Multimodal spatial availability - the case of low emission zones in Madrid

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

Keywords: Multimodal, Accessibility, Equity, Policy scenarios, Low emission zones,

ABSTRACT

An increasing number of studies within the domain of transport are concerned with the inequities in accessibility to opportunities. A dimension of these inequities arise from differences in access by mode type (e.g., the number of work opportunities that can be reached using a car as opposed to transit in a city). However, methods assessing multimodal accessibility in the literature fall short as aspects of competition for opportunities and the explicit methodological acknowledgement of opportunities being *finite* are lacking. In this vein, this paper presents an extension of *spatial availability*, a singly-constrained competitive accessibility measure, for the context of multimodal accessibility analysis. We first illustrate the features of spatial availability that lends itself to multimodal analysis. We then demonstrate its use on the case study of Low Emission Zones in Madrid (Spain) and highlight how this policy intervention changes the accessibility of populations using different modes. In summary, spatial availability can be used to create and interpret multimodal policy intervention scenarios unlike previous methods: this creation and interpretation can help regions envision a more sustainable and equitable access-to-opportunity landscape by better identifying differences in accessibility afforded by different modes.

INTRODUCTION

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

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

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

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

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

A BRIEF REVIEW OF MULTIMODAL ACCESSIBILITY MEASUREMENT METHODS

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

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

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

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

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

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

A synthetic example: calculating accessibility for multiple modes considering finite opportunities

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 (e.g., a neighbourhood has 1,000 spatially available jobs out of 100,000 jobs in the total region). The general formulation of spatial availability V_i is shown in Equation (1):

$$V_i = \sum_{j=1}^{J} O_j F^t_{ij} \tag{1}$$

where:

- F^t_{ij} 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., $\sum_j O_j = \sum_i V_i$)

Spatial availability measure is introduced in Soukhov et al. (14). The unique feature in the measure is the balancing factor F^t_{ij}, a proportional allocation mechanisms, which ensures that the V_i calculated for each i sums to the total number of opportunities. Through F^t_{ij}, spatial availability is a *competitive* and *constrained* accessibility measure that handles the number of opportunities in the region in a finite way. 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, allocate opportunities to i in proportion to the size of the population at i (the mass effect) and the cost of reaching opportunities at j (the impedance effect). F^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. This value can be seen to represent spatial availability as it is a proportion of the opportunities in the region (i.e., $\sum_j O_j = \sum_i V_i$).

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

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

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

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

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

Where:

- m is a set of modes used by populations in the region $m = 1, \cdots, M$.
- 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., $\sum_j O_j = \sum_i V_i = \sum_m \sum_i V_i^m$)

Consider the following synthetic example: Figure 1 depicts a region with population and jobs at three population centers (A, B, C) and three employment centers (1, 2, 3). The population at each population center is divided into two sub-groups, 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 A, close to the Urban area's equally large employment center B, and has a population that is smaller than the Urban center 2 and larger than the Satellite center 3. The Urban population center has the largest number of population using slower mode x, followed by the Suburban then Satellite area. This synthetic example was inspired by the single-mode example used in Shen (17) and reconfigured in Soukhov et al. (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 Suburban center A using the faster mode z. From the other perspective, sub-populations located further away from jobs, close to dense populations, and using high cost travel mode x are at a job opportunity access *disadvantage* relative to the other sub-populations. This could be the sub-populations using the slowest mode x at either Urban B or Satellite C area. From the perspective of inequities, the competition for opportunities between different mode-using populations (i.e., how well the land-use and transport system may serve some and not others), matters.

TABLE 1: Summary description of the synthetic example: accessibility values at each origin per mode m at each origin i and aggregated between modes for each i.

i	m	V_i^m	S_i^m	a_i^m	V_i	a_i
A	x	18,959.86	27,292.18	0.95	65,872.91	1.32
	z	46,913.04	44,999.80	1.56	65,872.91	

TABLE 1: Summary description of the synthetic example: accessibility values at each origin per mode m at each origin i and aggregated between modes for each i.

i	m	V_i^m	S_i^m	a_i^m	V_i	a_i
B	x	30,863.43	27,292.18	0.62	134,255.38	0.90
	z	103,391.95	44,999.80	1.03	134,255.38	
C	x	2,034.49	2,240.38	0.68	9,871.71	0.99
	z	7,837.22	3,745.89	1.12	9,871.71	
TOTALS		210,000.00	150,570.22	N/A	210,000.00	N/A

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 (**??**). We use a negative exponential impedance function $f(c_{ij}) = \exp(-\beta \cdot c_{ij})$ with $\beta = 0.1$ for both x and z modes for all accessibility measures calculations.

The Hansen-type measure S_i^m is presented for each origin and mode in third column of Table (**??**). For all i, the sub-population using the faster mode z has higher S_i^m values than the x using sub-populations. Additionally, S_i^m is equal for both mode using populations in population centers A and B. This is the case because S_i^m does not consider *competition*, it only relies on reflecting the count of opportunities that may be potentially interated 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 for mode x or 10, 25, or 80 minutes for mode 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 a global maximum or any sort of benchmark as the measure is *non-constrained*. To connect this example to literature, this method of modal accessibility calculation is used in the work of Tahmasbi et al. (15); they compare differences in S_i^m values between modes in a relative and comparative sense, but make no further interpretation of the S_i^m values.

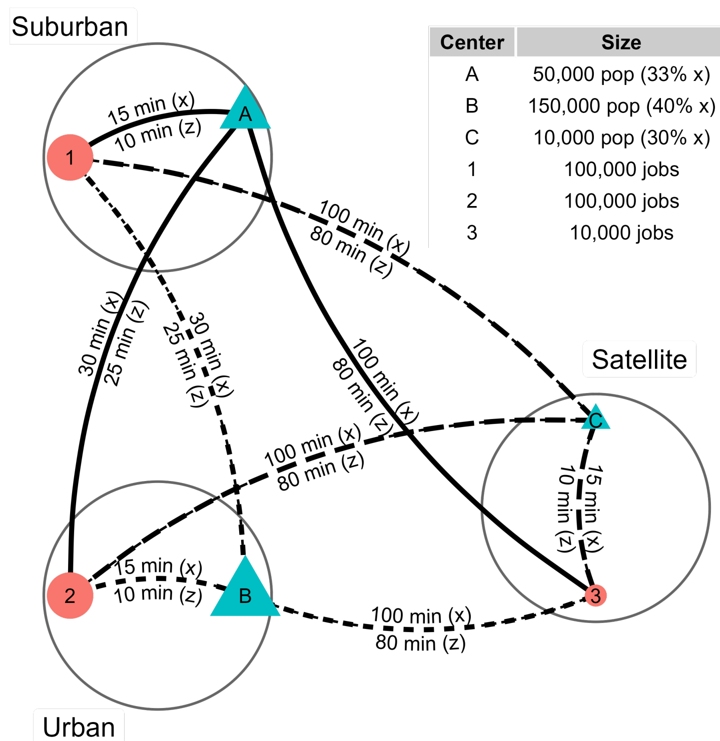
In the fourth and sixth column in Table (**??**) the Shen-type measure is calculated: first for both origin and mode a_i^m as well as aggregated by the weighted mean mode-population ($\sum_m \frac{P_i^m}{P_i} * a_i^m$) to represent a value for each origin a_i. Unlike S_i^m, this measure considers *competition*.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

potential jobs per potential job-seeking population compared to

for the slow mode x population. What is the significance of these values? The difference between these modes is equal to

, but



Center	Size
A	50,000 pop (33% x)
B	150,000 pop (40% x)
C	10,000 pop (30% x)
1	100,000 jobs
2	100,000 jobs
3	10,000 jobs

FIGURE 1: Modified synthetic example from Shen (1998) with locations of employment centers (in orange), population centers (in blue), number of jobs and population, and travel times for two modes (slower x mode and faster z mode).

a_im
1.56

a_im
0.95

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 Tao et al. (20) to calculate modal a_i^m values and the aggregated a_i is implemented in the work of Carpentieri et al. (21). However, similar to the Hansen-type measure, these works discuss relative and spatially comparative differences in values, they do not make further interpretation of the a_i^m or a_i themselves. This may be because the Shen-type measure is *non-constrained*, this is no benchmark or global maximum to which comparisons can be drawn from. Being unable to do so makes the interpretation of competition between modes challenging to tease out.

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 (**??**), 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 for instance, the sub-population using faster mode z captures 27,953.18 more spatially available jobs (of the $210,000$ jobs in the region) than the sub-population using mode x. The numerical difference have 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 (**??**). Again looking at center A, A is allocated 65,872.91 spatially available opportunities for both modes. 71% of this spatial availability allocated to A is assigned to the z-using population despite representing 66% of the population at A.

Spatial availability can be further aggregated to better interpret competition between modes. Across the entire region, 137,500 use the faster mode z (65% of the region population). However, z-using populations accounts for 75% of the region's total spatial availability - the rest is allocated to the population using x (of which represents 35% of the population). Notably, the x population captures 10% less spatial availability to opportunities than its population proportion.

Since spatial availability is constrained and has an interpretable meaning of a proportion of the total opportunities in the region, the values have a new significance. Inequality in spatial availability values can be explored through a variety of approaches. For instance, consider travel times. The z population using the faster mode z accounts for 69% of the potential travel time traveled in the region: 6% less travel time than the proportion of spatial available opportunities that the z population has access to. Meaning z population travels less potential minutes overall and has more spatial availability of opportunities than the population using the slower mode x.

Alternatively, these inequities in spatial availability between mode-using populations can be explored through proportional benchmarks. A spatial availability per capita as presented in Equation (4) is defined at each population center, mode, and/or regionally:

a_im
0.62

a_im
0.62

$$v_{im} = \frac{V_{im}}{P_{im}} \tag{4}$$

The spatial availability per capita values v_i^m for A, B, and C for the slower mode x is 0.95, 0.62 and 0.68 respectively. The benchmarks for x mode are evidently lower than the averages at: 1.32, 0.9 and 0.99 respectively. Especially for B and C.

The average for the faster mode z with values of: 1.56, 1.03 and 1.12 respectively. Once again, we see the competitive advantage on a per capita bases that populations have to opportunities when commuting using the faster mode.

In what follows, we further explore competition between multimodal accessibility and how competition between different modal-users is captured by spatial availability through an empirical example.

EMPIRICAL MULTIMODAL SPATIAL AVAILABILITY

Data inputs: Madrid's LEZ and travel survey

Low emission zones (LEZ) have been implemented as a climate change policy intervention to reduce GHG emissions, improve air quality, and support sustainable mobility in many countries. Though rules vary depending on legal aspects and cultural norms, LEZ aim to deter or reduce traffic in specially designated zones under the penalty of fines and/or seizure of vehicle. In practice, this limits the volume of traffic by excluding vehicles by license plate, fuel type, or by introducing tolls.

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

In 2017, a LEZ was implemented in the capital city of Madrid following the goals set out in the national agenda: to fight climate change, cut nitrogen dioxide levels for the benefit of people's health, and prioritize people's movement in the city. 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). They were expanded in 2023 to just 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 in the future. 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

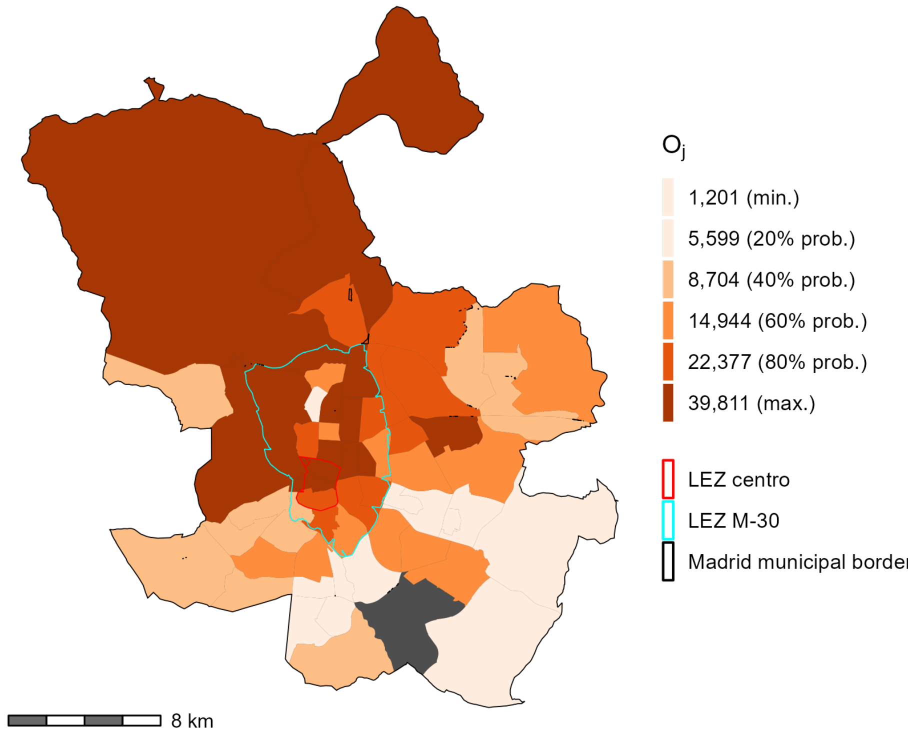


FIGURE 2: Jobs O_j taken by people living and working in Madrid as reported by the 2018 travel survey.

of fossil fuel internal combustion engine vehicles), are banned from driving into the area unless they are used by residents or meet other exemptions (25). This restriction impacts approximately half of all car that made trips into LEZ Centro.

From the perspective of restriction for passenger transport, LEZ are a policy of *geographic discrimination*. LEZ actively change how people access opportunities by making the travel impedance more costly for car-mode users. If seeing opportunities as finite, this discrimination allows populations to access opportunities by other modes more readily than before. In this way, the policy changes the multimodal competitive accessibility landscape of the city. Though the cost of travel for modes do dynamically change as a result of the LEZ implementation (i.e., potentially less car congestion, potentially more transit congestion), the focus of this empirical example is to demonstrate the spatial availability, by mode, of the city of Madrid after the 2017 implementation of the LEZ Centro.

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

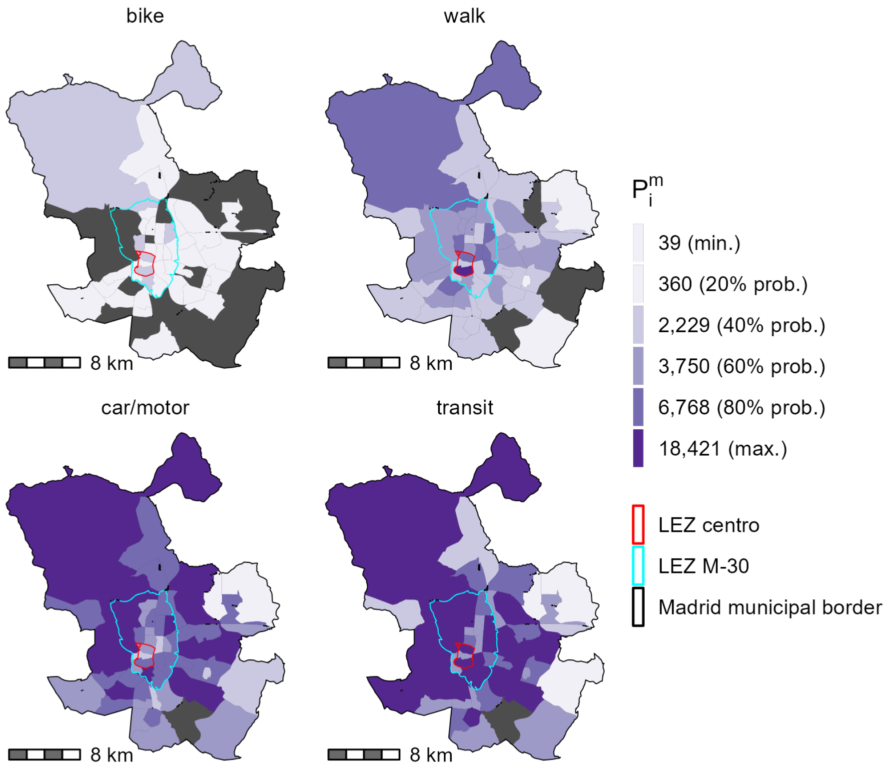


FIGURE 3: Population living and working in Madrid, by four summarized modal categories, P_i^m as reported by the 2018 travel survey.

cyan boundary represents the LEZ that will be within the boundaries of the M-30 highway in 2023 and is present in the plots as a spatial reference for areas in proximity to the LEZ Centro.

The total sum of jobs O_j that are held are shown in Figure 2 and the populations that go to a work destination by four modal categories P_i^m, is reflected in Figure 3. The modal categories represented in Figure 3 were summarized for the following trip mode types: - Car/motor: all cars and operating modes (e.g., cab, private driver, company, rental care, main driver, passenger, etc.) and all public, private or company motorcycle/mopeds. - Transit: all bus, trams, and trains - Bike: all bicycle trips (e.g., private, public, or company bike trips) and “other” types of micromobility options - Walk: walking or by foot

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

From Figure 2, it can also be seen that biking and walking trips are less common than motorized trips at 1% and 15% respectively. The distribution of walking and biking trips appear to be similar to that of transit trips. This is to be expected as active transport and a higher diversity of land-use spatially occurs with transit infrastructure.

The travel time for each trip is provided within the 2018 survey. These travel times, per modal category, are used to calibrate mode specific travel impedance functions $f^m(c_{ij}^m)$. To illustrate the modal differences in travel lengths, summary descriptive per mode are detailed as follows:

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

To calculate the mode specific travel impedance functions $f^m(c_{ij}^m)$ from the 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. This distribution is then used to derive impedance functions as done in previous accessibility research (e.g., works of 26, Horbachov and Svichynskyi (27), and Batista et al. (28)). Maximum likelihood estimation and the Nelder-Mead method for direct optimization available within the R {fitdistrplus} package (29) is used. As shown as shown in Figure 4, based on goodness-of-fit criteria and associated diagnostics, the gamma and log-normal probability density function (line curves) are selected as best fitting curves for the motorized and non-motorized modes respectively. The selection of functional form aligns with examples used in the literature (e.g., Reggiani et al. (30)). Overall, the plots in Figure 4 display the probability of travel given a trip travel time, based on actual travel behaviour from the 2018 survey. These ‘probability of travel’ at each travel time for each mode are realized observations reflect the land-use, the transport system, and the population travel preferences/behaviour in Madrid.

Results: spatial availability V_i^m and V_i

Using the data inputs outlined, spatial availability of jobs are calculated for each of the four modal categories at the level of traffic analysis zones in Madrid, V_i^m. The spatial distribution of the

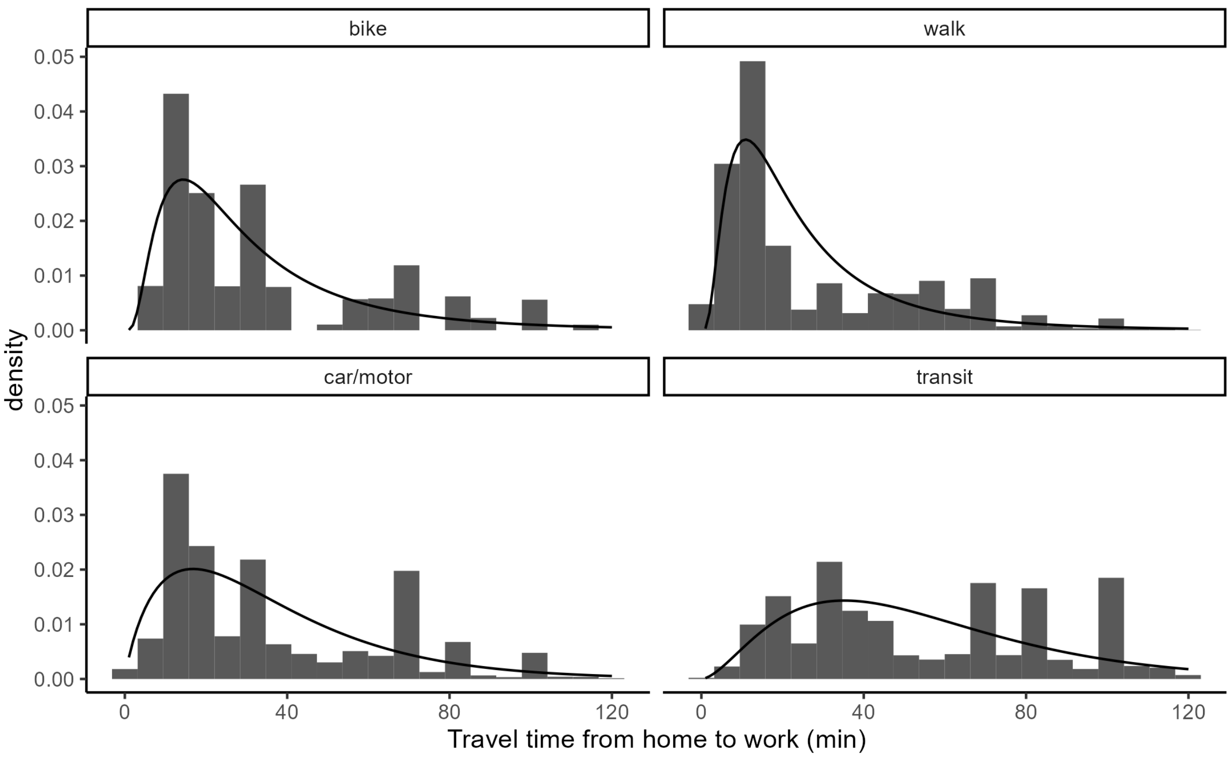


FIGURE 4: Fitted impedance function curve (line) against empirical TLD (bars) per mode.

resulting calculations are demonstrated in this section.

Figure 5 displays the spatial availability values for the four modal categories at the level of the spatial units used in the 2018 travel survey. These values represent a proportion of the total number of the 847,574 jobs in the region that are *spatially available* to the population located at the i based on the travel impedance of the mode (relative to the travel impedance of all modes) and the mode-using population size at the i (relative to the population size of all modes and i). Since population, their job locations, and associated travel times are used to calculate V_i^m, Figure 5 demonstrates values that represent the *realized* spatial availability of jobs in Madrid. In other words, if someone decided to move into a neighbourhood at an i, the amount of jobs that are spatially available to them based on the population within their i and their travel impedance for their used m, both relative to the city, is captured by the value of V_i^m.

In Figure 5, the difference in the magnitudes of V_i^m values between m can be observed. The majority of V_i^m is allocated to the populations using motorized modes. This is to be expected as commuting using motorized modes represents 84% of the population (37% (car/motor) and 47% (transit)). However, these modal options capture 95% of the total spatial availability in Madrid. In particular, the car/motor using population is allocated disproportionately more V_i^m than its modal population (37% of the population vs. 48% of the V_i^m) compare to the transit using population and its relatively proportional V_i^m value (15% of the population vs. 47% V_i^m).

How does the V_i^m advantage allocated to car-using population arise? From the perceptive of finite opportunities, V_i^m is allocated to car-using populations from less competitive modal populations. How competitive one mode is compared to other modes varies spatially, but over-

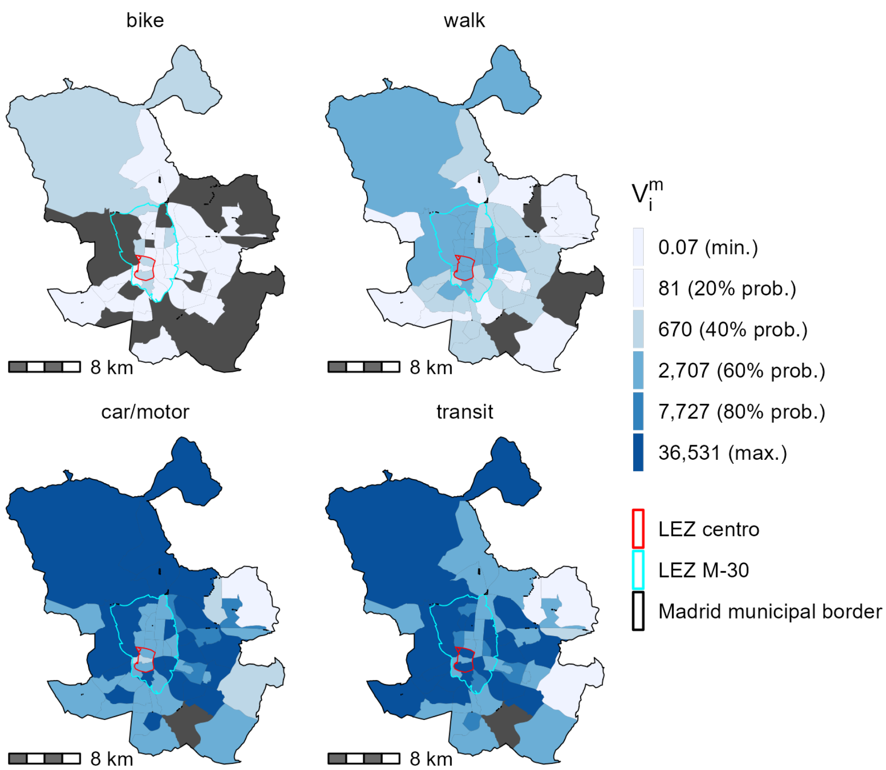


FIGURE 5: Spatial availability of job opportunities per origin and mode V_i^m in Madrid as reported by the home-to-work origin destination flows from the 2018 travel survey. 2017 central LEZ is shown in blue. 2023 expanded LEZ boundaries shown in red.

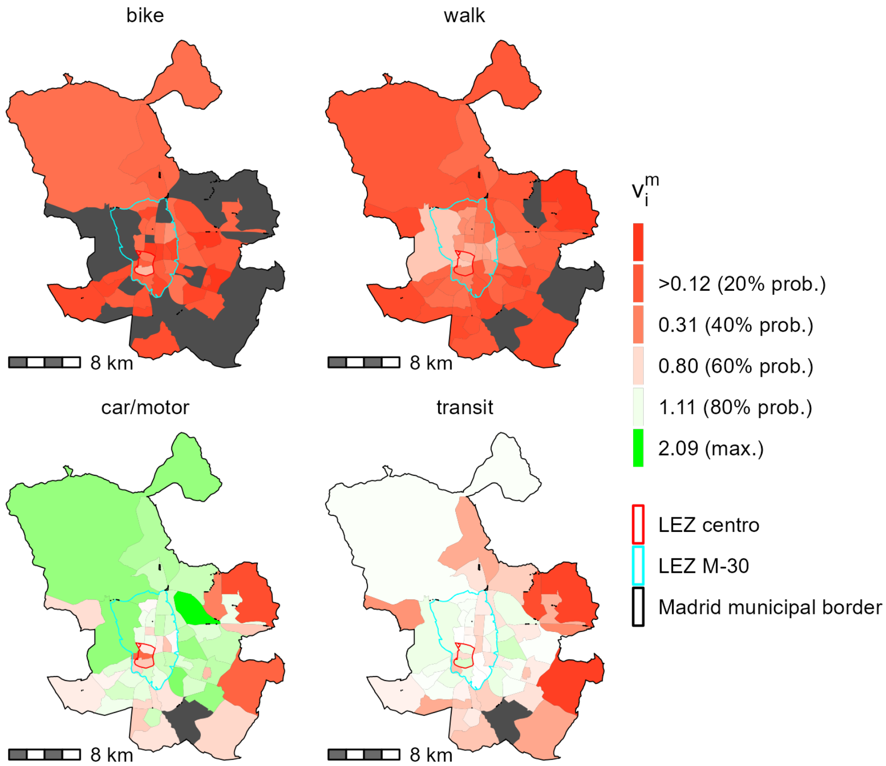


FIGURE 6: Spatial availability of job opportunities per capita per origin and mode v_i^m in Madrid as reported by the home-to-work origin destination flows from the 2018 travel survey. 2017 central LEZ is shown in blue. 2023 expanded LEZ boundaries shown in red.

all car-using populations capture more opportunities per car-using population than other modal populations. Namely, though walking and cycling populations represent 14.74% and 1.16% respectively, $V_i^m = walk$ and $V_i^m = bike$ is 4.43% and 0.23% in the region respectively. These modes are less competitive, especially compared to the car/motor mode, as a result of: 1) their lower travel impedance values at longer travel times (see Figure 4 at travel times beyond ~30 minutes), 2) their low population values values overall, and 3) 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.

Furthermore, there are spatial differences in the competitive advantage of spatial availability between modes. Figure 6 visualizes v_i^m, the spatial availability 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 representation of spatial availability relative to the mode-using population in many of the origins for the car plot (bottom right, denoted with green v_i^m values above 1). These plots also visualize areas that are awarded disproportionately low spatial availability, represented in shades of red. Interestingly, spatial availability for the car mode within the LEZ Centro is below 1 (red). For all other modes, the area with the LEZ is relatively higher than the modal averages or even green in the case transit-using populations. This difference in spatial availability can be seen as a direct result of the LEZ Centro - the observed reduction of opportunities within the

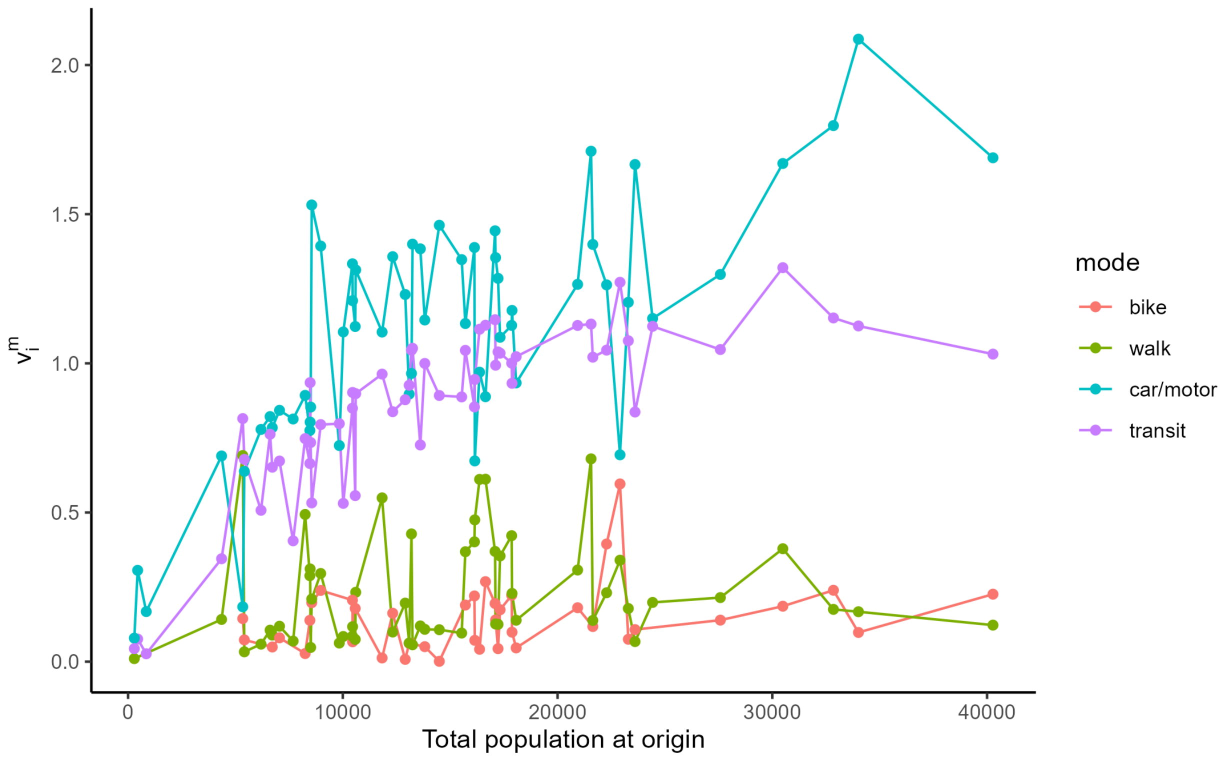


FIGURE 7: Spatial availability of job opportunities per capita per origin and mode v_i^m in Madrid as reported by the home-to-work origin destination flows from the 2018 travel survey represented by sorted total population per origin.

LEZ Centro boundaries being accessed by car-using populations allows lesser competitive modes to interact with these opportunities.

Furthermore, Figure 6 makes it evident that transit-using population's spatial availability to jobs is relatively balanced (i.e., many zones are white). Additionally, values for non-motorized modes are higher in origins that have higher transit accessibility. Transit accessibility and non-motorized modes do not appear to be in direct competition as a result of different travel impedance weighting . It is not visually clear in the plots but as demonstrated in a line plot of v_i^m sorted by total population in Figure 7, it can be observed that transit is only close to or above 1 when car accessibility is relatively low. From Figure 7 we can also observe that overall, motorized modes capture more spatial availability per capita than non-motorized modes.

Discussion and conclusions

Location-based accessibility measures like the Hansen-type measure, Shen-type measure, and spatial availability all have a commonality - they are a weighted sum of opportunities assigned to each spatial unit in a region. In this way, they can be interpreted as a score that represents how many opportunities can be potentially interacted with by the population at each spatial unit. How the weight and sum of the potentially interacted opportunities is what defines the type of accessibility measure. Within this paper, the location-based accessibility measures known as spatial availability, a singly- *constrained* and *competitive* measure, is extended for the case of capturing multimodal accessibility to opportunities. A synthetic example and then an empirical case of LEZ in Madrid are detailed to demonstrate the multimodal extension of the spatial availability measure.

The spatial availability measure is capable of capturing a new interpretation of multimodal competition that previous accessibility measures have not yet done. We can hypothesis that populations using modes with lower travel impedance, when competing for a finite set of opportunities, will capture more opportunities. However, with spatial availability, the number of spatially available 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.

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 highly varies spatially and between modes. The car and transit modes have the highest spatial availability, with the car mode having highest availability with exception to the areas with LEZ Centro. This finding reflects real conditions: since car travel has been highly restricted within the LEZ Centro, much fewer car-using population and much more people are entering using other modes relative to the areas surrounding the LEZ Centro. This difference in car-using population 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.

Currently, conventional *non-constrained* accessibility measures are difficult for planners to operationalize for a variety of reasons. They have also been criticized for being difficult to compute and difficult to interpret as they are a ratio of supply to demand (2). With spatial availability, the magnitude of opportunities that are available as a proportion of all the opportunities in the region is equal to V_i. As a result of its proportional allocation mechanism it can be easily extended into multimodal applications, pertinent to model policy scenerios in our cities that are becoming increasingly multimodal. This flexibility and interpretation of the spatial availability measure 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 newfound interpretation of accessibility measures. With a plot of spatial availability values, one can begin asking, how much is enough and what level is too much. These interpretations were difficult to be made with accessibility measures in the past.

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#AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: AS, JSL, AP.; data collection: AS, JSL, AP.; analysis and interpretation of results: AS, 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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