Multimodal spatial availability: a singly-constrained measure of competitive accessibility considering multiple modes

Anastasia Soukhov [1] [*], Javier Tarriño-Ortiz [2], Julio A. Soria-Lara [2], Antonio Páez [1]

1 Department of Earth, Environment and Society, McMaster University, Hamilton, Canada
2 Centro de Investigación del Transporte (TRANSyT), Universidad Politécnica de Madrid, Madrid, Spain

* Corresponding author: soukhoa@mcmaster.ca (AS)

Abstract

An increasing number of studies within the domain of transportation planning are concerned with the inequities in accessibility to opportunities. A dimension of these inequities arises from differences in access by mode type (e.g., commuting using a car as opposed to transit). However, methods implemented in current accessibility literature are lacking within the context of multimodal analysis. This paper presents an extension of spatial availability, a singly-constrained competitive accessibility measure, for the context of multimodal accessibility analysis. We first illustrate the features of spatial availability that lend itself to multimodal analysis. We then demonstrate its use on the case study of Low Emission Zones in Madrid (Spain) and highlight how this policy intervention changes the accessibility of populations using different modes. In summary, spatial availability can be used to create and interpret multimodal policy intervention scenarios unlike previous methods: this creation and interpretation can help regions envision a more sustainable and equitable access-to-opportunity landscape.

Introduction

Implementing urban policies that re-shape cities through accessibility gains (i.e., the *potential to interact* with opportunities as a result of land-use mix and transport systems as originally defined by [1]) have been widely applied within the transportation literature and is increasingly discussed by planners [2–5]. An important challenge in the identification of interventions that equitably transform cities is the effective evaluation of *trade-offs*: cities are complex and dynamic ecologies, and advantaging one component of the city can disadvantage another area, population, or sub-component In this way, policy evaluation should take a *systems* approach [6]. One way of considering systems is from the perspective of the *finite*. As an illustration, consider the amount of transport space within a city: the amount is typically finite so re-allocating road space away from one mode directly impacts the performance of the others (see the literature on road space reallocation e.g., [7]). Evaluating policy impacts in the context of *finity* provides a way to contextualize the balance of trade-offs that the citizens of a city should tolerate.

From the perspective of urban transport systems, location-based accessibility measures have been used in the context of policy evaluation. For instance, [8] assesses the transit accessibility gains to healthcare and employment opportunities for disadvantaged neighbourhood in Columbus, Ohio, USA after the transit system's re-design and introduction of a rapid bus system. However, a limitation of this study, like others that implement accessibility measures, is they do not calculate results under a *constrained* framework i.e., one of *finity*. The citizens of Columbus should experience quantitative accessibility gains - but is it at the expense of access using other modes? As another example, [9] implements a modified cumulative opportunity measure to assess differences between private vehicle and transit system accessibility to jobs in Melbourne, but a similar question remains: does the accessibility afforded to the private vehicle using population come at the expense of accessibility losses to transit users?

[8] and [9] both use *non-competitive* accessibility measures. There is a branch of location-based accessibility measures that do incorporate the effect of competition for opportunities by the population in the region. However, we argue that these existing methods fall short in acknowledging the *finity* of opportunities. For instance, [10] applies a competitive measure, two-step floating catchment approach (2SFCA), for the case of access to healthcare services in Florida for both a multimodal network and a single modal network. While the differences in modal access are discussed, the question of how the advantage in access afforded by one mode over another impacts access for different mode users is unanswered.

This question of how much one mode-using population can access at the expense of another mode-using population is a pertinent equity question in the evaluation of policy scenarios that are multimodal. For instance, consider the impact of a low emission zone (LEZ). LEZ is a policy of spatial and modal discrimination: the circulation of vehicles that are excessively polluting are restricted in specific regions. In the recognition that opportunities are finite, the implementation of a LEZ explicitly reduces the access that the population using polluting vehicles has to opportunities. This restriction allows the population using other more sustainable modes to potentially have a higher level of access than before the LEZ implementation. This evaluation is especially urgent as LEZ are currently in effect in cities globally; their reception has been mixed [11] and may be having negative impacts on disadvantaged populations who have become mobility-restricted [12,13]. Measures that evaluate the accessibility of modes given both *constrained* and *competitive* considerations are lacking in the literature, but are needed, to evaluate such policy interventions impact on accessibility.

In [14], we introduce spatial availability, a type of location-based accessibility measure that is both *constrained* and *competitive*. In this paper, we extend the spatial availability measure into a multimodal framework and explore its use in answering the question outlined: *"given opportunities are finite, how many are available to a given location depending on the mode used?"*. The answer to this question quantifies how many opportunities can be accessed, considering competition, for different modes. To foreground this exploration, in Section 2, we discuss short falls of a few existing location-based measures in comparison to spatial availability through a synthetic example. In Section 3, the spatial availability of an empirical example of the LEZ in the city of Madrid, Spain is calculated. We demonstrate how the restriction of car circulation could have impacted the spatial availability of opportunities for each sub-population using transit, cycling and walking modes. In Section 4, we provide concluding remarks on the strengths of the use of spatial availability as a multimodal accessibility measure and potential future uses in policy planning scenarios.

A review of multimodal accessibility measures

Location-based accessibility indicators are quantitative measures of *potential* interaction with opportunities for locations within a given region: they are a product of the relationship between land-use and transport systems. Arguably the most commonly used location-based measured are cumulative opportunity measures and weighted cumulative opportunity measures [2]. These measures weight the opportunities that can be potentially interacted with from origin i to destination j based on some sort of travel cost function (e.g., travel time, fare, travel distance) otherwise known as a travel impedance function $f^m(c_{ij}^m)$. Many weighted cumulative opportunities (often referred to as the gravity-based measure) originate from the measure proposed by [1], which can take the following multimodal form: $S_i^m = \sum_j O_j f^m(c_{ij}^m)$ where m is a set of modes which have mode-specific travel costs (c_{ij}^m) and travel impedance functions $f^m(\cdot)$.

The Hansen-type measure does not consider competition between modes nor is it constrained. As an example, the work of [15] uses the Hansen-type measure to measure the potential interaction with retail locations using walking, public transit, and car modes m. S_i^m is the sum of retail locations j that can potentially be interacted with under the travel impedance as calculated for each i and m. In other words, each i has three S_i values, one per m. In this work, they demonstrate that the car mode has the highest $S_i^{m=car}$ values in the majority of i, i.e., populations using a car can potentially interact with the most retail opportunities than populations using other modes. However, the higher $S_i^{m=car}$ values are not a result of lower S_i^m values for other modes: it is not assumed that car-using populations potentially accessing more opportunities take away potential opportunities for other populations within the measure (no consideration for competition). This measure is also not constrained: there is no global maximum for S_i or S_i^m values, they are presented as a population normalized accessibility index. This makes the interpretation of the 'potentially interacted opportunities' relative to the region, making comparisons of the results across different regions challenging.

However, opportunities in a region can be considered finite. There are only so many school-seats, hospital capacity, jobs, etc., in a region and if one person interacts with an opportunity at a given time, it is taken. As such, if one person is advantaged and has the ability to reach more opportunities through a lower travel-cost mode, than they have more opportunities to potentially interact with more opportunities than other people. From the other perspective, their are fewer opportunities left to be potentially interacted with for populations using higher travel-cost modes. In this way, populations using modes with a higher travel impedance are at a higher access disadvantage than populations using lower travel impedance modes. This recognition is the motivation behind integrating *competition* for opportunities within multimodal accessibility measures. Arguably one of the most popular competitive location-based accessibility measures is the two-step floating catchment area (2SFCA) approach popularized by [16] who simplified the approach proposed by [17] (with similar considerations for competition in [18] and [19]).

The Shen-type accessibility measure's formulation is: $a_i^m = \sum_j \frac{O_j f^m(c_{ij}^m)}{\sum_m D_j^m}$ where D_j^m is the potential demand for opportunities equal to travel impedance weighted population $\sum_i P_i^m f^m(c_{ij}^m)$. In this way, the Shen-type measure can be understood as a ratio of the potential opportunity supply over the potential demand for opportunities. The measure considers competition, but it is *non-constrained.* A score of competitive potential accessibility associated is associated with each location i for each mode m, but there are no global maximums. In other words, it is difficult to interpret the meaning of differences in Shen-type accessibility scores between modes.

To illustrate, [20] calculates a_i^m to jobs for different income-group populations in Shenzhen (China) using $m =$ public transit and $m = car$. They demonstrate that i with low-income populations have lower a_i^m than i with higher-income populations. Further, they demonstrate that $a_i^{m=\text{public transit}}$ is lower than $a_i^{m=\text{car}}$ at many i, arguing that this may put i with lower-income populations in a further disadvantage. a_i and/or a_i^m are used to compare relative spatial differences in overall competitive accessibility and modal competitive accessibility, but because there is no global maximum, making it is difficult to interpret the significance between differences in a_i^m values. Questions such as: what is the impact that competition has on the difference in a_i^m values? How does impact vary spatially? And what is the interpretation of this difference? are left unanswered.

Spatial availability improves on previous multimodal accessibility approaches as it considers *competition* in the potential interaction with opportunities in a *constrained* framework (e.g., finite opportunities). This is done by considering: 1) competition between mass effect (e.g., the advantage of sub-populations residing in relatively low population-density and high opportunity-proximate areas) and 2) competition between travel impedance (e.g., sub-populations with relatively low travel-impedance) through a proportional allocation mechanism. The following sub-section demonstrates how spatial availability compares to the Hansen-type and Shen-type measures through a synthetic example.

Multimodal spatial availability V_i^m

In brief, we define the *spatial availability* at i (V_i) as the proportion of all opportunities in the region O that are allocated to location i from all opportunity destinations j. V_i is a value of how many opportunities are available to each location i out of all the opportunities in the region. The general formulation of spatial availability V_i is shown in Equation (1):

$$V_i = \sum_{j=1}^{J} O_j F_{ij}^t \tag{1}$$

Where:

- F_{ij}^t is a balancing factor that depends on the demand for opportunities O_j and cost of movement in the system $f(c_{ij})$.
- V_i is the number of spatially available opportunities at i; the sum of V_i is equivalent to the total sum of opportunities in the region (i.e., $\sum_j O_j = \sum_i V_i$)

The spatial availability measure is introduced in [14]. Spatial availability's unique feature is the balancing factor F_{ij}^t, a proportional allocation mechanisms, that ensures the V_i calculated for each i sums, across all i in the region, to equal the total number of opportunities in the region. As such, spatial availability is a *competitive* and *constrained* accessibility measure as F_{ij}^t handles the number of opportunities in the region in a finite way (proportional allocation). F_{ij}^t consists of two components: a population-based balancing factor $F_i^p = \frac{P_i}{\sum_i P_i}$ and an impedance-based balancing factor $F_{ij}^c = \frac{F_{ij}^c}{\sum_j F_{ij}^c}$ that, respectively, allocate opportunities to i in proportion to the size of the population at i (the mass effect) and the cost of reaching opportunities at j (the impedance effect).

F_i^p and \$ F^c_{ij}\$ are calculated for each i such that they both equal 1 when summed across all i in the region (e.g., $\sum_i F_i^p = 1$ and $\sum_i F_{ij}^c = 1$). These balancing factors are combined multiplicatively to yield F_{ij}^t which ensures that a proportion of the opportunities O_j are allocated to each i accordingly. In other words, assuming a finite number of opportunities in the region, F_{ij}^t proportionally allocates O_j to each i such that the resulting V_i value represents the number of opportunities *spatially available* to the population at i. This value can be seen to represent spatial availability as it is a proportion of the opportunities in the region (i.e., $\sum_j O_j = \sum_i V_i$).

The focus of this paper is to extend V_i for multimodal applications. To do so, the balancing factors are reformulated to yield a proportional value for the set of modes m used by populations at each i. As these factors are proportional, F_i^{pm} and F_{ij}^{cm} can be summed up across each m at each i and across all i to equal to 1. They are also similarly combined multiplicatively to obtain their joint effect, represented as the combined balancing factor F_{ij}^{tm} detailed in Equation (2).

$$F_{ij}^{tm} = \frac{F_i^{pm} \cdot F_{ij}^{cm}}{\sum_{m=1}^{M} \sum_{i=1}^{N} F_i^{pm} \cdot F_{ij}^{cm}} \tag{2}$$

Where:

- The population balancing factor for each m at each i is $F_i^{pm} = \frac{P_i^m}{\sum_m \sum_i P_i^m}$
- The cost of travel balancing factor for each m at i is $F_{ij}^{cm} = \frac{f(c_{ij}^m)}{\sum_m \sum_i f(c_{ij}^m)}$

Implementing F_{ij}^{tm}, the following Equation (3) demonstrates the multimodal configuration of spatial availability V_i^m:

$$V_i^m = \sum_{j=1}^{J} O_j \; F_{ij}^{tm} \tag{3}$$

Where:

- m is a set of modes used by populations in the region.
- F_{ij}^{tm} is a balancing factor F_{ij}^t for each m at each i.
- V_i^m is the spatial availability V_i for mode m at each i; the sum of V_i^m for all m at each i is equivalent to the total sum of opportunities in the region (i.e., $\sum_j O_j = \sum_i V_i = \sum_m \sum_i V_i^m$)

Synthetic example

Consider the following: Figure 1 depicts a region with population and jobs at three population centers (A, B, C) and three employment centers (1, 2, 3). The population at each population center is divided into two sub-populations, one using a faster mode z and another using a slower mode x, to travel to employment centers. Population center A is Suburban: it is closest to its own relatively large employment center at 1, close to the Urban's equally large employment center 2, and has a population that is smaller than the Urban B and larger than the Satellite C. B has the largest x-using population, followed by then A, then C. This synthetic example was inspired by the single-mode example used in [17] and reconfigured in [14].

From the perspective of access to a *finite* amount of opportunities in the region ($210,000$ jobs), the sub-population that is most proximate to jobs, furthest from densely populated centers, and is using the lowest travel-cost mode z can potentially access the most job opportunities. This appears to be the sub-population at A using z. From the other perspective, sub-populations located in opposite conditions (i.e., further away from jobs, close to dense populations, and using x) are at a relative job opportunity access *disadvantage*. From the perspective of inequities, the competition for opportunities between different mode-using populations matters as it reflects how well the land-use and transport system serves (or doesn't serve) them.

Table 1. Accessibility values at each origin per mode m at each origin i and aggregated between modes for each i for the synthetic example.

i	m	S_i^m	a_i^m	V_i^m	a_i	V_i
	x	27,292.18	0.95	15,696.89		

Table 1. Accessibility values at each origin per mode m at each origin i and aggregated between modes for each i for the synthetic example.

i	m	S_i^m	a_i^m	V_i^m	a_i	V_i
A					1.36	67,482.61
	z	44,999.80	1.57	51,785.72		
B	x	27,292.18	0.64	38,170.03	0.88	132,638.94
	z	44,999.80	1.05	94,468.91		
C	x	2,240.38	0.68	2,035.86	0.99	9,878.45
	z	3,745.89	1.12	7,842.59		
TOTALS		150,570.22	N/A	210,000.00	N/A	210,000.00

The calculated S_i^m, a_i^m and V_i^m accessibility values for each i and m are shown in the middle three columns and are aggregated for each i in the final two columns in Table 1 . We use a negative exponential impedance function $f(c_{ij}) = \exp(-\beta \cdot c_{ij})$ with $\beta = 0.1$ for both x and z modes for all accessibility measures calculations.

The Hansen-type measure S_i^m is presented for each origin and mode in third column of Table 1 . For all i, the z-using sub-population has higher S_i^m values than the x-using sub-populations. Additionally, S_i^m is equal for both mode-using populations in A and B. This is the case because S_i^m does not consider *competition*, it only relies on reflecting the count of opportunities that may be interacted with as a product of $f^m(c_{ij}^m)$. Recall, populations in A and B have the same travel impedance to employment centers 1, 2 and 3 (either 15, 30, or 100 minutes using x or 10, 25, or 80 minutes using z). As such, these the calculated S_i^m values are the same for both A and B. Furthermore, the total sum of S_i^m in the region is equal to 150,570.2. This value is difficult to interpret: it represents the weighted sum of opportunities that may be interacted with within the region based on travel impedance. It cannot be interpreted as any sort of benchmark since the measure is *non-constrained*. To connect this example to literature, S_i^m is calculated in the work of [15]; they compare differences in S_i^m values between modes in a relative and comparative sense, but make no further interpretation of the S_i^m values.

In the fourth and sixth column in Table 1 the Shen-type measure is calculated: first for both origin and mode a_i^m as well as aggregated by the weighted mean mode-population ($\sum_m \frac{P_i^m}{P_i} * a_i^m$) to represent a value for each origin a_i. Unlike S_i^m, this measure considers *competition*. For instance, the x-using populations in A and B centers do not have the same a_i^m values as the z-using. In fact, A has the highest values a_i^m and a_i values since this center has the smallest travel impedance to opportunities (lower than at C, A and B are equal) and has one of these lowest proximity to a relatively high amount of population (lower than at B).

However, the Shen-type measure is *non-constrained*: the total sum of a_i^m or a_i is practically meaningless since it represents a sum of ratios. For instance, the z-using sub-population at A has a value of 1.57 potential jobs per potential job-seeking population compared to 0.95 for x-using sub-population. What is the significance of these values? The difference between these modes is equal to 0.62, but 0.62 of what? How many more job opportunities are z users interacting with than x users? When a_i^m is aggregated to a_i as shown in the sixth column, the values face similar interpretability issues. The Shen-type measure is implemented in the previously discussed work of [20] to calculate modal a_i^m values and the aggregated a_i is implemented in the work of [21]. However, similar to the Hansen-type measure, these works discuss relative and spatially comparative differences in values, they do not make further interpretation of the a_i^m or a_i themselves. This may be because the Shen-type measure is *non-constrained*, this is

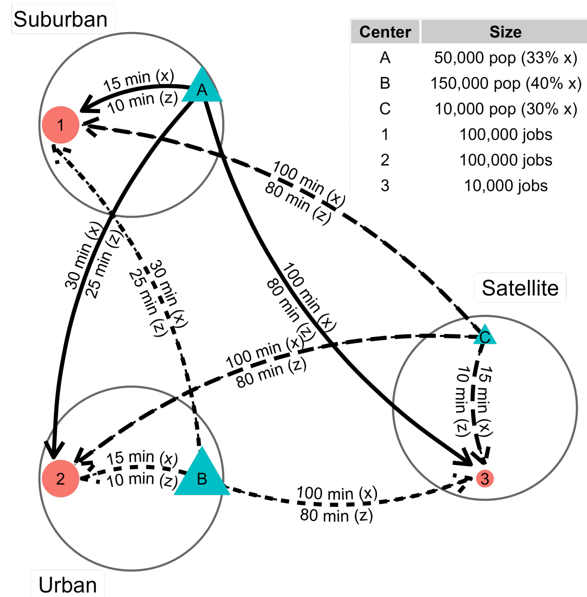

Fig 1. Multimodal synthetic example: locations of employment centers (in orange), population centers (in blue), number of jobs and population, and travel times for two modes (slower mode x and faster mode z).

no benchmark or global maximum to which comparisons can be drawn from.

By contrast, spatial availability V_i considers competition and is constrained such that the total sum of values is equal to the total number of opportunities in the region (i.e., $210,000$ jobs). Seen in fifth column of Table 1 , V_i^m for the same mode-using populations in A and B are not the same (as this measure considers competition). In fact, at A, the z-using sub-population captures 36,088.84 more spatially available jobs (of the $210,000$ jobs in the region) than the sub-population using mode x. The numerical difference has a practical interpretation.

Furthermore, V_i^m values for an i can be aggregated across m and compared across i ($V_i = \sum_m \sum_i V_i^m$) as a result of the proportional allocation mechanism. This aggregation, V_i, is shown in the seventh column in Table 1 . Again looking at center A, A is allocated 67,482.61 spatially available opportunities for both modes. 77% of this spatial availability allocated to A is assigned to the z-using population despite representing 66% of A's population.

Spatial availability can be further aggregated to better interpret competition between modes. Across the entire region, 130,000 people use z (62% of the region population). However, the z-using population accounts for 73% of the region's total spatial availability - the rest is allocated to the x-using population (38%of the total population). Notably, the x-using population captures 11% less spatial availability to opportunities than its population proportion. This understanding can lead us to ask normative questions such as, how unequal should opportunity access for the two mode-using populations be? Can the lower-travel-cost populations spare some spatial availability if a policy of modal-restriction (like a LEZ) was introduced?

Since spatial availability is constrained and has an interpretable meaning as a proportion of the total opportunities in the region, the values at i have a new significance. Inequality in V_i^m values can be explored through a variety of approaches. For instance, consider travel times. The z-using population accounts for 67% of the potential travel time traveled in the region: this is 7% less travel time than the proportion of spatial available opportunities that is allocated to them. In other words, the z-using population travels less minutes overall and has more spatial availability of opportunities than the x-using population using the slower mode x.

Alternatively, inequities in spatial availability between mode-using populations can be explored through proportional benchmarks. A spatial availability per capita v_i^m as presented in Equation (4):

$$v_i^m = \frac{V_i^m}{P_i^m} \tag{4}$$

The v_i^m values for A, B, and C for the x-using sub-populations are 0.95, 0.64 and 0.68 spatially available jobs per capita, respectively. The v_i^m for the z-using sub-populations are much higher, with values of: 1.57, 1.05 and 1.12 respectively. The x-using population, especially at B and C, are directly impacted by the jobs that are spatially available to the z-using population *in addition to* the mass effect (occurring at B, high population density) and high travel impedance (occurring at the Satellite C).

If, lets say, the planning goal is to have one spatially available job per mode-using population, a policy intervention can be put in place, to reduce the v_i^z values and increase v_i^x values. This demonstration is to show how simply the V_i^m framework can be manipulated quantify the competitive (dis)advantage in a multimodal application. In what follows, we further explore competition between multiple modes through an empirical example.

Empirical example: Madrid LEZ

Multimodal data and methods

Low emission zones (LEZ) have been implemented as a climate change policy intervention to reduce GHG emissions, improve air quality, and support sustainable mobility in many countries. Though rules vary, LEZ aim to deter/reduce traffic in designated zones under threat of penalty (e.g., fines, seizure of vehicle). From the perspective of restriction for passenger transport, LEZ are a policy of *geographic discrimination* as they change how people access opportunities by making the travel impedance more costly for car-mode users. If seeing opportunities as finite, this discrimination allows populations to access opportunities by other modes more readily than before. In this way, LEZ change the multimodal competitive accessibility landscape of a city.

Spain is one of a few countries with active LEZ and plans to expand their implementation as specified in their climate-change-related plans: *Plan Nacional Integrado de Energía y Clima 2021-2030* [22] and *Plan Nacional de Control de la Contaminación Atmosférica* [23]. Specifically, the national Spanish law 7/2021 (*Ley de Cambio Climático y Transición Energética*) will require all municipalities to implement LEZ by 2023 if they meet at least one of the following requirements: (i) municipalities >50,000 inhab.; (ii) islands; and (iii) municipalities > 20,000 inhab. when air quality exceeds limits specified in *RD 102/2011 de Mejora de Calidad del Aire* [24].

In 2017, LEZs were implemented in the Spanish capital city of Madrid following the goals set out in the national agenda . In geographic scope, the 2017 boundaries of the LEZ were relatively small (covering 4.72 km^{2}) and within the center (i.e., LEZ Centro). These boundaries were expanded in 2023 to inside of the M-30, a highway in proximity to the city center (i.e., LEZ M-30) and the city has plans to further spatially expand the LEZ. Within the 2017 LEZ Centro implementation, all cars, motorcycles and freight with environmental label A or B (higher polluting classification, associated with older make and model of fossil fuel internal combustion engine vehicles), are not

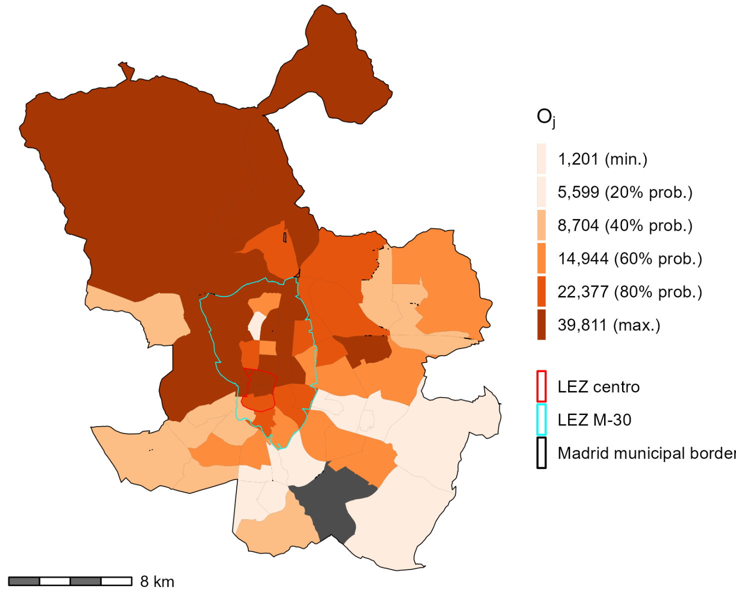

Fig 2. Jobs O_j taken by people living and working in Madrid as reported by the 2018 travel survey.

permitted to enter the area unless they are used by residents or meet other exemptions. This restriction impacted approximately half of all car trips that were typically made into the LEZ Centro [25].

For this case study, we use V_i^m to quantify the competition of spatially available opportunities between modes after the LEZ Centro implementation. Particularly, we demonstrate how V_i^m can be used to spectate on how the restriction of car mobility in areas around/within the LEZ Centro allowed the other, more sustainable but often with higher travel impedance modes, to become more competitive.

The 2018 Community of Madrid travel survey ([26]) is the source of data for this empirical example: it is a representative survey that reflects a snap-shot of the travel patterns for one typical day of the working week (e.g., n=222,744 trips with representative population elevation factors). In this paper, a sample of the travel survey is used, namely the residential home origin to work destination trips of all modes and those that originate and end in the city of Madrid. These totals are displayed in Figure 2 and Figure 3. Both figures are displayed at the level of traffic analysis zones (i and j) that correspond to the survey. The red boundary represents the LEZ Centro in effect in 2017 and thus those travel patterns of car-restriction reflected in the survey. The cyan boundary represents the LEZ that will be within the boundaries of the M-30 highway in 2023 and is present in the plots as a spatial reference for areas in proximity to the LEZ Centro.

The total sum of jobs O_j that are held are shown in Figure 2 and the populations that go to a work destination by four modal categories P_i^m, is reflected in Figure 3. The modal categories represented in Figure 3 are summarized for the following trip mode types:

- Car/motor: all cars and operating modes (e.g., cab, private driver, company, rental care, main driver, passenger, etc.) and all public, private or company motorcycle/mopeds.
- Transit: all bus, trams, and trains,

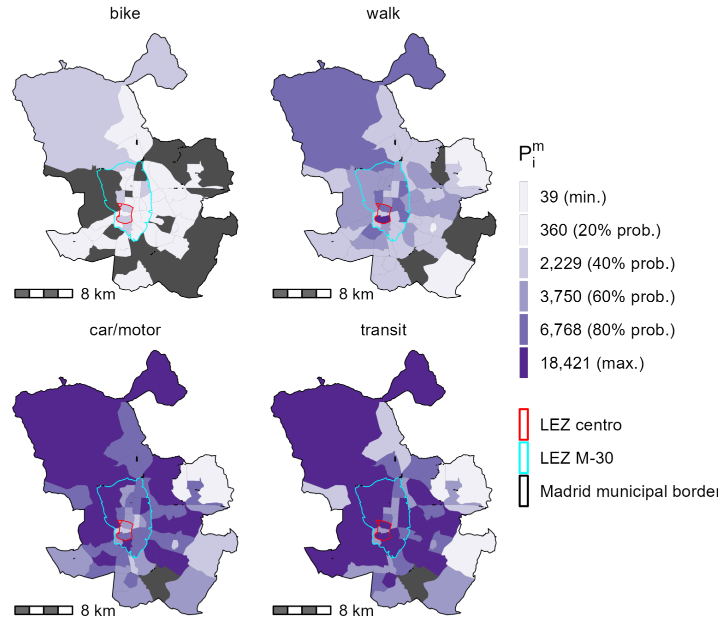

Fig 3. Population living and working in Madrid, by four summarized modal categories, P_i^m as reported by the 2018 travel survey.

- Bike: all bicycle trips (e.g., private, public, or company bike trips) and "other" types of micromobility options,
- Walk: walking or by foot,

From Figure 2, it can be seen that the largest concentration of jobs are within, near, and to the north of the LEZ Centro. The population that is accessing those jobs by mode (Figure 3), appear spatially distinct. Car and transit trips represent 37% and 47% of the modal share respectively. The population that travels using transit is more spatially distributed than those using cars - particularly near and within LEZ Centro. This distribution could be a result of a variety of factors including: transit coverage and service within with city, effective car infrastructure outside of the M-30, and/or the impact of the Central LEZ itself.

From Figure 3, it can also be seen that biking and walking trips are less common than motorized trips at 1% and 15% respectively. Noteably, there is a positive trend between the populations of walking and biking trips in zones and populations of transit trips. This positive trend is higher than for car trip populations.

The travel time for each trip is provided within the survey. These travel times, per modal category, are used to calibrate mode-specific travel impedance functions $f^m(c_{ij}^m)$. To illustrate the modal differences in travel lengths, summary descriptive per mode are detailed:

- Car/motor: 36 min (min:0 min., Q2: 15 min., Q3: 55 min., max: 120 min.)
- Transit: 55 min. (min:1 min., Q2: 30 min., Q3: 80 min., max: 120 min.)
- Bike: 34 min. (min:5 min., Q2: 15 min., Q3: 40 min., max: 115 min.)
- Walk: 27 min. (min:1 min., Q2: 10 min., Q3: 45 min., max: 119 min.)

To calculate $f^m(c_{ij}^m)$ from the survey travel times, a concept known as the trip length distribution (TLD) was used. A TLD represents the proportion of trips that are taken at a specific travel cost such as travel time (i.e., probability density distribution of trips taken by travel cost). This distribution is then used to derive impedance functions

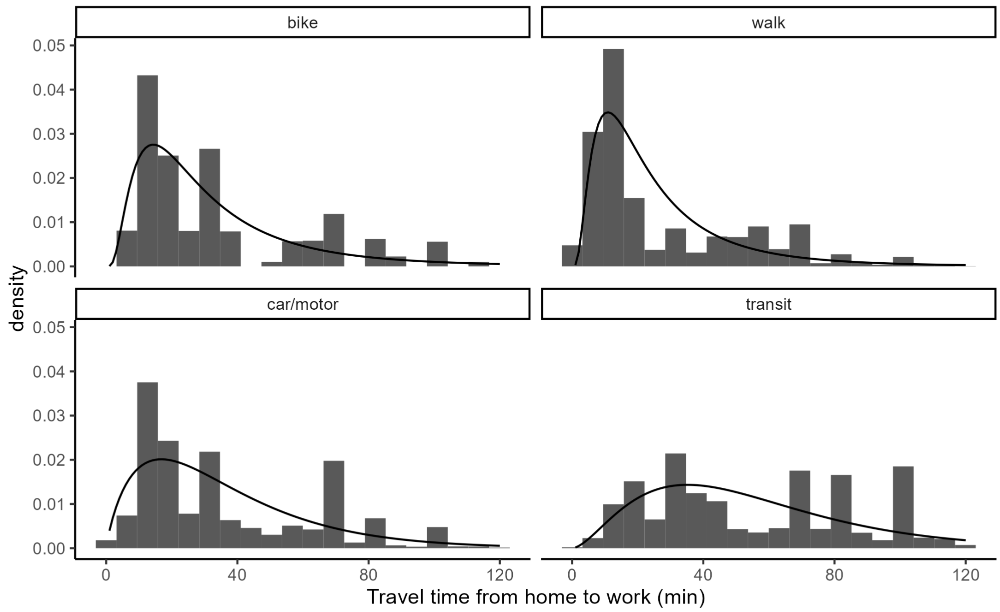

Fig 4. Fitted impedance function curve (line) against empirical TLD (bars) corresponding to the home-to-work origin-destination flows from the Madrid 2018 travel survey.

(e.g., done in the accessibility works of [27], [28], and [29]). Maximum likelihood estimation and the Nelder-Mead method for direct optimization available within the R {fitdistrplus} package [30] is used to fit the impedance functions. As shown as shown in Figure 4, based on goodness-of-fit criteria and associated diagnostics, the gamma and log-normal probability density function (line curves) are selected as best fitting curves for the motorized and non-motorized modes respectively. The selection of functional form aligns with empirical examples in other regions [14,31,32]. Overall, the plots in Figure 4 display the probability of travel given a trip travel time, based on trip flows from the survey. These 'probability of travel' at each travel time for each mode are realized observations that reflect the land-use, the transport system, and the population travel behaviour in Madrid.

Results

The spatial availability of jobs V_i^m is calculated for each of the four modal categories m at the level of traffic analysis zones i in Madrid and demonstrated in Figure 5.

V_i^m is a proportion of the total number of the 847,574 jobs in the region and is visualized in Figure 5. Since V_i^m is calculated based on the likelihood of travel from observed home-to-work journeys, the values can be understood as the number of full-time jobs that are spatially available to the full-time working population at that i and their associated m, relative to all the jobs in the city. V_i^m is the number of jobs that are *spatially available* to a m-using population located at i, relative to the travel impedance and size of *all* populations in the region.

Notable are the differences in the magnitude of V_i^m between modes in Figure 5. The majority of V_i^m is allocated to car- and transit- using populations. This is to be expected, as the population that commutes using these modes represents 84.1% of the total population. Differences in V_i^m values within mode-using populations also exist: car-using populations outside of the M-30 region appear to have greater V_i^m values,

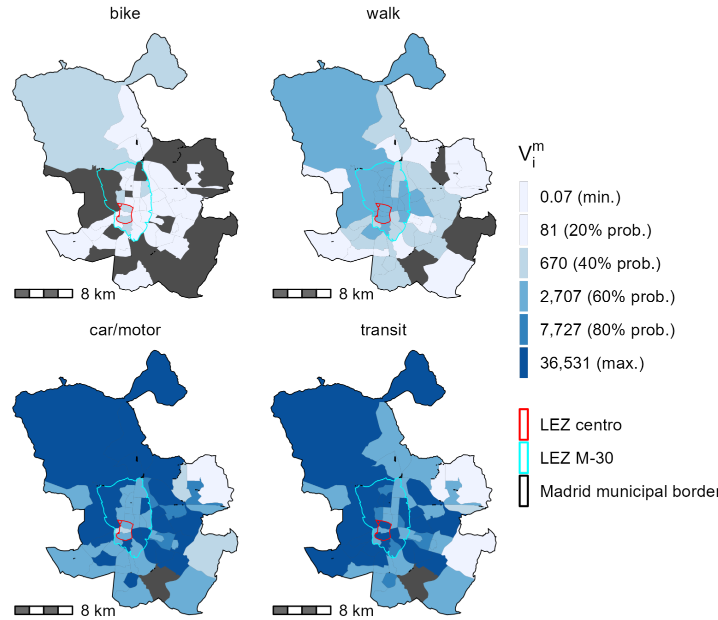

Fig 5. Spatial availability of job opportunities per origin and mode V_i^m in Madrid. Calculated using the home-to-work origin-destination flows from the 2018 travel survey.

while some i areas inside the M-30 appear to have higher V_i^m values for the transit-using populations. Overall, the magnitude of V_i^m values for the bikers and walkers are lower than car and transit but the highest V_i^{bike} and V_i^{walk} values tend to be allotted to is within the M-30 and is that have higher $V_i^{transit}$ values.

The differences between the mode-using population and their mode-specific spatial availability highlights the competitive advantage offered to certain modes in certain spatial extents. As summarized in the left-most columns in Figure 6, the 'car/motor' and 'transit' populations represent a combined 95.3% of the total spatial availability in the city. However, the 'car/motor' using population is allocated disproportionately more V_i^m than its size compared to the transit-using population. The car-using and transit-using population is 36.6% and 47.5% respectively, but is allocated 48.0% and 47.3% respectively, of the city's spatial availability. When treating the number of opportunities that can be reached as a finite value (total: 847,574 opportunities), fewer opportunities are spatial availability to the lesser competitive modes-using populations, in this case walking and cycling. These modes are less competitive as a result of: their lower travel impedance values at longer travel times (see Figure 4 at travel times beyond ˜30 minutes); their low population values values overall; and higher populations present in origins with high motorized mode commuting. These factors all contribute to the the car/motor mode being most advantaged in capturing spatially available job opportunities overall.

There are spatial variations in the competitive advantage of the car-using populations. The proportion of car-using population in the Centro is smaller and has higher travel impedance values relative to the inputs in other areas and mode-using populations. The LEZ Centro implementation further restricts the car-advantage as it shifted more than half of all car trips into the LEZ to another mode [25]. This restriction decreased the number of car-using population from is going into the LEZ Centro (an area with a large number of jobs overall, see Figure 2), thus increasing the mass effect for non-car modes and resulting in proportionally higher v_i^m values for non-car modes. As such, the lower amount of access to opportunities by car-mode

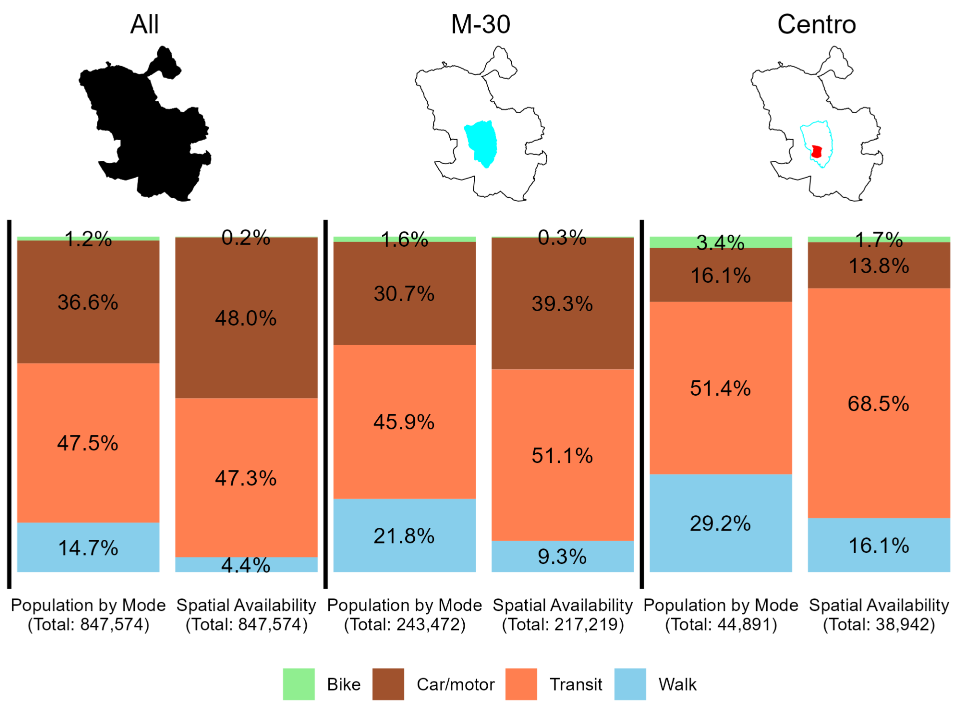

Fig 6. Displays the proportion of the working population by mode and spatial availability of job opportunities by mode aggregated for three spatial areas. From left to right, the city of Madrid (All), the area within the M-30 highway (M-30),the area within the Centro region (Centro).

allows more opportunities in the LEZ to be available by populations using other modes.

As summarized in the two right-most columns in Figure 6, the proportion of spatial availability allocated to the car-using population in the Centro (13.8% or 5,373 opportunities). As a comparative reference, this is less than the proportion of the car-using population in the Centro (16.1%), evidently less then the proportion of car-using population in the city, and is the opposite of the trend overall (left-most columns) and within the M-30 (middle columns). More opportunities are spatial availability to non-car using populations within the Centro, particularly transit-using populations (68.5% of spatially available jobs in the Centro despite representing 51.4% of the population in the Centro and 47.5% in the city overall).

From Figure 6, it is also summarized that there is a higher proportion of opportunities spatially available to walking and cycling populations in the Centro than in the City overall and in all areas within the M-30. Notably, within the Centro, 1.7% and 16.1% of opportunities are spatially available to bike and walk modes respectively, while their populations represent smaller proportions of 1.2% and 14.7% of the population overall. Though the proportion of spatial availability for these mode-using populations is still lower than the proportion of mode-using population located in the Centro, these modes are more competitive within the Centro than outside of the Centro. By restricting the more competitive car mode through the LEZ, the advantage in the spatial availability of opportunities afforded to the otherwise lesser competitive modes is made apparent.

The spatial differences in the competitive dis/advantage of spatial availability between modes can also be visualized per origin. Figure 7 visualizes v_i^m, the spatial availability V_i^m divided by the mode-population. v_i^m values above 1 are represented in increasing red shades, values below 1 are represented in increasingly green shades, and values equal to 1 are white. These plots illustrates the discussion of the disproportionately high over-allocation of spatial availability relative to the mode-using population in many of the origins for the car/motor mode (bottom left plot, areas denoted with green v_i^m values above 1). These plots also visualize areas that disproportionately capture lower spatial availability (under 1), represented in shades of red. It can be observed that the transit-using population's spatial availability to jobs is relatively balanced (i.e., many zones are white), while the non-motorized modes v_i^m values are low (under 1) overall.

Interestingly, as also represented in Figure 6, v_i^m for car/motor within and near the LEZ Centro is near or below 1 (white/red) in Figure 7 while all non-car modes have relatively higher v_i^m values. Though the spatial availability from before the LEZ Centro implementation is unknown, Figure 7 provides a benchmark for quantifying potential LEZ implementations in the future (given 2018 travel conditions). Figure 7 also shows that many areas within the M-30 have high (white/green) v_i^m values for car-mode, signaling that the spatial expansion of the LEZ Centro stands to increase the spatial availability of jobs for non-car mode using populations.

Discussion and conclusions

Location-based accessibility measures like the Hansen-type S_i^m, Shen-type a_i^m, and spatial availability V_i^m measures share a commonality; they are a weighted sum of opportunities assigned to each spatial unit i in a region. In this way, they all can be interpreted as a score of how many opportunities can be potentially interacted with by the population at i. How the weight and sum of the potentially-interacted-with opportunities is considered is what defines the type of accessibility measure.

Within this paper, the location-based singly- *constrained* and *competitive* accessibility measure, known as spatial availability V_i [14], is extended for the case of

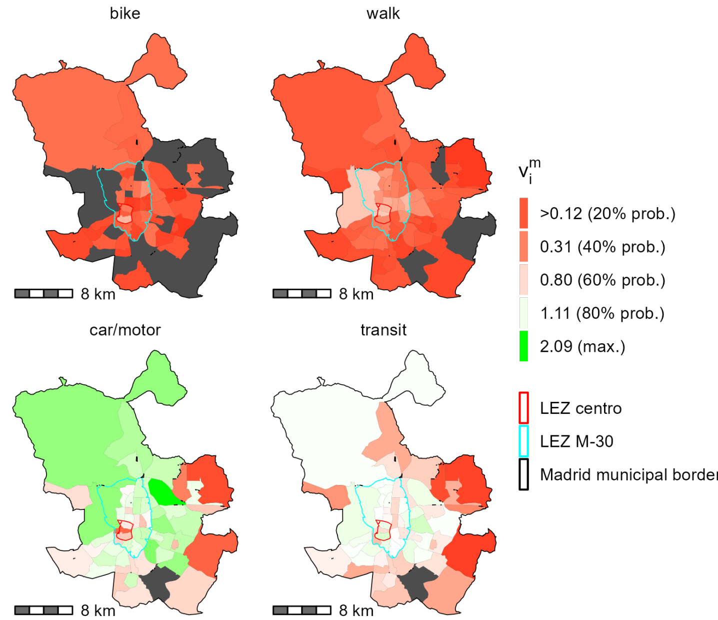

Fig 7. Spatial availability of job opportunities per mode-using capita by mode v_i^m per origin in Madrid. Calculated using the home-to-work origin destination flows from the 2018 travel survey.

capturing multimodal accessibility to opportunities V_i^m. A synthetic example and then an empirical case of LEZ in Madrid are detailed to demonstrate this multimodal extension.

The spatial availability measure is capable of capturing a new interpretation of multimodal competition that previous accessibility measures have not yet done. Competitive measures hypothesis that populations using modes with lower travel impedance, when competing for a finite set of opportunities, will capture more opportunities. With spatial availability, the number of opportunities that are captured (of the total opportunities in the region) by each mode can be individually calculated. From there, the difference between how many spatially available opportunities one mode captures versus another can be investigated. This is the advantage of the spatial availability measure, particularly its multimodal extension.

The flexibility and need for an accessibility measure such as spatial availability is pertinent in policy scenario evaluation. As showcased in the empirical example of the LEZ in Madrid, competition for job opportunity availability varies spatially *as well as* between modes. The car and transit modes have the highest spatial availability, with the car-mode having highest availability with exception to the areas within the LEZ Centro. Since car travel has been highly restricted within the LEZ Centro, fewer car-using people potentially interact with jobs within the LEZ Centro, leaving more *spatially available* jobs for non-car-using populations. This difference in car-using populations in locations accessing jobs within and immediately outside the LEZ Centro increases the competitiveness of the transit-using population (the second most competitive mode) as well as the non-motorized modes.

Spatial availability V_i^m can also be divided by the mode-using population at each i to yield mode-population normalized values. These values, reflected in Figure 7, can be used as a benchmark to investigate existing conditions and plan future LEZ implementation (i.e., target areas with exceptionally high car spatial availability such that more opportunities are available to other mode-users).

In summary, conventional *non-constrained* accessibility measures are difficult for planners to operationalize for a variety of reasons including issues of computation and interpretability [2]. With spatial availability, the magnitude of opportunities that are available as a proportion of all the opportunities in the region is equal to V_i. As a result of its proportional allocation mechanism, V_i can be naturally extended into multimodal applications. This flexibility is helpful to modelling policy scenarios in our cities that are increasingly multimodal. The interpretation of V_i allows for manipulation of V_i^m values to investigate differences of availability between neighbourhoods, modes, and regions, generate per capita benchmarks, and/or generate average values per population-group.

From a spatial equity perspective, spatial availability measure can provide researchers, policy makers, and citizens a new-found interpretation of accessibility measures. With a plot of spatial availability values, one can begin asking, how much is enough and what level may be too much. These interpretations were difficult to be made with accessibility measures in the past.

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All work is fully-reproducible and available within this GitHub repository.

Author contributions

The authors confirm contribution to the paper as follows: study conception and design: AS, JTO, JSL, AP.; data collection: AS, JTO, JSL.; analysis and interpretation of results: AS, JTO, JSL, AP.; draft manuscript preparation: AS, JSL, AP. All authors reviewed the results and approved the final version of the manuscript.

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