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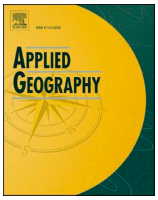

A time interval metric for cumulative opportunity accessibility

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ABSTRACT

Cumulative accessibility measures are the most-used accessibility metric and indicate the number of opportunities reached within a given travel time threshold. However, these measures require an ad-hoc choice of a single travel time threshold, which can influence the conclusions of transport project evaluations and equity analyses. In this paper, we introduce the time interval cumulative accessibility measure, a new metric that mitigates the impacts of arbitrary choices of trip duration on cumulative accessibility analyses while preserving computation and communicability advantages. The proposed indicator estimates the average (or median) number of opportunities that can be reached considering multiple minute-by-minute cutoffs within a given travel time interval. We demonstrate the new metric in a case study assessing how a planned subway expansion could impact employment accessibility in Fortaleza, Brazil. Using sensitivity analyses with Monte Carlo simulations, we show that the proposed metric makes the results of accessibility estimates and equity analyses significantly less sensitive to ad-hoc methodological choices while yielding results that are very similar to those obtained with traditional threshold-based measures. Future accessibility-oriented research and planning could benefit from the way in which the proposed time interval cumulative opportunity measure provides more robust accessibility estimates without compromising the communicability of results.

1. Introduction

Accessibility can be broadly defined as the ease with which people can reach places and opportunities or, conversely, a characteristic of places and opportunities in terms of how easily they can be reached by the population (Kwan, 1998; Levine, 2020; Neutens et al., 2010). In the past decades, cumulative opportunity measures have become the most commonly used metric for accessibility analyses and for evaluating the accessibility impacts of transport policies (Boisjoly & El-Geneidy, 2017; Manaugh et al., 2015; Papa et al., 2015). This indicator is simple to calculate and communicate, as it tells the number of opportunities that can be reached under a given travel time threshold. However, an important limitation of cumulative opportunity measures is that they require an arbitrary choice of a single travel time threshold (Ben-Akiva & Lerman, 2021; Geurs & van Wee, 2004; Levinson & King, 2020; Vickerman, 1974), which has important, yet frequently overlooked, implications for data analysis and policy decision-making (Pereira, 2019). The selection of travel time cut-offs affects not only the analysis output in terms of the number of accessible opportunities. It can also significantly impact the conclusions of transport policy assessments, accessibility inequality analyses, and subsequent policy recommendations (Palmateer et al., 2016; Pereira, 2019). Moreover, this arbitrariness creates opportunities for advocates of a certain position to cherry-pick travel time cut-offs that support particular arguments or agendas.

In this paper, we propose the time interval cumulative accessibility metric, a new simple indicator that mitigates the sensitivity of accessibility analyses to the *ad-hoc* selection of travel time thresholds in traditional cumulative opportunity measures. The time interval cumulative accessibility calculates the average (or the median) number of opportunities that can be reached within a given travel time interval. It is a place-based measure of accessibility that can be used in the same way and shares the same advantages as traditional threshold-based cumulative opportunity metrics, as it has low data requirements, and it is easy to calculate and communicate. Although the proposed metric still requires the arbitrary selection of a time interval, its main advantage is that it significantly reduces the sensitivity of results to the *ad-hoc* choices of trip duration. To demonstrate the new accessibility indicator in this paper, we assess how a planned subway expansion will likely impact employment accessibility levels and inequalities in the city of Fortaleza

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(Brazil). We compare the results using both the time threshold- and interval-based cumulative accessibility metrics and use Monte Carlo simulations to examine the extent to which these results are sensitive to using different time thresholds and intervals.

This paper contributes to the literature by proposing a simple accessibility measure that mitigates the problems generated by the arbitrariness of travel time duration in cumulative opportunity accessibility metrics while keeping the advantage of the indicator interpretability. This new indicator can be used to measure the accessibility levels of entire populations/regions or specific socioeconomic groups in cross-sectional analyses, as well as to assess the impact of policy interventions over time. The method can also be used in the analysis of accessibility inequalities between groups or neighborhoods. While the proposed time interval cumulative accessibility keeps the advantages of traditional threshold-based cumulative accessibility measures, the time interval approach works as a simple yet robust mechanism to mitigate the sensitivity of accessibility results to *ad-hoc* choices of travel time cut-offs.

The remainder of this article is organized as follows. Section two presents a brief literature review. The third section describes the proposed time interval cumulative accessibility measure. Section four presents the case study of Fortaleza, and the data and methods used in this paper. The fifth section presents the results. Finally, section six presents the discussions and conclusions.

2. Literature review

There is a growing interest among researchers and transport agencies in how they can incorporate accessibility measures into urban planning practices, and use these measures to assess the accessibility and equity impacts of transport interventions (El-Geneidy et al., 2016; Papa et al., 2015). To do so, most researchers and agencies use cumulative accessibility measures and select a single travel time threshold usually defined based on observed average travel times, which commonly varies between 30 and 60 min (Boisjoly & El-Geneidy, 2017; Manaugh et al., 2015). However, there is no strong reason to believe that average travel time from observed travel patterns is the single and best reference to set a time threshold (Páez et al., 2012). Moreover, the traditional approach of selecting a single travel time cut-off becomes particularly problematic in the assessment of transportation and land-use projects because it does not capture any changes in accessibility conditions below or above the selected threshold (Geurs & van Wee, 2004; Pereira, 2019). For example, consider a hypothetical subway expansion that significantly improves access to jobs in a given neighborhood by reducing the travel time to the central business district (CBD) from 40 to 20 min. If one sets a 60-min time threshold to assess the accessibility impact of this hypothetical project, the accessibility benefits experienced in the neighborhood would not be captured, despite the substantial reduction in travel time to the CBD.

Few studies have tried to address this limitation of cumulative opportunity measures by conducting sensitivity analyses with multiple accessibility estimates under different time thresholds (e.g. Bittencourt & Giannotti, 2021; El-Geneidy et al., 2016; Herszenhut et al., 2022; Klar et al., 2023; Palmateer et al., 2016; Pereira, 2019). The work of Palmateer et al. (2016), for example, analyzed the employment accessibility impact of a BRT project in the Twin Cities Metropolitan Area (USA). The authors found that the overall accessibility impact could be more than 3 times higher considering a 40-min threshold when compared to a 60-min threshold. In an extreme case, they have also found that the intervention could reduce accessibility by −0.3% if a threshold of 10 min were considered. In another study, Pereira (2019) assessed a BRT project in Rio de Janeiro (Brazil), looking at its impacts on both accessibility estimates and inequality levels. The author found that the average accessibility benefit of the BRT would be between three to five times larger when using a 30-min threshold compared to 90 and 120 thresholds. Moreover, the author also found that using shorter travel times (30 or 60 min) would suggest that the BRT could reduce the accessibility gap between the rich and the poor, while longer thresholds (90 and 120 min) would lead to neutral effects on inequality levels.

Conducting these sensitivity analyses in accessibility estimates helps us grasp the boundary effect of the modifiable temporal unit problem (MTUP), a statistical bias related to the arbitrary selection of a phenomenon's duration, such as a travel time threshold (Pereira, 2019). While sensitivity analyses are important to make sure accessibility estimates are not simply artifacts resulting from *ad-hoc* methodological choices, they generate a greater number of results, making research findings harder to communicate to policymakers and others who lack the in-depth technical knowledge to make sense of different scenarios. In this sense, sensitivity analyses can hinder the interpretability of cumulative opportunity measures, which is one of their main advantages in the first place. In addition, sensitivity analyses do not solve the problem regarding which travel time threshold should be considered and it might make policy decision-making even more complex if the results from different thresholds diverge.

In a recent study, Kapatsila et al. (2023) advocates using a time threshold equal to the average travel time observed in the region would be preferable. This is based on their finding that this threshold makes cumulative opportunity measures highly correlated with gravity-based accessibility indicators, which better reflect how travel behavior changes with increasing travel costs. However, their study shows that, depending on the chosen decay function, the correlation between cumulative and gravity-based accessibility for public transport becomes highest at various different time thresholds which are generally 20 min apart and which could fall anywhere between the median travel time and the average travel time plus one standard deviation. As such, it is not so obvious from their results which threshold value should be chosen. The argument made by Kapatsila et al. (2023) also ignores the fact that a single travel time threshold, regardless of how correlated it is with gravity-based models, still does not capture changes in accessibility conditions below the selected threshold, as mentioned above. Moreover, the analysis conducted by the authors considers aggregated city-level correlations, and thus overlooks how the correlation between cumulative and gravity accessibility varies across space and for different income groups. Finally, the argument proposed by Kapatsila et al. (2023) builds on a positive approach to setting a time threshold that tries to reflect observed travel patterns (Páez et al., 2012). If one chooses a normative (i.e. prescriptive) approach, it becomes even less clear that one should choose the average travel time observed in the region as the acceptable threshold. In either case, choosing the average travel time as a threshold still leaves the boundary effect of MTUP unaddressed, which we aim to do with the time interval cumulative measure presented in the next section.

3. The time interval cumulative accessibility measure

To mitigate the negative impacts of choosing *ad-hoc* travel time thresholds when conducting accessibility analyses, we propose a new time interval cumulative accessibility metric. The time interval cumulative measures the average (or the median) number of opportunities that can be reached considering multiple minute-by-minute time thresholds within a given travel time interval. To illustrate this, Fig. 1 presents a schematic figure that compares the relationship between travel time duration and accessibility estimates following (a) the usual practice found in the literature with time thresholds, and (b) our proposed approach with time intervals. Whilst in the former approach each travel time cut-off has a correspondent accessibility estimate, in the latter, each time interval also returns a single accessibility value, but which is calculated as the average (or median) of several accessibility estimates (one per minute) within the interval. The figure shows that the traditional threshold-based cumulative accessibility metric becomes identical to an interval-based cumulative measure with a time window of size zero.

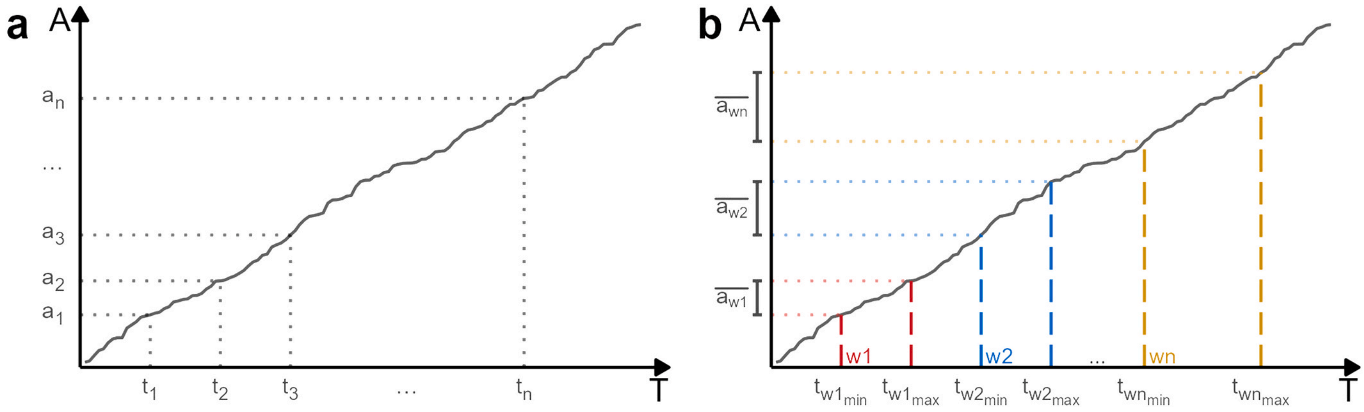

Fig. 1. The schematic relationship between travel-time and cumulative accessibility estimates, following (a) the usual approach, choosing individual travel-time thresholds, and following (b) the proposed approach, choosing time intervals.

Obs. The X-axis ("T") represents the travel time. The Y-axis ("A") represents the accessibility levels, i.e. the number of accessible opportunities.

The equation of a traditional threshold-based cumulative accessibility measure (TCA) is presented in equation (1). This indicator measures, for each origin point, how many opportunities can be reached within a given travel time threshold.

$$TCA_{oT} = \sum_{d=1}^{n} P_d f(t_{od}) \qquad \text{Equation (1)}$$

Where:

TCA_{oT} is the cumulative accessibility of the origin o within the travel time threshold T;
P_d is the number of opportunities (jobs) in the destination d;
t_{od} is the travel time (minutes) between origin o and destination d;
$f(t_{od})$ is the travel time impedance function, which can take the values of 0 or 1, depending on whether the travel time between the origin o and the destination d is higher (0) or lower (1) than the travel time threshold T.

The proposed time interval cumulative accessibility metric (ICA) is defined in Equation (2). In this particular study, we will be using the mean statistic to summarize the accessibility estimates inside each time interval.

$$\begin{aligned} &ICA_{oI} = mean(\{TCA_{oT} \forall T \in I\}) \\ &I = [T_{min}, T_{max}] \end{aligned} \qquad \text{Equation (2)}$$

Where:

ICA_{oI} is the average cumulative accessibility of the origin o within the travel time interval I;
I is a minute-by-minute distribution of travel time cutoffs within a given time interval between T_{min} and T_{max}.

Similarly, as in other accessibility metrics, the start and end cut-offs of time intervals can be chosen according to different normative or positive criteria (Páez et al., 2012). For example, a time window between 10 and 40 min could be defined based on what is deemed normatively acceptable for the population of a given city to reach health services by public transport. Alternatively, one could set a time interval that best represents commonly observed trips captured in travel surveys, such as the average commute time plus and minus one standard deviation.

The definition of a time interval still involves some arbitrariness, just like any other accessibility metric also relies on parameters that are defined *ad-hoc*, such as cut-off points in traditional cumulative measures or decay functions and factors in gravitational models. The main advantage of the proposed time interval approach is to mitigate the impacts of such *ad-hoc* choices on the conclusions of accessibility estimates and accessibility inequality analyses.

Another advantage of calculating accessibility with a time interval approach is to make it easier to incorporate accessibility analysis into policy decision-making. While it can be important to run sensitivity analysis calculating multiple accessibility estimates with multiple time thresholds, it is not self-evident which threshold should be chosen from a policy perspective. This can be particularly problematic when different threshold choices lead to very different conclusions and policy recommendations. In this sense, estimating accessibility and inequality levels with a time interval instead of sensitivity analysis with multiple time thresholds makes it easier to communicate accessibility analyses to policymakers and in planning documents. The interpretation of the proposed metric is quite similar to the traditional cut-off-based cumulative accessibility interpretation. For example, setting an interval of 20–40 min means that the indicator captures the average (or median) number of opportunities that can be reached between 20 and 40 min from a given place using a given transport mode.

The proposed metric can also capture the accessibility impacts of transportation and land-used interventions with more nuance, as traditional threshold-based cumulative metrics do not capture any changes in accessibility conditions below or above the selected threshold (Geurs & van Wee, 2004; Pereira, 2019). This is also one of the reasons why using a time interval cumulative metric is different from using a threshold-based metric with a cutoff point at the middle of the time interval. Finally, the time interval cumulative metric shares important strengths with the traditional cumulative opportunity accessibility: it is straightforward to calculate and demands little computational resources. To make it readily available for other researchers and practitioners, the proposed measure has been implemented in the "accessibility" R package (Pereira and Herszenhut, 2022), which makes it very easy for users to calculate time interval cumulative accessibility measures provided they have travel time estimates and land use data.

The proposed accessibility measure can also be used in the analysis of accessibility inequalities. To address this issue, the proposed indicator can be used to calculate the average or the mean accessibility inequality over multiple minute-by-minute travel time thresholds within a given travel time interval. In this case, the time interval indicator can be used combined with any inequality metric, such as the Palma ratio or the Gini and Theil indexes (see the results section).

4. Materials and methods

In this section, we provide an overview of the study area and the new

East subway line, currently under construction in Fortaleza. We also give more details about the data and methods used in the paper. In particular, we assess the accessibility impacts of the proposed transport intervention using both threshold- and interval-based cumulative accessibility metrics and examine the extent to which the results of the project appraisal are sensitive to the selection of time thresholds and intervals using Monte Carlo simulations. The data and code to reproduce this paper are publicly available on Github[1].

4.1. Case study of Fortaleza (Brazil)

The municipality of Fortaleza, Brazil is located in northeast Brazil. Fortaleza is the fifth most populous municipality in Brazil, with an estimated population of 2.7 million inhabitants (IBGE, 2021) distributed in 312.35 km^2, and it has a human development index (HDI) of 0.754 (IBGE, 2011).

The city of Fortaleza is currently building a new subway extension, the East line (colored in red in Fig. 2). This subway line is expected to start its operation in 2024. Once finished, it will be 7.3 km long, crossing Fortaleza's CBD and connecting with the South and West subway Lines, with the Parangaba-Mucuripe light rail, and with a major bus terminal in Papicu on the east side (Fig. 2). The East line will have four underground stations (SEINFRA, 2021), which together will provide greater connectivity to other mass rail transport lines.

The population of Fortaleza is mostly concentrated in the central-western region of the city, although there are some areas of high population density in the southeast of the city (Fig. 2). Like most urban centers in Latin America, Fortaleza has a well-defined core-periphery population distribution, with most of the high-income population living near the city core, while most of the low-income population lives in the urban peripheries (Fig. 2).

The distribution of formal jobs in Fortaleza can be seen in Fig. 3. Most of the formal jobs are located in Fortaleza's CBD, which is where the proposed Metro East Line is going to be implemented.

4.2. Data

To develop the accessibility analysis presented in this study, we divided the municipality of Fortaleza into a spatial grid of hexagons that were used to aggregate population and land use data. We have used the H3 grid with level 9 resolution[2], in which each cell has a short diagonal of 357 m and an area of 0.10 km^2. The choice for a spatial grid in hexagonal format was motivated by the fact that this type of aggregation better represents spatial phenomena with important neighborhood and connectivity components of networks and movement paths (Birch et al., 2007).

Population and income data were extracted from the 2010 demographic census (IBGE, 2010), the latest information available for Brazil. The census data provides estimates of population counts and their socioeconomic characteristics at the census tract level. The population and household income per capita estimates were assigned to the H3 hexagons using a dasymetric interpolation. The data on jobs were obtained from the 2019 edition of the Identified Annual Social Information Report (RAIS, in Portuguese), a database of administrative records on formal employment organized by the Brazilian Ministry of the Economy. The methods used to geolocate formal jobs and the dasymetric process to estimate the population with income in H3 hexagons are presented in detail in Pereira et al. (2022).

The street network data used in this paper comes from OpenStreetMap (OSM). We also used topography data from SRTM (Farr et al., 2007) at a spatial resolution of 30 m, extracted via satellite imagery from the US Space Agency (NASA). These datasets are important to account for elevation profiles when measuring travel time by foot.

Finally, the public transportation network in GTFS format and the expected changes in the network with the new East Line were obtained from the Urban Transportation Company of Fortaleza (ETUFOR), the Secretary of Infrastructure of the state of Ceará (SEINFRA), and the Metro Company of Fortaleza (METROFOR). These changes include the new East subway line as well as increases in frequencies of the other rail services in Fortaleza. These additional changes to the transport network are summarized in Table 1:

A summary of the databases used in this study is presented in Table 2.

4.3. Transport intervention scenario

To assess the accessibility impact of the new East subway line in Fortaleza, we compare accessibility estimates between a baseline (current) and a future scenario. The baseline consists of the accessibility levels of Fortaleza calculated using the GTFS data of the public transport network in October 2019. Meanwhile, the future scenario keeps the current public bus system while including the expansion of the new East Line and the increased frequency of the other rail lines, which allows us to capture the combined impact of investments in the subway and LRT on people's access to opportunities.

We calculated separate travel time matrices and accessibility estimates for each scenario. After calculating accessibility levels under both scenarios, we analyzed how accessibility inequalities would change between the two scenarios. This allows us to grasp the distributional impacts of the planned transport investments, by looking at how accessibility impacts are distributed among population groups of different income levels and neighborhoods in the city.

4.4. Travel time estimates

A key step to calculate accessibility is to estimate travel times from all origins to all destinations in the study area. To estimate these travel time matrices, we consider the centroids of the spatial grid of the H3 hexagons as the origin and destination of trips. The travel time estimates were calculated using r5r, an open-source computational package for routing multimodal transportation networks developed in R (Pereira et al., 2021). r5r generates realistic travel time estimates that account for all steps of the trips between origins and destinations, including the time to access and egress the public transport system, waiting times for vehicles, and the actual travel time through the transportation network, including eventual transfers.

Previous research has shown that travel times can fluctuate due to variability in service levels and the exact departure time (Conway et al., 2017). To circumvent this issue, we calculated multiple travel time matrices departing every 1 min during the peak period (between 6 a.m. and 8 a.m.) and considered the median travel times between origin-destination pairs to generate our accessibility estimates. The parameters used to calculate the travel time matrices are summarized in Table 3.

4.5. Inequality metric

To measure the accessibility gap between high- and low-income populations, we use the Palma Ratio (Palma, 2011), an index commonly used in the literature to examine accessibility inequalities (Guzman & Oviedo, 2018; Herszenhut et al., 2022; Liu et al., 2021). This index is defined, in the context of transportation planning, as a ratio between the average accessibility of the richest 10% of the population divided by the average accessibility of the poorest 40% (Equation (2)). Values greater than 1, therefore, indicate that the wealthiest population has higher accessibility than the poorest, and values smaller than 1 point to the inverse situation.

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[1] Available at https://github.com/ipeaGIT/time_interval_cum_access.

[2] Available at https://eng.uber.com/h3/.

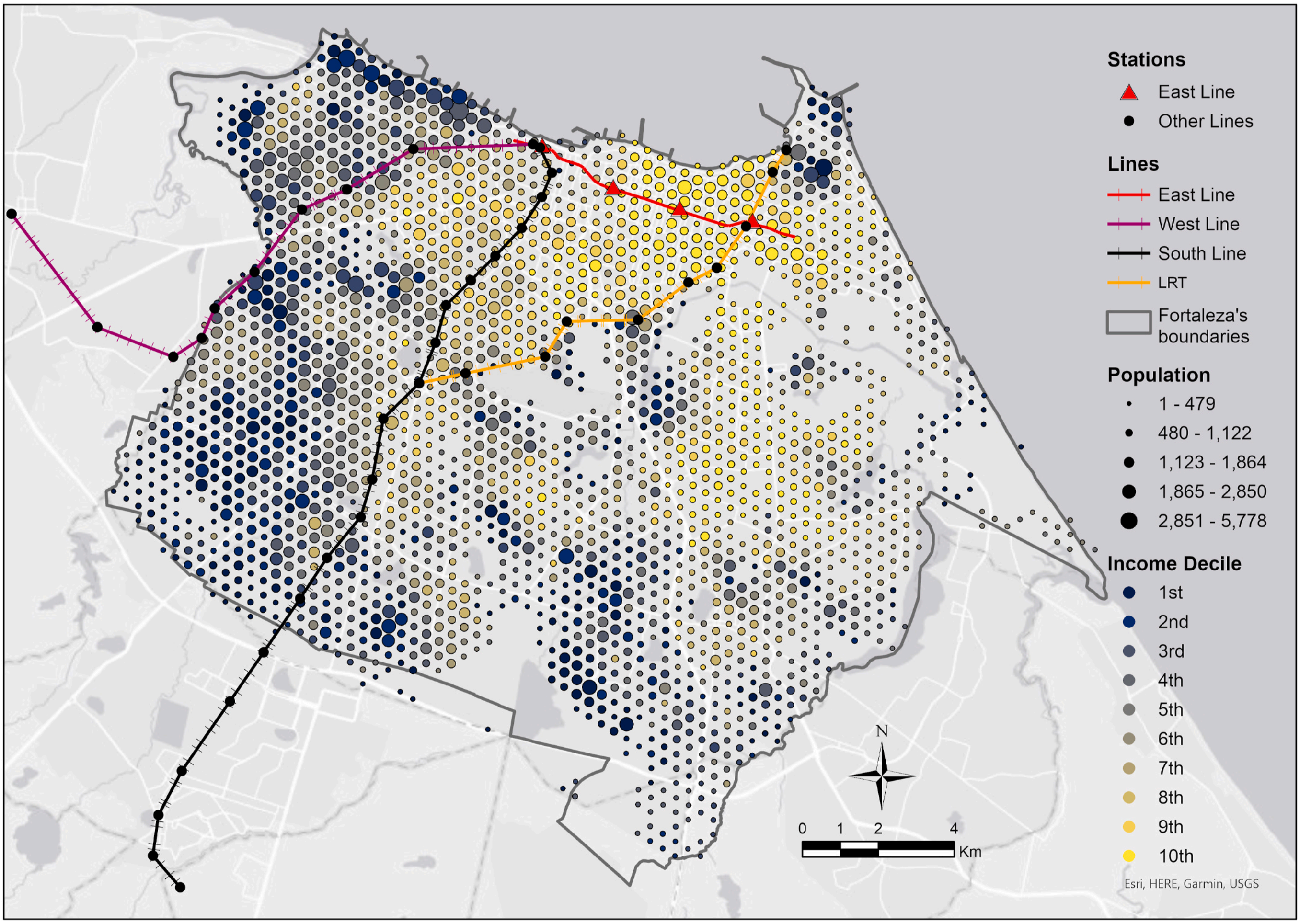

Fig. 2. Distribution of the population according to income decile.

$$P = \frac{\underline{A}_{top10}}{\underline{A}_{bottom40}} \qquad \text{Equation (3)}$$

Where:

P is the Palma Ratio index;
$\underline{A}_{top10}$ is the average gain of accessibility of the richest 10%;
$\underline{A}_{bottom40}$ is the average gain of accessibility of the poorest 40%.

4.6. *Monte Carlo simulations*

As previously mentioned, using different travel time thresholds to calculate accessibility lead to very different results. However, different time intervals may likewise lead to different accessibility estimates. We need to investigate how much the results from these two approaches vary due to *ad-hoc* choices of max trip duration. The idea being that a smaller variability indicates that the accessibility measure gives more robust and reliable results which are less dependent on arbitrary methodological choices.

To measure the extent to which accessibility estimates are sensitive to the choices of time thresholds and intervals, we use a probabilistic Monte Carlo simulation composed of 10,000 rounds. In each round, we (a) randomly select four travel time thresholds and four travel time intervals between 20 and 90 min,[3], (b) estimate the average accessibility and inequality levels using these thresholds/intervals, and (c) calculate the standard deviation of these accessibility and inequality estimates. By the end of the Monte Carlo simulation, we have a distribution of 10,000 standard deviations for each indicator for each grid cell, which we use to assess the variability of results for the travel time threshold and interval measures. Higher standard deviations indicate that results are susceptible to larger variations due to *ad-hoc* choices of time thresholds/intervals. As long as the interpretation of measures and the overall magnitude of accessibility and inequality levels is kept similar, an accessibility metric with a smaller standard deviation means we can be more confident on the research conclusions and policy recommendations derived from such estimates.

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[3] Researchers and practitioners usually use three to four cut-offs when conducting accessibility temporal sensibility analysis, which is why we decided to use four cut-offs/intervals scenarios in the analysis. We have conducted the same analysis with a higher number of cut-offs and intervals but our conclusions remained the same. We have not added these additional analyses to the paper for the sake of brevity.

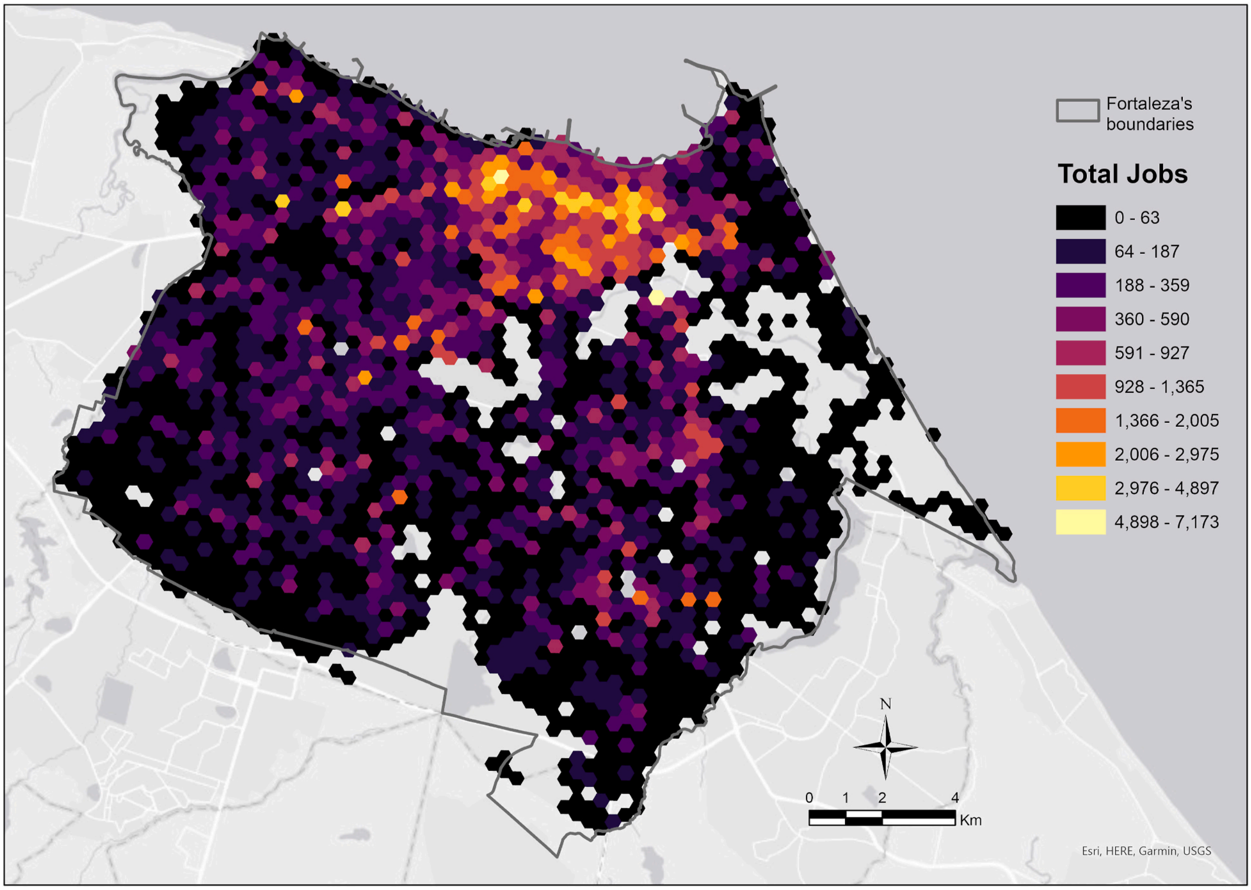

Fig. 3. Spatial distribution of formal jobs in Fortaleza, 2019.

Table 1
Operational changes in other rail services.

Line	Frequency (trips per hour per direction)	
	Before	After
South Line	4	10
West Line	2	5
LRT Parangaba-Mucuripe	2	8

Table 2
Databases used in the study.

Data	Source	Year
H3 hexagons	H3 (Uber)	2019
Public transport GTFS	Metrofor; Etufor	2019
Street network	OpenStreetMap	2019
Location of jobs	RAIS (ME)	2019
Population and income data	Population census (IBGE)	2010
Topography	SRTM (NASA)	2000

Table 3
Routing parameters used in r5r.

Parameters	Value
Maximum travel time by public transport	2h
Walking speed	3.6 km/h
Maximum walking distance to access and egress public transport	1000 m

5. Results

5.1. Overall accessibility levels

To illustrate how accessibility estimates can vary across travel time thresholds, we calculated the cumulative accessibility to jobs for the current and future scenarios using several minute-by-minute cut-off values ranging from 1 to 120 min (Fig. 4A). The small difference between blue and black lines suggests that the proposed subway expansion could have limited impacts on employment accessibility. Moreover, these impacts only become more pronounced when considering travel time thresholds between 50 and 75 min. To take a closer look at these results, we show in Fig. 4B the accessibility gains from the subway investment by calculating the differences in accessibility between the current and the future scenarios. Because these accessibility gains also vary greatly across areas of the city, we also show in this figure the interquartile range of accessibility gains to capture the variation in accessibility gains experienced across hexagonal cells.

The maximum accessibility gain is found when considering a time threshold of 68 min. As can be seen in Fig. 4B, though, the accessibility gain is zero in the interquartile range up to 33 min of travel time. This suggests that the threshold-based cumulative accessibility would not capture any improvement in employment accessibility considering trips shorter than 33 min. Similarly, the new subway line would provide little to no accessibility benefits considering time thresholds longer than 118 min. This is because even in the current scenario the population of Fortaleza could already reach all jobs in under 118 min.

Looking at the spatial distribution of access to jobs, we see how accessibility levels vary greatly across space for different travel time cut-offs and intervals (Fig. 5). Nonetheless, we see in this example how the results look very similar when comparing accessibility estimates for a

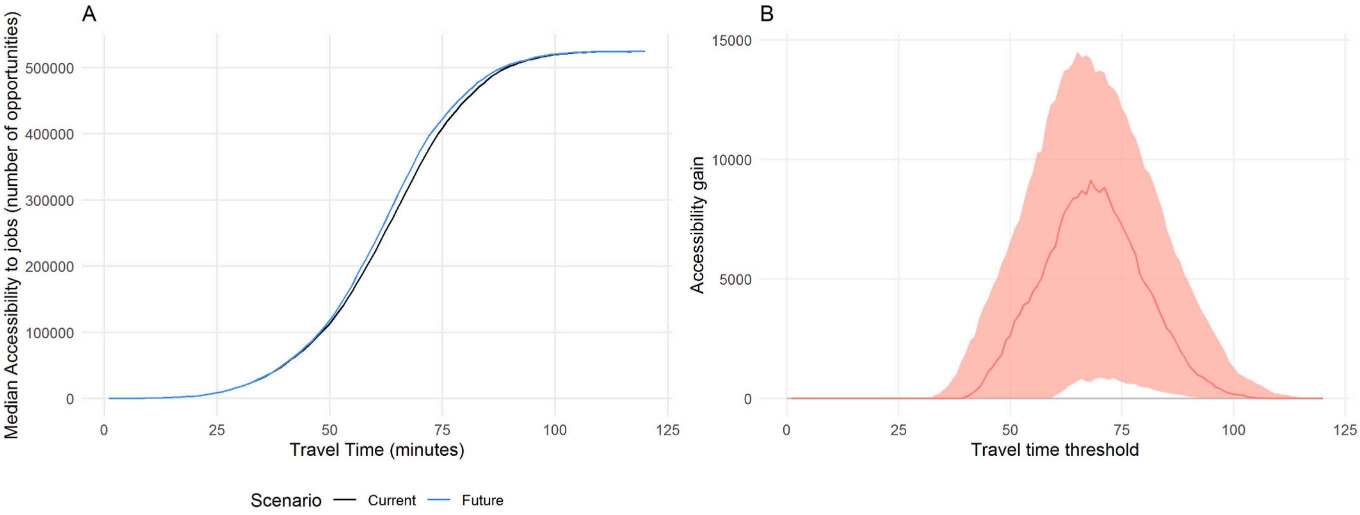

Fig. 4. The median accessibility to jobs across hexagonal cells (A) and the median and interquartile range of accessibility gains (B) using travel time thresholds ranging from 1 to 120 min.
Obs: shaded area shows the interquartile range, between the 25th and 75th percentiles.

selected time threshold versus the time interval of that threshold plus and minus 10 min. In the city of Fortaleza, after the subway expansion, a traditional threshold-based metric indicates that people would access on average 17,975 jobs considering a 30-min threshold, and 118,455 jobs with a 50-min cutoff. Similarly, a time interval measure indicates that people would access on average 21,675 jobs between 20 and 40 min, and 129,393 jobs between 40 and 60 min. Regardless of the travel time cut-off and travel time interval, the spatial distribution of accessibility levels is very similar between both indicators. Simple Pearson correlation analyses comparing the accessibility estimates derived from both indicators are strongly correlated, with correlation between X and Y, with p-values statistically significant at 0.001.

The difference between both measures can be better seen in Fig. 6, which shows how accessibility gains are spatially distributed. While both measures indicate the same areas as the most impacted by the transport intervention, the time interval metric results in a slightly smoother surface, with smaller accessibility differences between neighboring hexagons. Again, the results from both indicators are strongly correlated, with Pearson coefficients ranging between W and Z, with p-values statistically significant at 0.001.

To highlight how different time thresholds and intervals can influence the results of accessibility estimates, we performed a Monte Carlo simulation with 10 thousand rounds. In each round of the simulation, we calculated the average accessibility of the city under different time thresholds and intervals randomly selected, and then calculated the standard deviation of the results in each round using both accessibility metrics. Fig. 7 shows the distribution of these standard deviations for (A) the current scenario, and for (B) the expected accessibility gains between scenarios. In both cases, accessibility results calculated using traditional threshold-based cumulative metrics tend to present much higher standard deviations. This is because, using the cut-off metric, there is a greater chance that accessibility estimates will be extreme. Choosing intervals allows for a reduction in this effect, which significantly decreases the chance of biased results due to less variability. Time interval cumulative accessibility presents smaller standard deviations, which get even smaller for larger travel time windows.

Each round of our Monte Carlo simulation gives for each hexagonal cell of our spatial grid the accessibility estimates considering four randomly selected travel-time cut-offs and time intervals, and the standard deviation of these estimates. After calculating the average of these standard deviations across the 10 thousand simulations, we are able to examine how the standard deviations generated by both accessibility measures are distributed in space (Fig. 8) and across different socioeconomic groups (Fig. 9). Fig. 8 maps the spatial distribution of the average standard deviations of accessibility estimates in (A) current scenario and (B) future accessibility gains using different travel time cut-offs and travel time intervals. The results show that the time sensitivity is not evenly distributed in space. Areas with the highest standard deviation (i.e. areas more prone to bias) are the areas that originally had intermediate levels of accessibility. Nonetheless, the results based on time interval cumulative opportunity tend to be less sensitive to ad-hoc choices of time interval, presenting much lower standard deviations everywhere in the city.

Just as the sensitivity of accessibility analysis to time threshold choices is not evenly distributed in space, it also varies by socioeconomic groups. In Fig. 9 we show how the standard deviation of accessibility estimates using both metrics vary depending on accessibility and income levels. Each dot in the figure is a hexagonal cell colored by its income decile. Considering the cut-off approach (Fig. 9A), it can be observed that most high-income hexagons have higher accessibility levels while having intermediate to high standard deviations. On the other hand, low-income hexagons tend to have lower levels of accessibility and lower standard deviations. This can be explained because the low-income population in Fortaleza tends to be more concentrated in the urban peripheries where public transport supply can be very heterogeneous. By contrast, using the time interval approach (Fig. 9B) generates lower biases overall, and these biases are more evenly distributed across income groups.

In summary, the fact that the threshold- and interval-based accessibility indicators present very similar results (Figs. 5 and 6) but the interval measure presents much lower standard deviations (Figs. 7–9) is a strong indicative that the proposed time interval cumulative measure retains the advantages of the threshold-based metric while at the same time being less sensitive to the boundary effect of MTUP. These results call us to examine in the next section how estimates of accessibility inequalities could also be sensitive to time thresholds and intervals.

5.2. Accessibility inequalities

This subsection illustrates the extent to which the evaluation of the impact of transportation projects on accessibility inequalities is sensitive to the boundary effect of MTUP, and it demonstrates how project evaluations using the time interval metric are substantially less sensitive to the ad-hoc methodological choice of trip duration. Transport accessibility inequalities can vary substantially depending on the time threshold of choice. To illustrate this, Fig. 10 shows the Palma ratio for

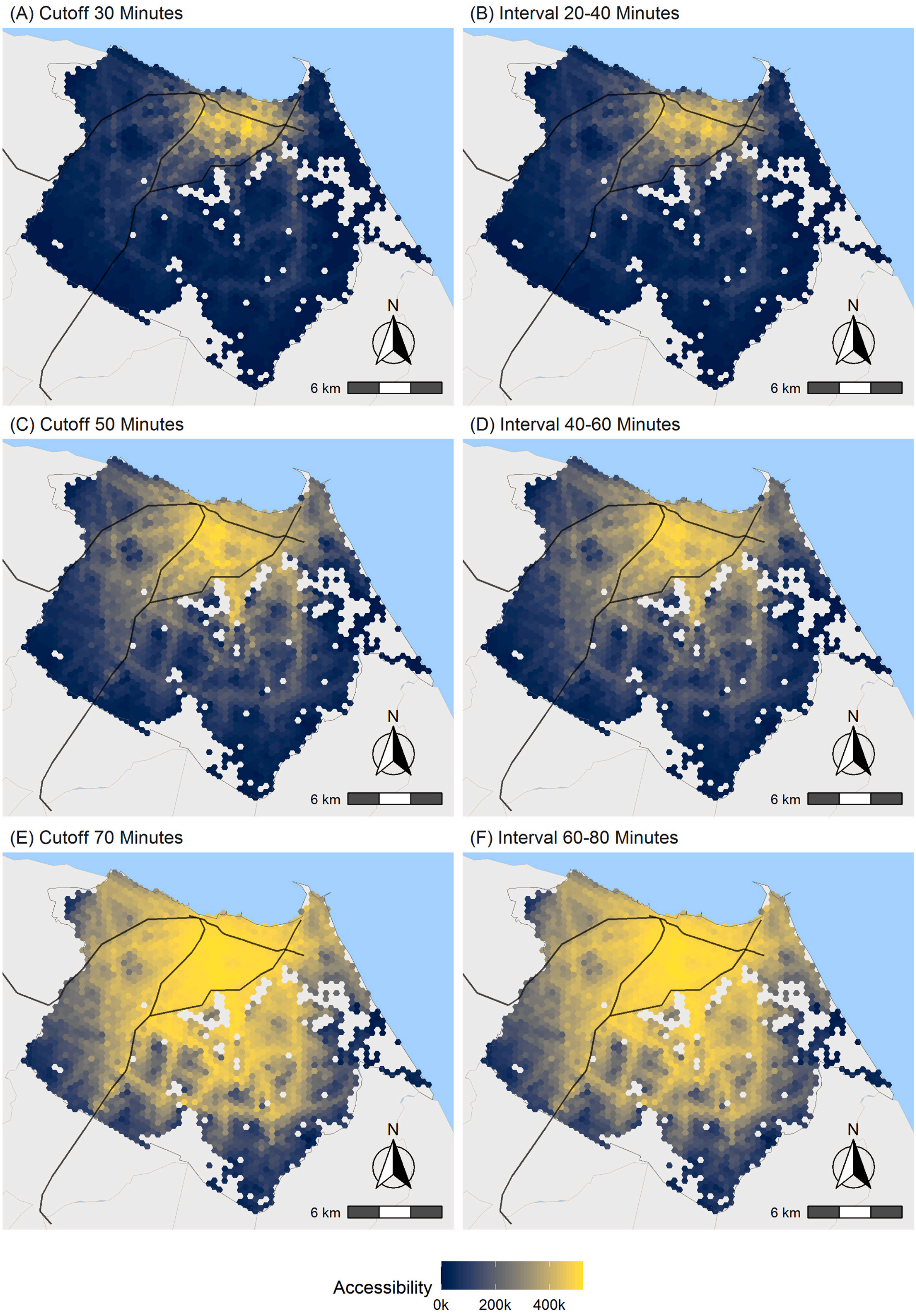

Fig. 5. Accessibility to jobs (future scenario) using different travel time cut-offs and intervals.

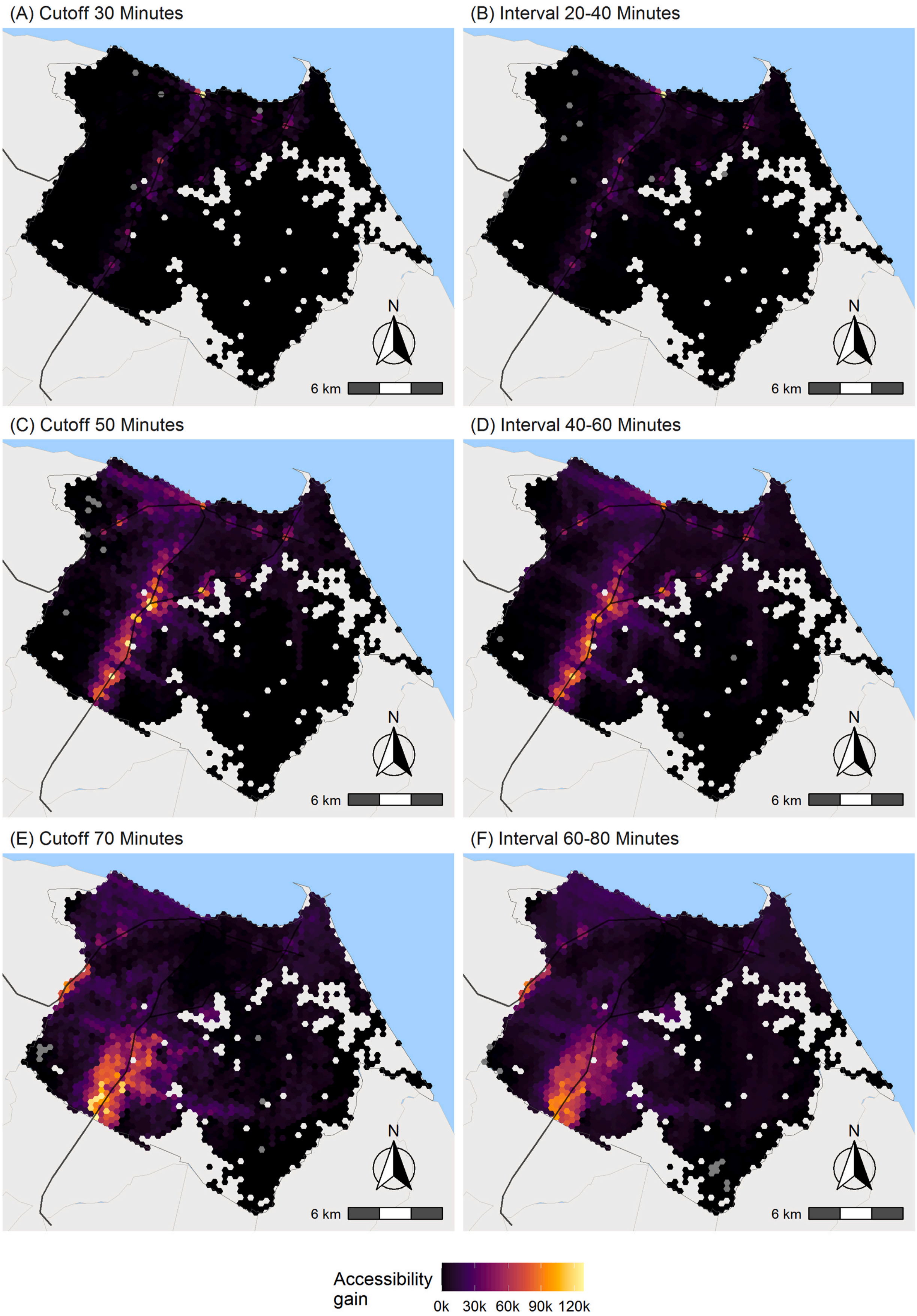

Fig. 6. Job accessibility gains using different travel time cut-offs and intervals.

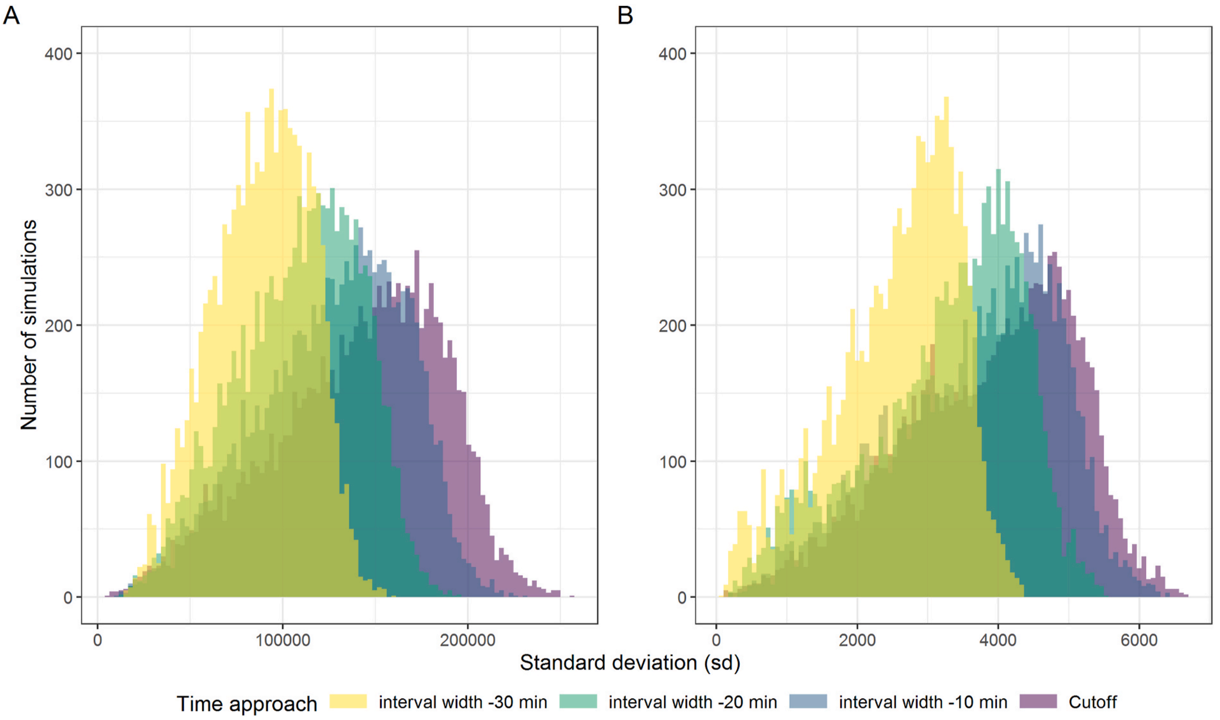

Fig. 7. Standard deviation distribution of accessibility simulations using cut-offs and time intervals, (A) total accessibility, and (B) gain of accessibility.

the current and future scenarios using multiple minute-by-minute cutoff values ranging from 1 to 120 min. Again, this result illustrates how the ad-hoc choice of travel time can substantially influence the results of transportation equity analyses. Inequalities in access to employment in Fortaleza are very high for lower cut-offs and decrease asymptotically with higher travel times. The higher inequalities in lower travel times reflect the proximity of the high-income population to the center of Fortaleza, where large numbers of job opportunities are concentrated. The subway expansion in the future scenario would only impact the Palma ratio at travel times ranging from 30 to 80 min, when there is a slight decrease in the Palma ratio, indicating a more equitable scenario.

Using the same Monte Carlo simulations as before, we calculated the extent to which accessibility inequalities measured with the Palma ratio are sensitive to different cut-offs and time intervals (Fig. 11). The results show that the standard deviations are much lower when considering the time interval accessibility measure than threshold-based accessibility. This difference becomes even more pronounced with a time interval of 30 min. This suggests that inequality analyzes are much more sensitive (prone to bias) when using traditional cumulative accessibility metrics with hand-picked cut-offs.

6. Discussion

Our results show that the proposed time interval cumulative measure yields very similar results to those obtained when using traditional threshold-based cumulative accessibility (Figs. 5 and 6), while significantly reducing the variability between estimates calculated using different trip duration limits (Figs. 7–9 and 11). This is true when looking both at the overall accessibility levels in the future transport scenario, after the subway construction, and at the future accessibility gains that result from this intervention. We also find that the spatial distribution of these accessibility levels and gains are nearly identical using both metrics. From a practical perspective, this means that the time interval cumulative measure estimates are less susceptible to the boundary effect of MTUP than estimates from the traditional threshold-based cumulative metric, while preserving the easy communication and interpretation of results.

We also find that the variability of results due to trip duration choice is not evenly distributed across space and income groups. The variability is substantially larger in areas with intermediate levels of accessibility, mostly occupied by middle- and high-income classes. This means that the sensitivity of threshold-based cumulative metrics to the boundary effect of MTUP can be particularly problematic for transportation equity analysis. Since the proposed time interval cumulative metric can substantially minimize the biases related to *ad-hoc* choices of trip duration, the equity assessment of the subway expansion is substantially less dependent on the selection of time intervals than on the selection of time thresholds.

In summary, the main difference between the time interval cumulative measure and the traditional threshold-based metric is that the proposed measure significantly mitigates the boundary effect of MTUP because its results are more robust (less sensitive) to *ad-hoc* choices of trip duration. This is particularly important in a context where measuring accessibility using a single travel time threshold without questioning the policy and equity implications of this choice is the standard practice adopted by academic scholars and transport agencies. In other words, the proposed measure gives results that are more reliable and reduces the risk of opportunistic analyses that cherry picks trip duration values that support particular policy views and agendas.

Moreover, the time interval cumulative measure shares some of the main advantages of the traditional threshold-based cumulative measure, namely the easy communication and the few data and computing requirements to calculate it, making it a compelling metric to be incorporated into transport policy and planning. Finally, the proposed indicator mitigates the fact that the traditional measure does not capture any accessibility change that happens just below or above the selected cutoff, which makes it more sensitive to incremental changes in the transport network and better reflects how people perceive accessibility in practice. Although gravity-based accessibility metrics may also mitigate the boundary effect of MTUP, these measures are recognized for being difficult to communicate and interpret (Geurs & van Wee, 2004; Kwan, 1998; Neutens et al., 2010). These findings suggest that the proposed time interval cumulative accessibility metric could give a valuable contribution to the field of accessibility research.

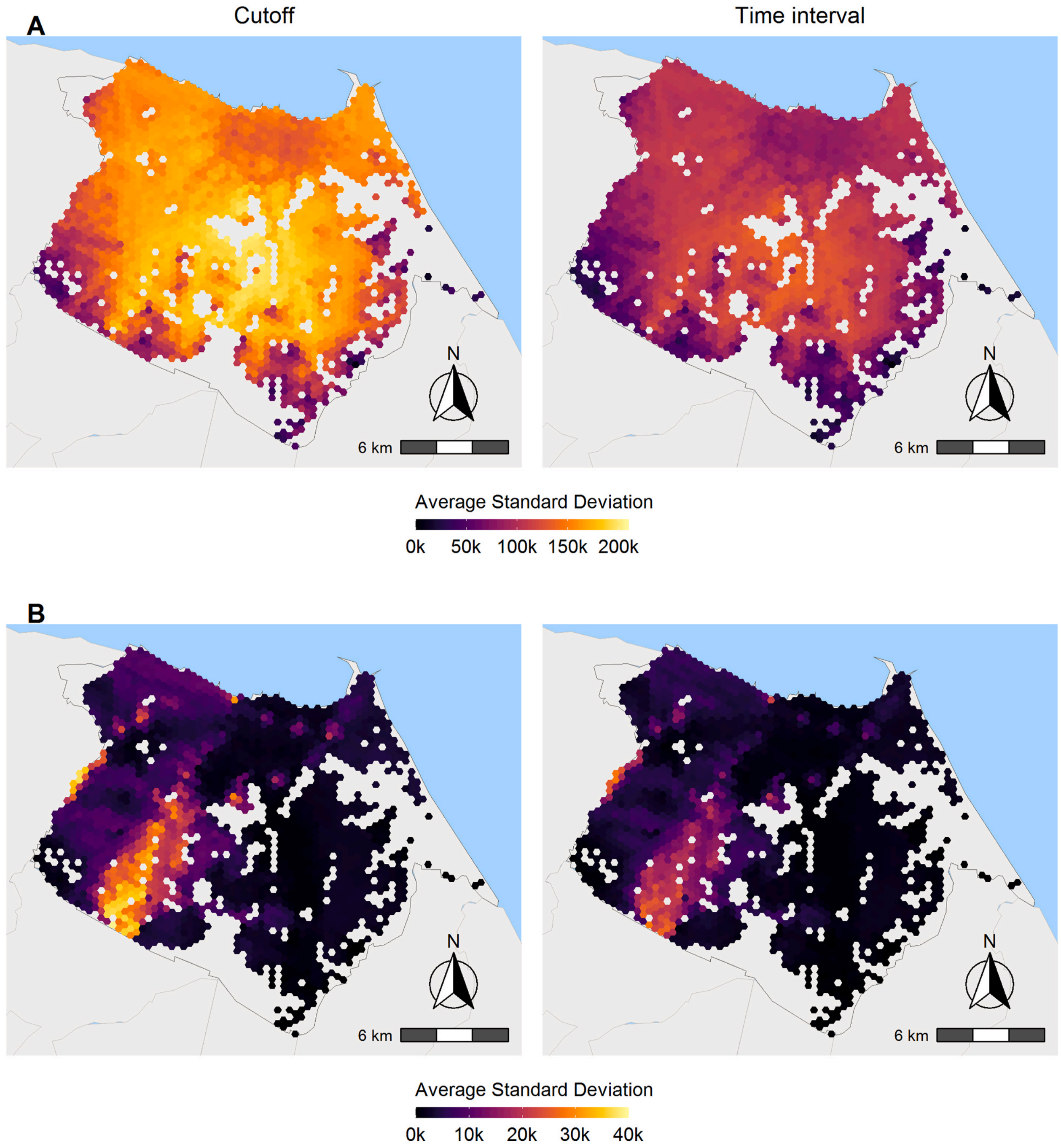

Fig. 8. The average standard deviation of accessibility estimates in (A) current scenario and (B) future accessibility gains using different travel time cut-offs and travel time intervals.
Obs. For this example, we used time intervals of random sizes with a minimum size of 10 min in the Monte Carlo simulations.

7. Conclusion

This study proposed a new accessibility metric that uses a time interval approach for cumulative opportunity accessibility measure. According to this metric, the cumulative accessibility of a given place is measured as the average (or median) number of opportunities that can be reached within a given travel time interval. Using a planned subway expansion in Fortaleza as a case study, we compared how the time interval cumulative opportunity measure and the-traditional threshold-based cumulative measure can be used to assess the impacts of a transport intervention on overall levels of job accessibility and on accessibility inequalities. We also conducted several sensitivity analyses using Monte Carlo simulations to test the extent to which the results for our analysis are sensitive to time intervals and time threshold choices. We conclude that the proposed time interval cumulative accessibility measure yields similar results and a similar interpretation from a traditional threshold-based cumulative metric, with the advantage of being significantly less sensitive to the *ad-hoc* selection of trip duration, thus mitigating the boundary effect of MTUP.

The results of any accessibility analysis might be sensitive to the input data and setting. Future studies are necessary to examine the extent to which the benefits of the interval cumulative accessibility metric demonstrated in this paper would also hold when the indicator is used in different contexts. Furthermore, one limitation of the time

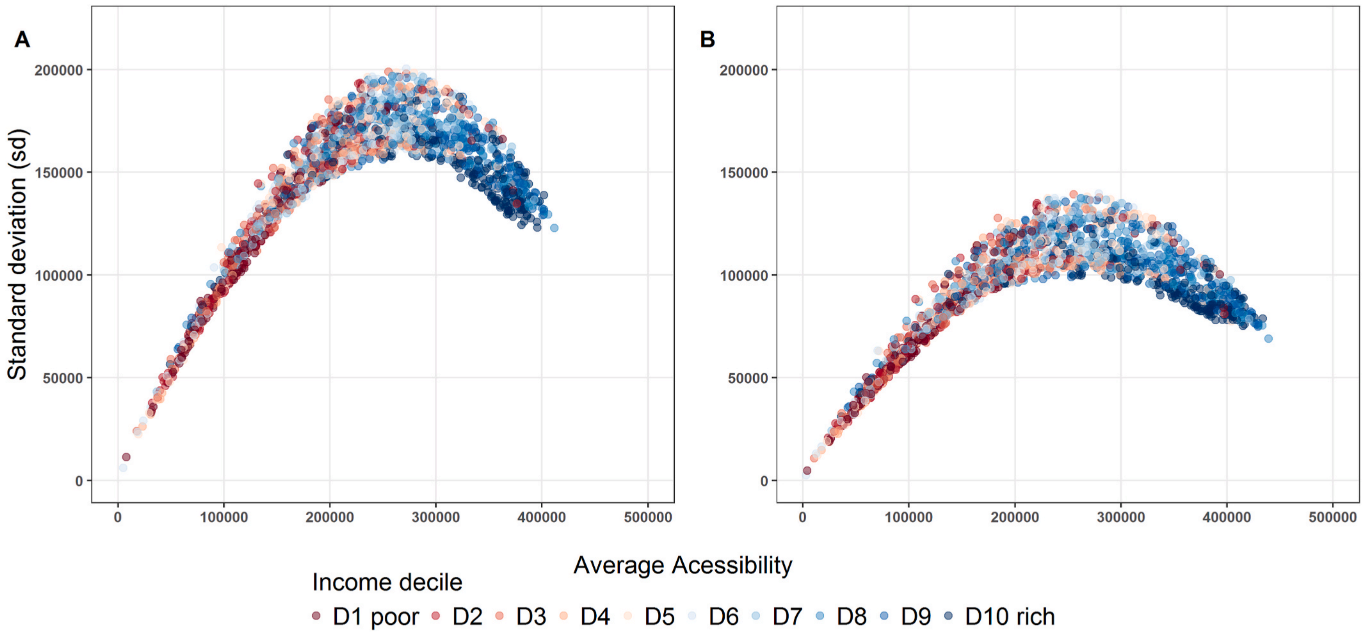

Fig. 9. The average accessibility of hexagons by income decile and their standard deviation for the cut-off approach (A) and for the time interval approach (B). Obs. For this example, we used time intervals of random sizes with a minimum size of 10 min in the Monte Carlo simulations.

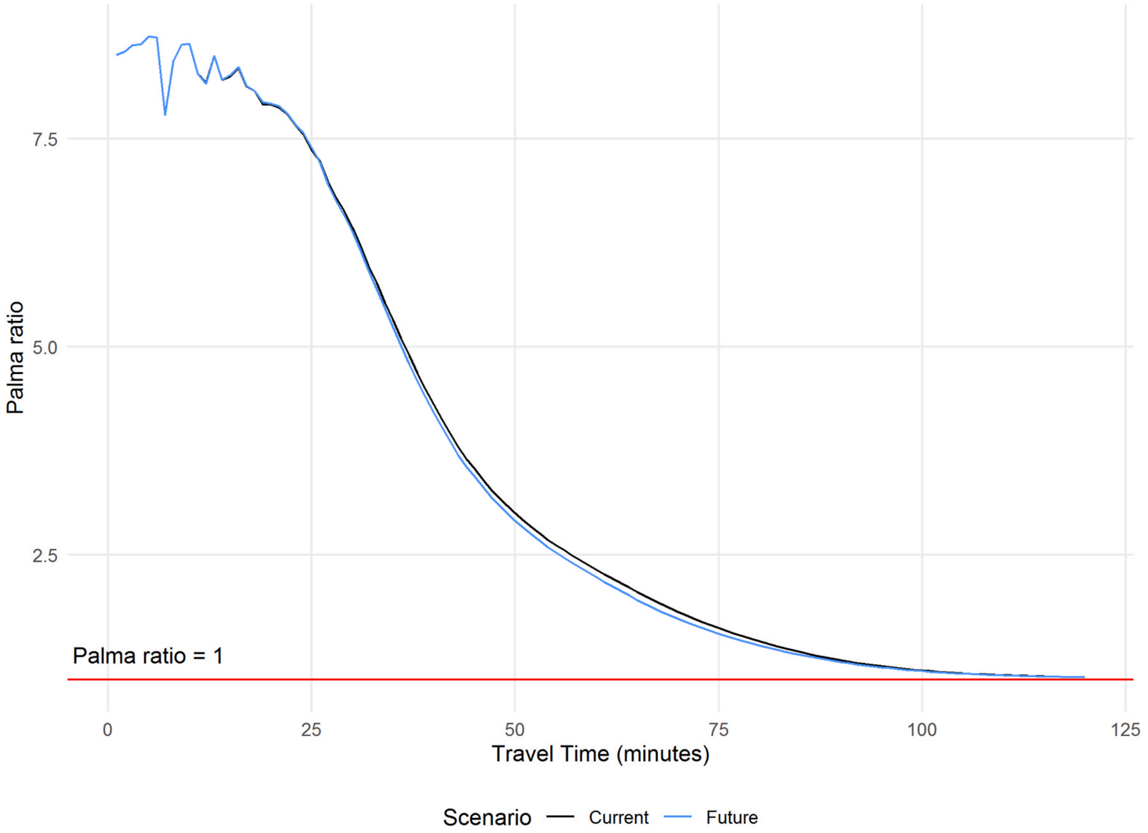

Fig. 10. Palma Ratio by travel time cut-off.
Obs. Horizontal red line indicates where the Palma ratio equals 1.

interval cumulative accessibility metric involves an *ad-hoc* choice of a time interval. Another limitation is that it considers all opportunities under the interval equally accessible, regardless of whether they are 15 or 40 min away, for example. In these aspects, the proposed time interval indicator shares a couple of the same limitations as traditional cutoff-based cumulative measures of accessibility. Moreover, just as there is no single best time threshold for every accessibility analysis, there is no ideal time interval. The appropriate start point and width of the time interval are likely to vary depending on the local context, trip purpose, and transport mode. Nonetheless, as shown in the results

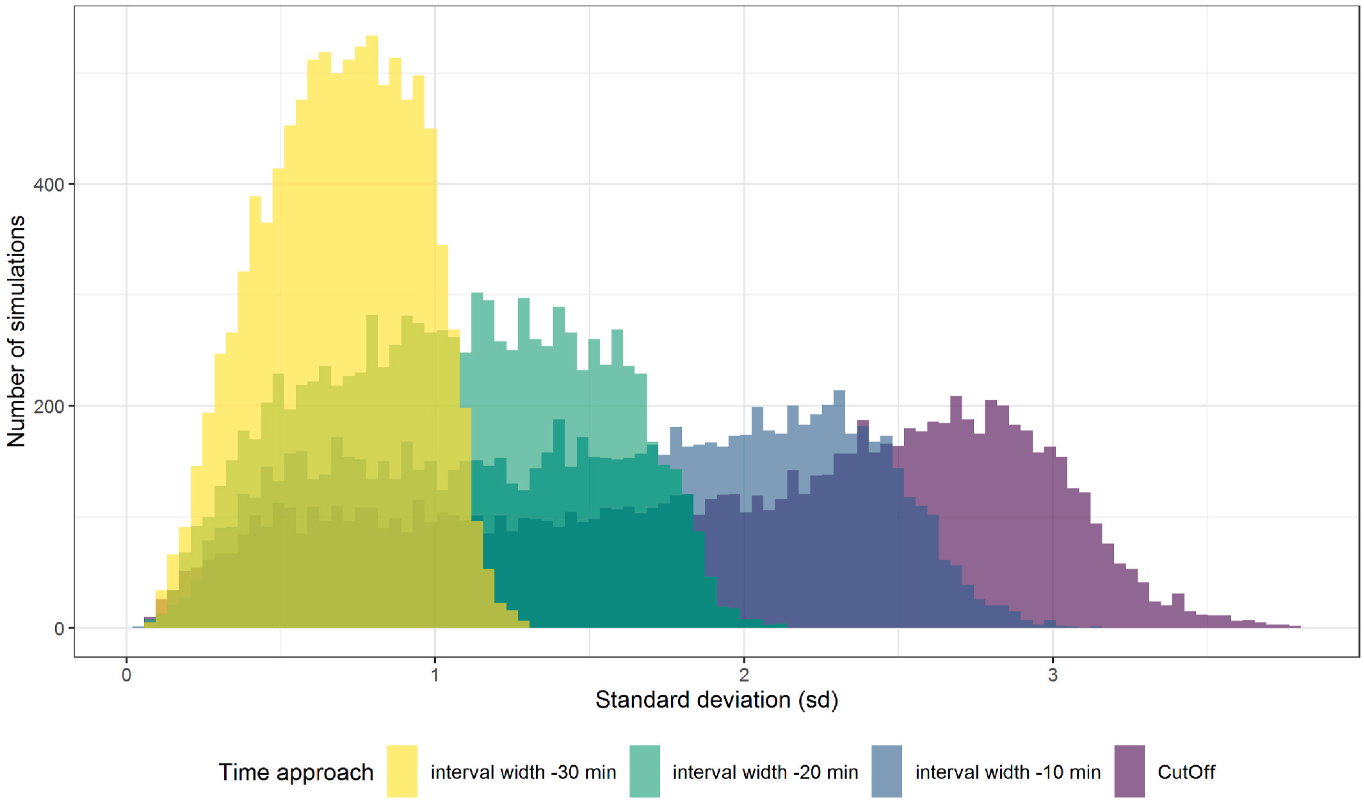

Fig. 11. The standard deviation of the Palma ratio using different travel time cut-offs and travel time intervals.

section, there is a tradeoff between the width of the time interval and the sensitivity of the results. In practice, this tradeoff could be an additional resource to guide the selection of time intervals for specific case studies. For example, this tradeoff can help inform researchers and practitioners when adopting a normative approach (Páez et al., 2012) regarding what range of trip duration could be considered reasonable/acceptable for a given transport mode and activity.

We believe the proposed accessibility metric could help future studies advance transport accessibility research with more robust estimates without compromising the communicability of results. The new time interval indicator could also open new questions for a future research agenda. For example, future studies could advance our understanding of the extent to which the sensitivity of accessibility results to time intervals and thresholds could vary across cities, by transport mode or type of activities (employment, health care, etc). Additionally, the proposed metric currently only looks at a summary measure of accessibility within the time interval. Yet, other studies could examine the continuous distribution within the time interval to generate more sophisticated estimates capturing uncertainties intervals. Finally, just as we propose to use time intervals to reduce the arbitrary effects of time threshold choices in cumulative measures, a similar approach could be used to summarize the accessibility results using different decay parameters in gravity-based accessibility models.

CRediT authorship contribution statement

Diego Bogado Tomasiello: Investigation; Methodology; Software; Writing – original draft, Visualization, Writing – review & editing.

Daniel Herszenhut: Investigation; Methodology; Software; Writing – original draft, Visualization, Writing – review & editing.

João Lucas Albuquerque Oliveira: Investigation; Methodology; Software; Writing – original draft, Visualization, Writing – review & editing.

Carlos Kaue Vieira Braga: Data curation; Investigation; Methodology; Software.

Rafael H. M. Pereira: Conceptualization; Data curation; Investigation; Methodology; Software; Project administration; Supervision; Visualization; Writing – original draft, Writing – review & editing.

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