Cities 177 (2026) 107334

Contents lists available at ScienceDirect

Cities

journal homepage: www.elsevier.com/locate/cities

Rethinking congestion as lost access, and its equity implications

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ARTICLE INFO

Keywords:
Urban congestion
Road congestion, accessibility
Transportation equity
Brazil

ABSTRACT

Urban congestion and social disparity are persistent problems in large cities worldwide. However, congestion is typically assessed from a mobility perspective using traffic performance measures, with limited attention to its impact on urban accessibility inequality. Here, we propose reframing congestion, not merely as problem of slower speeds and longer travel times, but as lost access to opportunities due to excess time in traffic, that mostly affects lower income communities. To illustrate this, we estimate the impact of congestion on employment accessibility in Brazil's 20 largest cities, analyzing how these effects vary spatially and by income level. Using historical GPS-based traffic speed data, we compare the number of jobs reachable by car within a 15–45-minute window during morning peak versus free-flow conditions. Across all cities, low-income communities face the most severe impacts, with an average 24.8% reduction in accessibility, compared to just 5.6% among high-income groups. These findings are used to discuss broader research and policy implications of reframing congestion as lost access that reinforces spatial social disparities. From an equity standpoint, this paradigm shift enables a more comprehensive understanding of how the adverse effects of congestion are distributed across social groups – an insight not captured by traditional traffic metrics. This approach also reveals the spatially and socially uneven impacts of congestion, opening avenues for future research on how it may exacerbate accessibility poverty and inequality.

1. Introduction

Every day, millions of people find themselves trapped in the snarl of traffic congestion, a problem that has become increasingly prevalent in large urban areas across the globe (Sweet, 2014; UN-Habitat, 2022; Zhang et al., 2023). Urban congestion occurs when travel demand exceeds road capacity (Iacono & Levinson, 2010), but it has far-reaching implications other than its immediate effects on slower speeds and longer travel times (Downs, 2005). High levels of congestion shrink market reach and worker mobility, thereby diminishing potential economies of agglomeration and hindering job creation and city productivity (Broersma & van Dijk, 2007; Weisbrod et al., 2003). Congestion also exacerbates greenhouse gas emissions and environmental pollution levels (Green et al., 2020; Lu et al., 2021; Öztürk et al., 2025), which depreciates property values near congested streets (Tang, 2021). Moreover, congestion has severe public health impacts (Requia et al., 2018), including increased traffic accidents (Retallack & Ostendorf, 2019), cardiorespiratory diseases (Hoek et al., 2013), and mental health problems (Liu et al., 2022).

Transport congestion has a complex relationship with accessibility. Areas with high densities of people, jobs, and services tend to have higher accessibility because of colocation and proximity effects. As a result, these same areas also attract more people and trips, which can overload transport systems, increase traffic congestion, and slow down motorized travel. In this sense, congestion is not inherently negative, since it often reflects the agglomeration economies of dense and economically active cities. However, when congestion becomes excessive, it can signal agglomeration diseconomies, reducing the accessibility advantages that density and proximity would otherwise provide. This relationship is also dynamic: the spatial distribution of activities and individuals' mode choices both shape congestion and are themselves shaped by it.

Previous research typically looks at urban congestion as a mobility problem, using traffic performance metrics to measure congestion in terms of reductions in traffic throughput and vehicle speed that lead to longer travel times (Boarnet et al., 1998; Duranton & Turner, 2011; Rao & Rao, 2012). However, much less attention has been paid to the impact of congestion on urban accessibility: the ease with which people can

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https://doi.org/10.1016/j.cities.2026.107334
Received 29 May 2025; Received in revised form 30 April 2026; Accepted 29 June 2026

access opportunities such as economic activities and public services. This is particularly true for the unequal impact of congestion on different income groups' access to opportunities. This is a significant gap in the literature, especially considering the growing consensus that enhancing access to opportunities is a key benefit of well-functioning transportation and land use systems (Levine et al., 2019; Levinson & King, 2019).

Here we propose reframing congestion, not merely as a problem of slower speeds and longer travel times, but as missed access to opportunities due to excess time lost in traffic that mostly affects lower income neighborhoods. Put it simply, the idea is to measure congestion levels in terms of its impact on access to opportunities by comparing how accessibility levels differ between peak periods versus under free-flow conditions. We argue that this reframing of congestion provides novel insights into research and policy, particularly into our understanding of how the adverse effects of congestion are distributed spatially and across different socioeconomic groups. To illustrate these insights, we build on a large-scale comparative analysis where we examine the effects of congestion on employment accessibility in Brazil's 20 largest cities. Urban congestion has been a growing problem in the country, as the average daily commute time in metropolitan areas has seen a significant increase, from 72 min in 2001 to 82 min in 2015, according to the most recent estimate (Pereira et al., 2021). Moreover, Brazil is one of the largest and most urbanized middle-income countries in the Global South with extremely high levels of social inequality, making it a particularly interesting context for this study. Using spatially detailed land use data as well as historical GPS-based traffic speed data at the road segment level, we compare the number of jobs that can be reached by car during the morning peak hours with those accessible under free-flow conditions, and examine how accessibility loss varies spatially and across income levels.

This paper aligns with a growing body of literature advocating a shift in urban transportation policy from a focus on mobility to one centered on accessibility (Banister, 2011; Levine et al., 2019; Levinson & King, 2019), as well as with studies that analyzed the effect of congestion on accessibility outcomes (Mondschein & Taylor, 2017; Moya-Gómez & García-Palomares, 2017; Moyano et al., 2021). This study helps advance previous research on urban congestion and accessibility in different ways. First, a conceptual reframing of congestion through an accessibility lens provides a more comprehensive assessment of congestion from an integrated perspective of transportation and land use systems. Second, it demonstrates how viewing congestion as lost access helps identify which neighborhoods and socioeconomic groups are potentially more affected by congestion, going beyond merely identifying heavily congested streets. This is particularly relevant to address transportation justice concerns and to understand the role that congestion might play in shaping transportation equity. Furthermore, the paper also shows how congestion rankings of cities can change depending on whether congestion is assessed through an accessibility lens or the conventional mobility-based approach of measuring road congestion with traffic performance measures. Finally, this is the first study to provide comprehensive evidence on the impact of road congestion on employment accessibility, and its inequality, across multiple cities in a Global South context.

The remainder of this article is organized as follows: Section 2 presents the literature review on congestion emphasizing its impact on urban accessibility. Section 3 outlines the methods and data employed. Section 4 presents the results. Sections 5 and 6 present the discussions and conclusions, respectively.

2. Traffic congestion and accessibility

Different methods have been used to quantify the intensity of urban congestion and analyze its impacts. Traditional mobility-based methods measure congestion intensity at the street segment level with some form of speed reduction index that assesses how the travel time or average speed to traverse a road segment varies between peak and off-peak hours (Adler et al., 2021; Akbar et al., 2023; Saberi et al., 2020). Other traditional methods focus on traffic throughput, and involve comparing the actual volume of vehicles traversing a road segment in a given period to the theoretical volume that could have passed through, based on the segment's capacity and posted speed limit (Çolak et al., 2016). At their core, these mobility-based approaches focus on congestion as a problem of traffic flow efficiency. While these methods can identify the streets more directly affected by congestion, they fall short in indicating which populations or neighborhoods may be most affected in their daily trips.

As the accessibility literature gained traction in the last decades (Geurs & van Wee, 2004; Levinson & King, 2019), a few studies started investigating the effect of road congestion on accessibility. In Europe, Moya-Gómez and García-Palomares (2017) investigated accessibility by car in eight metropolitan regions, finding that London, Paris, and Rome were the cities where congestion most significantly affected access to opportunities. In another study, Moyano et al. (2021) analyzed the impact of the economic recovery following the 2008 economic crisis on congestion in Madrid, Spain. The authors found that the recovery resulted in an uneven spatial increase in congestion levels, disproportionately reducing accessibility for the poorest groups.

In North America, Owen and Murphy (2021) ranked the 50 most populous metropolitan areas in the U.S. based on the impact of traffic congestion on job accessibility by car. Their results suggest the existence of a "ring of congestion" in which individuals departing from locations near the central business district experience smaller accessibility losses than those departing from areas outside the central business district. This study echoes the findings of Mondschein and Taylor (2017), who calculated the accessibility of neighborhoods in Los Angeles and observed that central neighborhoods are more resilient to congestion because a significant portion of the population makes short trips and/or opts for walking. In Canada, Higgins et al. (2019) investigated the impact of congestion on job accessibility and its effects on real estate around two highways in Hamilton, Canada. The authors found that the potential for real estate appreciation in highly accessible areas tends to be eroded in areas with greater pollution and congestion.

In summary, most of the literature on the effects of congestion on access to opportunity has focused primarily on cities in Europe and North America, where urban transportation and land use patterns are often substantially different from cities in the Global South. Moreover, few authors, with the exception of Moyano et al. (2021), have explored the uneven effect of congestion on the accessibility of different socioeconomic groups. Despite their contributions, these studies do not fully articulate the research and policy implications of shifting the focus on congestion from mobility to accessibility inequality.

3. Methods

To measure the impact of urban congestion on job accessibility, we used historical road speed data from the StreetMap Premium (ESRI, 2023) database. This data is similar to the TomTom Speed Profiles data set, used in previous studies by Moya-Gómez and García-Palomares (2017), Moyano et al. (2021), and Owen and Murphy (2021). Travel time matrices for free-flow conditions were calculated with departures at 4:00 a.m., similar to Owen and Murphy (2021). However, unlike previous studies, which typically calculate travel times during the morning peak hour using a single departure time, we calculated median travel times considering multiple departures every 15 min from 6:00 a.m. to 8:00 a.m. This was done to reduce potential biases resulting from the arbitrary choice of a single departure time (Pereira, 2019; Stępniak et al., 2019), generating representative travel time matrices for the entire morning peak period.

The method used in this study involved four steps. The first step was to aggregate spatial data on population and employment onto a spatial grid of hexagons. This gave each hexagon cell the total resident population, the average per capita income of its population, and the number of jobs. The second step was to calculate travel time matrices by car between all possible origin-destination pairs in the city, considering the centroids of the hexagons. This calculation was performed separately for the morning peak period and during free-flow. The third step was to calculate the average number of jobs accessible from each hexagon within a travel time interval. Finally, in the fourth step, we analyzed how this level of accessibility during the morning peak period compares to the accessibility one would have in a free-flow scenario, and how these differences in accessibility vary spatially between different regions within each city and between income groups. The data and code used in this paper are publicly available at https://github.com/ipea/congestion_as_lost_access.

3.1. Data

The spatial distribution of the population was extracted from the statistical grid (IBGE, 2016), with a resolution of 200 × 200 m in urban areas and 1 × 1 km in rural areas. The household per capita income was obtained from the 2010 Demographic Census (IBGE, 2016) by census tract and then interpolated for each cell of the statistical grid using a dasymetric spatial interpolation operation. Employment totals and locations were obtained from the 2019 Annual Report of Social Information (RAIS) from the Ministry of Labor. Addresses of formal jobs were geocoded using the proprietary ArcGIS Pro software and the Google Maps API (Google, 2023). Both population and employment data were spatially aggregated using a hexagonal grid as the unit of analysis. The grid was created using the H3 hierarchical index (Brodsky, 2020) at resolution 9, resulting in hexagons with an area of 0.11 km^2. Hexagons in each city were categorized according to the income quintile based on the per capita income distribution of each city. A more detailed description of the geolocation and spatial data aggregation process can be found at Pereira, Braga, et al. (2022). The population and spatial employment distribution data used in this article can be downloaded via the R package aopdata (Pereira, Herszenhut, et al., 2022).

To estimate job accessibility by car, we used historical traffic speed information on streetways obtained from the proprietary StreetMap Premium database (ESRI, 2023). This database provides information on the average vehicle speeds captured by GPS on each street segment every minute of the day over a 2-year period. The reference period for the data was from the first quarter of 2018 to the first quarter of 2020. The data is aggregated for each day of the week, allowing us to capture speed variations and optimal routes between different weekdays and departure times throughout the day.

3.2. Travel time matrices

The second step of the method is to estimate the population's access to jobs by calculating travel time matrices between the centroids of the grid cells for each city. Using the Network Analyst extension from ArcGIS Pro, two car travel time matrices were generated for the 20 cities analyzed. First, the free flow matrix was calculated for trips departing at 4:00 a.m. on a typical Sunday. Second, the morning peak matrix was calculated for trips departing on a typical Wednesday between 6:00 a.m. and 8:00 a.m. The exact choice of departure time can arbitrarily influence the results (Pereira, 2019). To minimize this problem, we calculated eight travel time matrices with departures every 15 min from 6:00 a.m. to 8:00 a.m., and then calculated the median travel times between each origin-destination pair.

3.3. Accessibility calculations

One of the most widely used accessibility indicators in the literature is the cumulative accessibility measure (Boisjoly et al., 2020; Levinson & King, 2019). This metric captures the number of opportunities that can be reached within a certain travel time threshold and has several advantages because it is easy to communicate and calculate (Geurs & van Wee, 2004). However, one of the main disadvantages of this indicator is that its results are heavily influenced by the maximum travel time considered in the analysis (Pereira, 2019). This is known as the "boundary effect" of the modifiable temporal unit problem (MTUP), where the results of an analysis can be skewed by an ad-hoc methodological choice regarding the duration limit of the phenomenon being analyzed (Pereira, 2019).

To address this issue, we used the new time-interval cumulative accessibility measure (TICAM) (Tomasiello et al., 2023). This measure indicates the average number of opportunities accessible within a travel time interval, considering multiple minute-by-minute cutoffs within that interval. The TICAM (Eq. 1) preserves the ease of calculation and interpretation of the traditional cumulative metric but is less sensitive to arbitrary choices of travel time limits and better represents the variation in travel times in accessibility.

Here, we calculated accessibility by car using travel-time thresholds ranging from 15 to 45 min. This interval was chosen because it aligns well with observed average commuting times by car in the selected cities, which range from 23 and 45 min (see Table 1). The use of multiple thresholds also helps reduce sensitivity to any single cutoff point, particularly across cities of different sizes and spatial structures. This interval can also be justified from a normative perspective (Páez et al., 2012), as it captures travel time limits may be considered broadly acceptable while reflecting the need to bring people closer to opportunities and reduce opportunity deserts.

$$
\begin{aligned}
TICAM_{oI} &= mean(\{CMA_{oT} \forall T \in I\}) \\
CMA_{oT} &= \sum_{d=1}^{n} P_d f(t_{od}) \\
I &= [\mathrm{T}_{\min}, \mathrm{T}_{\max}]
\end{aligned}
\tag{1}
$$

where:

$TICAM_{oI}$ is the average cumulative accessibility of the origin o within the travel time interval I;

CAM_{oT} is the cumulative accessibility of the origin o within the travel time threshold T;

P_d is the number of job opportunities in the destination d;

t_{od} is the travel time in minutes between origin o and destination d;

I is a minute-by-minute distribution of travel time thresholds within a given time interval between $T_{\min}$ and $T_{\max}$.

It is important to note that, in the case of small cities, it may be necessary to select a different time interval with lower thresholds. Otherwise, all opportunities may be reachable during peak hours within the lower bound. In such cases, the resulting measure would not be sensitive to the effects of congestion on accessibility.

3.4. Accessibility loss due to congestion

The impact of congestion on accessibility was calculated for each hexagon of the grid cell. It is calculated as one minus the ratio of the average number of accessible jobs during the morning peak and the average number of jobs that would be accessible under free flow (Eq. (2)). Thus, a cell is compared to itself while keeping as constant the distribution of residents and opportunities and the transportation infrastructure capacity. Thus, accessibility loss due to congestion is estimated for each cell, which allows one to examine in fine spatial detail how congestion impacts different areas and the sociodemographic groups in those areas.

$$
ALC = 1 - \frac{Acc\ Peak}{Acc\ free\text{-}flow} \tag{2}
$$

where:

ALC is the accessibility loss due to congestion;

Acc Peak is the average job accessibility during the peak;

Acc free-flow is the average job accessibility during the free-flow.

Travel times calculated for departures on Sunday at 4 a.m. are not

Table 1
Statistics on population, motorization rates, and employment accessibility in Brazil's 20 largest cities.

Municipality	Population (2022)	Population density	Cars per 100 individuals (Dez./2022)	Average commute time by car (2022)	Accessible jobs during the peak (A)	Accessible jobs during free-flow (B)	Congestion impact
	1000×	(pop/km^2)					1 - (A / B)
São Paulo	11,451	13.554	53	39.2	974,426	1,644,025	46.40%
Rio de Janeiro	6221	10,581	34	42.8	576,951	889,196	36%
Brasília	2817	5243	49		247,555	328,202	27.80%
Maceió	957	8964	22	29.9	127,294	157,928	19.70%
Salvador	2418	14,778	26	32.9	378,196	463,802	18.80%
Guarulhos	1291	8975	38	39.7	224,310	270,783	17.30%
Belo Horizonte	2315	9235	75	31.2	569,431	674,334	16.20%
Manaus	2063	8141	20	33.3	278,728	325,271	14.60%
Fortaleza	2428	10,656	26	30.3	439,138	511,143	14.30%
Belém	2817	5243	49	29.4	162,787	185,037	12.40%
Recife	1488	11,616	27	31.3	363,593	409,520	11.30%
Goiânia	1437	5156	45	26.1	310,258	344,309	10.40%
Campinas	1138	4990	55	28	270,728	300,073	10.20%
Porto Alegre	1332	6945	45	28.3	355,157	390,913	9.50%
Natal	751	9028	32	24.9	164,196	180,365	9.10%
Curitiba	1773	5836	64	26.7	521,237	569,127	8.60%
Duque de Caxias	808	6702	25	42.4	100,904	110,220	8.50%
São Luís	1037	6724	21	27.9	155,569	167,527	7.40%
São Gonçalo	896	8460	26	45.1	80,872	83,536	3.20%
Campo Grande	897	3626	36	23.3	177,840	181,733	2.20%

Employment accessibility calculated as the average number of jobs accessible by car within a 15–45 min travel time interval.
Source: IBGE (2022) and SENATRAN (2022).

intended to represent a realistic accessibility condition, but rather to serve as a hypothetical proxy for a near–free-flow network scenario, as commonly used in congestion studies. This counterfactual is used to estimate the upper bound of accessibility in the absence of congestion and, by comparison with a typical Wednesday morning peak, to isolate the accessibility loss attributable solely to congestion. Therefore, all job opportunities are held constant and included in the accessibility calculations, regardless of opening hours.

4. Results

As an initial exploration, we compare how using different methods to measure congestion lead to different rankings of city-level congestion. In Fig. 1 we rank Brazil's 20 largest cities by their average congestion calculated in terms of accessibility loss, and two mobility-based metrics, average commute time by car extracted from the 2022 census, and the speed reduction index published by TomTom. The figure shows that the rankings based on accessibility and commute time present similar results. In both rankings, the municipalities of São Paulo and Rio de Janeiro have the highest congestion levels, while Recife, Porto Alegre,

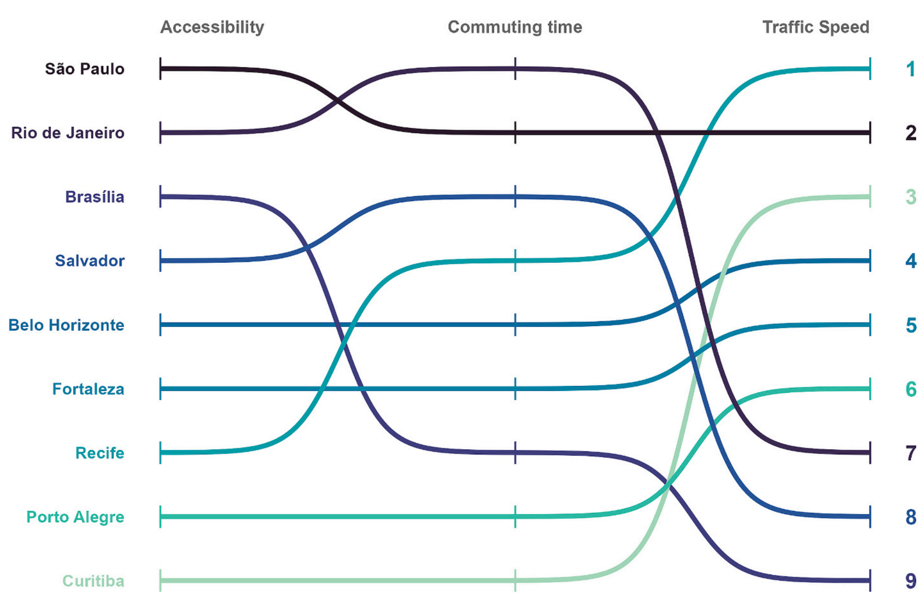

Fig. 1. Ranking of the most congested cities in Brazil according to different approaches to measure congestion.
Source: Accessibility calculated based on travel times computed with ArcGIS StreetMap Premium (ESRI, 2023) for the period 2018–2020. Estimates of commuting time by car are based on the 2022 Demographic Census (IBGE, 2025). Traffic speed reduction comes from TomTom data for the year 2022 (TomTom, 2022). Note: Only the nine Brazilian cities covered by the annual TomTom congestion ranking were included in the figure.

and Curitiba are among the least congested. There are also only small variations in the rankings for cities like Brasília, Salvador, Belo Horizonte, Porto Alegre, and Curitiba. By contrast, the ranking based on traffic speed produces a dramatically different result. For example, Recife, which appeared as one of the three least congested cities in the previous rankings, now stands out as the most congested city in the country, and Brasília, which appeared as the third most congested city, now appears as the least congested city.

These differences between rankings can be partly explained by three reasons. First, TomTom's speed reduction index considers the average time it would take to travel 10 km, which does not necessarily correspond to the average distance people travel in each city. As a consequence, it may underestimate the level of congestion in cities where people travel on average further than 10 km, as may be the case in cities such as São Paulo, Brasília or Rio de Janeiro. Second, TomTom's methodology considers the average speed reduction across road segments, but it overlooks how many people actually experience those speed reductions. Meanwhile, while the commuting time approach to measure congestion accounts for an important chunk of the daily travel time each individual reports spending in traffic, it ignores differences in the distances traveled and, consequently, how travel speed is affected by congestion.

By measuring congestion levels from an accessibility perspective, on the other hand, we compare the number of jobs that a person could potentially reach from a given location under free-flow versus peak traffic conditions. This approach differs from others in that it captures the impact of congestion from an integrated transportation and land use perspective, considering how the opportunities people can access are affected both by the reduction in speed due to traffic saturation and by the spatial co-location of population and activities. It should be noted, however, that this approach does not necessarily account for travel behavior. This is because the calculation of accessibility is based on a potential travel cost matrix between all possible origin-destination pairs and not on the actual origin-destination pairs of the trips that people make in their daily lives. Nevertheless, people's level of accessibility tends to be correlated with the time they spend on their home-to-work commutes (Cui et al., 2019; Levinson, 1998), which helps explain why the rankings of the most congested cities are similar when considering methodologies that focus on accessibility and commuting times.

Focusing only on the analysis of the impact of congestion on job accessibility, the results show substantial heterogeneity across Brazil's 20 largest cities (Table 1 and Fig. 2). These results reveal that, in the least congested cities (such as Campo Grande and São Gonçalo), average employment accessibility drops by less than 5% during the peak time compared to free-flow traffic conditions. By contrast, in the most congested cities (like Rio and São Paulo), people can access on average 36% to 46% fewer jobs during peak time than under free-flow conditions. It is important to note that larger cities, with higher concentrations of jobs and population, experience the greatest congestion impacts. This pattern reflects the close relationship between the spatial concentration of opportunities, travel demand, and mobility conditions. Larger employment centers attract a higher volume of trips, which intensifies pressure on the transport system and leads to greater congestion impacts, even when infrastructure supply is relatively higher.

Fig. 2. Congestion level in terms of the average loss of employment accessibility by income quintiles of the population. Percentage reduction in the number of jobs accessible by car within a 15–45 min travel interval during peak hours compared to free-flow conditions in Brazil's 20 largest cities.

The results from Table 1 and Fig. 2 show the congestion level of each city in terms of the average loss in employment access across the entire population. However, there is great heterogeneity in the congestion levels experienced across different socioeconomic levels. Across all cities, low-income communities face the most severe impacts from congestion, experiencing an average 24.8% reduction in job accessibility, compared to just 5.6% among high-income groups —highlighting the inequitable burden of traffic delays. In cities with marked inequalities, such as São Paulo and Belo Horizonte, congestion reduces the employment accessibility of the poorest populations three to eleven times more than that of the wealthiest. In São Paulo during the peak period, the wealthiest income group loses access to approximately 20.4% of the jobs reachable under free-flow conditions, while the lowest income group loses more than 56.4%.

The uneven impact of congestion on low- and high-income populations largely results from the combination of two factors: the spatial patterns of co-location between jobs and income classes, and the spatial patterns of traffic saturation. To illustrate this, Fig. 3 shows the distribution of the population by income quintile and jobs. For the sake of brevity, the figure includes only three cities — Curitiba, Fortaleza, and São Paulo – selected for presenting low, medium, and high levels of congestion, respectively. As in most cities in the Global South, urban land in Brazilian cities tends to be more expensive the closer it is to the city center, where jobs are concentrated. As a result, high-income populations tend to live closer to these central areas. Although these areas concentrate most of the road network with higher levels of traffic saturation, this proximity to employment centers means that the high-income groups living in these areas need to spend less time travelling to access jobs, making them less affected by congestion. By contrast, lower-income populations tend to live in peripheral areas where land is more affordable. Consequently, they become more vulnerable to congestion because they need to travel longer distances and to traverse the more congested roads that connect to central areas where jobs are concentrated.

The impact of congestion on job accessibility varies substantially within cities. Fig. 4 presents the job accessibility under free-flow and peak scenarios, and accessibility loss due to congestion for the cities of Curitiba, Fortaleza, and São Paulo. The central areas of the municipalities have the highest concentration of jobs and therefore the highest accessibility, both at free-flow and peak hours. Thus, although these areas typically have the most congested streetways, they are the regions where job accessibility is less affected by congestion. This is largely due to their proximity to job centers, which allows the population living in these areas to quickly access a significant number of jobs within relatively short travel times.

By contrast, congestion tends to have a greater impact on job accessibility for those living in the peripheral areas of cities, where a more significant drop in accessibility is observed during peak hours. The maps in Fig. 4 show that the regions where job accessibility is most impacted are the areas farthest from the city centers, such as the southern zones of Curitiba and the western zones of Fortaleza.

The impact of congestion is relatively small in the far south and far east of São Paulo. This is because these regions are very far from job centers, and therefore, it is not possible to reach these centers within the travel time interval used (15–45 min), even in a free-flow traffic scenario. In addition, the income panel in Fig. 3 shows that the poorest families (first income quintile) live in these regions. Given the very low level of accessibility shown in Fig. 4, the situation for this income group can be described as an opportunity desert. The distances between these neighborhoods and job centers are so high that the land use component could make the most significant difference in improving accessibility. Even a substantial improvement in the efficiency of the transport system through the increase in travel speeds wouldn't be able to significantly improve their accessibility due to these long distances, underscoring the importance of increasing the proximity between jobs and residential areas.

5. Discussion

The results of this study are consistent with similar studies conducted in other countries. Similarly to the research by Mondschein and Taylor (2017) for Los Angeles in the United States, we also find the urban central areas in Brazil are the locations where employment accessibility are the least affected by congestion, despite also being the areas with higher road traffic bottlenecks. These results point to an apparent paradox: on the one hand, the greater concentration of density and proximity of people and economic activities in central urban areas contributes to the creation of agglomeration diseconomies, such as traffic congestion, due to the excessive demand for cars by people wanting to access the opportunities concentrated in these regions. On the other hand, it is precisely this density and proximity that allows residents of central areas to be less affected by traffic congestion, as their access to opportunities requires short distances that are easier to travel by car, public transit and active modes.

We also find that congestion tends to lead to greater loss of access to opportunities for low-income populations in Brazilian cities, as similarly observed by Moyano et al. (2021) for Madrid, Spain. These findings complement an extensive literature on spatial mismatch by showing that low-income populations not only often reside farther from job opportunities (Gobillon et al., 2007), they are also more vulnerable to the agglomeration diseconomies caused by congestion. Moreover, these results also contribute to the transportation equity literature. They show how congestion can be a significant accessibility barrier for low-income individuals, and that it plays a key role in deepening the inequality in access to opportunities between the rich and the poor. Based on this accumulated evidence, we suggest that the uneven impact of urban congestion may constitute an additional mechanism that helps explain the lower prospects of upward social mobility among certain socioeconomic groups and neighborhoods in cities (Buchholz & Storper, 2025; Connor & Storper, 2020).

It is important to highlight, though, some methodological considerations. Our analysis measures accessibility to formal employment, which represents an important limitation. This approach may not fully capture the employment opportunities that lower-income populations actually pursue, many of whom work informally in their own neighborhoods. However, our focus on formal employment by car captures not what poor populations currently do, but what they aspire to access and what spatial barriers prevent them from accessing. Moreover, car and public transit accessibility are spatially correlated in Brazilian cities, and congestion also affects bus-based public transport and ride-hailing services. Additionally, our municipal-level analysis represents lower-bound estimates of congestion impacts, as it excludes substantial cross-municipal flows. For instance, in the São Paulo and Rio de Janeiro metropolitan regions, cities like Guarulhos and Duque de Caxias are substantial municipalities in their own right, yet maintain strong functional integration with their core cities through daily commuting metropolitan flows. Treating them as separate analytical units misses metropolitan congestion impacts. Future research should examine accessibility at the metropolitan scale and incorporate informal employment locations. Finally, it is important to acknowledge that hypothetical increases in travel speeds may induce changes in travel behavior and, over longer time horizons, lead to the reallocation of jobs and housing. However, modeling such behavioral and land-use responses is beyond the scope of this study, which aims to assess how congestion, given a fixed spatial distribution of opportunities, constrains access to jobs.

The results obtained for Brazil's 20 largest cities underscore the importance of a number of public policy recommendations to reduce congestion, which have already been supported by the literature in this area. However, these must be carefully designed to avoid exacerbating existing inequalities. A promising policy would be the implementation of urban tolling policies in major Brazilian cities. Urban tolls have been implemented in major metropolitan areas around the world, such as

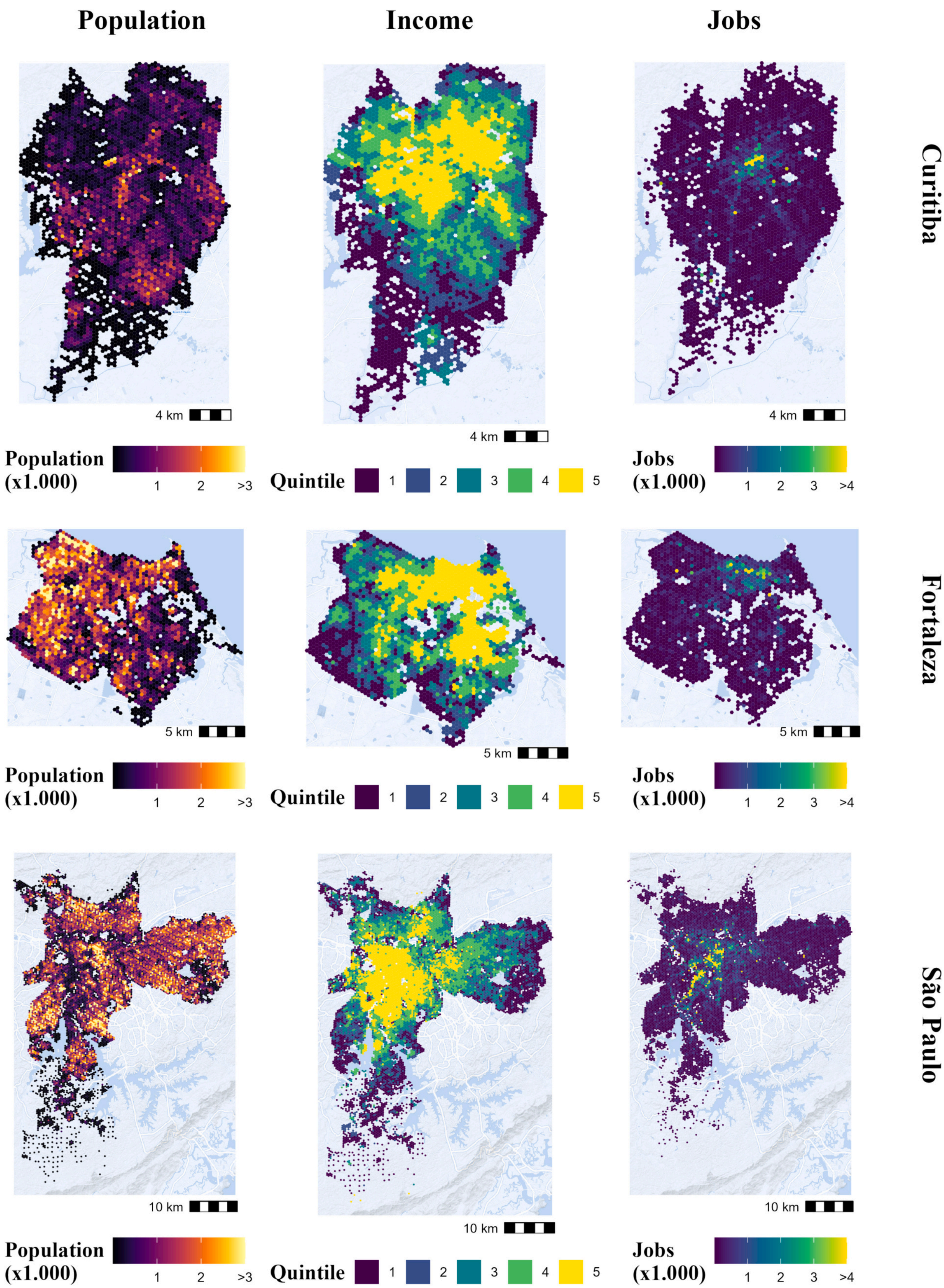

Fig. 3. Distribution of total population, income quintiles, and jobs in Curitiba, Fortaleza, and São Paulo.
Source: population and income data come from the 2010 census, while job data come from the 2019 RAIS.

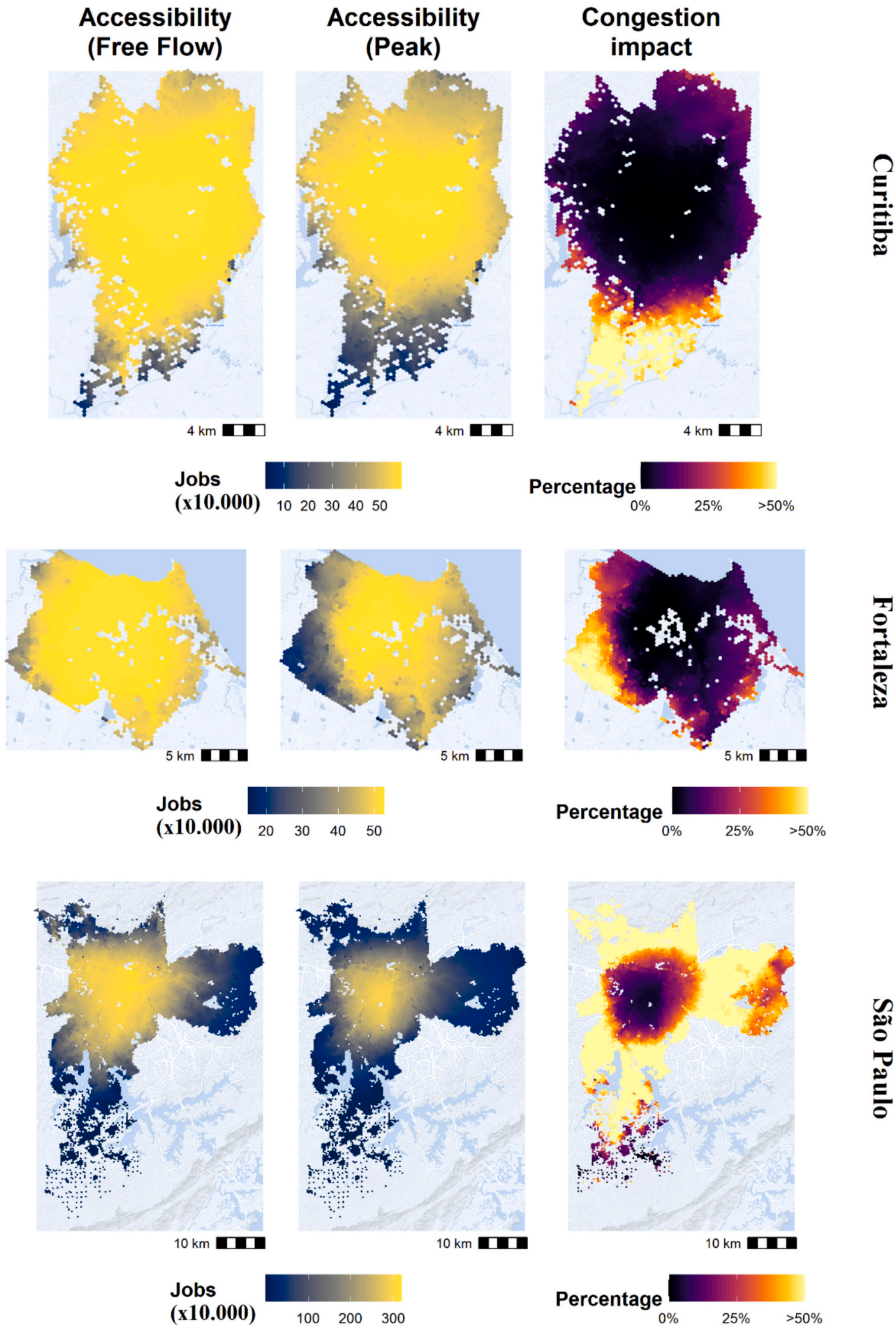

Fig. 4. Spatial distribution of employment accessibility by car within a 15 to 45-minute travel interval under free-flow and peak periods, employment accessibility loss due to congestion in Curitiba, Fortaleza, and São Paulo.

London (Tang, 2021), Stockholm and Gothenburg (Börjesson & Kristoffersson, 2018), Singapore (Santos, 2005) and more recently in New York (Cook et al., 2025). Across all of these previous experiences, congestion charging schemes have proven to be an effective measure to reduce congestion. In the Brazilian context, implementing tariff policies applied equally to all vehicles would also affect suburban and peripheral populations who already deal with lack of access and low-quality services, deepening accessibility inequalities rather than ameliorating them.

Another recommendation is to increase the supply and coverage of public mass transit systems, which can have a direct impact on reducing urban congestion (Adler et al., 2021). Policies that promote active transportation, such as implementing and improving bicycle and pedestrian infrastructure, can reduce congestion, CO_2 emissions, and provide public health benefits as well (Woodcock et al., 2018).

Finally, Brazil's three largest metropolises exhibited particularly low accessibility levels among peripheral low-income communities, a situation that could be at least partially mitigated by implementing social housing policies closer to city centers, or promoting a denser mixed-use development in peripheral areas. This could bring formal employment opportunities closer to low-income populations, addressing root causes of accessibility inequality. Transportation interventions must be pursued alongside land-use transformation, which is the most equitable long-term approach. However, such interventions face formidable structural barriers in the Brazilian context. Despite progressive constitutional provisions, urban planning tools pursuing spatial social fairness are implemented with significant resistance from real estate markets, land speculators, and conservative politicians, resulting in little de facto change in land use patterns.

6. Conclusions

In this work, we proposed a reframing of urban congestion, conceptualizing it not merely as a problem of reduced speeds and increased travel times, but more fundamentally as a constraint on access to opportunities resulting from excessive time lost in traffic. We evaluate congestion by its impact on accessibility, comparing the levels of access to opportunities during the morning peak period against those observed under free-flow traffic conditions. This makes explicit the inequality of that impact across different income groups.

To illustrate this approach, we measured urban congestion through its effects on job accessibility across Brazil's 20 largest cities. The analysis further examined the impacts of congestion on population groups stratified by income level. The results showed that the municipalities where traffic congestion has the greatest impact on job accessibility are São Paulo, Rio de Janeiro, and Brasília, respectively. The study found that congestion disproportionately affects low-income communities, highlighting the inequitable burden of traffic delays. On average across cities, congestion reduces the number of accessible jobs by 24.85% for the low-income population, compared to a 5.6% reduction for the wealthiest population.

Analyzing congestion through an accessibility lens enables a better understanding of congestion impacts from an integrated transport and land use perspective. This is because the accessibility measure takes into account not only the connectivity and performance of transportation systems, but also the spatial patterns of co-location of people and activities. However, since the co-location of people and activities and the capacity of the road infrastructure remain constant in the peak and off-peak periods, the difference in accessibility between these two periods allows us to isolate the effect of congestion on accessibility due to excessive demand for motorized travel.

This study has also shown that, from an equity standpoint, reframing congestion through an accessibility perspective provides new insights into which neighborhoods and socioeconomic groups are most affected by congestion. This is not possible with traditional mobility-based methods that analyze congestion using traffic metrics such as speed reduction index. The study also showed how this approach to accessibility produces results that are quite different from those obtained using traditional methods. While traditional methods that focus on vehicle mobility indicate that congested roads are generally concentrated in the city center, the focus on accessibility reveals that those most affected by congestion are not those who live in the center, as they already have a high level of accessibility for relatively short trips. On the contrary, the emphasis on accessibility shows that the most affected people are those living farther away, who cannot access opportunities in the city center due to the traffic saturation that makes the center impermeable for those outside.

The work has some limitations. First, as discussed earlier, our analysis focuses on formal employment accessed by car, which may not capture informal work patterns or public transit experiences of lower-income populations. Second, accessibility estimates from travel time matrices consider potential trips between all origin-destination pairs and do not consider the number of people who actually travel between specific hexagons, which can introduce bias into the results. In addition, the traffic data is a model derived from two years of traffic data coverage (2018–2020), and there may be variations in quality across municipalities, which may also affect the accuracy of the results. Finally, the difference in the impact of congestion on the rich and the poor that we find is likely to be underestimated. There are two reasons for this. First, low-income populations have significantly higher rates of public transportation use, which generally offers lower speeds and reduced accessibility. Second, the low-income population tends to make longer trips than the high-income population, exposing them more to traffic delays due to congestion.

A possible extension of this work would be to investigate how these variations in congestion levels between cities and within each city might be associated with different patterns of public transit provision and urban form variables such as land use, density, compactness, and contiguity, measuring the co-location of jobs and residents. Exploring these relationships could help identify their mechanisms and deepen the understanding of urban factors that influence congestion formation. In addition, the work could be refined to include accessibility by public transport based on historical GPS data to capture the impact of congestion on public transit users. Other studies could also dive deeper in exploring from a spatial-temporal perspective how the variation in traffic conditions throughout the day lead to daily expansion and contraction of spatial accessibility for different socioeconomic groups and transportation modes.

From a public policy perspective, the reframing of congestion from an accessibility perspective could assist in delineating high-traffic areas for the implementation of urban tolling. This approach could also be used to help identify which neighborhoods - particularly peripheral areas - would benefit the most by policies that support urban development, attracting jobs opportunities and increasing land use mix, which would lead to greater local accessibility. Similarly, the approach of measuring congestion in terms of accessibility loss could be used to assess the impact of urban toll policies and other transportation and land-use policies on access to opportunities. In addition, it could provide relevant insights about the effectiveness of congestion charge policies and their role in promoting more equitable cities.

CRediT authorship contribution statement

Diego Bogado Tomasiello: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis. **Vanessa Gapriotti Nadalin:** Writing – review & editing, Investigation. **Rafael H.M. Pereira:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Project administration, Methodology, Investigation, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no competing interests.

Acknowledgments

This work was supported by the Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq) [grant number: 307585/2025-5].

Data availability

The data and code used in this paper are publicly available at https://github.com/ipea/congestion_as_lost_access.

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