \cdot F_{2,1}^{p} = 300 \cdot \frac{240}{360} = 200 \\ V_{3,1}^{p} = O_1 \cdot F_{3,1}^{p} = 300 \cdot \frac{120}{360} = 100 \end{array} \tag{5}$$

It can be seen that 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}), proportionally 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 (6).

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

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 allocates more jobs to closer locations through an impedance function. To continue illustrating, assume that the impedance function is a negative exponential function and assume that β (which modulates the steepness of the impedance effect and is an empirical parameter) is the value of 1 for simplicity. 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 (7).

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

We can see that the proportional allocation factor for P_3 is larger than P_2 since the distance to O_1 is shorter. Using the travel cost proportional allocation factors F_{ij}^c as defined in (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 (8).

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

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 both population and travel cost factors to accurate reflect demand; these two components are in line with how demand is conventionally modelled in accessibility calculations. 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 (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 (9).

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

As can be seen, fewer number of 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, availability is simply the sum of (2) for all opportunities J (i.e., $V_i = \sum_{j=1}^{J} V_{ij}$). This quantity represents opportunities (e.g., jobs) that can be accessed from i and that are *not* allocated to a competitor: therefore the weighted sum of available opportunities. Compare V_i to the singly-constrained gravity model (see Wilson (1971)) . In essence, 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 (10).

$$v_i = \frac{V_i}{P_i} \tag{10}$$

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

$$\begin{aligned} v_{2,1} = \tfrac{V_{2,1}}{P_2} = \tfrac{179.4}{240} = 0.8 \\ v_{3,1} = \tfrac{V_{3,1}}{P_3} = \tfrac{120.6}{120} = 1.0 \end{aligned} \tag{11}$$

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 capita.

Where the overall ratio of jobs to population in the region is $300/(240 + 120) = 0.83$, the spatially available jobs per capita at k is closer to unity.

Empirical Example: Spatial Availability and Accessibility of Jobs in the GGH

In this section, we use two empirical examples to demonstrate how the spatially uneven multiple-counting of opportunities (i.e., conglomeration effect) inherent to the accessibility measure (1) introduces spatial bias and obscures interpretability. This conglomeration effect is highlighted by calculating spatial availability (2) and comparing the relative difference between the two measures. 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

Table 2: Descriptive statistics of the TTS 2016 dataset for the Greater Golden Horshoe Area

	Trips	Travel_Time
	Min. : 1.00	Min. : 0.00
	1st Qu.: 14.00	1st Qu.: 13.00
	Median : 22.00	Median : 20.00
	Mean : 33.44	Mean : 23.39
	3rd Qu.: 38.00	3rd Qu.: 30.00
	Max. :1129.00	Max. :179.00
	NA	NA's :3507

urban periphery. Both examples are based on the same empirical data set for home-based work trips in the Greater Golden Horseshoe (GGH) area. We first introduce the data used, then calibrate the impedance function, and finally illustrate the two examples.

Data

The 2016 Transportation Tomorrow Survey (TTS) data for 20 municipalities contained within the GGH area in the province of Ontario, Canada (43.6°N 79.73°W) is used within this section (Figure 2). This data set includes home-based origins and employment destinations defined by centroids of Traffic Analysis Zones (TAZ) (n=3764), the number of jobs (n=3081900) and workers (n=3446957) at each origin and destination, and the trips from origin to destination for the morning home-to-work commute (n=3446957).

Also included are travel times and cost of travel from origin to destination by car; travel times are calculated using the R package `r5r` (Rafael H. M. Pereira et al., 2021) and an impedance function based on these travel times is derived. It is important to note that for simplicity, all trips within this data set are assumed to be taken by car, and the travel time is calculated from an origin TAZ centroid to a destination TAZ centroid. The centroid is snapped to the nearest street line by `r5r` and the travel time is calculated for all trips assuming a car travel mode and a department of 7:00am on Wednesday October 2021, an arbitrary date selected by the authors. Additionally, only travel times less than or equal to 180 mins (3 hrs); this threshold represents 99% of trip's travel times which are summarized in the descriptive statistics in Table 2. All data and data preparation steps can be freely explored in companion R data-package `AccessPack`.

Calibrating an Impedance Function

In the toy data set introduced in the Numerical Accessibility Example section, an arbitrary negative exponential function describing travel cost (as a function of distance) was used as the impedance function to derive both accessibility and spatial availability. In this empirical data set, since the travel time is calculated based on the existing street network in the GGH, an empirical trip

Figure 2: The TTS 2016 study area within the Greater Golden Horseshoe in Ontario, Canada.

length distribution (TLD) is defined and used to derive an impedance function. For background, a TLD is the representation of the likelihood that a proportion of trips are taken at a specific travel cost and are widely used to derive impedance functions in accessibility research .

The empirical TLD for this data set is represented by black data points in Figure 3). As can be observed, this empirical distribution appears to follow a gamma distribution, as such, this theoretical distribution along with other common TLD distributions such as log-normal and exponential distributions were fitted to the empirical TLD. The maximum likelihood estimation method and Nelder-Mead method for direct optimization available within the `fitdistrplus` package (Delignette-Muller and Dutang, 2015) was used . Based on goodness-of-fit criteria and diagnostics presented in Appendix Figure 14 and 13, the gamma distribution was selected and is represented as a red line in Figure 3.

The resulting calibrated gamma distribution, which serves as the impedance function for the empirical data set, is given in the following general form where the estimated 'shape' is α, the estimated 'rate' is β, and $\Gamma(\alpha)$ is defined in (12). The calculated shape and rate parameter is 2.019 and 0.094 respectively. We would like to reiterate that this impedance function, though it is derived using empirical data, assumes all home-to-work trips in the 2016 TTS data set are all taken by car. In reality there is a modal split but for illustrative purposes, the same impedance function is used to calculate accessibility and spatial availability in the following examples.

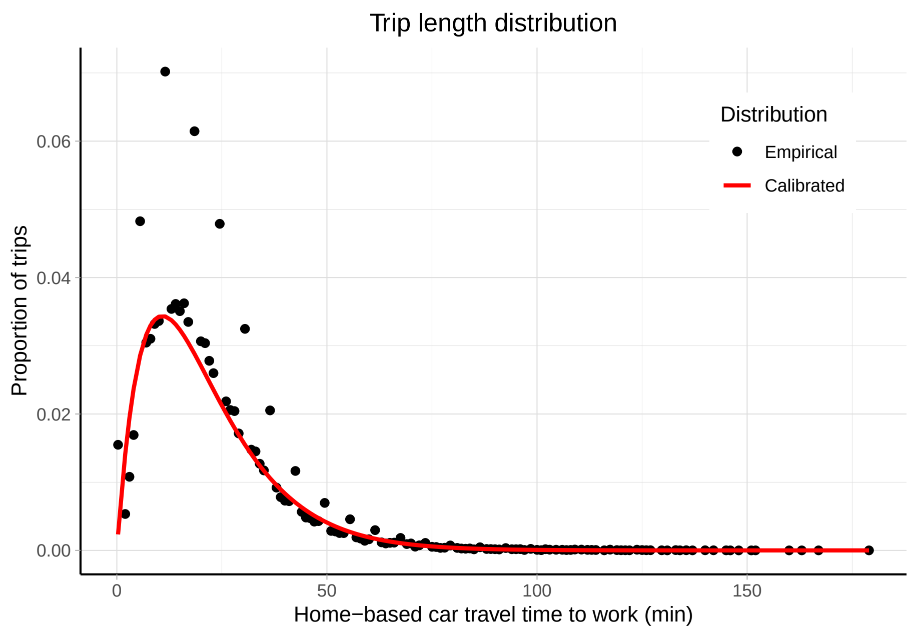


Figure 3: Empirical TTS 2016 home-based car trip length distribution (black) and calibrated gamma distribution impedance function (red)

$$\begin{aligned} &f(x,\alpha,\beta) = \frac{x^{\alpha-1}e^{-\frac{x}{\beta}}}{\beta^{\alpha}\Gamma(\alpha)} \quad \text{for } 0 \leq x \leq \infty \\ &\Gamma(\alpha) = \int_0^{\infty} x^{\alpha-1}e^{-x}\,dx \end{aligned} \tag{12}$$

Access to jobs in Toronto

Toronto is the largest city in the GGH and represents a significant subset of workers and jobs in the GGH; 50% of workers in the GGH travel to jobs in Toronto and 72% of jobs are located within Toronto. As later discussed, this significant subset of jobs illustrates the first issue associated with the accessibility measure conglomeration effect : neglecting to include the single-constraint overestimates job access for TAZ with a low proportion of workers that are next to TAZ with a high proportion of jobs and workers.

Accessibility is first calculated and presented in Figure 4. The higher the accessibility value, the more accessible places of employment are to home-based origins. It can be briefly summarized that the accessibility values follow a radial trend where the majority of TAZs in Toronto have high accessibility values and values decrease in TAZs which are further from the city boundary. This finding is echoed in many studies and indicates that the closer one lives to Toronto, the more opportunities for employment they will have access to.

Next, job access is calculated using the spatial availability measure and is present alongside the accessibility plot in Figure 4. Similar to the accessibility plot, the higher the value the more the more access that TAZ has to jobs in the city of Toronto. However, since spatial availability constraints the total number of opportunities counted, high values of spatial availability can be seen as higher access to *available* jobs and we can observe which TAZs have job access values which are above or below the regional average of 638.

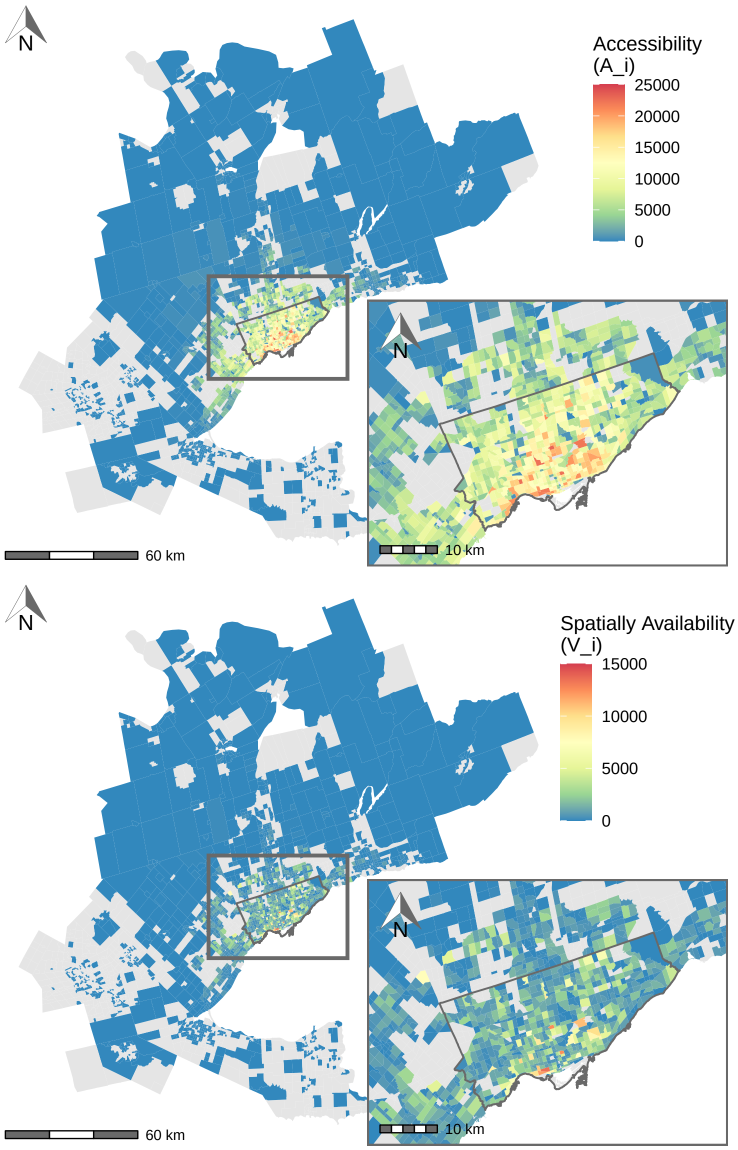


Figure 4: Calculated accessibility (top) and spatial availability (bottom) of employment from origins in the GGH to destinations in the City of Toronto.

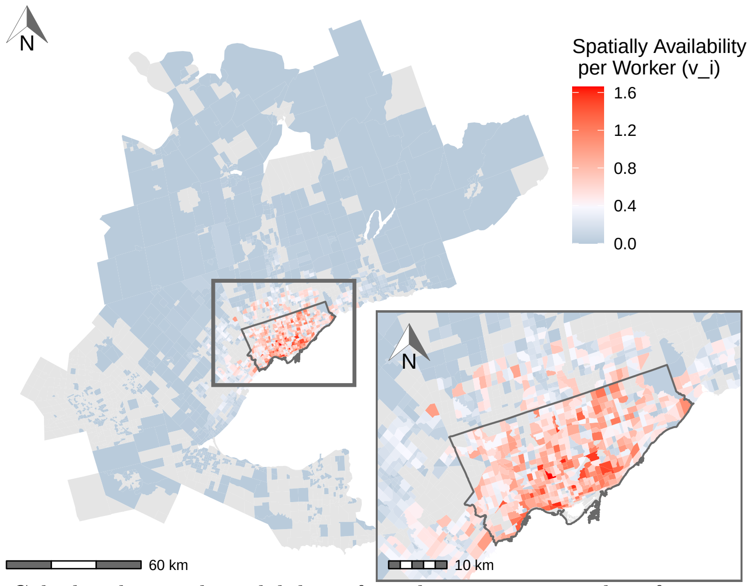


Figure 5: Calculated spatial availability of employment, per worker, from origins in the GGH to destinations in the City of Toronto.

The visual differences between accessibility and spatial availability plots in Figure 4 are stark. The TAZ within and 10-20 km outside of Toronto's boundary have relatively lower access values (i.e., fewer reds and oranges) as measured by spatial availability than as measured by accessibility. There are also more pockets of low job access (i.e., blues) within the city of Toronto when measured by spatial availability; this observation is in line with empirical quantitative work describing the spatially uneven job accessibility landscape in Toronto .

To enhance the interpretability of spatial availability, job access can be normalized to provide more meaningful insight on 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 (0.38) available jobs per worker in the GGH to jobs located within the city of Toronto. Overall, similar to the non-normalized spatial availability measure, this figure demonstrates that job access is lower within and around Toronto than the accessibility measure. We can also observe a similar uneven spatial distribution of job access within Toronto (as also shown in the spatial availability plot in Figure 4) where job access is consistently far about the average and often greater than 1 job per worker for the soouth-central and south-west TAZ in Toronto, this trend is not as pronounced in the south-east and other pockets in the City. This uneven distribution of job access has been explained by some studies to be a result of...
.

Access to jobs in the GGH

In this section we calculate job access for *all* jobs in the GGH for all origins in the GGH using both accessibility and spatial availability measures. As will be later elaborated, the full TTS data set demonstrates the second issue associated with the conglomeration effect expressed by the accessibility measure. More specifically, this issue underestimates job access for TAZ which are on located in the periphery of the GGH and have relatively-low proportion of workers and are relatively isolated (by travel cost) from the Toronto which has the highest density of jobs. The first issue, namely the over estimation of the TAZs which are on the outer limits outside the Toronto border can also be observed.

Accessibility and spatial availability are both calculated and presented in Figure 6. Interestingly, despite the majority of jobs being located within Toronto - general trends are similar for both accessibility plots but not for both spatial availability plots. For instance, the accessibility values follow a radial trend where the majority of TAZs in Toronto have high accessibility values and values decrease in TAZs which are further from the city boundary. However, it can be seen that the radial effect is less pronounced and TAZs outside of Toronto appear to have a higher accessibility score. Conversely, spatial availability does not appear to follow a radial trend as depicted in the previous plot in Figure 4. Job access, as measured by spatial availability, appears much more even throughout the GGH (in comparison to job access as measured by accessibility). This can be noted in higher values around the north east and south west periphery TAZs and more moderate values in and around Toronto. This distribution of job access in the GGH may be more realistic as qualitative and quantitative studies have demonstrated that as operating costs continue to increase in Toronto, more and different types of employment centers are operating in the periphery of the GGH .

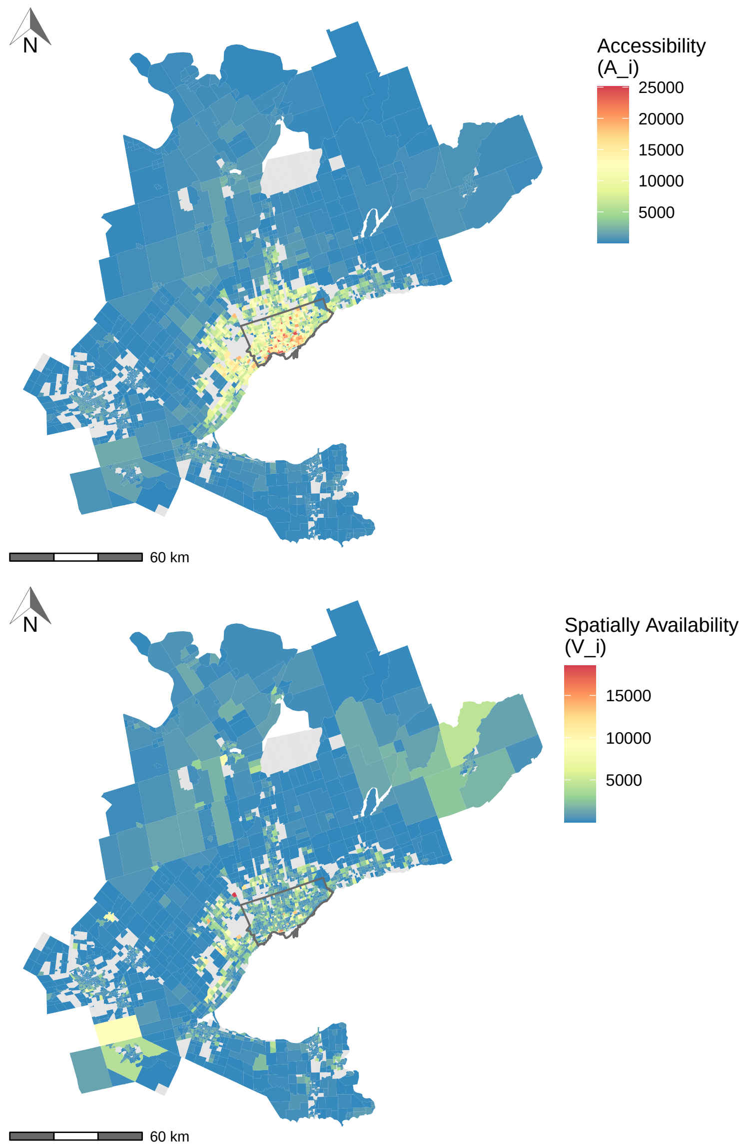


Figure 6: Calculated accessibility (top) and spatial availability (bottom) of employment from origins in the GGH to destinations in the GGH.

Similar to the per capita spatial availability figure for jobs in the Toronto (Figure 5), Figure 7 depicts which TAZs have above average, below average, and average (0.89) access to jobs per capita considering all jobs and workers in the GGH. We can some similar general trends, such as a higher concentration of jobs per capita are available in TAZs which are within the city of Toronto. However, the plot is distinct and more similar to the spatial availability plot for this data set, where we can see the jobs per capita values are more evenly distributed throughout the GGH, relative to the trends in the accessibility plot. We can also see higher jobs per capita in employment areas in different cites such as Mississauga and Burlington (south-west of Toronto), Waterloo and Brantford (even more south-west of Toronto), and Hamilton and Niagra (south of Toronto).

Again, spatial availability can also be represented on a per-worker basis and a similar trend between spatial availability in Figure 5 can be seen for all GGH jobs in Figure 7. Interestingly, when considering the jobs which are *available*, many areas outside of Toronto have similar jobs per capita values as TAZ in Toronto. This is contrary to the common belief that Toronto is one of the only hubs for employment opportunities . Urban centers in Brantford, Guelph, Missauga, Burlington, and Niagra have TAZs which are far above the the average jobs per capita and compare to TAZ within Toronto. This suggests that these less densely populated areas may have sufficient employment opportunities for their population and this finding is obscured when only considering the accessibility measure for job access.

It is also worth noting that within the full sample of the GGH, there is almost two times more jobs per capita than the rate for Toronto jobs per GGH capita. 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. The causes for this trend are numerous and can include . . . . as mentioned by study .

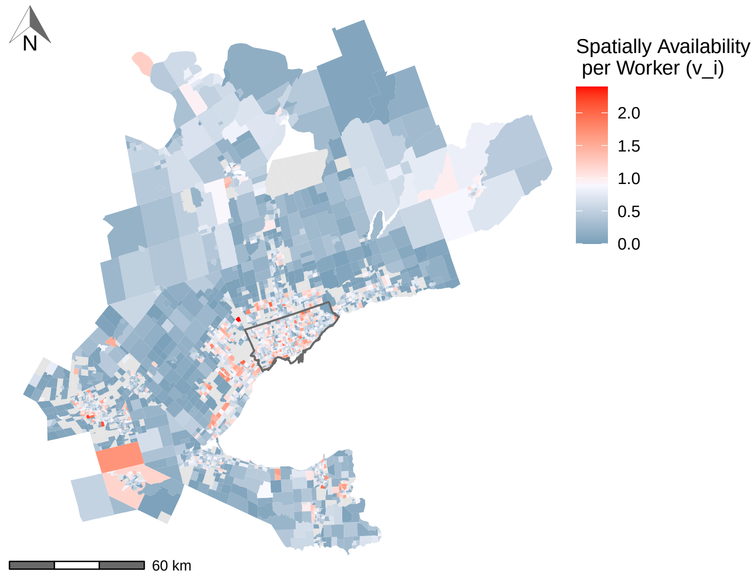


Figure 7: Calculated spatial availability of employment, per worker, from origins in the GGH to destinations in the City of Toronto.

Discussion

We have used both accessibility and spatial availability to measure access to jobs and have visually compared trends for the empirical GGH data set in the previous section. To build on these findings, a thorough comparative discussion is detailed in this section in which we return to the two issues produced by the conglomeration effect as 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^I_{ij} and V^I_{ij}. This re-scaling process is done since accessibility cannot be meaningfully compared through normalization on a per worker basis since the methodology inherently multiple-counts opportunities which is not the case for spatial availability. Re-scaling is repeated for both measures for the subset of jobs in Toronto and for all jobs in the GGH and differences are calculated as described in Equation 14.

$$
\begin{aligned}
A^I_{ij} &= \frac{A_{ij}}{\max(A_{ij})} \cdot 100 \\
V^I_{ij} &= \frac{V_{ij}}{\max(V_{ij})} \cdot 100
\end{aligned}
\tag{13}
$$

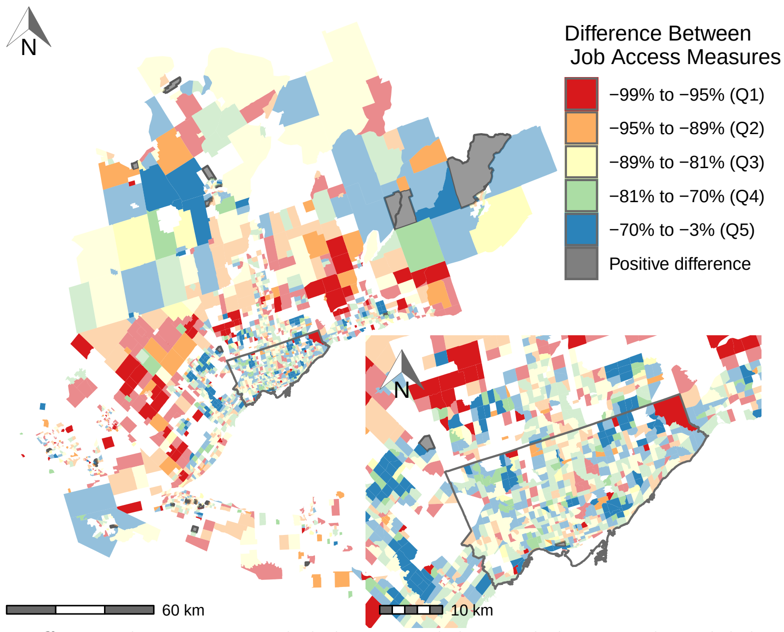


Figure 8: Difference between re-scaled the accessibility and the spatial availability job access measure in the context of employment from origins in the GGH to destinations in the City of Toronto. Values are expressed in five quantile ranges. Vivid TAZs represent a significant spatial autocorrelation and dimmed TAZs represent a non-signficant autocorrelation as measured by Local Moran's I. TAZs with values which are higher than re-scaled accessibility (positive difference) are shown fully in grey.

$$Dif_{ij} = \frac{V_{ij}^{I} - A_{ij}^{I}}{A_{ij}^{I}} \cdot 100 \tag{14}$$

Overestimating jobs access (issue 1)

For the subset of jobs in Toronto and all origins in the GGH, 98.9% of TAZ have re-scaled spatial availability values whcih are lower than re-scaled accessibility values. Of this 98.9%, the spatial availability value is on average -80.64% different than the accessibility value and the difference ranges between -2.95% to -99.9%. Furthermore, to emphasis the similarity of this difference measure between neighbourhing TAZs, the spatial autocorrelation is calculated using Moran's I statistic (Anselin, 1995) and TAZ with a significant p-value ($p \leq 0.10$) are more vividly presented. Figure 8 displays the described plotted comparison, where the more negative the value, the more the accessibility measure overestimation job access relative to spatial availability for each TAZ. It should be noted that although the majority of TAZ job access values are overestimated by accessibility, the 23 TAZ which are underestimated are shown in grey.

We can see from Figure 8 that when we re-scale both job access values, accessibility consistently overestimate job access compared to the spatial availability measure for jobs within the city of Toronto and all people within the GGH who travel to Toronto for work. Overestimation ranges from -100% to -3% and is on average -81%. However, while job access is consistently overestimated, it is overestimated in a variable way. The TAZs with the largest difference in measure are depicted in red and orange (quantiles 1 and 2) and can be seen, in sometimes concentrated clusters (as indicated by the 2044 TAZs with a significant Moran I's statistic) approximately 10-20 kms outside of Toronto city border and along the south side of the GGH. These TAZs also have a relatively low density of people who work in Toronto and as such the difference between measures has a significant correlation (0.877) with the number of workers in each TAZ.

Nonetheless, the density of workers within each TAZs alone does not fully explain the variation in overestimation. The number of opportunities and the travel cost also factors in the calculation of both accessibility and spatial availability. From the perspective of accessibility A_i, job access does not consider opportunity-constraints and as such the extensively overestimated TAZs benefit from overestimated job access without any competition considerations from their more dense and more centrally located neighbours (within the city of Toronto) and their more peripherally located but more relatively more worker-dense peripheral neighbours. Spatial availability V_i considers this competition by proportionally allocating jobs to these TAZs relative to their travel cost and worker population. In other words, these overestimated TAZs reflect the incident in which travel cost outpaced the number of workers and thus the proportionately allocated opportunities are significantly fewer when measured by spatial availability V_i instead of accessibility A_i.

Underestimating jobs access (issue 2)

Next, 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, 17%% of TAZ are underestimated. These underestimated TAZ are plotted in figure … alongsie the overestimated TAZ for comparison. Of the underestimated TAZ, the spatial availability value is on average 214.7% different than the accessibility value and the difference ranges between 0% to -99.9%. The overestimated TAZ have a spatial availability value that is on average 214.7% different than the accessibility value and the difference ranges between 0% to -99.9%. Moran's I is not plotted but the statistics is significant (i.e., there is spatial autocorrelation) for the full data set ($p < 0.001$ for all difference values).

As observed from Figure 9, 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 city of Toronto and the Greater Toronto Area (GTA) is located but are in proximity to other, smaller, employment areas within smaller municipalities . It can be understood

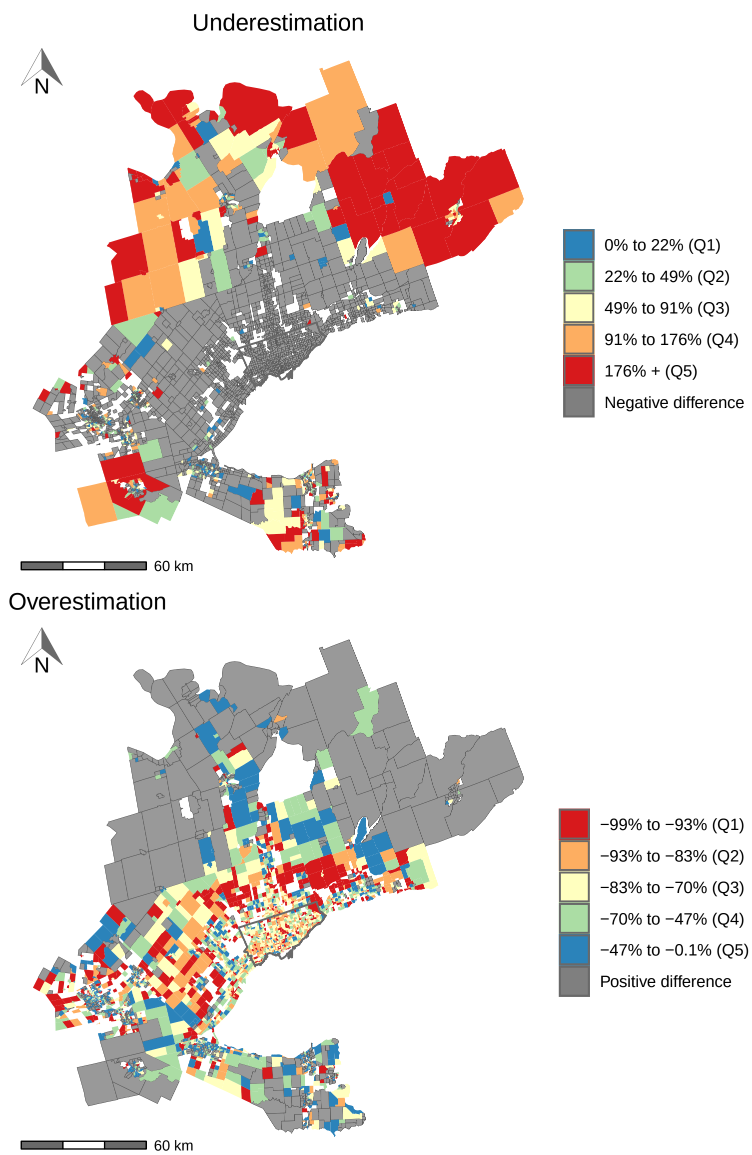


Figure 9: Difference between re-scaled the accessibility and the spatial availability job access measure in the context of employment from origins in the GGH to destinations in the City of Toronto. Values are expressed in five quantile ranges. Vivid TAZs represent a significant spatial autocorrelation and dimmed TAZs represent a non-signficant autocorrelation as measured by Local Moran's I only for underestimated TAZs. TAZs with values which are higher than re-scaled accessibility (positive difference) are shown fully in grey.

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-counting 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 capita (Figure 7) where we can see that commercial areas throughout the GGH 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 6).

Next, it is worth explaining why accessibility's multiple counting does not also result in the underestimation of job access when considering only considering the jobs available in Toronto. As depicted in the previous Figure 8, almost all TAZ are overestimates (i.e., accessibility values are *higher* than spatial availability). Within this subset of jobs in these peripheral TAZ, spatial availability is proportionally allocated based on their high (compared to the region) travel cost and Toronto-working population. In essence, these TAZ experience moderately high job competition and thus have low spatial availability. When accessibility is calculated, these peripheral TAZ have low accessibility as a result of the multiple-counting which occurs within and around Toronto but when the two measures are compared, however, accessibility is still *higher* than spatial availability. 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 Figure 9. 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 (compare spatial availability per capita within these periphery TAZ in Figure 5 and Figure 7). 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 than the spatial availability resulting in underestimated TAZ.

It is also worth noting that the right panel of Figure 9, by contrast, depicts all the TAZ with overestimated job access (i.e., re-scaled accessibility values are larger than re-scaled spatial availability values). Similar to the difference between measures depicted in the previous Figure 8 for the subset of jobs located in Toronto, these TAZ which are mostly within the GTA reflect an increased accessibility as a result of multiple-counting of jobs and a comparatively low spatial availability as a result of high job competition. Overall, within the full set of jobs in the GGH, the first and second issue associated with accessibility's conglomeration effect are observed.

Contextualizing Spatial Availability Use Cases

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-exhaust and applications outside of employment are tenable and warranted.

To illustrate these two additional examples, we return to the toy data set initially introduced in Background section.

Available Jobs for Specialized Working Populations

Suppose that population centers 1 through 8 are not all eligible for employment at the three employment centers 1, 2, and 3. 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 toy data set, we consider that only population center 1 and 2 are eligible for employment at Employment Center 1. Next assume that jobs in employment center 2 can be taken by individuals in population centers 3, 4, 5, 7, and 8. Lastly, jobs in Employment Center 3 require qualifications available only among individuals in population centers 5, 6, 8, and 9. 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 10.

For higher interpretability, we can view Figure 11 which demonstrates a plot of spatial availability per captia 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 11, we see that population center 5 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 11, we see that the job access for population centers in the blue catchment decrease as job competition increases. However, we also observe that access marginally increases for the population centers in the yellow catchment and the regional spatial availability per capita increases slightly to 0.964.

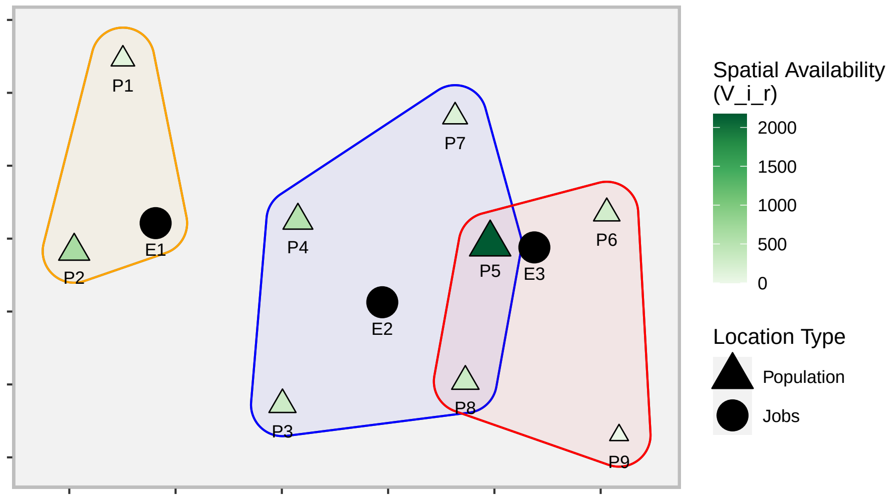


Figure 10: Spatial availability of jobs from population centers assuming catchment restrictions for the simple toy data set

Alternative Use Case 3: Available Workers for Employment Centers

Moving away from catchments in this next use case, we can easily switch the demand and opportunity roles of the employment centers and population centers. In this way, this use cases examines the pool of workers available (demand) to each employment center by considering the workers as the opportunities. We caculate spatial availability in the same way by proportionally allocating jobs to workers based on travel cost and numbers of jobs. Figure 12 presents the spatial availability generally and per capita.

Plot the spatial availability of workers per job in Figure 12

Conclusing remarks

we argue that the proposed measure offers higher interpretability as it opportunity per capita values can be derived to benchmark regional results and per capita values can be compared across regions more meaningfully.

Words go here.

still does not tell us how many accessible opportunities will lead to participation/positive outcomes; it does come closer… this is an important question for equity analysis.

we propose that spatial availability be seen as a type of *spatial mismatch* and an evolution of the *balanced floating catchment* approach (BFCA) . Historically, literature has iteratively improved measures assessing access to oppor-

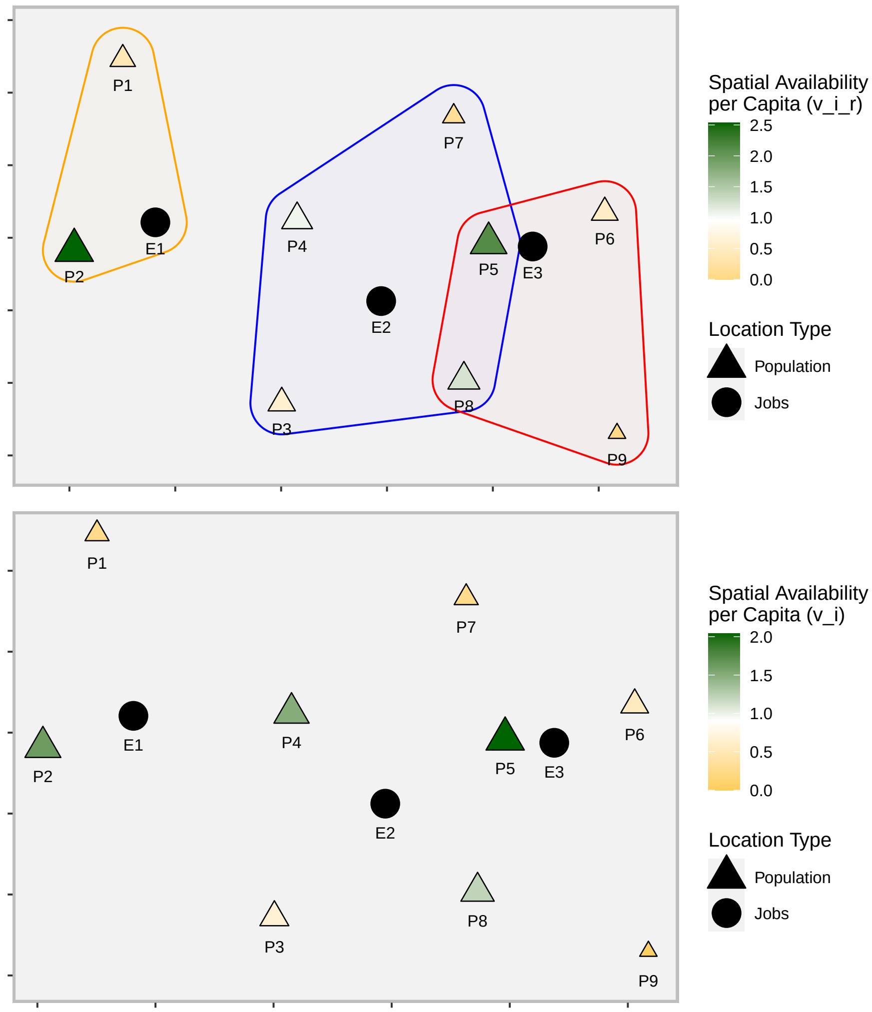


Figure 11: Spatial availability of jobs per capita for each population centers with catchment restrictions (top) and without catchment restrictions (bottom) for the simple toy data set

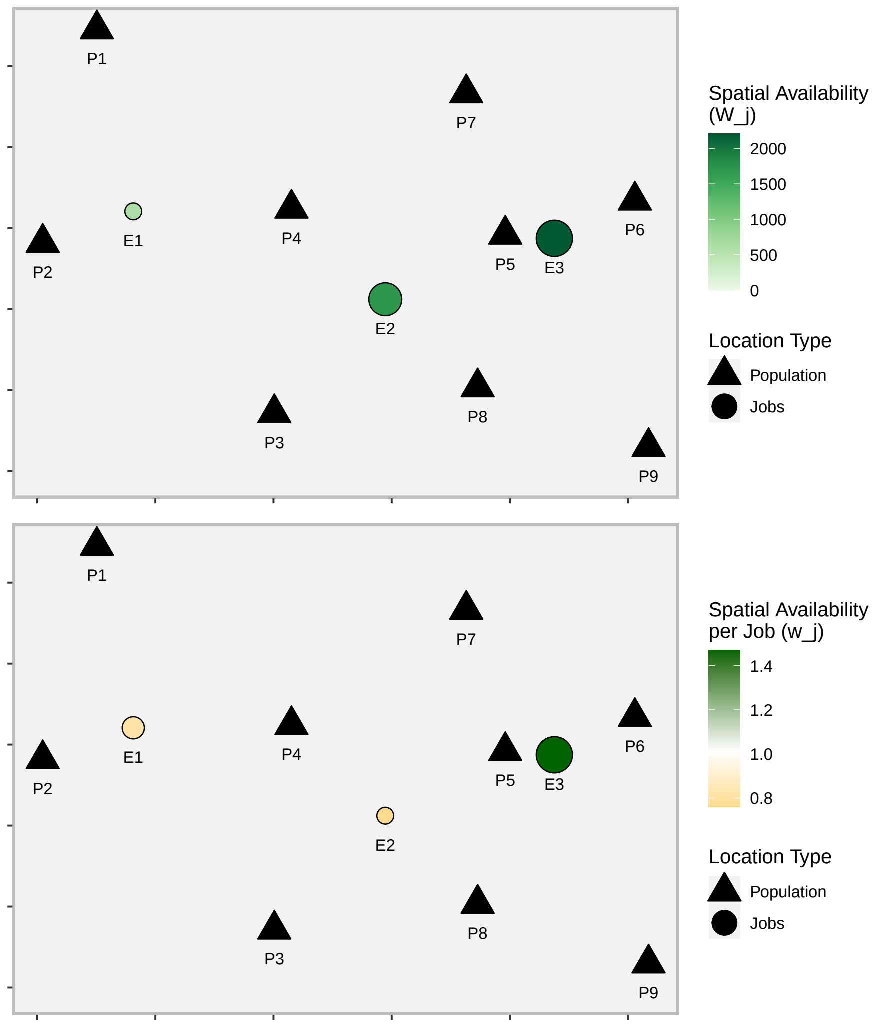


Figure 12: Spatial availability of workers for each employment center (top) and the spatial availability of workers per job for each employment center (bottom) for the simple toy data set

tunities. 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 suspitable 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.

Similar to the accessibility measure, it should be noted that spatial availability is only as robust to the MUAP as the input data allows. For instance, in the empirical example present, the measure of *job access* still only considers population, opportunities, and travel times from the centroids of TAZs. However, unlike the accessibility measure, spatial availability can be meaningful calculated on a per population basis at higher resolutions because of the proportionality property.

Further, the measure of spatial availability can be a useful way to distinguish between low accessibility/low population centers, which may enjoy higher availability than the accessibility value may suggest, and contrariwise, high accessibility/high population centers (which potentially can result in lower availability due to competition). For instance, as presented in the toy data set, more remote, smaller population centers can have sufficient spatial availability by being in close proximity to the smaller employment centers; however this sufficiency is obscured by accessibility measure by conglomerating accessibly of population centers which are more central to more (and larger) employment centers. Conversely, referring to the empirical GGH example, the TAZs that are relatively close to the Toronto job destinations but have a relatively low number of workers receive sufficiently high values of accessibility and signficantly lower spatial availability values; this trend is opposite to what is experienced in the toy data set and is a result of higher job competition (i.e. job opportunities are more highly allocated to TAZs with lower travel costs and higher worker populations). Measuring access to opportunities is a multi-scale problem; since the number of opportunities are preserved, different scales, populations, and time-windows can be incorporated within the measure without introducing additional spatial basis.

Fundamentally, accessibility measure's methodology results in the overestimation of *jobs access* since it simply sums the count of destination opportunities based on travel cost to opportunities; the measure does not include factors to

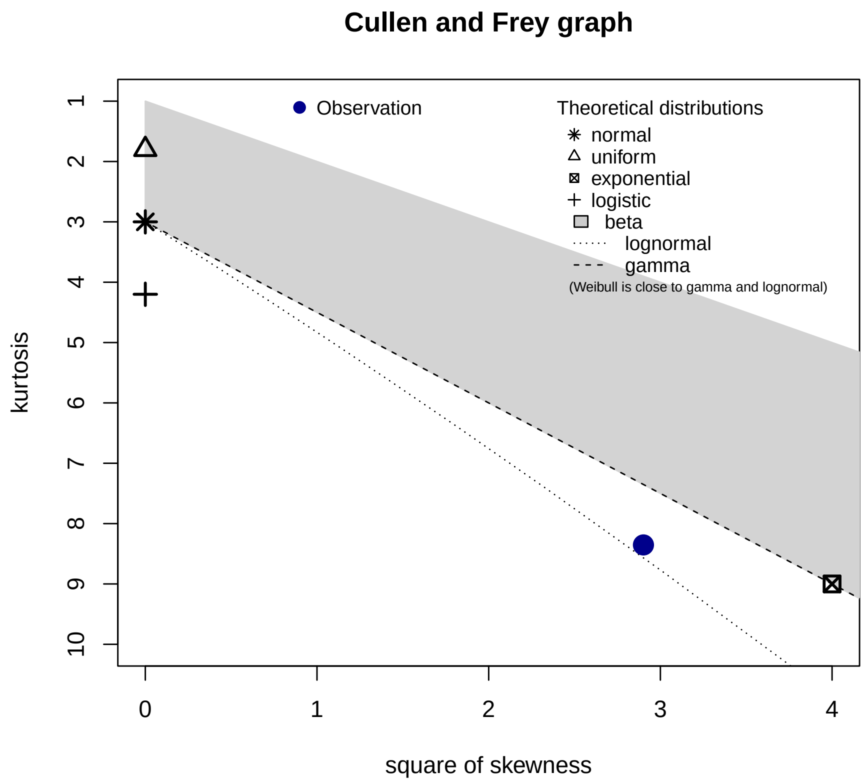


Figure 13: Cullen and frey graphy for the complete empirical 2016 TTS travel time data set.

bound the summation so origins, hypothetically, can have infinite *opportunity access*. This property can be practical for calculating *opportunity access* for opportunities which have large capacities and are *non-competitive* such as large natural parks and beaches. These non-competitive opportunities can be considered infinitely divisible as they offer more 'spots' at any given time than the population. However, often times opportunities are not divisible but are in fact indivisible and competitive meaning, such as the numerical and GGH empirical example of *jobs access*, where only 1 worker can access 1 job at any given time. In these cases, spatial availability measure can be used to calculate the *opportunity access* in which the report values are numerically meaningful, the MUAP is potentially addressed, and *opportunity access* values across regions, neighbourhoods, and spatial scales can be compared.

Appendix

`summary statistics`

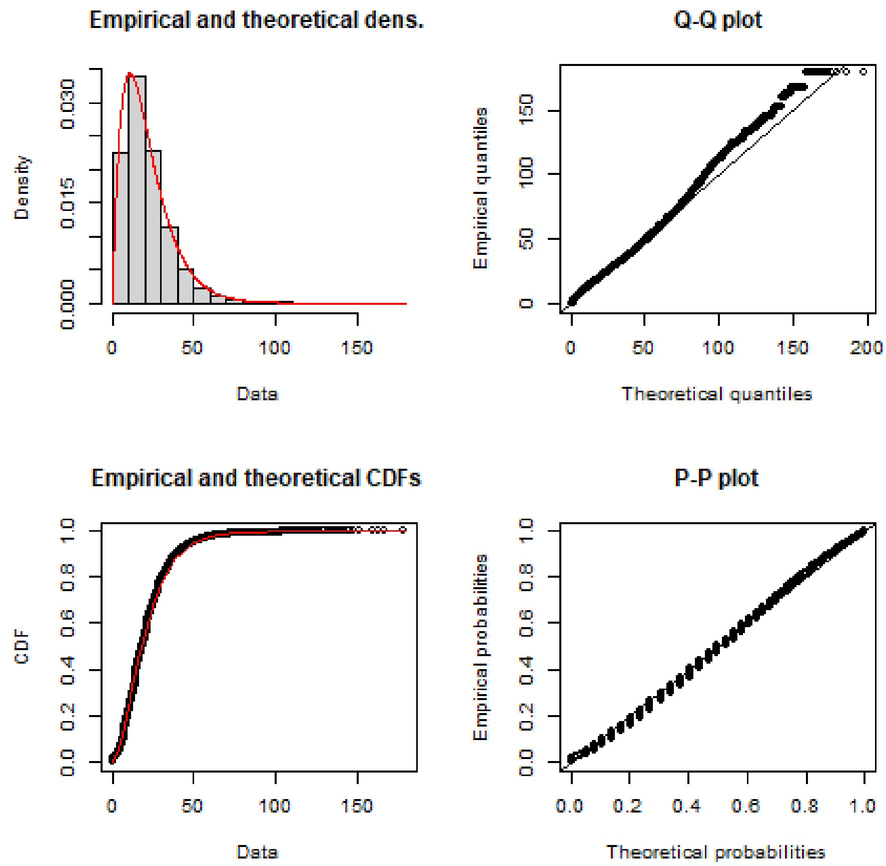


Figure 14: Diagnostics associated with the fitted gamma distribution.

```
------
min:  0.1   max:  179
median:  18
mean:  21.4344
estimated sd:  14.61254
estimated skewness:  1.703326
estimated kurtosis:  8.353363
```

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