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

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## Abstract

Recent research has tried 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 [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. Other types of opportunities are at the very least subject to congestion: 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, [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, [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 them by guaranteeing that each opportunity is counted only once - in other words, treating opportunties 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 [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 finity of the 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 this is in fact just one example 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 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 travellers 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 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 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 ($f^m(\cdot)$).

The Hansen-type measure is not constrained, and as a result does not consider the opportunities as finite. As an example, the work of [20] uses the Hansen-type measure to measure the potential interaction with retail locations using walking, public transit, and car modes as $m$. $S_i^m$ 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, each $i$ has three $S_i^m$ values, one per $m$. In this work, they demonstrate that the car mode has the highest $S_i^m$ values in the majority of $i$, i.e., populations using 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 modes is analyzed as if the others did not exist, which would be reasonable for an inexhaustible opportunity, but is more questionable when the opportunity is subject to congestion. Since the measure is measure is also not constrained, and each opportunity can be and often is counted multiple times within and between modes, the sum of accessibility is not a meaningful quantity. To improve interpretability, $S_i^m$ values are presented as standardized accessibility index in this work, from the lowest value of 0 to the highest value of 1. This presentation or discussion of Hansen-type accessibility measures is common in the literature [e.g., in 21,and 22].

However, this representation of results can make the interpretation of results challenging *because* values are region-relative and lacking numeric meaning. Zones will always have values from between 0 to 1 represented, but is a zone with a low value for pedestrian-modes and a high value for car-modes notable? And if notable, what does the difference in these standardized values tangibly mean for planners? By how much should transport systems and land-use configurations be changed to improve conditions? And in what way can these existing methods be used to track progress over time? Or between regions? This is challenging to track, since certain values will always be relatively 'low' and 'high'. Alternatively, modal accessibility calculated using the Hansen-type measure is also presented without standardization, as in the work by [23]. Often, the meaning of the accessibility value itself is not interpreted, as it is difficult to state what having access to 30,000 employment opportunities by car but having 10,000 employment opportunity by transit tangibly signifies.

However, once opportunities in a region are interpreted as finite, a new meaning is taken on. As considered in the long tradition of accessibility work, capacity of opportunities is limited and thus is subject to competition by population [11,14,24–28]. There are only so many school-seats, hospital capacity, employment opportunities, etc., in a region and if one person interacts with an opportunity at a given time, it is taken: the supply of an opportunity and the demand for that opportunity are two components of accessibility. The competition consideration is especially important in the case of multiple modes. For instance, people in a zone who are advantaged with a relatively low travel-cost mode have the ability to potentially interact with more opportunities than other people. Due to this advantage, through the perspective of finite opportunities, there are fewer opportunities left to be potentially interacted for everyone else, especially zones with populations using higher travel-cost modes. This recognition is the motivation behind integrating *competition* for opportunities within modal accessibility measures.

Arguably, one of the most popular competitive location-based accessibility measures is the two-step floating catchment area (2SFCA) approach popularized by [12] who simplified the approach proposed by [11] (with similar considerations for competition in [28] and [29]). 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 $\sum_i P_i^m f^m(c_{ij}^m)$ and the remaining variables are repeated in the Hansen-type measure. The Shen-type measure per mode ($a_i^m$) can be understood as a ratio of the travel impedance-weighted supply of opportunities for the $m$-using population in $i$ over the ravel impedance-weighted demand for opportunities. In this way, it considers competition but the measure remains *non-constrained* meaning resulting values are not associated with global maximums. In other words, it is difficult to interpret the meaning of differences in Shen-type accessibility scores between modes in similar ways as reflected for Hansen-type measures.

To illustrate, [30] 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 multimodal 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 unaddressed.

Spatial availability improves on previously discussed multimodal accessibility approaches using the Hansen-type measure and the Shen-type measure by taking into account *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 $F^t_{ij}$ handles the number of opportunities in the region in a finite way (proportional allocation). $F^t_{ij}$ consists of two components: a population-based balancing factor $F^p_i = \frac{P_i}{\sum_i P_i}$ and an impedance-based balancing factor $F^c_{ij} = \frac{F^c_{ij}}{\sum_j F^c_{ij}}$ that, respectively, allocates 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).

$F^p_i$ and $ Fˆc_{ij}$ are calculated for each $i$ such that they both equal 1 when summed across all $i$ in the region (e.g., $\sum_i F^p_i = 1$ and $\sum_i F^c_{ij} = 1$). These balancing factors are combined multiplicatively to yield $F^t_{ij}$ 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, $F^t_{ij}$ 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 $i$. 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 accessibility 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, $F^{pm}_i$ and $F^{cm}_{ij}$ 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 $F^{tm}_{ij}$ detailed in Equation (2).

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

Where:

- The population balancing factor for each $m$ at each $i$ is $F^{pm}_i = \frac{P^m_i}{\sum_m \sum_i P^m_i}$
- The cost of travel balancing factor for each $m$ at $i$ is $F^{cm}_{ij} = \frac{f^m(c^m_{ij})}{\sum_m \sum_i f^m(c^m_{ij})}$

Implementing $F^{tm}_{ij}$, the following Equation (3) demonstrates the multimodal configuration of spatial availability $V^m_i$:

$$V^m_i = \sum_{j=1}^{J} O_j \ F^{tm}_{ij} \tag{3}$$

Where:

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

## An illustrative synthetic example

Consider the following Figure 1, it 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

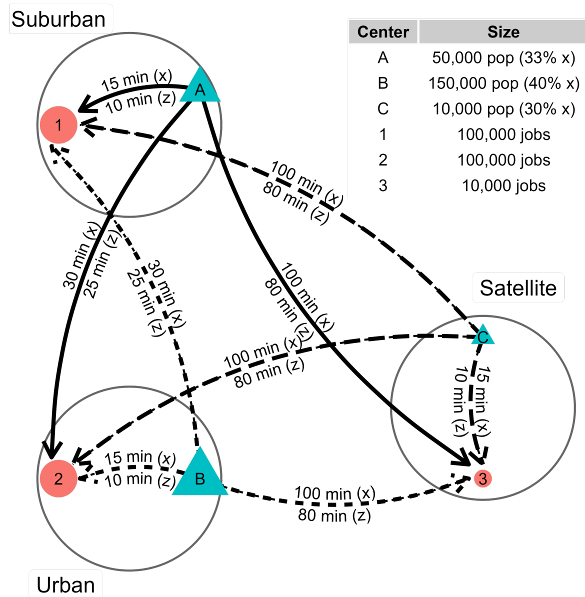


**Fig 1.** Multimodal synthetic example: locations of employment centers (in orange), population centers (in blue), number of jobs and population, and travel times for two modes (slower mode x and faster mode z).

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 [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, 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 mode $z$. 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*. The competition for opportunities between different mode-using populations matters from the perspective of inequities as it reflects how well the land-use and transport system serves (or doesn't 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 | | |
| 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 $f^m(c_{ij}^m) = \exp(-\beta \cdot c_{ij})$ 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 since $S_i^m$ 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 [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.

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 [30] to calculate modal $a_i^m$ values and the aggregated $a_i$ is implemented in the work of [31]. 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 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 [32,33]. Though rules of exclusion 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 specific car-mode users. When considering opportunities as finite in a region, this discrimination could allow certain 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*

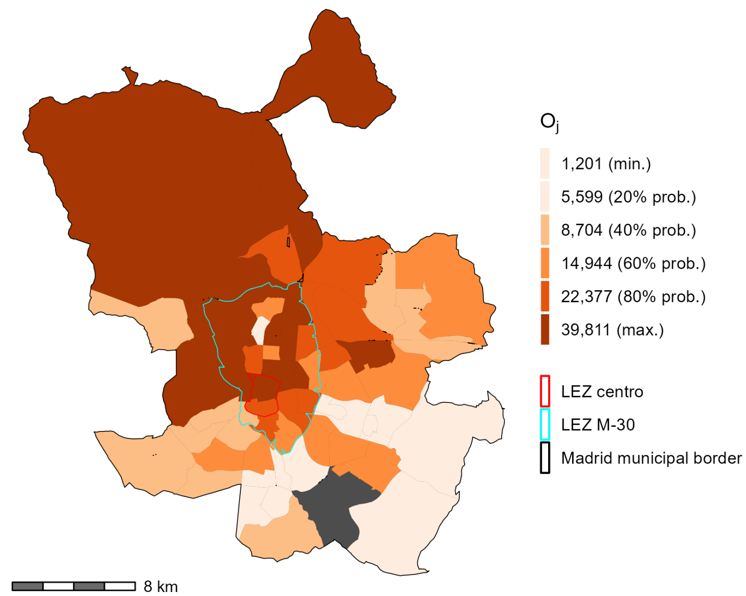


**Fig 2.** Jobs $O_j$ taken by people living and working in Madrid as reported by the home-to-work flows in the 2018 travel survey. Gray TAZ has no jobs.

*Integrado de Energía y Clima 2021-2030* [34] and *Plan Nacional de Control de la Contaminación Atmosférica* [35]. 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* [36].

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 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 [37].

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 [38] is the source of data for this empirical example: it is a representative survey that reflects a snap-shot of the travel patterns for a typical day of the working week in 2018. Specifically, it includes 222,744 trips taken from a representative sample of 85,064 households across the traffic analysis zones (TAZ) representing the Community of Madrid (population of 6,507,184 over 3 years old) through population elevation factors.

In this empirical example, we only use a sub-set of the survey, specifically

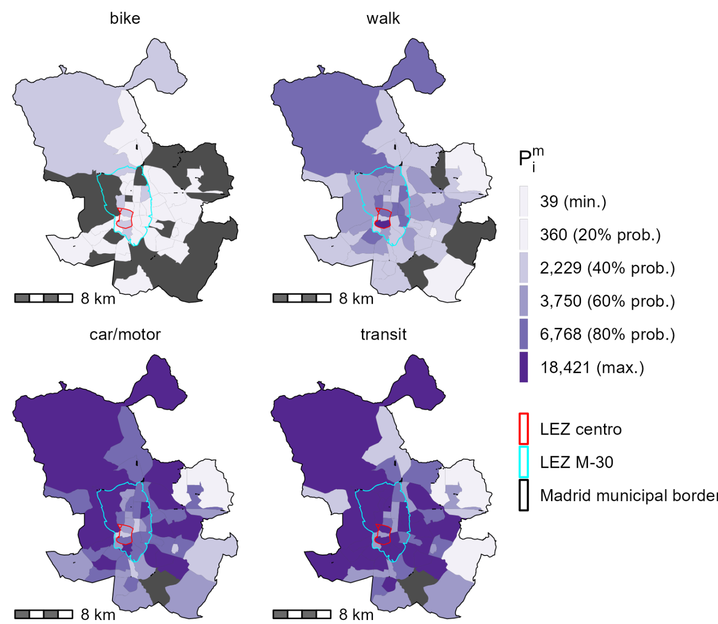


**Fig 3.** Population living and working in Madrid by four summarized modal categories $P_i^m$ as reported by the home-to-work flows in the 2018 travel survey. Gray TAZs have no population.

home-to-full-time-work trips, by all modes, to demonstrate multimodal spatial availability of employment opportunities. The total population who travels to full-time work from an origin (i.e., the worker), and the destinations (i.e., the employment opportunity), for the City of Madrid (a sub-set of the Community of Madrid) is visualized in Figure 2 and Figure 3. Both figures are displayed at the level of TAZ (the $i$ and $j$ zones) 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 four modal categories represented in Figure 3 are created through the grouping of similar mode types as provided in the survey, by the authors discretion. 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.

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 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 observed 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 time lengths, summary descriptive per mode are detailed:

- 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)

To calculate $f^m(c_{ij}^m)$ from the survey travel times, a concept known as the trip length distribution (TLD) is 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 in the derivation of travel impedance functions (e.g., done in the accessibility works of [39], [40], and [41]). 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 [42]. 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 form aligns with empirical examples in other regions [14,43,44]. 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), mean and standard deviation parameters are 3.2372212 and 0.7575986 for bike and 2.9918042 and 0.7575986 for walk.

Represented in Figure 4 are four plots visualizing the estimated probability density functions (represented as black lines) over top the binned travel time data from the 2018 survey. The estimated probability density functions can be interpreted as the probability of travel (y-axis) given a trip travel time (x-axis), based on trip flows from the 2018 travel 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 (according to the 2018 survey). A trip that leaves $i$ is assigned a probability of travel value (y-axis) based on the mode and travel time of that trip to work: this probability value is the input $f^m(c_{ij}^m)$.

Notably, plots in Figure 4 can be observed across modes if curious to know what trips are more likely to occur using what mode depending on trip length (as informed by the observed 2018 survey). Trips >5 minutes do not occur frequently for any mode, as such trips with short trip lengths are assigned a lower travel impedance $f^m(c_{ij}^m)$ value. One reason that >5 minute trips do not frequently occur as a result of land-use (residential and job mismatch): not everyone lives in immediate proximity to their workplace. In terms of the non-motorized modes, shorter trips occurred more frequently overall for walking populations, particularly around 15 minute lengths, so a trip of

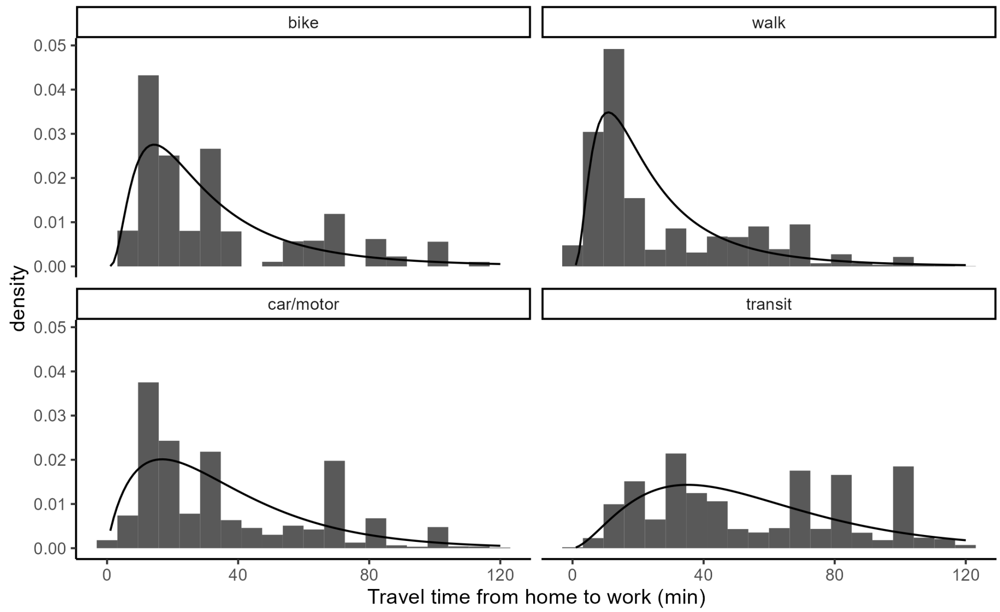


**Fig 4.** Fitted impedance function curve (line) against empirical TLD (bars) corresponding to the home-to-work origin-destination flows from the Madrid 2018 travel survey.

approximately 15 minutes is assigned the highest $f^m(c_{ij}^m)$. For biking populations, longer travel times are more common so though the highest $f^m(c_{ij}^m)$ value also corresponds to approximately 15 minutes, the curve is more spread out and values decrease less rapidly at longer travel times than for the walk mode curve. 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 observations demonstrate that, based on a given mode and travel time, a trip is more or less likely to occur and is accordingly represented in the cost of travel balancing factor $F_{ij}^m$ for $V_i^m$.

## Results

As it is worth re-iterating, the empirical example reflects 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 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 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

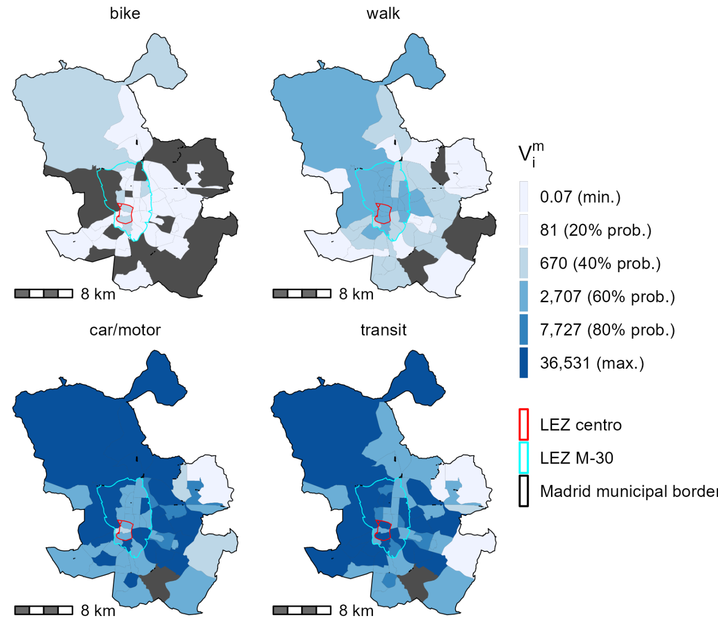


**Fig 5.** Spatial availability of job opportunities per origin and mode $V_i^m$ in Madrid. Calculated using the home-to-work flows from the 2018 travel survey. Gray TAZs have no population.

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, 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 $i$s within the M-30 and $i$s 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 [37]. This restriction decreased the number of car-using population from $i$s going into the LEZ

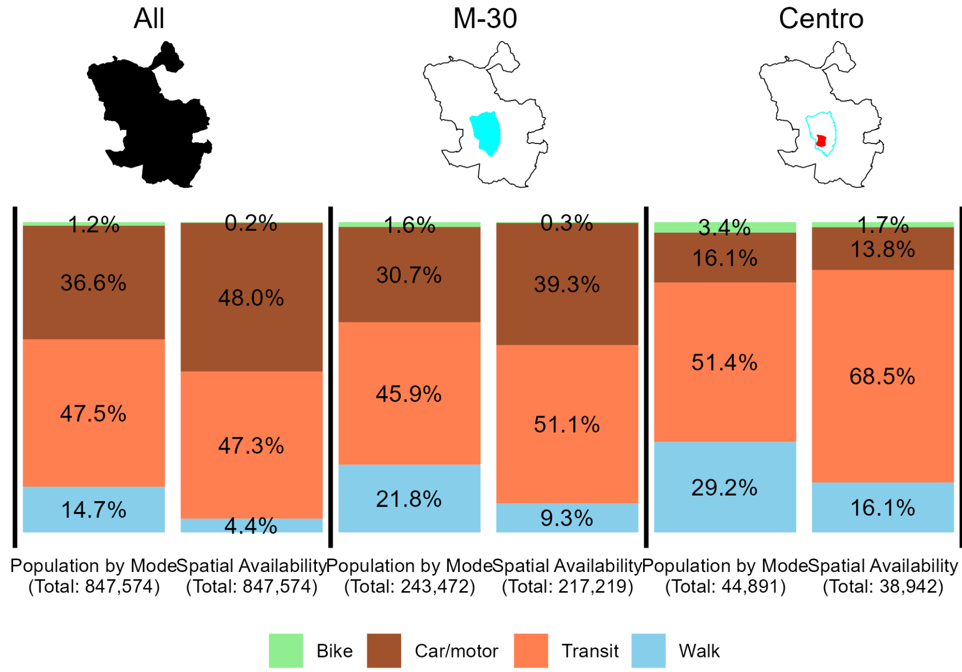


**Fig 6.** Displays the proportion of the working population by mode and spatial availability of job opportunities by mode aggregated for three spatial areas. From left to right, the city of Madrid (All), the area within the M-30 highway (M-30),the area within the Centro region (Centro).

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 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

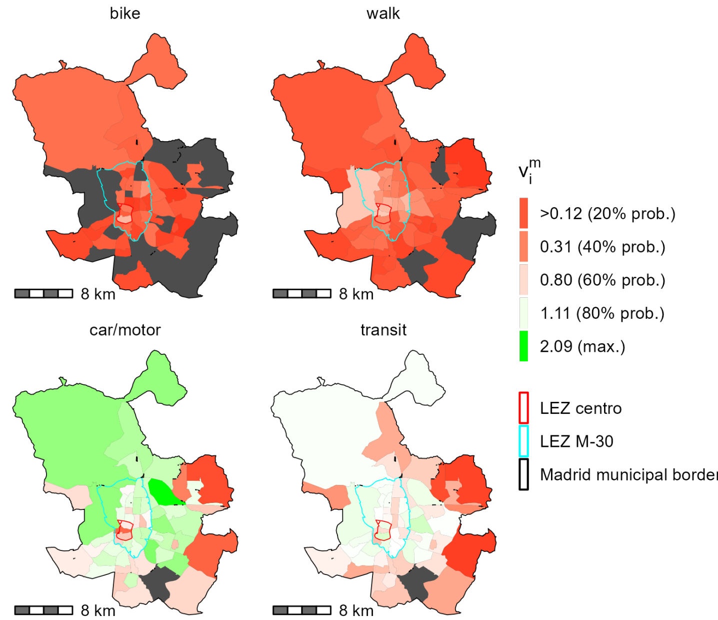


**Fig 7.** Spatial availability of job opportunities per mode-using capita by mode $v_i^m$ per origin in Madrid. Calculated using the home-to-work flows from the 2018 travel survey. Gray TAZs have no population.

between modes can also be visualized per origin. Figure 7 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 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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