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

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Abstract

Recent research has aimed to address the way opportunities are counted in accessibility analysis. In conventional accessibility measures, opportunities are often multiply counted, which leads to values of accessibility that are difficult to interpret. Constraining the calculations to match a known quantity ensures that the measurements sum up to a predetermined quantity (i.e., the total number of opportunities), and so each value can be meaningfully related to this total. A recent such effort is spatial availability, a singly-constrained accessibility measure. In this paper we extend spatial availability for use in the case of multiple modes or, more generally, heterogeneous population segments with distinct travel behaviors. After deriving a multimodal version of spatial availability We proceed to illustrate its features using a synthetic example. Next, we apply it to an empirical example in Madrid. We conclude the paper with suggestions for future research.

Introduction

Accessibility is a key concept in the analysis of land use and transportation systems [e.g., 1,2,3], and one that is coming of age from the perspective of planning too [see, *inter alia*, 4,5–8]. Beginning with the work of Hansen [1], accessibility measures have been widely used to evaluate the efficiency of transportation systems when combined with the distribution of opportunities in space [e.g.,]. As such, it is a holistic measure of spatial systems that measures the ease of reaching destinations [9,10].

In practice, the most common form of accessibility measure is based on the gravity model. These measures are sums of weighted opportunities around a focal point (i.e., a potential origin), based on how expensive it is to reach them. Recent research in accessibility analysis has paid attention to the way opportunities are counted in the pertinent calculations. Conventionally, the sums are not constrained, which means that the same opportunity can enter the sum for different origins. Counting the same opportunity multiple times treats it as if it was inexhaustible. But opportunities in general are not inexhaustible, and in fact some of them are by definition exclusive: for example, once a job is taken up by someone in the population, the same job is no longer available for any other person to take. More generally, opportunities are subject to congestion: for example, multiple people can avail themselves of the services of the same family doctor, but the more people who do, the more congested the service will be.

The issue of congestion was the motivation for the development of floating catchment area approaches in accessibility analysis [11,12]. While these approaches purport to account for congestions, Paez et al. [13] demonstrate that in general they do not solve the issue of multiple counting of opportunities, thus leading to biases in the calculation of total demand and supply, sometimes inflating them, other times deflating them. In response to this, recent research has paid closer attention to the way opportunities are counted in accessibility analysis. [13], for example, tackle floating catchment area methods and introduce a normalization of the impedance matrix to allocate the population and then the level of service proportionally. More recently, Soukhov et al. [14] introduced a singly-constrained measure of accessibility, called spatial availability, that employs a similar, but more sophisticated proportional allocation mechanism. The work of these authors shows that floating catchment area methods can be seen as singly-constrained accessibility measures, and improve on existing approaches by guaranteeing that each opportunity is counted only once - in other words, treating opportunities as *finite*. The proportional allocation of spatial availability constrains the calculations to match a known quantity, therefore ensuring that the measurements sum up to a predetermined quantity (i.e., the total number of opportunities), and so each value can be meaningfully related to this total.

A limitation of spatial availability as introduced by Soukhov et al. [14] is that it was developed for the case of a homogeneous population, for example for the case of a single mode of transportation. However, the finite nature of opportunities makes the analysis of heterogeneous populations very relevant. In the case of multiple modes of transportation, people who travel by slow modes (e.g., active modes) can usually reach fewer opportunities than people who travel by faster modes and whose range is typically far wider (e.g., car). This implies that slower travelers will often face increased competition for local opportunities from travelers who can reach said opportunities from farther afield.

The objective of this paper is to address this limitation of spatial availability. Our primary motivation is to extend spatial availability for the case of multimodal accessibility, but it is worthwhile noting that this is in fact just one case of heterogeneous populations (i.e., travel by different modes). The method itself can easily accommodate other forms of heterogeneity, for example variations in travel behavior between older and younger adults [e.g., 15], the propensity of older adults to use different modes of transportation [16], the usually shorter trip lengths of children compared to grown-ups [e.g., 17], or the more limited travel ranges of single parents [e.g., 18].

The paper rest of this paper is organized as follows. In Section we discuss the use a synthetic examples with multiple modes to illustrate some relevant issues; this helps us motivate the derivation of the new spatial availability expressions. This is followed in Section 3 by an empirical example using data from the city of Madrid after the implementation of its Low Emission Zones. Data for this example comes from the city's 2018 travel survey. The example shows the differences in spatial availability within and outside the LEZ for travelers using different modes, namely car, transit, cycling and walking. In Section 4, we provide concluding remarks on the strengths of the use of spatial availability as a multimodal accessibility measure, and discuss potential future uses in policy planning scenarios as well as directions for future research.

A brief review of multimodal accessibility

Location-based accessibility indicators are quantitative measures of *potential* interaction with opportunities for locations within a given region: they are summary measures of the relationship between land-use and transport systems. Arguably, the most commonly used are measures based on the gravity model [19], of which cumulative opportunity measures and weighted cumulative opportunity measures are particular forms [5]. These measures assign a weight to opportunities based on how easy it is to reach them. Given an origin (i) and a destination (j), an impedance function $f^m(c_{ij}^m)$ converts the cost of travel (e.g., time, money, generalized cost) into a score that represents the propensity for interaction. These measures originate from that proposed by [1], which can take the following form in the multimodal case: $S_i^m = \sum_j O_j f^m(c_{ij}^m)$ where m is a set of modes which have mode-specific travel costs (c_{ij}^m) and/or travel impedance functions ($f^m(\cdot)$).

Hansen-type accessibility is not constrained, which is to say it does not consider the opportunities as finite. To cite an example, Tahmasbi et al. [20] use Hansen-type accessibility to assess the potential interaction with retail locations by three modes: walking, public transit, and car (i.e., $m = w, p, c$). S_i^m is the sum of retail locations j that can potentially be reached under the travel impedance as calculated for each i and m. In other words, for each origin i three accessibility scores are calculated. In this work, Tahmasbi et al. [20] show that car travel affords the highest S_i^m values in the majority of i, i.e., travelers who use a car can potentially reach more retail opportunities than populations using other modes. However, higher S_i^m values for car do not affect the values of S_i^m for other modes: in effect, each mode is analyzed as if the others did not exist. Since the measure is not constrained, each opportunity is typically counted multiple times within and between modes, and as a result the sum of accessibility is not necessarily a meaningful quantity. The accessibility scores for the modes are often values that are difficult to interpret beyond making statements about relative size. For example, Lunke [21], researching the region of Oslo, reports accessibility scores for car in the order of tens of thousands of employment opportunities. The corresponding scores for transit are lower, but still often in the thousands or tens of thousands. As reported, the ratio of the transit to the car score can be lower than 0.2 (meaning transit gives access to less than 20% of the opportunities than car). But despite the discussion about "sufficient accessibility" (e.g., in the abstract), it is unclear what the unconstrained scores mean: is having access to but 10,000 jobs by transit insufficient? After all, 10,000 employment opportunities are still plenty of opportunities. These ratios can be found elsewhere in the literature [e.g., 22, and 9,15,18, and 8], and they are useful to assess when some members of the public are better or worse off than others, but they do not say much about how bad is "worse".

Besides ratios of accessibility, another way to improve interpretability of scores sometimes seen in the literature is to standardize them to lie in the range [0-1]. This adjustment is only helpful insofar as it facilitates relative comparisons, but interpretation of the scores remains challenging because the values are specific to a region and convey no meaning about the magnitude of the scores. In this approach, zones always have values between 0 and 1, but how remarkable is a zone with a low score for pedestrians and a high value for car? And if remarkable, what does the difference in these standardized values mean for planners? By how much should transport systems and land-use configurations be changed to improve conditions? And in what way can these scores be used to track differences over time? Or between regions? These questions lack straightforward answers since certain values will always be relatively 'low' or 'high', but do not track to a quantity that can be intuitively understood. Presentation or discussion of Hansen-type accessibility that has been standardized in this way is not uncommon in the literature [e.g., 23,24].

Once we understand opportunities to be finite, it is possible for an accessibility measure to take a crisper meaning. As considered in the long tradition of accessibility research, capacity of opportunities is limited and thus is subject to competition by population [11,14,25–29]. There are only so many school-seats, hospital capacity, employment opportunities, etc., in a region and if one person reaches an opportunity, it is taken: the supply of an opportunity and the demand for that opportunity are two components of accessibility. These are clear examples of opportunities that are clearly competitive. But we would go as far as to argue that every type of opportunity is subject to congestion or capacity constraint, even when the opportunities are conventionally seen as non-competitive. Amenities are a good example of this. For instance, standards for providing green spaces are often stated in the form of *exclusive access*, in units of amenity per capita. A case in point is Natural England, an organization that recommends an Accessible Natural Greenspace Standard such that the minimum supply of space is one ha of statutory Local Nature Reserves per thousand population[1]. Similarly, the World Health Organization [cited in 30] recommends that cities provide a minimum of $9m^2$ of green area per inhabitant. For our purposes, standards of this type translate into "how much of a resource can be offered to each individual that is not allocated to anyone else?". Green spaces often have large capacities, but they still have a capacity. Constraining accessibility is in this way a useful way to evaluate the congested availability of any type of opportunity. As development of sound standards is emphasized in the planning literature, in particular in regards to fairness in transportation [see 31], spatial availability analysis is a useful way to develop and assess standards.

The relevance of the considerations above is put in sharper relief when we think about the use of multiple modes (or heterogeneous populations). If we return to Oslo for a moment [21], we notice that the places that have high accessibility by transit are also the places that have *very high* accessibility by car (Figure 2). Those two populations are going for the same opportunities, and those travelling by transit have fewer to choose from to begin with. More generally, people in a zone who are advantaged with relatively cost of travel will have the ability to potentially reach more opportunities than other people. Due to this advantage, through the perspective of finite opportunities, there are fewer opportunities left for everyone else, especially for those who use modes that are slower or more expensive.

As noted in the introduction, competitive accessibility was the rationale for developing floating catchment area methods (FCA), popularized by [12,11,although similar, and earlier, developments are found in 29,32]. Shen-type accessibility is formulated as: $a_i^m = \sum_j \frac{O_j f^m(c_{ij}^m)}{\sum_m D_j^m}$ where D_j^m is the potential demand for opportunities equal to travel impedance weighted population $\sum_i P_i^m f^m(c_{ij}^m)$ and the remaining variables are repeated in the Hansen-type measure. Shen-type modal accessibility (a_i^m) can be understood as a ratio of the travel impedance-weighted supply of opportunities for m-mode in i over the travel impedance-weighted demand for opportunities. In this way, it considers competition. That said, the measure remains unconstrained, meaning both population *and* opportunities are multiply counted [see 13]. In other words, interpretation of differences in Shen-type accessibility scores between modes is fraught as it is for Hansen-type measures.

To illustrate, [33] calculate a_i^m to jobs for different income-group populations in Shenzhen, China using $m =$ public transit and $m =$ car. Their results indicate that zones with low-income populations have lower a_i^m than zones with higher-income populations. Further, they show that $a_i^{m=\text{public transit}}$ is lower than $a_i^{m=\text{car}}$ at many zones, arguing that this may further place those zones with lower-income populations at disadvantage. a_i and/or a_i^m are used to compare relative spatial differences in overall competitive accessibility and multimodal competitive accessibility, but because opportunities were doubly counted (entering the sums of both modes), this makes for uneasy interpretations of the differences in a_i^m between modes. Questions that this approach leaves unaddressed include: what is the impact of competition on the

[1] see https://redfrogforum.org/wp-content/uploads/2019/11/67-Nature-Nearby%E2%80%99-Accessible-Natural-Greenspace-Guidance.pdf

difference in a_i^m values? How does the impact vary spatially? And what is the interpretation of this difference?

Spatial availability improves on previously discussed accessibility approaches using the Hansen-type measure and the Shen-type measure by constraining the sum of opportunities, that is, by treating opportunities as finite. This is done by means of proportional allocation factors that follow well established principles of spatial interaction and the gravity model [see 34]. In Soukhov et al. [14] these factors consider: 1) the mass effect (e.g., the size of populations at different origins); and 2) the cost of travel from different zones (e.g., some sub-populations face relatively higher or lower costs). The following section introduces the multimodal form of spatial availability.

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) [see 14]:

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

Where:

- F_{ij}^t is a balancing factor that depends on the size of the populations at different locations that demand opportunities O_j, as well as the 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 identical to the total number of opportunities in the region (i.e., $\sum_j O_j = \sum_i V_i$); in other words, opportunities are dealt with as finite resources.

Compared to Hansen-type accessibility:

$$A_i = \sum_{j=1}^{J} O_j f(c_{ij}) \tag{2}$$

we see that spatial availability is, like Hansen's measure, a weighted sum of the opportunities. What makes spatial availability stand apart from other approaches is the weight used in the sum, balancing factor F_{ij}^t, implements a proportional allocation mechanisms to ensure that the sum of V_i is constrained to match the total number of opportunities in the region. As such, spatial availability is singly-constrained and naturally implements competition or congestion. F_{ij}^t consists of two parts. The first part is a population-based proportional allocation factor to model the mass effect of the gravity model:

$$F_i^p = \frac{P_i}{\sum_i P_i}$$

This factor makes opportunities available based on demand. Secondly, there is an impedance-based proportional allocation factor that model the cost effect:

$$F_{ij}^c = \frac{F_{ij}^c}{\sum_j F_{ij}^c}$$

This factor makes opportunities available preferentially to those who can reach them at a lower cost. F_i^p and F_{ij}^c are designed so 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 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 *available* to the population at i. Each zonal value 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 the measurement of multimodal applications (or more generally heterogeneous populations). To do so, the balancing factors need to be reformulated so that 1) the mass effect now accounts not only for the size of the population at i, but also the size of sub-populations within i; and 2) the cost of travel is not only for different zones, but by sub-populations within each zone (e.g., the cost of travel from i by car, transit, walking, etc.) When we introduce modes (or sub-populations) m, the proportional allocation factors need to satisfy the condition that F_i^{pm} and F_{ij}^{cm} can be summed across each m at each i and then 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} similar to that detailed in Equation (3). This factor is given by:

$$F_{ij}^{tm} = \frac{F_i^{pm} \cdot F_{ij}^{cm}}{\sum_{m=1}^{M} \sum_{i=1}^{N} F_i^{pm} \cdot F_{ij}^{cm}} \tag{3}$$

where:

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

Implementing F_{ij}^{tm}, the following Equation (4) gives the multimodal version of spatial availability V_i^m:

$$V_i^m = \sum_{j=1}^{J} O_j \ F_{ij}^{tm} \tag{4}$$

Where:

- $m = 1, 2, \cdots, M$ is a set of M modes (or sub-populations) of interest.
- 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., $\sum_j O_j = \sum_i V_i = \sum_m \sum_i V_i^m$).

Next we use a synthetic example to contrast multimodal accessibility and spatial availability.

An illustrative synthetic example

Consider the simple system shown in Figure 1. The figure shows a region with population at three population centers (A, B, C) and jobs at three employment centers (1, 2, 3). The population at each origin i is consists of two sub-populations, one using a faster mode z and another using a slower mode x, to travel to employment centers.

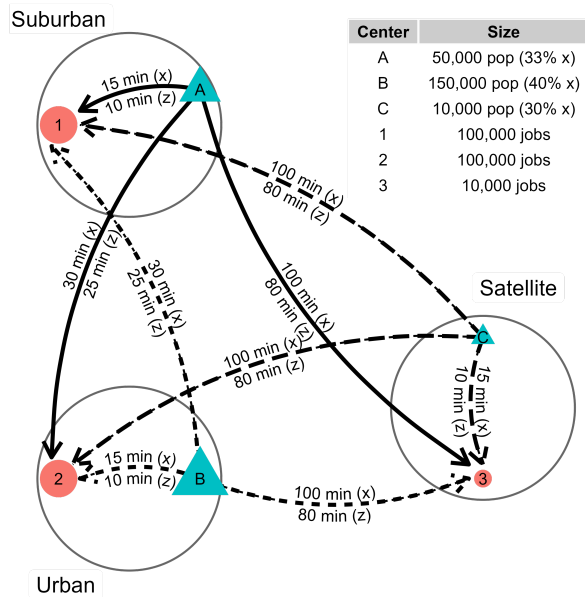

Fig 1. Multimodal synthetic example: locations of employment centers (in orange), population centers (in blue), number of jobs and population, and travel times for two modes (slower mode x and faster mode z).

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 is inspired by the single-mode example used in [11] 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 (low cost to reach), furthest from large populations (less competition), and uses the fastest mode z (greater range) can potentially reach the largest number of opportunities. This appears to be the sub-population at A using mode z. Sub-populations located in opposite conditions (i.e., more distant from jobs, close to large populations, and using slow mode x) are at a relative disadvantage. The competition for opportunities between different mode-using populations matters as it reflects how well the land-use and transport system serves (or does not serve) certain populations.

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	x	27,292.18	0.95	15,696.89	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		

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
TOTALS		150,570.22	N/A	210,000.00	N/A	210,000.00

The values calculated for S_i^m (Hansen-type accessibility), a_i^m (Shen-type accessibility), and V_i^m (spatial availability) 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 . As in the example in Shen [11], we use a negative exponential impedance function $f^m(c_{ij}^m) = \exp(-\beta \cdot c_{ij})$ with $\beta = 0.1$ for both x and z modes for all accessibility measures calculations. Notice that in this example we use the same impedance function but the travel times are different for the two modes. More generally, it is possible to use different impedance functions for the modes, as demonstrated in the empirical example below.

Hansen-type accessibility S_i^m is presented for each origin and mode in the third column of Table 1 . For all i, the travel by z results in higher values of S_i^m than travel by x. Lack of competition, or alternatively the assumption of an inexhaustible resource in the calculation of S_i^m, lead to a curious result. Since the 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), their values of S_i^m 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 lacks an intuitive interpretation: it represents the weighted sum of opportunities that may be reached within the region according to the travel impedance (i.e., the travel behavior and the characteristics of the modes) and does not usefully translate into any sort of benchmark. To connect this example to the literature, S_i^m is calculated in the work of [20]; 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. Large metropolitan regions will have large values and small regions small, but that is simply an artifact of size.

In the fourth and sixth columns in Table 1 the results for Shen-type accessibility are reported: 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 does considers *competition*. For instance, the population travelling by x from A and B do not have the same values of a_i^m as those travelling by z. In fact, A has the highest values a_i^m and a_i values since this center has the lowest travel impedance to opportunities (lower than at C, A and B are equal) and has faces relatively low competition, not being close to a relatively large population (lower than at B).

However, the calculations of a_i^m are not constrained: the total sum of a_i^m or a_i is practically meaningless since it represents a sum of ratios. For instance, the population travelling by z from A has a value of 1.57 jobs per job-seeking population compared to 0.95 for users of mode x. What is the meaning of these values? The difference between these modes is equal to 0.62, but 0.62 of what? How many more job opportunities can users of z reach compared to user of x? 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 aforementioned work of Tao et al. [33] to calculate modal a_i^m values and the aggregated a_i is implemented in the work of [35]. However, similar to Hansen-type accessibility, these works discuss relative and spatially comparative differences in values, but veer from interpretating the values of a_i^m or a_i themselves. In fairness, interpretation is complicated by the multiple counting of opportunities between zones and modes.

In 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 , the values of V_i^m in A and B are not the same within mode (as this measure considers competition). In fact, at A, users of mode z capture 36,088.84 more spatially available jobs (of the $210,000$ jobs in the region) than the sub-population travelling by x. The numerical difference is clear since it refers to opportunities out of the total.

Furthermore, the proportional allocation mechanism also means that the values of V_i^m for any origin i can be aggregated across m and compared between zones ($V_i = \sum_m \sum_i V_i^m$). 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 users of mode z 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, users of z account for 73% of the region's total spatial availability - while the remaining 27% is allocated to users of mode x who are 38%of the total population. Notably, the population who uses x have 11% fewer spatially available opportunities than its share in the population. This realization leads us to ask normative questions such as, how unequal should availability of opportunities be by mode? What intervention could help to redistribute spatial availability to sub-populations commensurate with their proportion of the total?

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 straighforward interpretation. Inequality in V_i^m values can be explored through a variety of approaches. For instance, consider travel times. The population of travelers who use z 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 population of users of z travels fewer minutes overall and has more spatial availability of opportunities than users of the slower mode x.

Alternatively, inequities in spatial availability between modes can be explored through proportional benchmarks. A spatial availability per capita v_i^m is presented in Equation (5):

$$v_i^m = \frac{V_i^m}{P_i^m} \tag{5}$$

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

If, let us say, the planning goal was to have one spatially available job per mode-using population, a policy intervention could be devised, to reduce the values of v_i^z (making it slower or more expensive) and increase he values of v_i^x (making it faster or les expensive). The purpose of this simple demonstration is to show how spatial availability can be used to quantify the competitive (dis)advantage in a multimodal application. In what follows, we demonstrate the use of multimodal spatial availability through an empirical example.

Empirical example: Madrid LEZ

Data and methods

The context for the empirical example is Madrid, in Spain. This city implemented a Low Emission Zone in 2017, to attend to goals set out in the national agenda to fight climate change, cut nitrogen dioxide levels, and prioritize people's movement in the city. Low emission zones (LEZ) elsewhere have been implemented as a climate change policy intervention to reduce GHG emissions, improve air quality, and support sustainable mobility [36,37]. Though the rules of exclusion vary, LEZ aim to deter/reduce traffic in designated zones under threat of penalty (e.g., fines, seizure of vehicle). In other words, LEZ are a policy of *geographic discrimination* as they change how people can reach opportunities by making the travel impedance more costly for specific forms of travel, typically cars. When considering opportunities as finite in a region, this discrimination reduces the competition of one mode and allows other modes to potentially thrive. In this way, LEZ aim to 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* [38] and *Plan Nacional de Control de la Contaminación Atmosférica* [39]. 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* [40].

In geographic scope, the 2017 boundaries of the LEZ in Madrid were relatively modest (covering 4.72 km^2) and only within the center (i.e., LEZ Centro). These boundaries were expanded in 2023 to the area inside the M-30, an orbital highway in proximity to the city center (i.e., LEZ M-30). Beyond this, the city has plans to spatially expand the LEZ. Within the 2017 LEZ Centro implementation, all cars, motorcycles and freight with environmental labels A or B (older makes and models of fossil fuel internal combustion engine vehicles), are not 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 typically travelled into what is now the LEZ Centro [41].

For this case study, we use spatial availability to quantify access to opportunities by different modes in Madrid. Particularly, we demonstrate how V_i^m can be used to derive insights into how the restriction of car mobility in areas around/within the LEZ Centro may have allowed other, more sustainable but often slower or more costly modes, to become more competitive.

The source of data for this example is the 2018 Community of Madrid travel survey [42]. This is a representative survey that gives a snap-shot of the travel patterns for a typical day of the working week in 2018. Specifically, it captures 222,744 trips as measured from a representative sample of 85,064 households across the traffic analysis zones (TAZ) in the Community of Madrid (population of 6,507,184 over 3 years old).

In this example, we use all home-to-full-time-work trips, by all modes. Figures 2 and 3 show the population of workers and the distribution of jobs in the City of Madrid. The zoning system is the trafric analysis zones used in the survey. The red boundary represents the LEZ Centro in effect in 2017. The survey already captures the travel patterns after the introduction of LEZ Centro. The cyan boundary represents the LEZ planned for for the boundaries of the M-30 highway 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 are shown in Figure 2 and the populations that go to a work destination by four modal categories P_i^m, is displayed in Figure 3. The modal

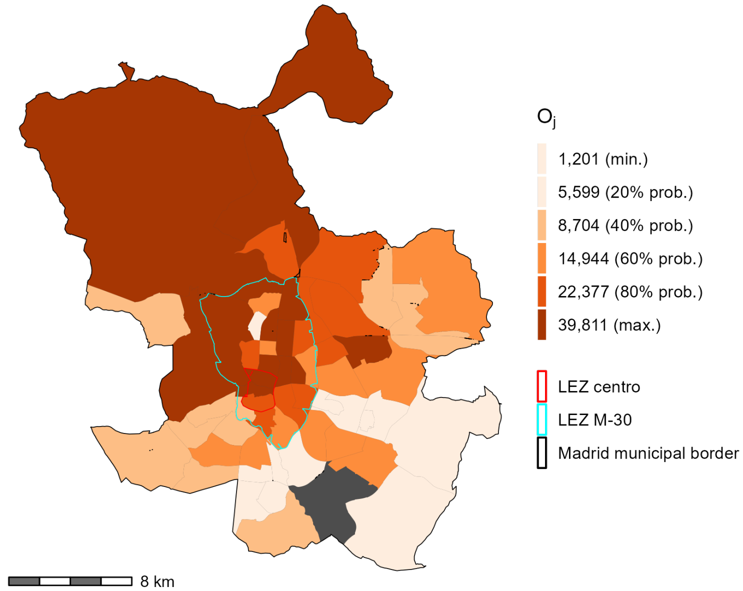

Fig 2. Jobs O_j taken by people living and working in Madrid as reported by the home-to-work flows in the 2018 travel survey. Gray TAZ has no jobs.

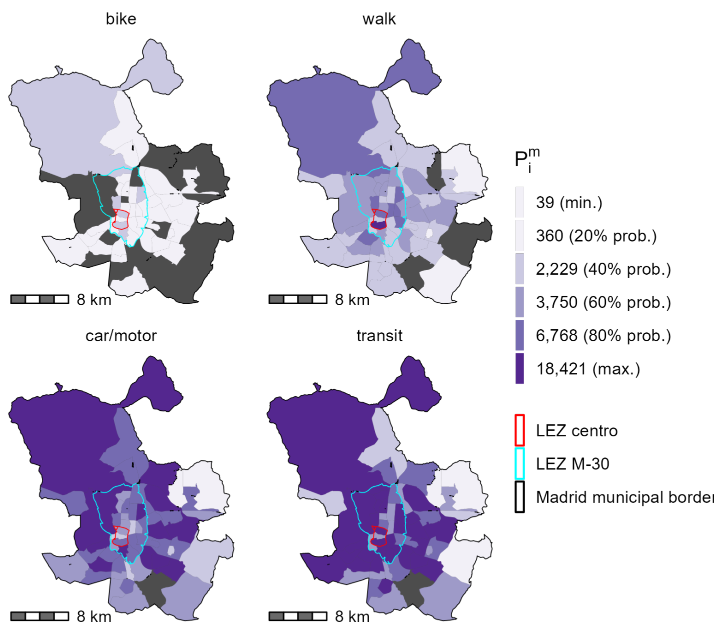

Fig 3. Population living and working in Madrid by four summarized modal categories P_i^m as reported by the home-to-work flows in the 2018 travel survey. Gray TAZs have no population.

shares in Figure 3 are calculated based on those measued in the survey. The modal categories and the mode types within each category are reported as follows:

- Car/motor: all cars and operating modes (e.g., cab, private driver, company, rental car, main driver of a private car, passenger in a private car) and all public, private or company motorcycle/mopeds.
- Transit: all bus, trams, and trains,
- Bike: all bicycle trips (e.g., private, public, or company bike trips) and "other" types of micromobility options,
- Walk: walking or by foot.

Some aggregation of modes is necessary to calculate the travel impedance functions by mode. From Figure 2, it can be seen that the largest concentration of jobs is within, near, and to the north of LEZ Centro. The populations with access to those jobs by mode (Figure 3) are spatially distinct. Travel by car and transit represent 37% and 47% of the modal share respectively. The population that travels by transit is more spatially distributed than those using cars - particularly near and within LEZ Centro. This distribution is likely caused by 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 LEZ Centro itself. From Figure 3, it can be seen that active travel is less common than motorized trips at 1% and 15% for cycling and walking respectively. Noticeably, there is a positive trend between the walking and cycling in zones where transit is also present. This positive trend is higher than for car trip populations.

Travel times are provided within the survey by mode. This information is used to calibrate mode-specific travel impedance functions $f^m(c_{ij}^m)$. To illustrate the modal differences in travel times, the following descriptive statistics per mode are presented:

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

Impedance functions $f^m(c_{ij}^m)$ are calibrated from the travel times in the survey via the empirical trip length distribution (TLD). An empirical TLD is given by the proportion of trips at various travel cost bins. This distribution is then used to estimate the parameters of a function for the travel impedance [as done in 43,44,45]. To fit the impedance functions, we use the Maximum likelihood estimation and the Nelder-Mead method for direct optimization available within the R {fitdistrplus} package [46]. Based on goodness-of-fit criteria and associated diagnostics, the gamma and log-normal probability density functions are selected as best fitting curves for the motorized and non-motorized modes respectively. The selection of functional forms aligns with empirical examples in other regions [14,47,48]. The shape and rate parameters for the gamma functions (motorized modes) are 1.8651852 and 0.051468for car/motor and 2.7566235 and 0.0499193 for transit; for the log-normal functions (non-motorized modes), the mean and standard deviation parameters are 3.2372212 and 0.7575986 for bike and 2.9918042 and 0.7575986 for walk.

Figure 4 includes four plots to visualize the calibrated impedance functions (represented as black lines) superimposed on the empirical TLD. The impedance functions can be interpreted as the propensity to travel (y-axis) given a trip travel time (x-axis). The functions reflect a combination of possibilities and preferences: the travel

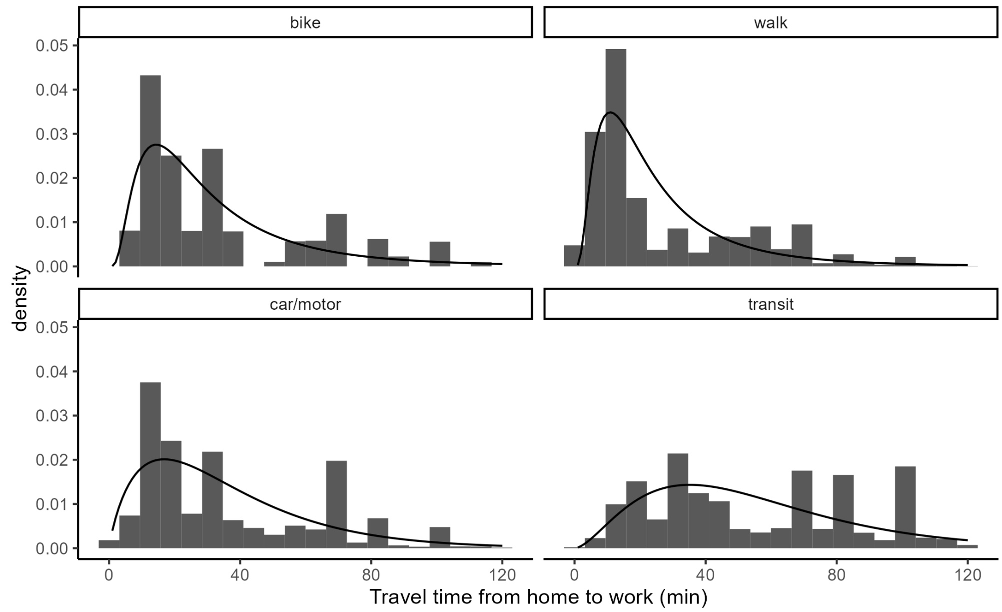

Fig 4. Fitted impedance function curve (line) against empirical TLD (bars) corresponding to the home-to-work origin-destination flows from the Madrid 2018 travel survey.

behavior given the transportation technologies available. For example, trips shorter than 5 minutes do not occur frequently for any mode; this reflects the spatial separation between places of residence and places of work commonly seen in many cities. In terms of the non-motorized modes, there is a preference towards walking trips around 15 minutes in duration, as seen from the highest value of $f^{walk}(c_{ij}^{walk})$. With respect to travel by bicycle, longer travel times are more common; although the highest value of the impedance also corresponds to approximately 15 minutes, the curve has a longer tail and values decrease less rapidly at longer travel times than is the case of $f^{walk}(c_{ij}^{walk})$. A similar trend can be observed for the motorized modal options where transit mode is more spread out than car/motor mode. All in all, these functions represent the propensity of travel by mode by duration of trip, which are needed to calculate the proportional allocation factors F_{ij}^m for V_i^m.

Results

At this point it is worthwhile to reiterate that the empirical example is a snap-shot of the calculated multimodal spatial availability using data from the 2018 travel survey. It is intended to visualize the spatial trends in availability of employment opportunities, by mode, and demonstrate how spatial availability can be interpreted to discuss the competitive advantage of lower travel impedance modes within Madrid Centro.

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

V_i^m is a proportion of the total number of 847,574 jobs in the region and is shown in Figure 5. Since V_i^m is calculated based on the population of workers and the distribution of jobs, 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

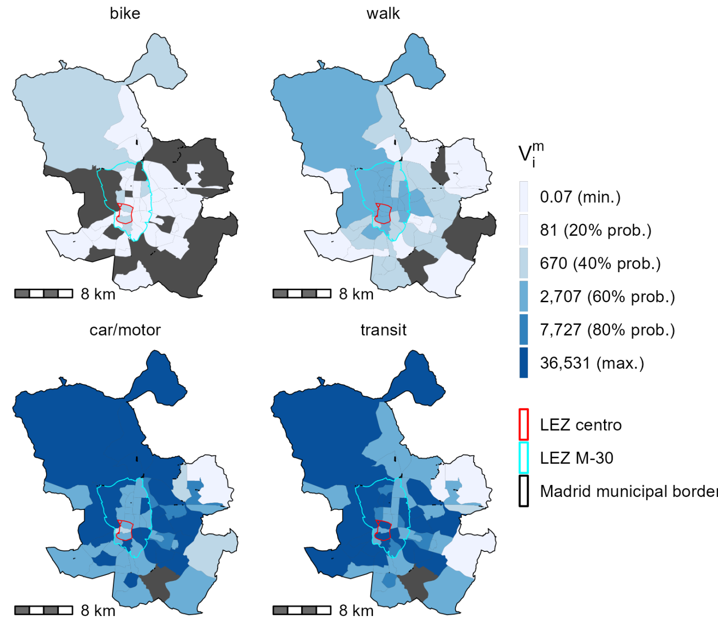

Fig 5. Spatial availability of job opportunities per origin and mode V_i^m in Madrid. Calculated using the home-to-work flows from the 2018 travel survey. Gray TAZs have no population.

of *all* populations in the region.

Some notable differences in the magnitude of V_i^m occur between modes as seen in Figure 5. The majority of V_i^m (which is to say of spatially available jobs) is allocated to those travelling by car and transit. This is to be expected, as the users of these modes represent 84.1% of the total population. Differences in V_i^m values within modes also exist in space: car users outside of the M-30 region appear to have greater V_i^m values, while some zones inside the M-30 appear to have higher V_i^m values for transit. Overall, the magnitude of V_i^m values for cyclists and pedestrians are lower than for car and transit but the highest values of V_i^{bike} and V_i^{walk} tend to be allotted to zones within the M-30 and origins with higher spatial availability by transit.

The differences between the shares of modes and their shares of spatially availabile opportunities highlights the competitive advantage afforded by certain modes, although this effect is not uniform in space. As seen in the left-most columns of Figure 6, 'car/motor' and 'transit' together can avail themselves of 95.3% of all jobs in the city. However, 'car/motor' has a disproportionate share of V_i^m relative to the population of users of this mode, compared to opportunities that are spatially available to transit users. The combined population of car and transit users is 36.6% and 47.5% respectively, but these populations are allocated 48.0% and 47.3% respectively, of the city's jobs. When treating the number of opportunities that can be reached as a finite value (total: 847,574 opportunities), fewer opportunities are spatially available to slower modes (i.e., walking and cycling), even taking into account that their share is smaller overall. These modes are at a disadvantage as a result of: the travel impedance for longer trips (see Figure 4; their low population values values overall; and larger populations in origins with high shares of travel by motorized modes. These factors all contribute to the the car/motor mode being most advantaged in capturing spatially available job opportunities overall.

Despite the big picture, it is important to note that there are spatial variations in the competitive advantage of cars. The proportion of travel by car in Centro is smaller

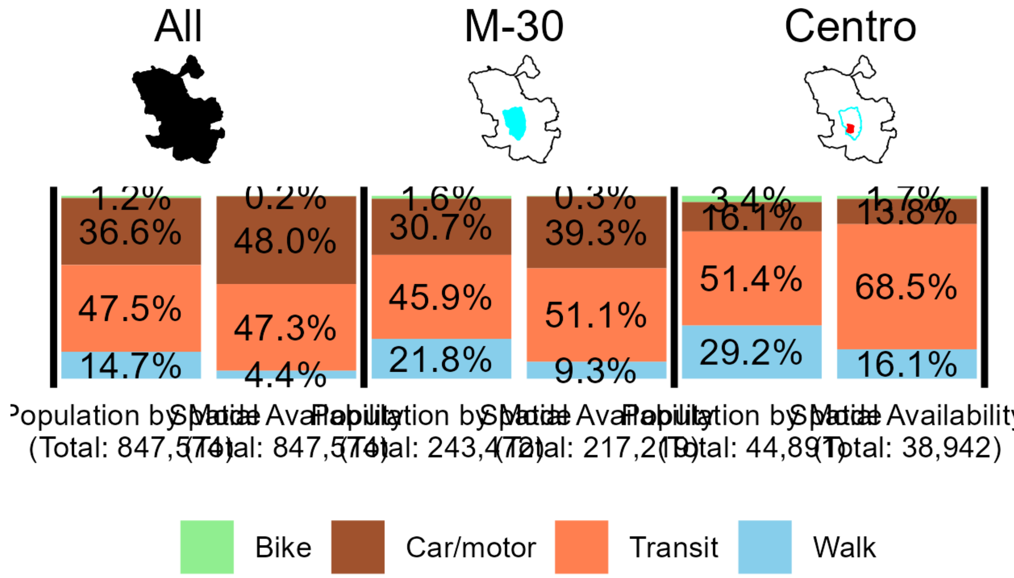

Fig 6. Displays the proportion of the working population by mode and spatial availability of job opportunities by mode aggregated for three spatial areas. From left to right, the city of Madrid (All), the area within the M-30 highway (M-30),the area within the Centro region (Centro).

and has higher travel impedance values relative to the inputs in other areas and by other modes. The LEZ Centro implementation further restricts the advantage of cars by shifting more than half of all car trips into the LEZ to modes [41]. This restriction decreased the number of trips by car from 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 allows more opportunities in the LEZ to be available to populations using other modes.

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

Figure 6 also shows that there is a higher proportion of opportunities that are spatially available to pedestrians and cyclists in Centro than in the City overall and in all areas within the M-30. Notably, within 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. Although the proportion of opportunities that are spatially available to these modes is still lower than the respective shares of the population located in the Centro, these modes are more competitive within the Centro than anywhere without. By restricting the ability of cars to enter Centro, the LEZ also contributes to level the playing field for slower modes, in particular cycling and walking.

The spatial differences in the competitive dis/advantage of spatial availability

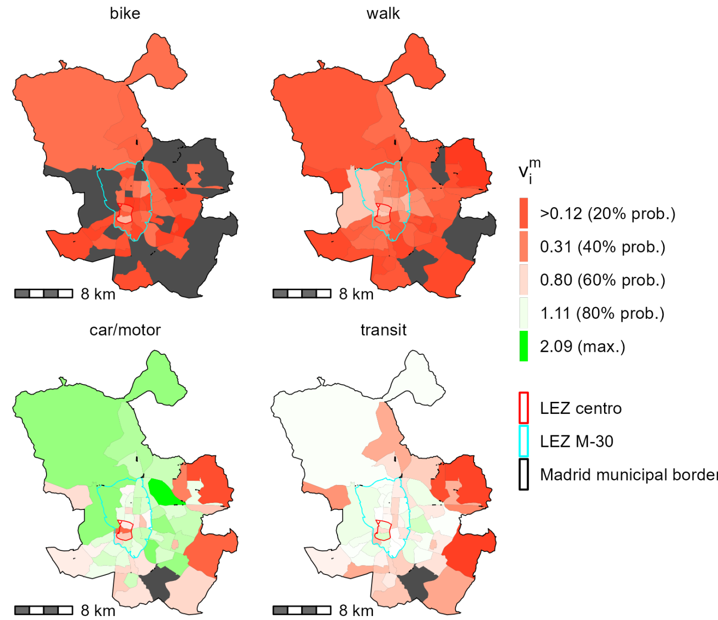

Fig 7. Spatial availability of job opportunities per mode-using capita by mode v_i^m per origin in Madrid. Calculated using the home-to-work flows from the 2018 travel survey. Gray TAZs have no population.

between modes can also be visualized per origin. Figure 7 shows v_i^m, the spatial availability V_i^m divided by the population that uses m. Values of v_i^m above 1 are shown in red and represent more than one spatially available opportunity per capita; values below 1 are shown in green, and represent less than one spatially available opportunity per capita; values equal to 1 are shown in white. These plots drive home the point of the disproportionately high over-allocation of spatial availability relative to the share of modes in many of the origins for car (bottom left plot, areas denoted with green v_i^m values above 1). These plots also show areas with disproportionately few spatially available opportunities (under 1). It can be observed that the spatial availability to jobs of transit users is relatively well balanced (i.e., many zones are white), while that for non-motorized modes is low (under 1) overall.

It is also interesting to note that v_i^m for car within and near LEZ Centro is close to or below 1 (white/red) in Figure 7, while in contrast all non-car modes have relatively higher v_i^m values. Since the values are comparable across regions and over time, Figure 7 provides a benchmark for quantifying potential LEZ implementations in the future. As Figure 7 also shows, many areas within the M-30 have high (white/green) v_i^m values for car, but the results for LEZ Centro give reasonable grounds to speculate that a spatial expansion of the LEZ to include all areas within the M-30 stands to increase the spatial availability of jobs for more transit, cyclcing and walking.

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 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 [5]. 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. In future work, we intend to use multimodal spatial availability to characterise the equity of multimodal accessibility losses and gains in varying LEZ policy scenario implementations.

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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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