
# Using New Urban Mobility Data in Accessibility Analysis

*Main Report*

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New Urban Mobility alliance

Title picture: *Cairo Bike* station in downtown Cairo, Egypt (11/08/22' TfC – Hazem Fahmy)

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## Glossary

| Acronym | Term |
|---|---|
| BRT | Bus Rapid Transit |
| COM | Cumulative Opportunities Measure |
| DRT | Demand-Responsive Transit |
| GBFS | General Bikeshare Feed Specification |
| GTFS | General Transit Feed Specification |
| LRT | Light Rail Transit |
| NUM | New Urban Mobility |
| OD | Origin-Destination |
| OSM | OpenStreetMap |
| PBF | Protocolbuffer Binary Format |
| PT | Public Transport |

# Terminology and Taxonomy of Modes

Definitions specified here are specific to this project but should also align with existing literature.

## Modes

***Car-based mobility:*** private automobiles; taxicabs; car-based ride-hailing and ride-sharing services.

***Active travel***: walking and cycling

***Collective Transport:*** public or mass transport. Vehicles where a group of strangers share a ride, either organized privately or through a public authority

***Micromobility***: small, lightweight vehicles that operate at speeds typically below 25km/h (bicycles, e-bikes, electric scooters, mopeds). They are ideal for trips up to 10km

***Bike share / e-scooter share***: the provision of micromobility vehicles for short-term rent (normally in exchange for a fee). This service can use ***docked*** or ***dockless*** vehicles

***Docked***: vehicles are borrowed from a dock and returned to a dock belonging to the same system.
***Dockless***: Free-floating bikes that do not require a docking station. Users can use GPS functionality on an app to find the nearest dockless bike, rent it, and then park it by the side of the road. Dockless bikes normally have geographic operating boundaries that users should stay within.

**Ride-hailing**: on-demand car or scooter trips that are normally ordered via a smartphone application (e.g. Uber)

**Ride-sharing**: similar to ride-hailing, but trips are shared with other passengers that are going in a similar direction. The vehicle makes stops along the way to pick-up and drop off passengers

**Demand-responsive transit (DRT)**: Services that operate on a schedule along a fixed path, but allow minor itinerary deviations in response to passenger demand

## Datasets

***General Transit Feed Specification (GTFS)***: A common format for modelling public transport supply. GTFS feeds capture the geographic path, operating schedule, and travel time for public transport routes. They can be consumed by multimodal journey planners to recommend itineraries.

***General Bikeshare Feed Specification (GBFS)***: Open data standard for shared mobility.

***Protocol Binary Format (PBF)***: efficient format for storing OSM data. Routing engines such as Open Trip Planner consume OSM road network data in the form of PBF files.

***GPS trackpoint:*** A GIS point representation of GPS points captured by moving vehicles. GPS coordinates normally include timestamps and vehicle speeds and can be used to calculate road segment level speed data.

***Origin-destination (OD) data***: data that captures movement between an origin and a destination. Origins and destinations are either point locations or zones. Non-geographic attributes include trip mode, time of day, and travel time.

***Cumulative Opportunities Measure (COM):*** a method of quantifying accessibility by cumulatively counting the number of opportunities reachable from an origin within a specified travel time threshold.

## Taxonomy of Modes

New Urban Mobility can be used to refer to a variety of transport options that have emerged over the past few years. Looking at Figure 1, we consider all modes with a red outline to be New Urban Mobility (NUM) modes (except for taxi-cabs). The focus of this research will be on incorporating micromobility modes (not all NUM modes) within an accessibility analysis framework.

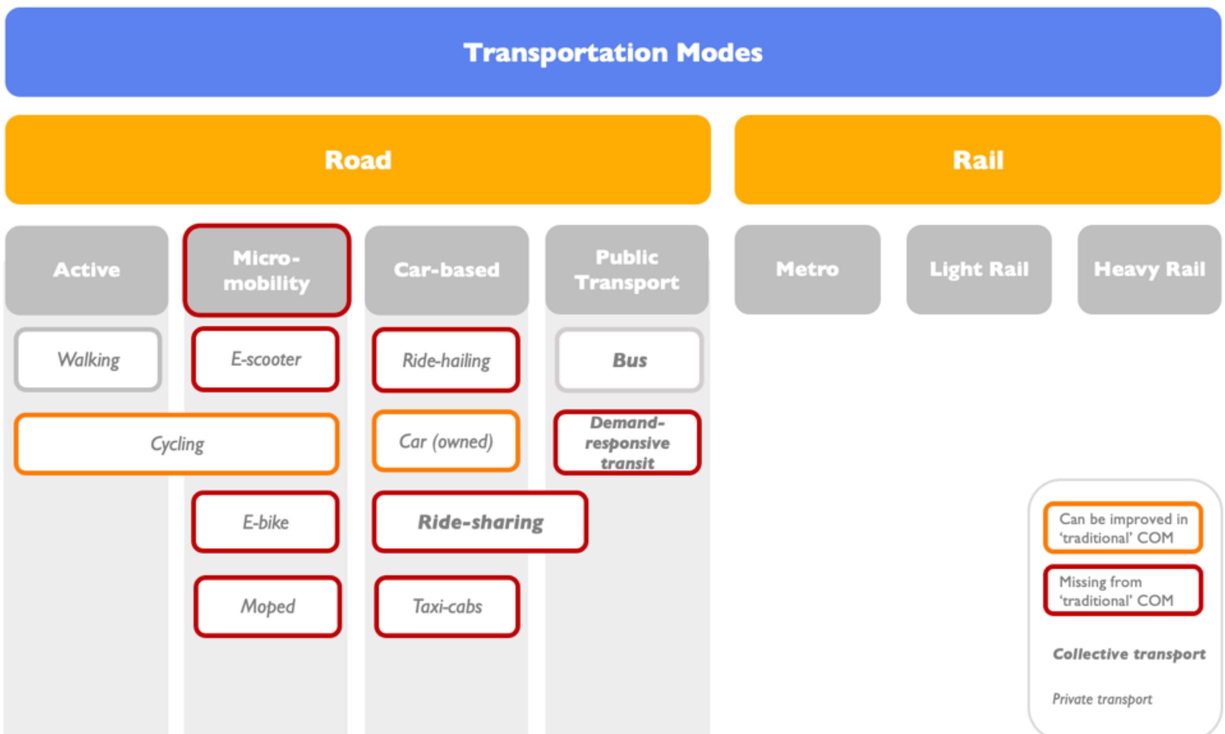


Figure 1: Road and rail mode taxonomy in relation to a Cumulative Opportunities Measure accessibility analysis

# 1 Project Overview and Objectives

New Urban Mobility (NUM) modes offer a novel way for commuters and travelers to leverage their city's public transport infrastructure and achieve their accessibility goals. The effect of these NUM modes is not adequately researched and understood by policymakers and the research community due to a lack of data and realistic representation in analyses.

In transport planning, accessibility refers to the ease with which people can reach destinations or activities. Accessibility analysis has gained importance in transport and land use research, planning and policy making. It is at the core of different research areas, such as comparing access to opportunities by different modes; evaluating travel time variations between sustainable modes of travel and cars; and assessing equity and environmental justice of transportation by analyzing the disparities in access to opportunities experienced by different demographic and socio-economic groups.

While there are many approaches to evaluate and quantify accessibility in the context of transportation planning, the most common ones are predicated on the degree to which an origin point is connected to all other points in a network-like structure. The measure of this connectivity is based on travel time between the origin and every destination. Therefore, an accurate analysis of the accessibility achieved by different modes must make use of real-world travel times and transit schedules as well as the realistic availability of NUM vehicles. Moreover, given the difficulty in obtaining data and software capable of enabling this analysis, such effort should make use of open-source data and tools whenever possible.

The objective of this work is to produce a reproducible open-source methodology to compute and compare the accessibility to jobs by different modes, or combinations of modes. Since real-world speeds are often unavailable to researchers, car-based mobility is often assigned a theoretical free flow speed on roads which results in a skewed conclusions in favor of car-based mobility over public transport. With the availability of real-world speeds as well as accurate transit schedules, we can realistically model the effect of micromobility on accessibility and compare it to the full journey taken for car-based mobility. The methodology for this report would enable researchers, policymakers, and private NUM providers to realistically compute and communicate the importance of investing in active and collective transportation as well as micromobility services.

To that end, the contributions of this report can be summarized as follows:

1. ***Incorporating realistic travel times in the analysis***. This will include:
    a. Identifying (publicly available) datasets that can be used to estimate travel times on road segments.
    b. Developing a methodology for calculating road segment speed data using available datasets. Speed data at different times of day will be calculated
    c. Enriching OSM road network data with calculated road segment speeds
2. ***Integrating NUM modes in the analysis:***
    a. Defining all datasets necessary to conduct the analysis.
    b. Outlining and implementing a methodology for integrating micromobility into multimodal routing engines

   c. Determining realistic mode combinations to use when running the analysis (i.e. which modes are regularly used together in the same trip, and which aren't)
   d. Incorporating spatiotemporal supply constraints when modelling the effect of micromobility modes on accessibility. Spatiotemporal constraints can include availability of vehicles at stations throughout the day and geographic boundaries
   e. ***Developing mode combination narratives to evaluate the contribution of (a) different modes and (b) specific combinations of modes, on people's access to job opportunities***
      i. Quantifying the accessibility gain from micromobility
      ii. Quantifying changes in the spatial distribution of accessibility within different time thresholds
3. ***Operationalizing equity parameters into the analysis framework*** *by*:
   a. Defining accessibility metrics of different socioeconomic and demographic groups.
   b. Using pre-defined indicators in scenario-modelling to determine the socioeconomic and demographic composition of beneficiaries

We also want to empower communities in varying global contexts, from developed and well-planned cities to developing cities with more informality in the transportation and mobility sector. The methodology we develop can be equally effective in any context, given the use of open-source and globally available data sources. Our research will focus on the following four cities: San Francisco Bay Area, Minneapolis-Saint Paul, Mexico City, and Cairo.

In the main body of the report, we outline our proposed methodology, provide a brief background on the cities chosen for analysis, and present our results. The report is accompanied by a technical appendix and an executive summary. The technical appendix includes an in-depth literature review, more details on the methodology used, and documentation of the datasets and analysis pipeline. The executive summary provides a concise overview of the main findings of the analyses and associated policy recommendations.

# 2 Methodology

Our goal is to produce an efficient and reproducible method of modelling accessibility with respect to micromobility scenarios developed in the most realistic way possible. In attempting to operationalize this model, we must make assumptions and simplifications that approximate, to the best of our abilities, the complex realities of accessibility in cities. Our adopted accessibility analysis protocol is the so-called Cumulative Opportunities Measure (COM). Since the COM method of accessibility is highly dependent on travel time, it is crucial that the travel times and mode availability modeled for each mode we are considering be as realistic as possible. To that end we propose the following sub-modules to deal with (1) realistic travel time calculations for private cars, (2) estimate accessibility gain due to micromobility using heuristic-based route choice, and (3) measuring the social and spatial equity implications of micromobility systems.

## 2.1 Multi and Inter-Modal Accessibility Analysis

Using the COM, we evaluate accessibility at a 60-minute threshold, as well as 45, 30 and 15 minutes. While 60 minutes may be seen as an acceptable commute time, smaller thresholds are necessary for other trip purposes. We divide the study area into zones of varying sizes[1] and calculate the number of opportunities that can be reached from each zone's centroid during the morning peak period of 7:30 am – 9:30 am.

$$A_i = \sum_{j=1}^{n} O_j \times w_{i,j}$$

$\boldsymbol{A_i}$ $= \textit{Accessibility score for origin zone } i$

$\boldsymbol{O_j}$ $= Opportunities\ in\ destination\ zone\ j$

$\boldsymbol{n}$ $= number\ of\ zones$

$\boldsymbol{t_{ij}}$ $= travel\ time\ from\ i\ to\ j$

$\boldsymbol{t_{max}}$ $= Cutoff\ travel\ time\ (60\ minutes)$

$\boldsymbol{w_{i,j}}$ $\begin{cases} 1\ if\ t_{ij} \leq t_{max} \\ 0\ if\ t_{ij} > t_{max} \end{cases}$

The analysis allows us to quantify the impact of different mode combinations on accessibility. Public transport alone is the baseline mode. Adding NUM modes can result in quicker access and egress travel times, and consequently, higher accessibility scores. The higher accessibility scores can be measured for each zone as the improvement in accessibility between a mode combination and the baseline mode, as shown in the following equation.

**Improvements in Accessibility or Accessibility Gain:**

$$A_{i,2-1} = A_{i,2} - A_{i,1} = \sum_{j=1}^{n} O_j \times (w_{ij,2} - w_{ij,1})$$

[1] The diameter of a hexagonal zone is proportional to the population density of the area it is in. we adopt this method for computational efficiency

$\boldsymbol{A_{i,2-1}} = \; Accessibility\ gain\ of\ Mode\ Combination\ 2\ relative\ to\ Mode\ Combination\ 1\ for\ origin\ zone\ i$

$\boldsymbol{O_j} \quad = \; Opportunities\ in\ destination\ zone\ j$

$$(\boldsymbol{w_{ij,2}} - \boldsymbol{w_{ij,1}}) = \begin{cases} 1\ if\ t_{ij,2} \leq t_{max}\ and\ t_{ij,1} > t_{max} \\ 0\ if\ t_{ij,2} \leq t_{max}\ and\ t_{ij,1} \leq t_{max}\ OR\ if\ t_{ij,2} > t_{max}\ and\ t_{ij,1} > t_{max} \end{cases}$$

## 2.2 Modelling Realistic Car Travel Times

To model realistic car travel times, we rely on Uber Movement and Mapbox datasets. These are rich datasets that have road segment speeds at different levels of temporal granularity; Uber Movement data is aggregated by hour, time of day (morning / evening peak), and quarter (e.g. January – March 2020). In these datasets, each road segment is matched to an OSM Way ID. This underscores the operability of the speed datasets because OSM networks are consumed by many routing engines. The data received is averaged over many months to avoid the impact of non-recurring events like construction work and weather events (Uber, n.d.). The data is matched to the latest OSM build of the road network to create an updated PBF file. Using real speed data in routing is not a feature of any open-source routing engine. Therefore, the real-world speeds are added to the OSM PBF file as a *maxspeed* tag, so that the routing engine can use it instead of its defaults. This is accomplished using a tool built specifically for this work and made available publicly to the transportation community.

In addition to real-world speeds, we consider a door-to-door approach to car-based mobility. The stages of a car-based trip are (1) walking from the origin to the parked car (access), (2) driving to a point near the destination, (3) looking for a parking spot (cruise), and (4) walking from the parking spot to the destination (egress).

For (1) and (2), we associate parking time with residential density, and use different values for inner and outer zones of the study area, as done by Salonen and Toivonen (2013). Time spent walking to and from the car is also derived from empirical studies (Weinberger, Millard-Ball, and Hampshire 2016). Stage (2) is performed using the r5 routing engine that relies on our updated road network.

## 2.3 Modelling Intermodal Travel Times

In addition to car travel, the other modes we consider can be combined into an intermodal trip with the aim of transporting the traveler in the lowest possible travel time. The main alternative to car travel is public transport with walking, bicycling, and micromobility, as possible combinations to, or replacements of public transport, that can reduce travel time and increase accessibility. To understand the increased accessibility provided by micromobility and active travel when combined with public transport, we need to model intermodal travel times with realistic mode combinations. Such mode combinations would consider:

- Direct (or main) mode
- Access/Egress modes
- Maximum access/egress travel distance allowed per mode

These mode combinations are outlined in Figure 2.

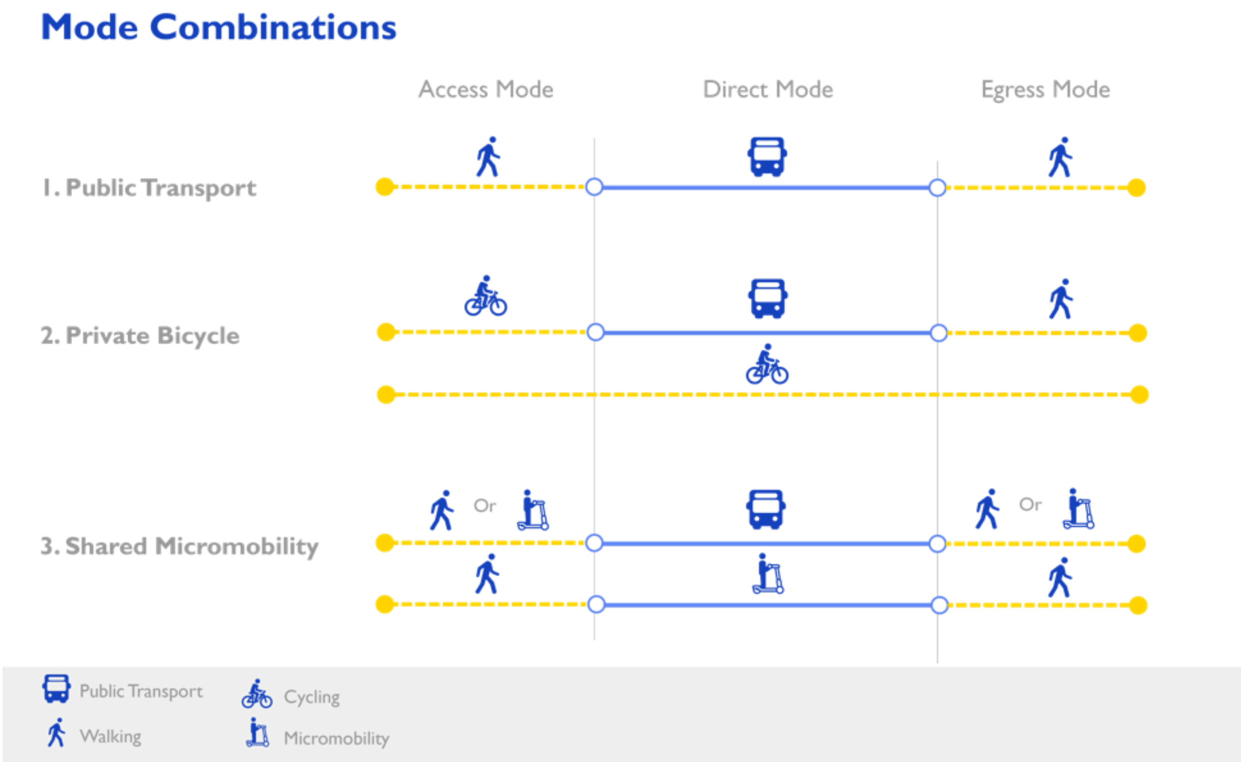


Figure 2: Mode combinations used in analysis

### 2.3.1 Public Transport: Travel Time and Distance

Public transport data is obtained from publicly available GTFS feeds. These feeds have data on existing routes, their itineraries, stops, and operating schedules. They are inputs to the routing engines that model realistic travel times between locations using a combination of graph-based algorithms (for street network routing of walking, cycling and car travel) and schedule-based algorithms (for public transport routing). Therefore, the use of GTFS feeds in computing the travel times by public transport ensures that the accessibility using this mode is sufficiently realistic.

### 2.3.2 Cycling: Route Choice, Travel Time, and Distance

Literature on cyclist typologies (Dill and McNeil 2013) has shown that the level of stress experienced by cyclists on roads is a major factor in willingness-to-cycle. In our approach to model realistic cycling routes, we cannot treat all roads equally as this would provide unrealistically optimistic results. Instead, we factor in the cycling Level of Traffic Stress (LTS) as defined by Dill and McNeil when evaluating cycling routes. We do so by assigning an LTS value to each road segment[2] based on their functional classes, speed limits and average traffic volumes, and the existence of cycling infrastructure (Furth, Mekuria, and Nixon 2016). Routing is prohibited on road segments with high LTS values, allowing us to calculate travel times that are representative for the majority of potential cyclists and not just the most confident.

[2] This is done using the r5 routing engine

Cycling route choices are also influenced by route hilliness. Research has shown that the number of people commuting by bicycle decreases significantly as route gradient increases (Lovelace et al. 2017). We use elevation models in our analysis to account for route hilliness in cyclist route choice.

#### 2.3.3 E-Bikes and e-scooters

We consider two main differences between traditional and electric motor-assisted micromobility vehicles: (1) travel speed and (2) the effect of road gradient on route choice and travel speed. One study examined the difference in speeds after matching on age, gender, trip purpose, and terrain, and found that the average moving speeds are 22.5km/h and 16.6km/h for e-bikes and traditional bicycles, respectively (Mohamed and Bigazzi 2019). We use the same speeds in our travel time calculations, capping them at the existing speed limits. Given that road gradient is less of an impedance for electrically assisted vehicles, we choose to ignore it when modelling e-bike and e-scooter travel times.

### 2.4 Shared Micromobility

When modelling travel time with the micromobility scenario, we focus on two aspects that distinguish it from traditional owned bicycles:

- *Geographic scope*: Micromobility services have a defined geographic scope, whether that is a service area (dockless) or station locations (docked). Unlike owned bicycles, shared micromobility services are only available in specific areas.
- *First/last-mile functionality*: Given reasonable travel distances, both owned bicycles and micromobility services can be used as the sole mode for an entire commute. However, when it comes to multimodal trips that include cycling, micromobility services can readily function as first and last-mile options in the same trip. This is because users can rent a shared bike and dock it near the transit stop, and then rent another bike at the end of the transit leg of the journey. However, owned bicycles are normally used as a first-mile solution only due to the impracticality (or infeasibility) or transporting bicycles on a bus or train journey.
- *Supply Constraints*: Micromobility services and their associated advantages can only be achieved if there is availability of vehicles. To model the varying nature of micromobility availability across the geographic area, we apply supply constraints to limit the improvements in accessibility by a factor proportional to their availability in a specific zone within the analysis time window.

The *geographic scope* component affects where micromobility is an option, and the *first/last-mile functionality* component affects the type of multimodal trips that can contain micromobility. Supply constraints, which can be regarded as a third aspect that differentiates shared micromobility from owned bicycles, are considered in the next section as they do not factor into the travel time computation.

#### 2.4.1 Access and Egress Travel Distances

For the access and egress legs of a trip, we define maximum distances for walking and cycling. These are derived from stated preference surveys of acceptable travel distances (Bachand-Marleau, Larsen, and El-Geneidy 2011). Using the speeds mentioned earlier, the values are converted to maximum travel times. A walking speed of 3.6 km/h is used.

Table 1: Maximum access / egress travel distance by mode

| Mode | Maximum access / egress distance (m) | Maximum access / egress time (min) |
|---|---|---|
| Walking | 650 | 10.8 |
| Micromobility (Cycling) | 2500 | 9 |
| Micromobility (Electric-Motor Assisted) | 3750 | 10 |

### 2.4.2 Supply Constraints of Shared Micromobility Systems

One major difference between shared micromobility and owned micromobility is availability. A user can ride an owned vehicle whenever they wish, whereas the usage of a shared vehicle is constrained by its availability. To present a more realistic estimate of accessibility using shared micromobility, we account for these supply constraints.

We choose to do so spatiotemporally, by looking at the station-level[3] availability of bikes for our chosen observation period. We use MDS data to determine the number of vehicles at each station for every minute during our observation period (see Figure 3 for an example on the distribution), and calculate the probability of finding a bike in a given observation period.

The probability of finding a bike at a station $(s)$ is calculated as:

$$s = \frac{t_{av}}{t_{total}}$$

$t_{av}$ $= number\ of\ minutes\ with\ bikes\ available > cut - off\ threshold$

$t_{total}$ $= Observation\ period\ (minutes)$

Intuitively, a station can be said to have available bikes if the number of bikes is greater than 0. However, most stations can have bikes that are officially in circulation but practically unusable (Kabra, Belavina, and Girotra 2020). We choose a cut-off threshold of 2 bikes, which is more forgiving than that used in previous literature, 5 (Kabra, Belavina, and Girotra 2020).

[3] Docked: station-level; Dockless: zone-level

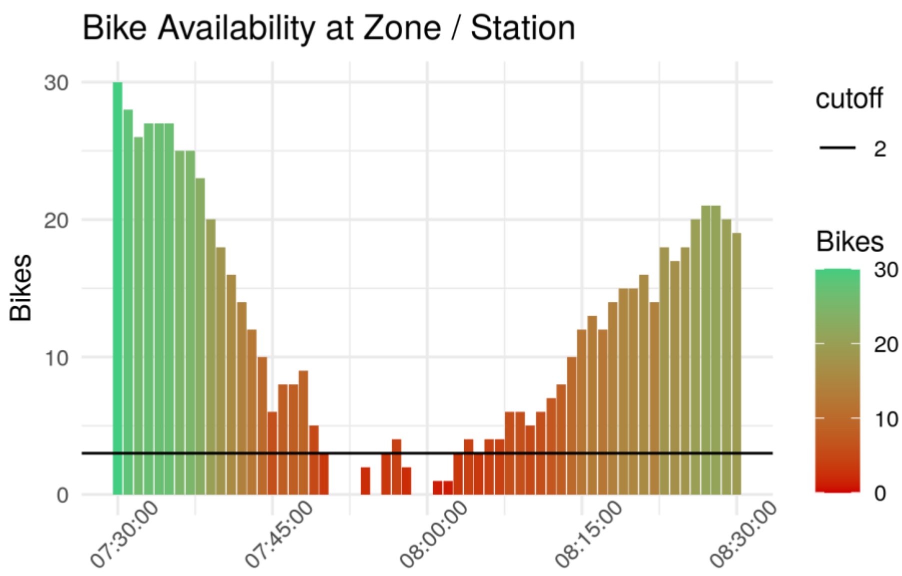


Figure 3: example station-level, temporal bike availability

The accessibility gain due to micromobility is only achieved by those who find a shared vehicle available during their trip. Compared to no supply constraints in vehicle availability, this reduced accessibility should only apply to opportunities that would otherwise not have been reached using public transport alone. To elaborate, if a zone's opportunities could have been reached in Mode Combination 1 (public transport alone) then the supply constraint on micromobility should not discount those opportunities because a traveller can always use public transport to reach those opportunities when there are no micromobility vehicles available. Whilst for zones that are only reachable within the maximum time threshold because of the addition of micromobility as an option in Mode Combination 3, the zone's opportunities are reduced by a factor proportional to the probability of finding a vehicle ($s$). When calculating the accessibility for each zone resulting from micromobility Mode Combination 3, the probabilities of finding a vehicle ($s$) at both the origin and destination are accounted for as follows:

**Accessibility Gain between mode combinations 3 and 1 given supply constraints at origin and destination:**

$$\boldsymbol{A}_{\boldsymbol{i},\mathbf{3-1}} = s_i \sum_{j=1}^{n} d_i \times d_j \times s_j \times O_j \times (w_{i,j,3} - w_{i,j,1})$$

Where:

$s_i = \textit{probability of finding a vehicle at origin zone}$

$s_j = \textit{probability of finding a vehicle at destination zone}$

$$d_i = \begin{cases} 1 \; if \; micromobility \; used \; as \; access \; between \; zones \; i \; and \; j \\ \frac{1}{s_i} \; if \; micromobility \; not \; used \; as \; access \; between \; zones \; i \; and \; j \end{cases}$$

$$d_j = \begin{cases} 1 \; if \; micromobility \; used \; as \; egress \; between \; zones \; i \; and \; j \\ \frac{1}{s_j} \; if \; micromobility \; not \; used \; as \; egress \; between \; zones \; i \; and \; j \end{cases}$$

$$O_j = Opportunities \; in \; destination \; zone \; j$$

$$(w_{ij,3} - w_{ij,1}) = \begin{cases} 1 \; if \; t_{ij,3} \leq t_{max} \; and \; t_{ij,1} > t_{max} \\ 0 \; if \; t_{ij,3} \leq t_{max} \; and \; t_{ij,1} \leq t_{max} \; OR \; if \; t_{ij,3} > t_{max} \; and \; t_{ij,1} > t_{max} \end{cases}$$

Given that $s_i$ and $s_j$ are necessarily less than 1, we set their values to 1 when micromobility is part of the only mode combination that reaches the destination within the travel-time threshold (we use a value of 1 to ignore the parameter when micromobility is not used). This is achieved using the binary parameters $d_i$ and $d_j$ in the equation above.

For docked micromobility vehicles, we only consider the probability of finding a bike and ignore the probability of finding an empty docking point at the end of a trip. Docked systems usually have many more docking stations than bikes (to allow for fleet rebalancing throughout the day), so we assign a probability of 1 to finding a dock (Kabra, Belavina, and Girotra 2020).

## 2.5 Equity Considerations

The final objective of the project is to analyse the equitable distribution of the beneficiaries of accessibility gain due to micromobility. We calculate the changes in accessibility as experienced by the populations of the zones witnessing these changes. Since the zones' population can be stratified into groups based on race[4] and household income, we calculate the changes in accessibility for each group.

The accessibility gain experienced by a zone's population can be expressed as a weighted average of the accessibility gain [jobs] of a group residing in the zone. We call this metric the Weighted Average Accessibility (WAA) by group. It is computed by dividing the sum-product of the accessibility of the zone *I* and the population of the group residing in that zone *m* with the total population of group m in the city as seen in the equation below.

$$Weighted \; Average \; Accessibility_m = \frac{\sum_i^n Pop_{i,m} \times A_i}{\sum_i Pop_{i,m}}$$

Where:

$Pop_{i,m} = Population \; of \; group \; m \; in \; zone \; i$

$A_i = Accessibility \; in \; zone \; i$

[4] This is applicable for US cities only. we use census data on racial composition and household income at the US census block level

The WAA can shed light on the accessibility per group and the discrepancy or inequity between different groups based on their residential locations. This can show where infrastructure investments can bridge the gap between the different population groups by improving the lowest scores without decreasing the accessibility scores of the highest groups.

Infrastructure interventions that result in a different accessibility score for each zone can be compared to the status quo by computing the WAA gain or improvement. To achieve this metric, we would only have to substitute the $A_i$ in the above equation with $A_{i,3-1}$ which represents the accessibility gain in zone I between mode combinations 3 and 1, namely the accessibility gain achieved by adding micromobility to the existing public transport access.

The goal of equitable policy is to bridge the gap between the existing accessibility levels between groups by improving the accessibility of groups with the lowest existing accessibility. This would first require assessing the variability of accessibility between groups and then gauging how different interventions affect that inequality. One metric that can quantify the existing inequity in accessibility and the effect of different mode combinations on it is the Gini coefficient and its visual representation, the Lorenz Curve.

### 2.5.1 Spatial variations in accessibility

The equation for WAA does not express the spatial distribution of the beneficiaries since that distribution is aggregated over all the zones. However, the spatial distribution of accessibility gains is displayed on choropleth maps along with the spatial distribution of the social/demographic distributions of the population to visually identify the benefits gained across the cities.

# 3 Demographics and Multimodality of the chosen cities

## 3.1 Cairo

### 3.1.1 Spatial distribution of people and jobs

With over 20 million inhabitants, the Greater Cairo Region (GCR) is the most populous urban agglomeration in Africa. The daytime population of the city is likely to be larger due to high levels of centralization of services and jobs. The government has been constructing New Urban Communities (NUCs) which act as suburbs to the GCR. While 8 of these NUCs have been built around Cairo since the 80s, the majority of the population is concentrated in the inner and central zones of the city (Figure 4). The outer zones, consisting of NUCs, only account for around 6% of the population, even though they occupy over 40% of the urban footprint of the GCR.

The same is true for jobs: Central Giza and Cairo have the highest job density, while only an estimated 10% of jobs exist in the NUCs. This could be explained by the presence of most government facilities in these areas. It remains to be seen what the effect of moving these jobs to the New Administrative Capital will have on commuting patterns. It should be noted that the visuals, and our analysis, do not include the NUCs. We consider this to be reasonable since the proposed bike share system in Cairo will be in central Cairo. Including the NUCs would entail a zoomed-out lens that diverts attention away from the focal point of central and inner Cairo.

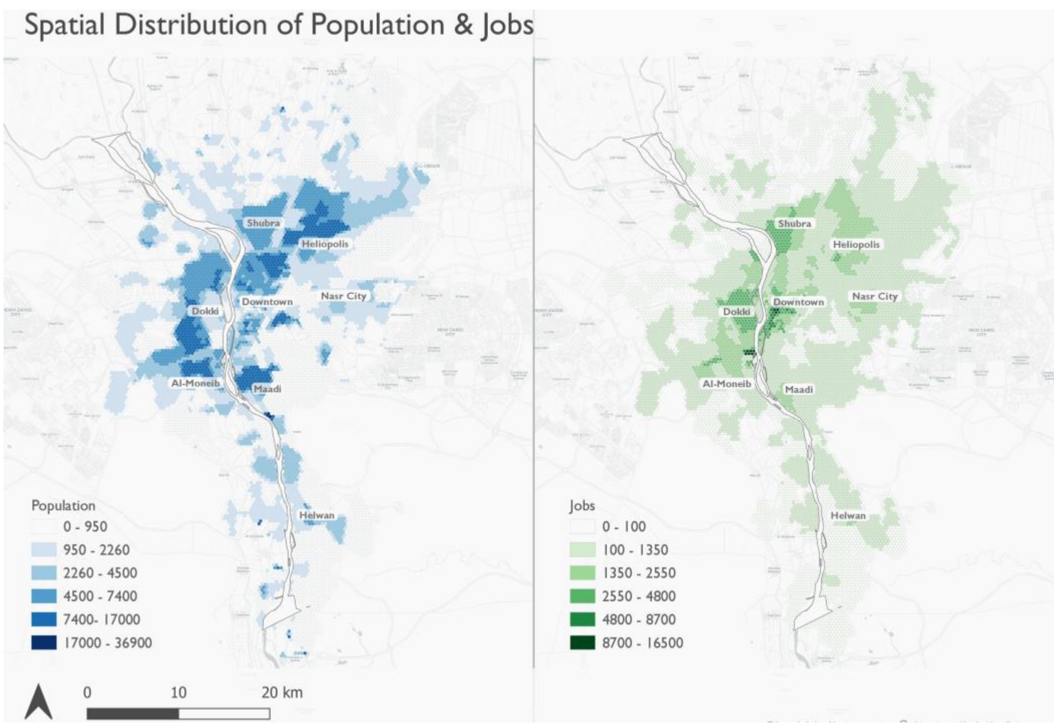


Figure 4: Population and Job distribution – Cairo

### 3.1.2 Spatial distribution of transport supply

The GCR is served by many public transport modes including Metro, Bus, Minibuses, Microbuses, Suzuki/Vans and Shared Ride Hailing vehicles. Light Rail Transit, Monorail and High-Speed Rail lines are currently under construction in GCR.

Microbuses provide most public transport services and carry the highest number of passengers. These are privately operated small 14-seaters which offer comparatively fast non-stop services on medium length routes. They typically operate on a fill-and-go arrangement with a low headway typically less than 10-minutes for each route. The Cairo Transport Authority (CTA) is a public company which operates large Bus (49-seater) and Minibus (29-seater) routes. CTA Buses and Minibuses carry a third to a quarter the number of passengers carried by Microbuses. CTA routes are less frequent, with headways between 20-minutes and 1-hour. Microbuses are more ubiquitous, as they tend to serve areas neglected by the CTA, while also operating on routes that are similar to those of the CTA.

Cairo's first bikeshare system, called Cairo Bike, launched in the summer of 2022. The project is primarily promoted by UN-Habitat and was initially supported by a grant from the Drossos foundation. The network will be delivered in 3 phases, the first of which is shown in Figure 5. The scope of the project includes 15 km of segregated bike lanes in downtown Cairo.

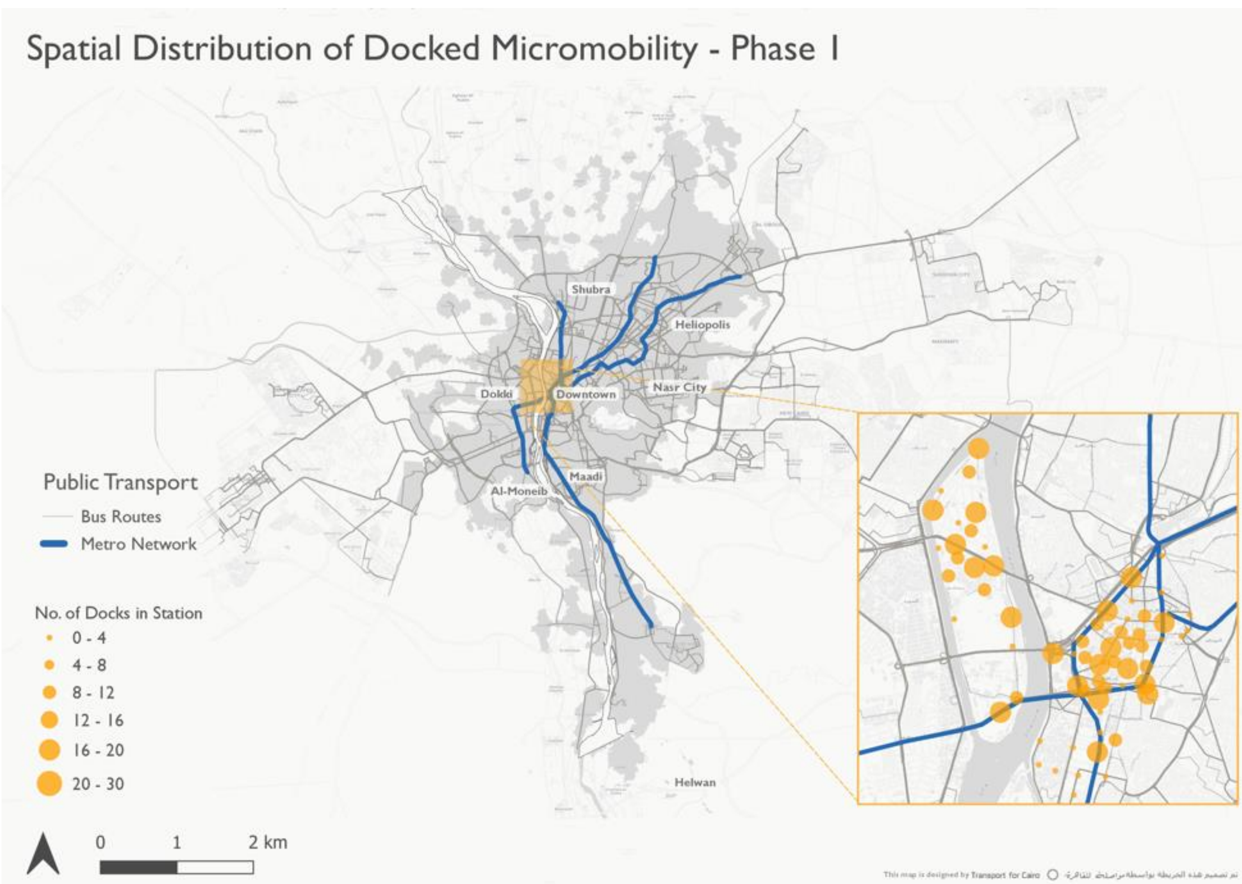


Figure 5: Phase 1 of the Cairo Bikeshare System

## 3.2 Mexico City

### 3.2.1 Spatial distribution of people and jobs

With a population over 9 million and an area of 1495 km², Mexico City is the largest and most populous urban agglomeration in North America. As of 2021, there were 4.5 million people employed in the city ("Ciudad de México: Economy, Employment, Equity, Quality of Life, Education, Health and Public Safety" n.d.). The most common job sectors include Sales, Dispatching, and Bus and Taxi drivers. Jobs are concentrated in the traditional centre of Mexico City, as shown in Figure 6.

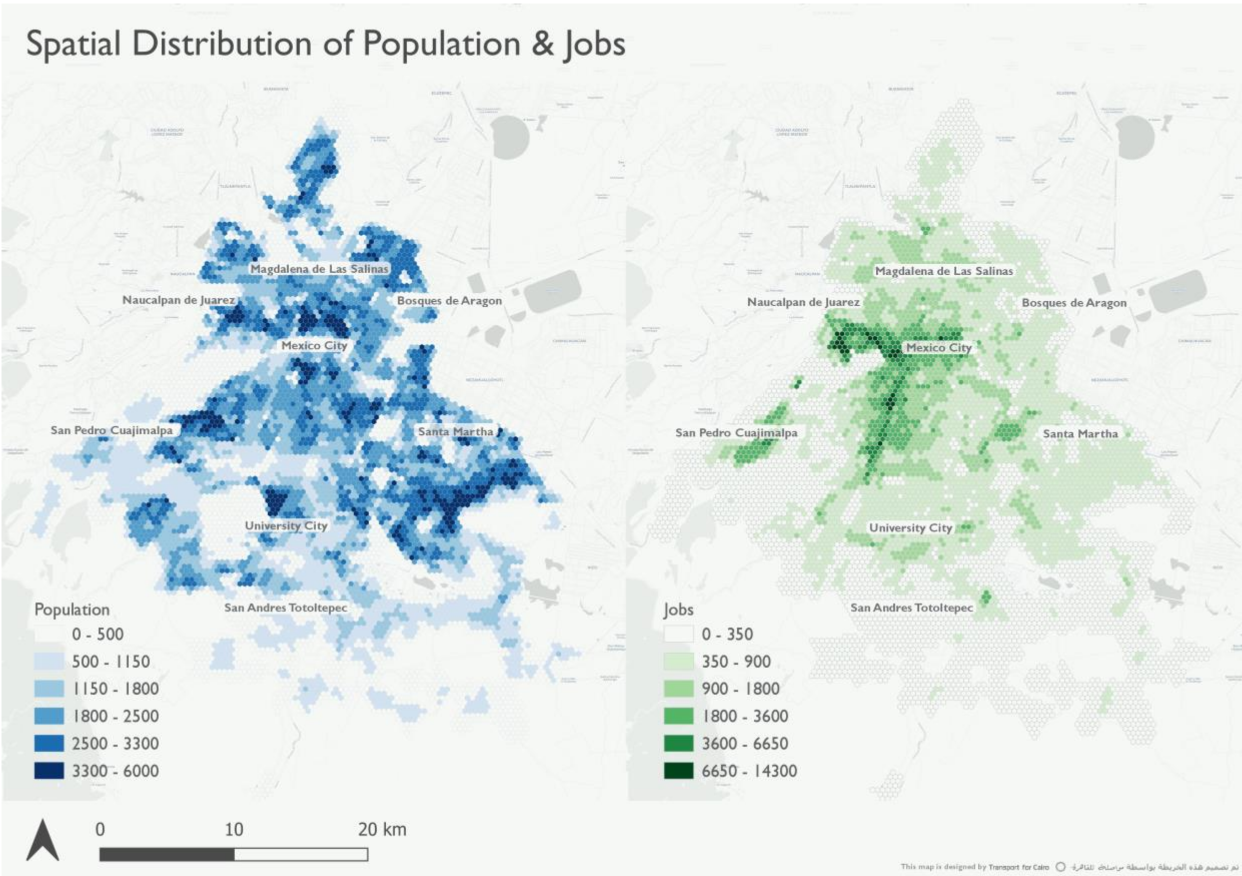


Figure 6: Population and Job distribution – Mexico City

### 3.2.2 Spatial distribution of transport supply

Several different transport modes operate in Mexico City. The city is served by a vast metro network, comprising of 12 lines, as well as a range of road surface transport options. These include 9 trolleybus lines (with a further 3 either planned or under construction), a bus rapid transit network (metrobus) with 7 lines, a huge microbus (or pesero) fleet. Two Cablebús lines operate to improve accessibility to neighborhoods in elevated parts of the city, with a another 2 planned.

In 2010, the city inaugurated a docked bikeshare network (ECOBICI). The network has almost 500 docking stations and is focused on the historic center of the city as well as some surrounding neighborhoods (Figure 7). The card used to access bikes at the docking stations also works for the metro, the light rail, and the metrobus, making for seamless transfers.

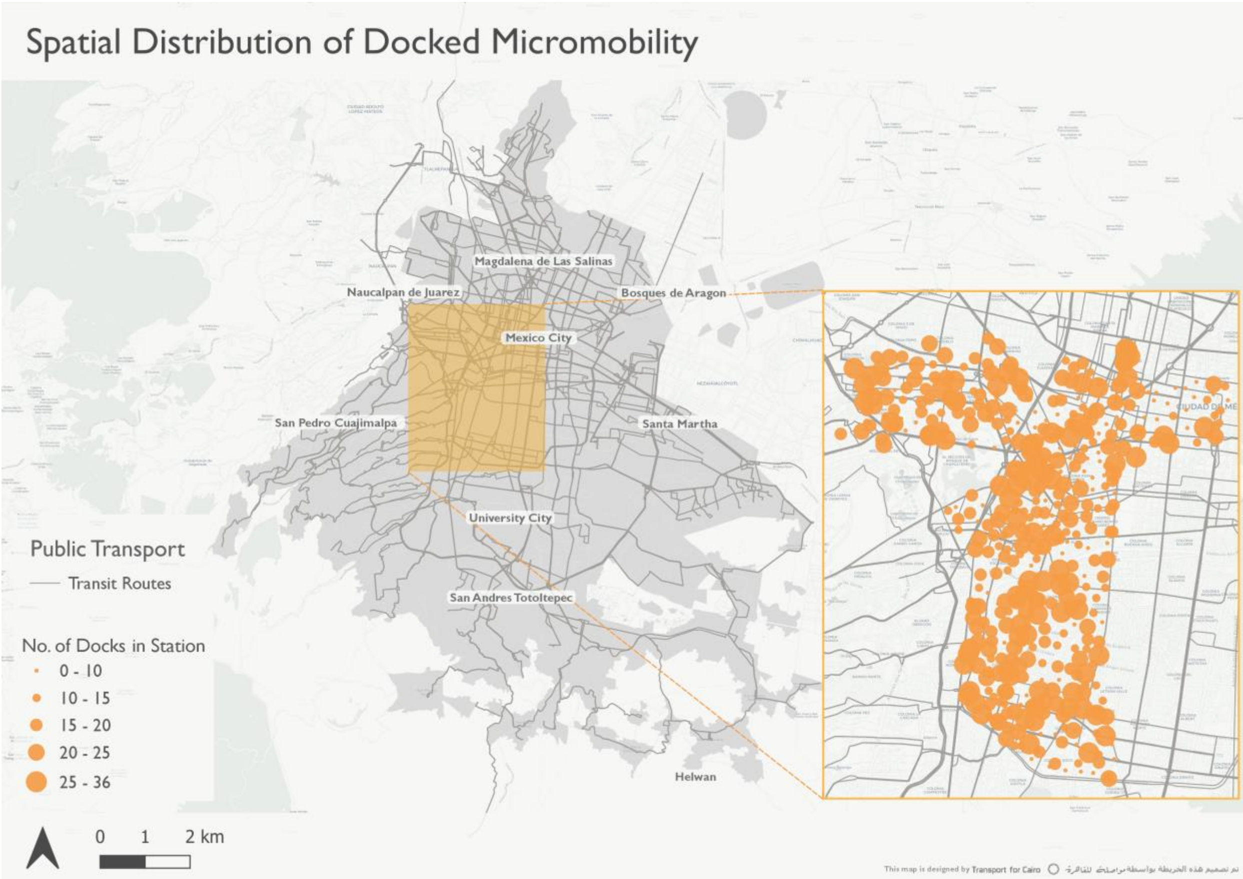


Figure 7: Docked micromobility (ECOBICI) – Mexico City

## 3.3 Minneapolis-Saint Paul

### 3.3.1 Spatial distribution of people and jobs

Minneapolis-Saint Paul, commonly known as the Twin Cities, joins the largest city in Minnesota with the state capital of Saint Paul. The Metropolitan Statistical Area includes 15 counties; however, we only include the 6 counties under the Metropolitan Council in our analysis due to their public transport connectivity with the center. They are Anoka, Carver, Dakota, Hennepin, Ramsey, Scott and Washington. The combined population of these counties is over 3 million inhabitants according to the 2020 Census.

The area is the second largest economy in the Midwest and the 13th largest in the USA[5]. As shown in Figure 8, the spatial distribution of jobs centers in Minneapolis on the left and Saint Paul on the right, with some smaller suburban job centers in the counties to the Southwest.

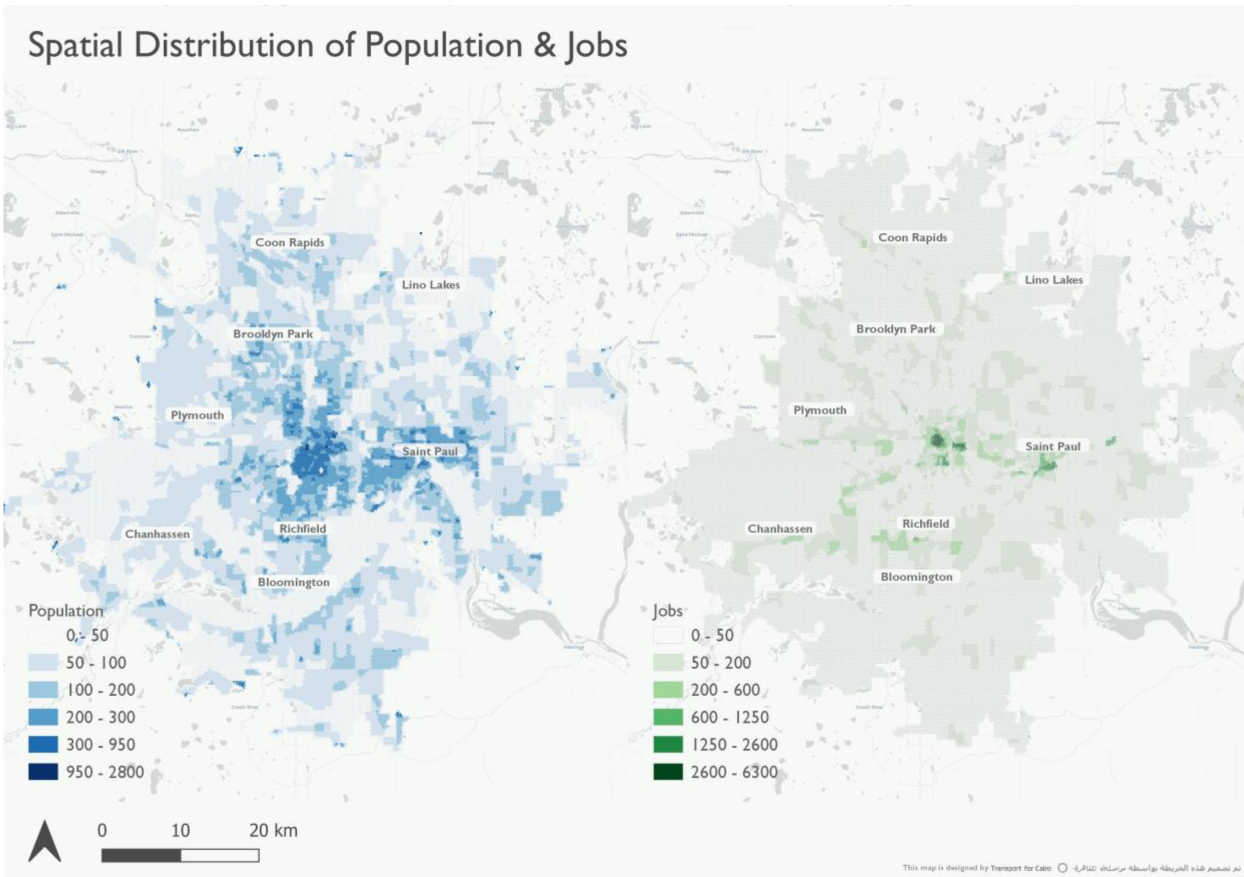


Figure 8: (Left) Distribution of population across the Minneapolis-Saint Paul study region (Right) the distribution of jobs in the region

[5] According to the Bureau of Economic Analysis <https://www.bea.gov/data/gdp/gdp-county-metro-and-other-areas>

### 3.3.2 Spatial distribution of transport supply

The Twin Cities area exhibits the typical shape of US cities with a historical core surrounded by suburbs connected by highways and little rail transit. There are 7 interstate freeways, 6 US Highways, and 19 major state highways that bisect the Twin Cities. On the other hand, MetroTransit provides almost all of the area's public transport, mainly bus routes, light rail, and one commuter rail line. There are 2 Light Rail Transit (LRT) lines connecting downtown Minneapolis with (Blue Line) the airport and commercial center and (Green Line) the University of Minnesota and Union Depot in downtown Saint Paul. There are an additional 4 Bus Rapid Transit (BRT) lines that either extend the LRT routes to southern suburbs (BRT Red extends to the South and Orange extends to Burnsville) or serve as upgrades to bus routes. One commuter rail line runs 40 miles north through northern suburbs.

The city also has several micromobility providers, both docked and dockless bicycles as well as e-scooters. Their service geography and station locations are limited to city of Minneapolis but not Saint Paul or the suburbs.

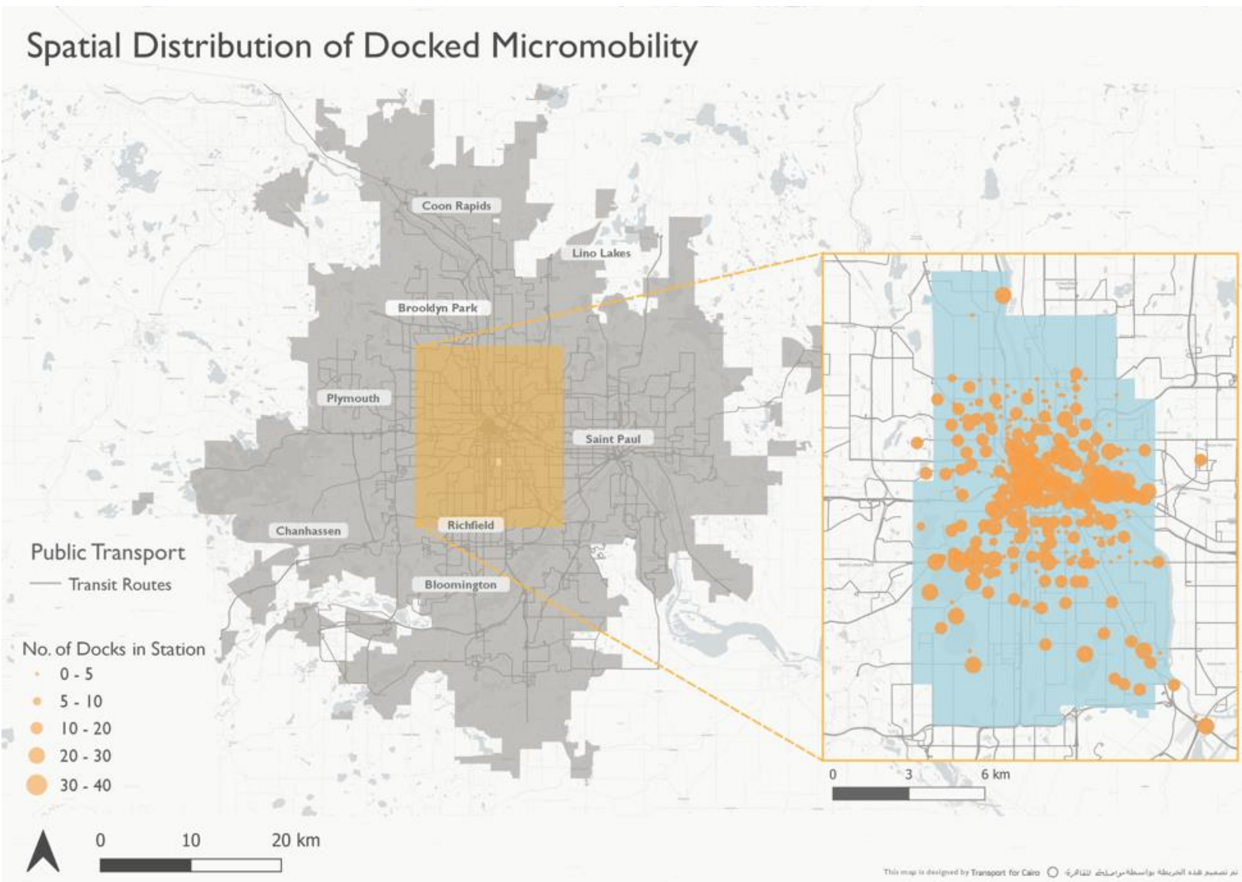


Figure 9: Spatial distribution of docked and dockless micromobility - Minneapolis

## 3.4 San Francisco

### 3.4.1 Spatial distribution of people and jobs

The five counties of the San Francisco (SF) Bay Area, chosen as our study region, are well connected by roads, bridges, buses, and rail. The study region includes more than six million residents of varying ethnic, racial, and economic groups. The concentrations of the populations can be seen in the left map of Figure 10, which shows highly populated centers in San Francisco city, San Jose, and Richmond.

The economic hubs of the SF Bay Area are in the central business districts of San Francisco and Oakland as well as in Silicon Valley. Silicon Valley roughly corresponds to Santa Clara Valley in the South Bay and along the peninsula of San Mateo. The area has the headquarters of some of the world's largest technology companies like Google, Apple, Meta, and Salesforce, to name just a few. It also has a significant concentration of venture capital money and all its associated jobs along the length of the Bay Area.

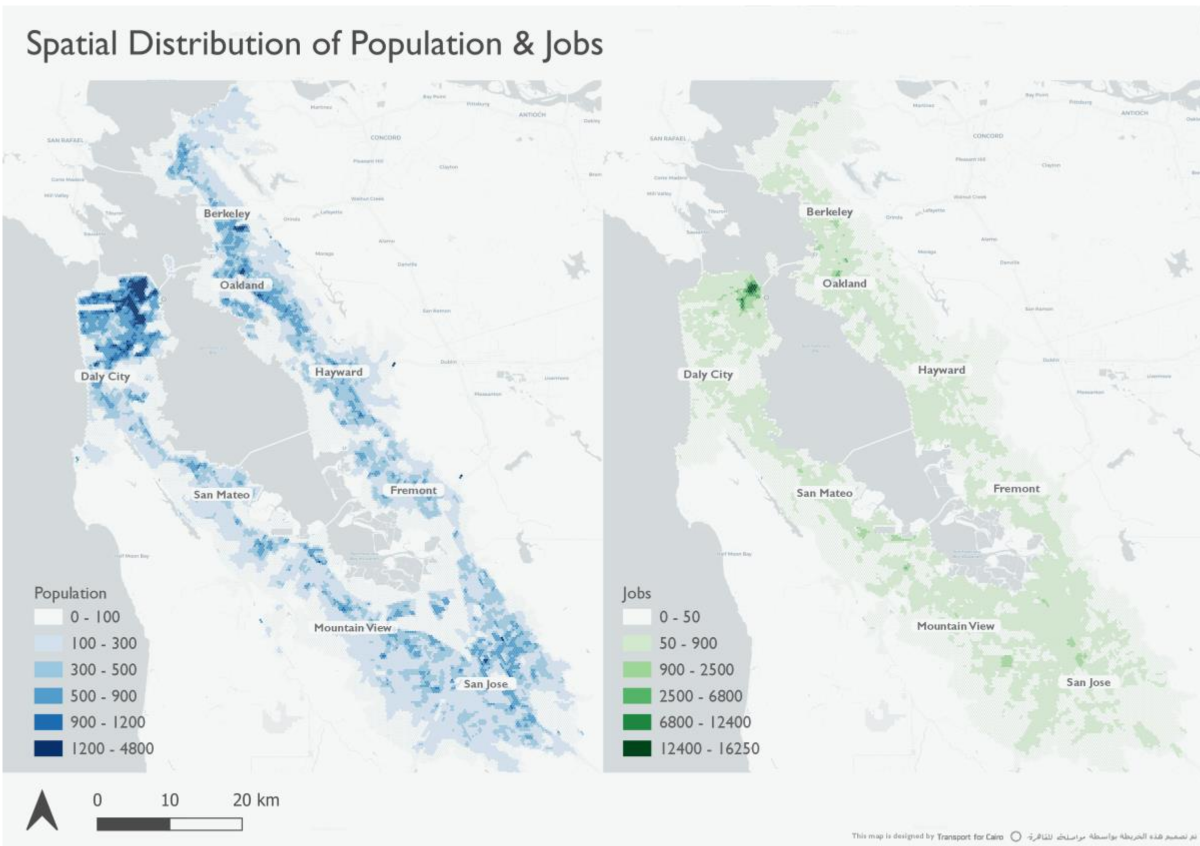


Figure 10: (Left) Distribution of population across the San Francisco Bay Area study region (Right) the distribution of jobs in the region

### 3.4.2 Spatial distribution of transport supply

The commuter rail system BART connects the counties across the North and South as well as San Francisco with the East Bay. Apart from BART, the San Francisco Bay Area's public transit is very decentralized, with each county operating its own public transit system. For example, the San Francisco

Municipal Transportation Agency (SF Muni) operates buses and streetcars in San Francisco; Alameda-Contra Costa Transit (AC Transit) operates in the entire East Bay from Richmond in the North to Fremont in the South and even crosses the bay to connect residents to the central business district of San Francisco; the Valley Transportation Authority (VTA) operates in the South Bay cities like San Josa, Santa Clara, Palo Alto and Fremont.

More than one micromobility provider operates in the area. Bay Wheels provides a regional docked bikeshare service that covers the counties of Berkeley, Emeryville, Oakland, San Jose and San Francisco. A hybrid fleet of classic and electric bikes are available in over 550 stations (shown in Figure 11). Dockless micromobility fleets are provided by both Spin and Bird, with both companies having electric scooters in San Francisco county.

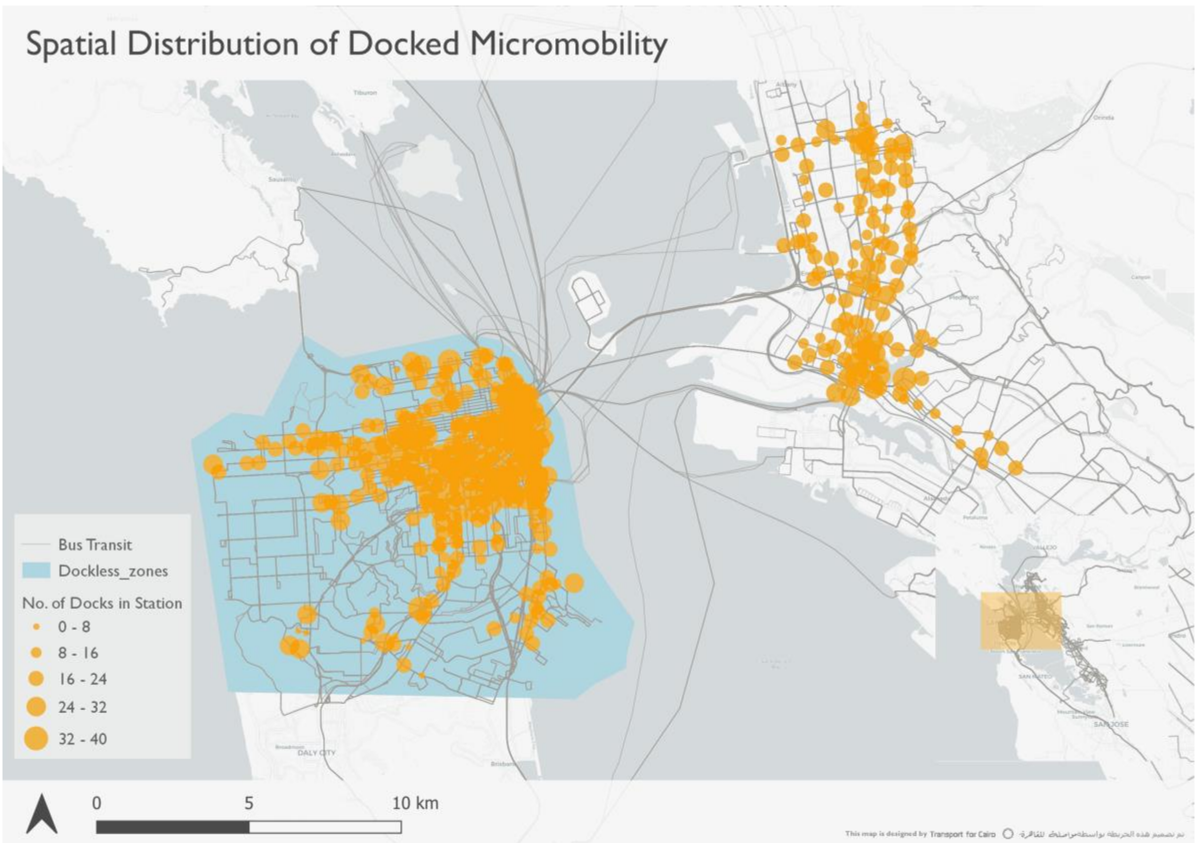


Figure 11: Spatial distribution of docked and dockless micromobility - San Francisco

# 4 Accessibility Results

## 4.1 Cairo

### 4.1.1 Accessibility by car

Accessibility by car is heavily influenced by congestion, as can be seen in Figure 12. If we do not account for congestion, we find that most zones in central Cairo have access to over 80% of jobs within 30-minutes of travel. When congestion is considered, the accessibility for most of these zones drops below the 60% threshold. The difference is less visible when we look at accessibility within 60-minutes, where people in most zones can reach over 80% of jobs with or without congestion.

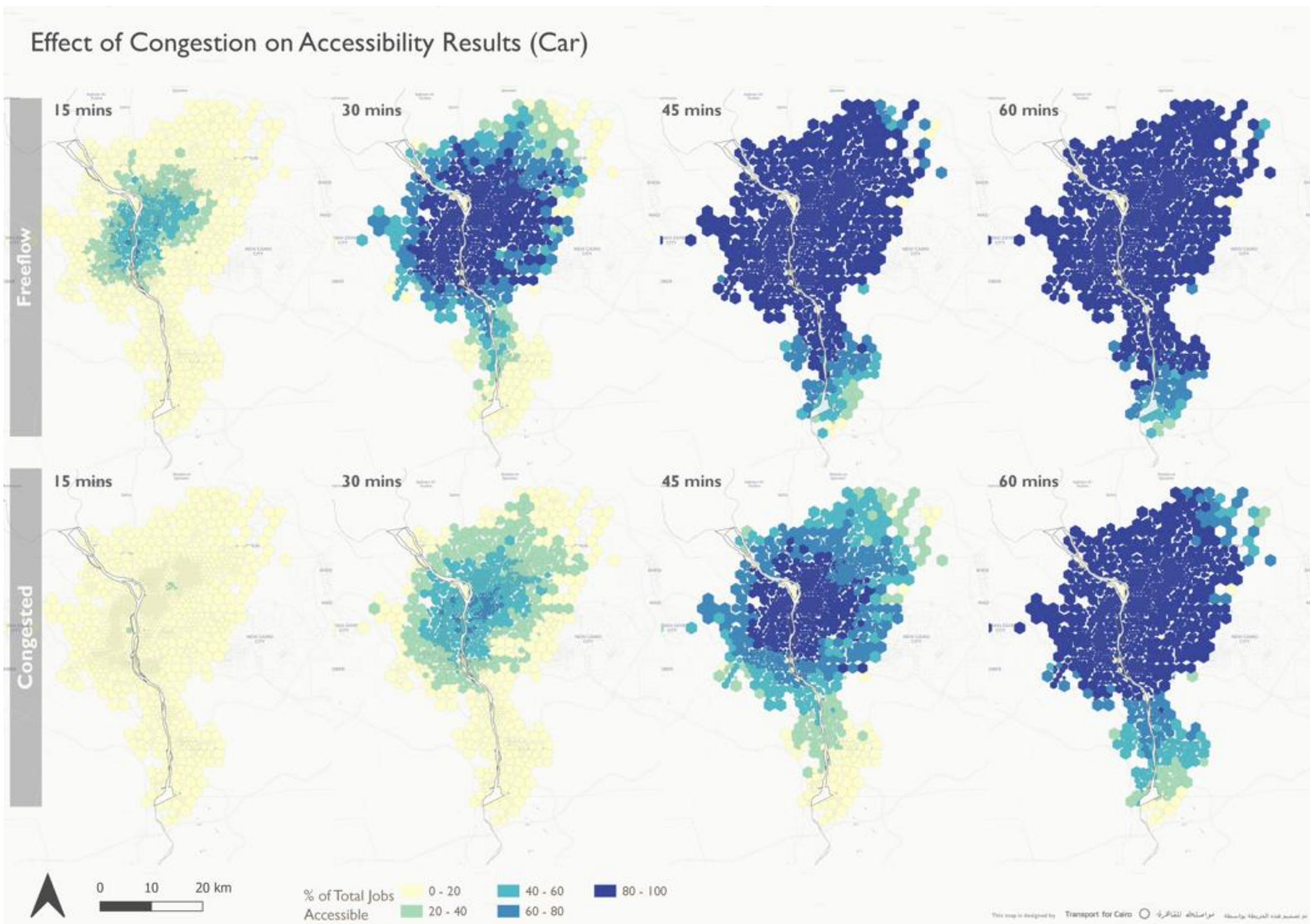


Figure 12: Effect of Congestion on Accessibility Results. (Top Row) Accessibility at Different Time Thresholds under Free Flow Conditions. (Bottom Row) Accessibility at Different Time Thresholds under Congested Conditions – Cairo

Parking and access/egress times also have a significant impact on accessibility by car. Most of the zones in central Cairo tend to have access to over 40% to 60% of jobs. However, accounting for non-travel time components of the trip restrains the accessibility to 40% only, as can be seen in Figure 13.

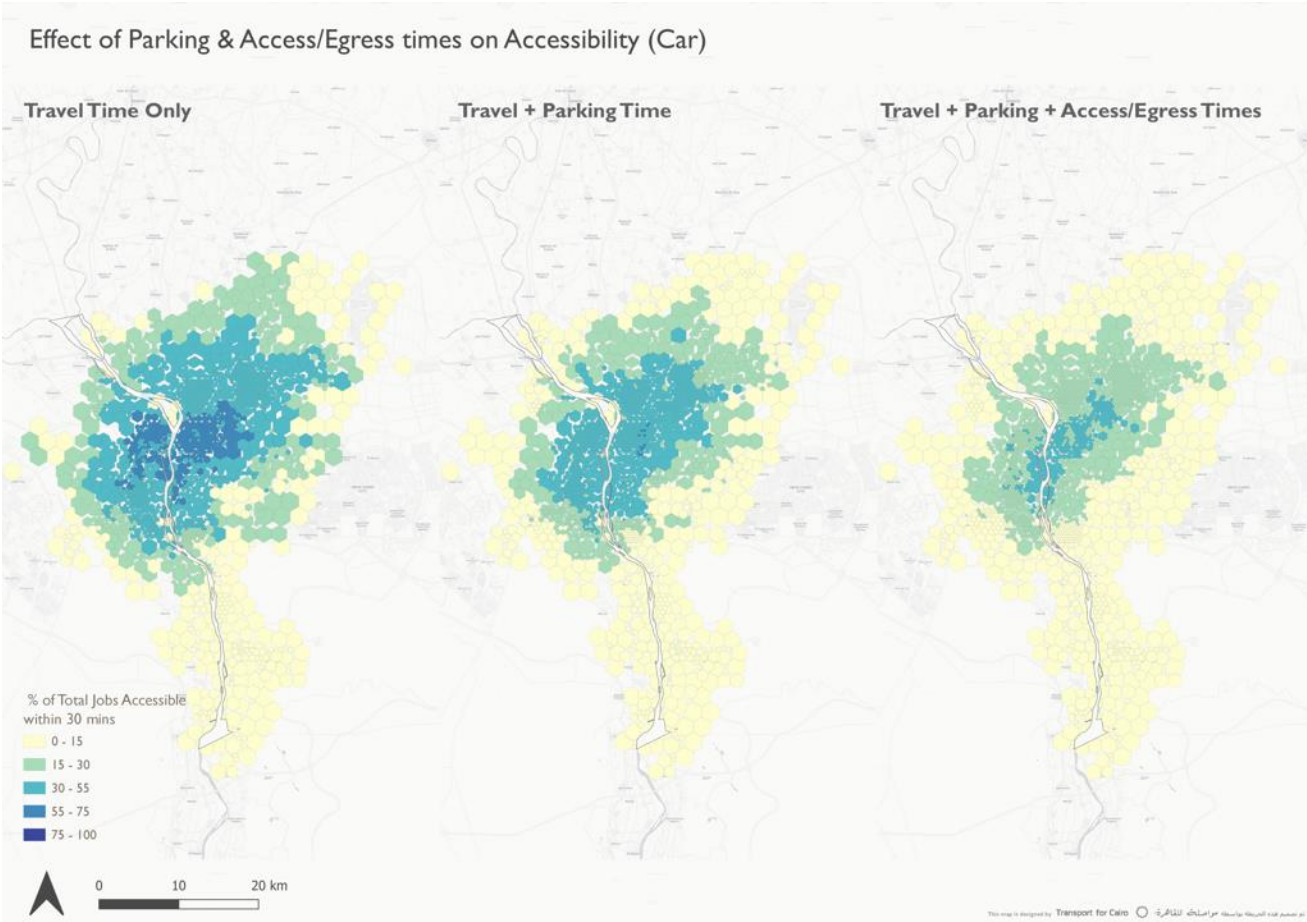


Figure 13: The Effect of Parking & Access/Egress times on Accessibility (30-minutes). (Left) Travel Time Only. (Right) Travel + Parking Time. (Right) Travel + Parking +Access/Egress Times (Cairo)

### 4.1.2 Multimodal and Intermodal accessibility

Figure 14 shows that accessibility by car is far better than by any other mode at the 45- and 60-minute time thresholds. At the 15- and 30-minute thresholds, bicycles are competitive alternative to cars, even outperforming cars for the former. The results for bicycles can be seen as an indicator for the full potential of shared micromobility, as this is what accessibility by micromobility would be like if docking stations were available everywhere. In fact, the docked micromobility results would be even higher than the bicycle results, as the combination of public transport and micromobility is faster than bicycles for some journeys.

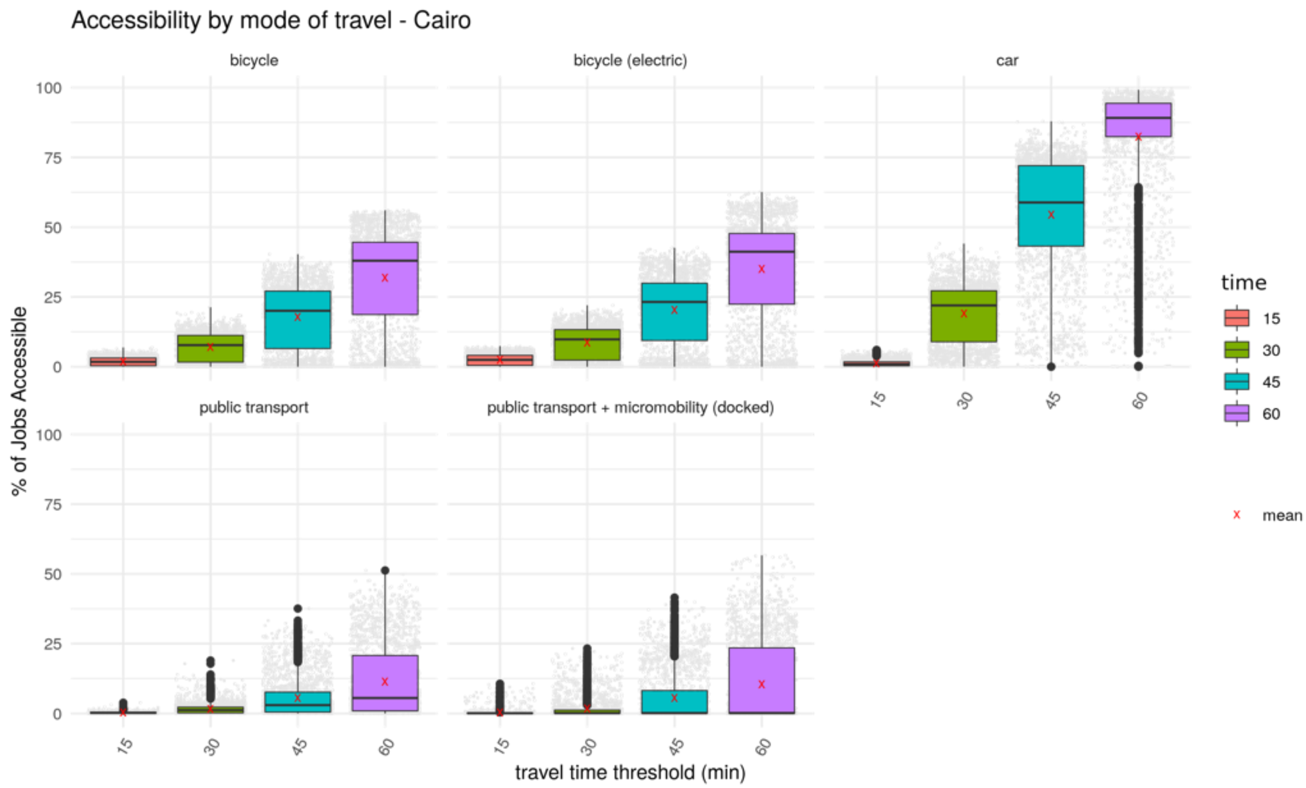


Figure 14: Distribution of accessibility for each mode (Cairo)

Figure 15 shows the spatial distribution of accessibility for different travel time thresholds, focusing on public transport. Public transport accessibility is low, especially for the shorter travel time thresholds. Micromobility consistently improves accessibility relative to public transport, but the spatial distribution of this improvement varies depending on the travel time threshold (Figure 16). At lower travel time thresholds, the improvement is more pronounced in central Cairo where the micromobility network is concentrated (Figure 5).

Figure 17 shows the distribution of improvement in accessibility in Cairo where the mean improvement, excluding the zones with zero improvement, increases initially with increasing thresholds, then stays relatively constant with a slight decrease at 30 minutes. The improvement associated with the 15-minute threshold is probably due to trips being made by micromobility instead of walking. At the 30- and 45-minutes travel time thresholds, the improvement expands to zones that are far from the docking stations in Central Cairo, indicating that micromobility is improving travel times for these zones by being used as a first/last-mile solution. Interestingly, a lot of the central zones that witnessed improvement for lower travel time thresholds no longer do so at the 60-minute threshold. This is expected as they are already well-connected and served by public transport, and therefore have good accessibility by public transport within 60-minutes. Improvements in zones outside the center are a result of public transport and micromobility integration. A good example of that is the improved accessibility extending in all directions along the paths of the Cairo metro.

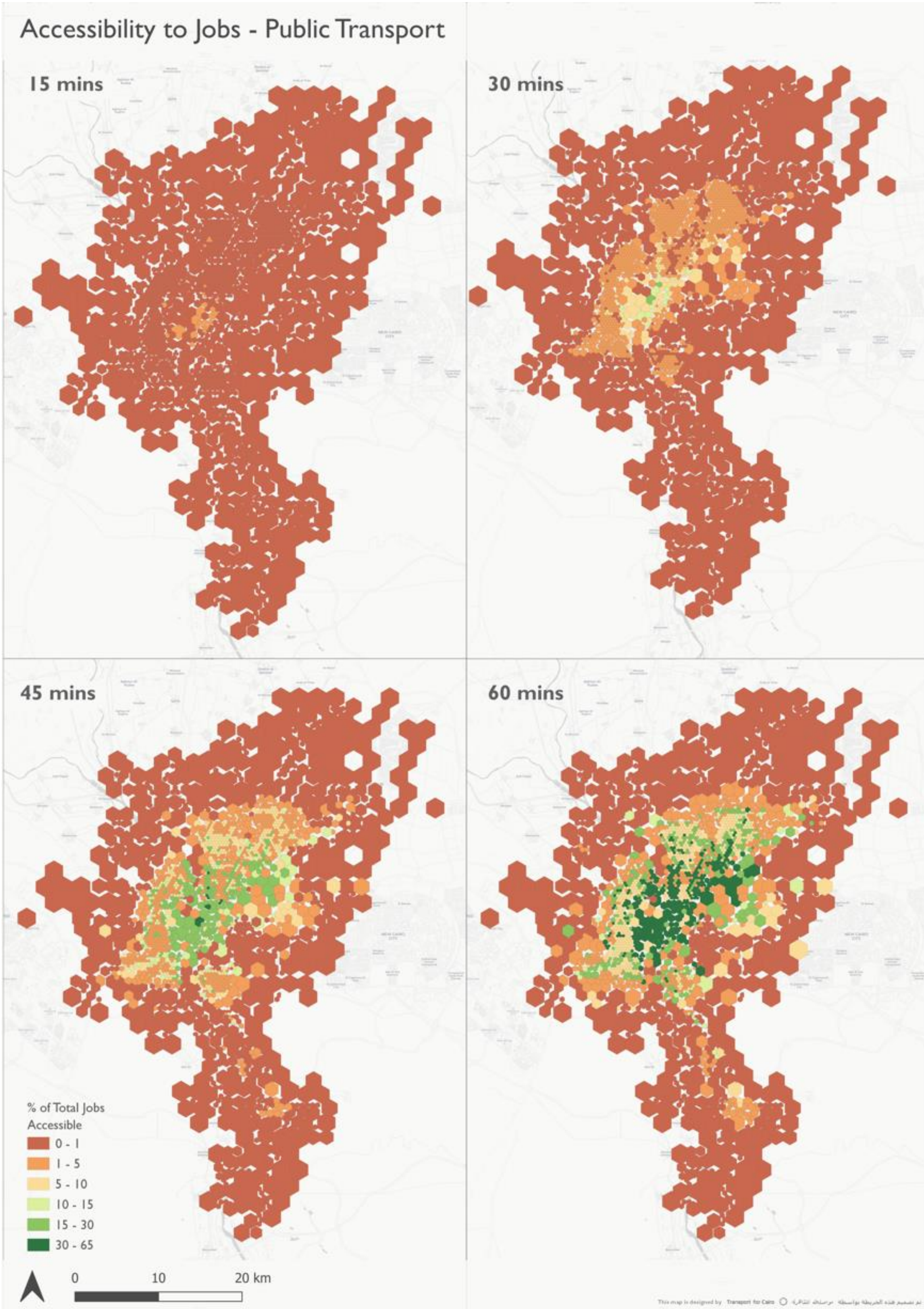


Figure 15: Accessibility by PT for different travel time thresholds (Cairo)

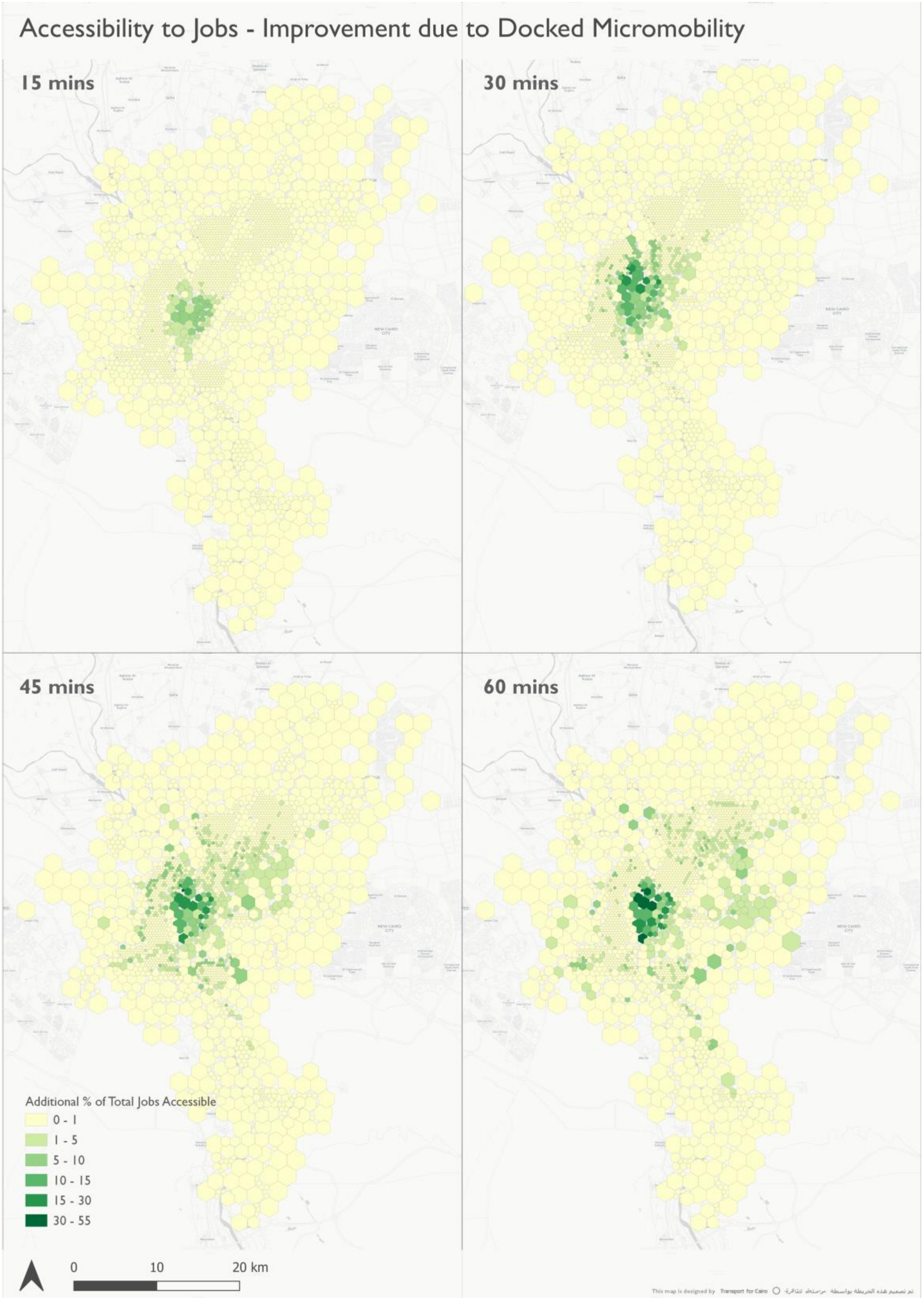


Figure 16: Accessibility gain due to micromobility (Cairo)

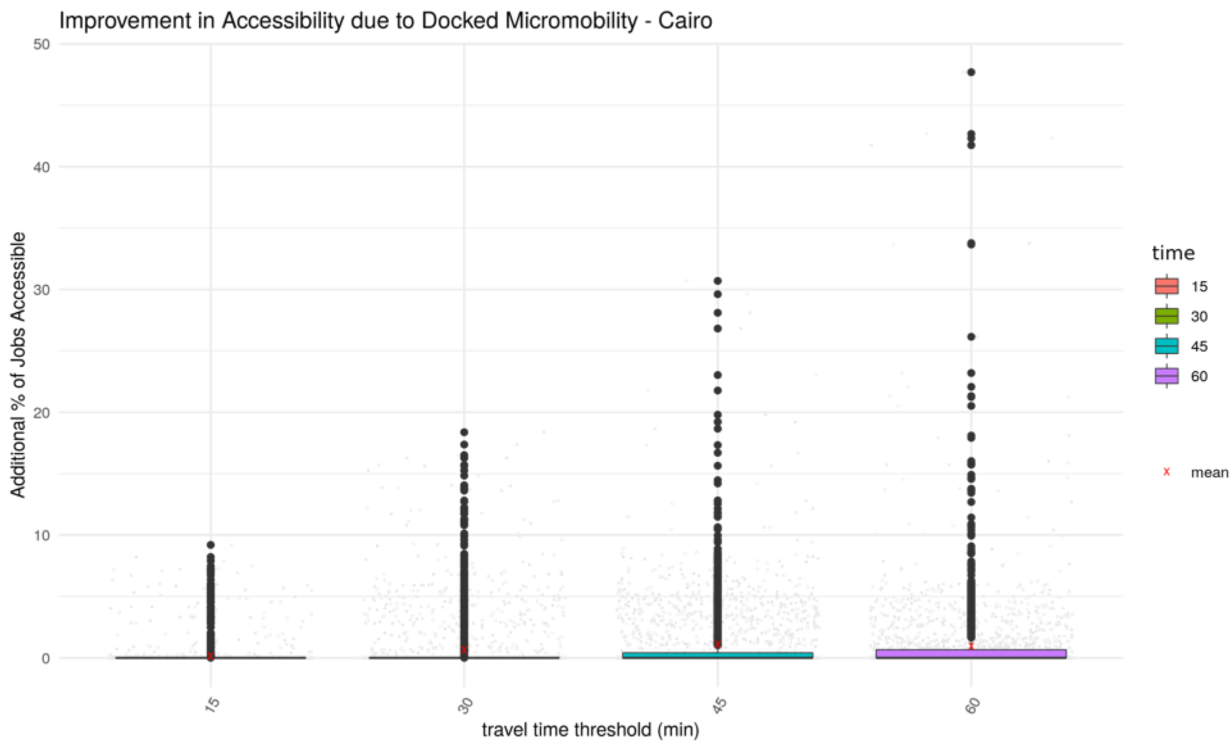


Figure 17: Improvement in accessibility due to docked systems for different travel time thresholds - Cairo

The accessibility maps shown thus far show accessibility with a strict threshold cut-off of travel time. This method of comparing accessibility gained due to micromobility obscured another value that may be felt by commuters which is the decreased travel time if micromobility is used over public transit alone. Figure 18 shows some of the most impacted OD pairs with connecting lines with varying hues of green and thickness that indicate the size of the percent improvement in travel time relative to public transit alone. It shows that the highly affected OD pairs start in downtown Cairo and go north where the alternative may not be as fast with public transit. Similarly, in Giza, West of the Nile River, short distances can be covered by micromobility in travel time improvements of 45-minutes or more. For someone whose daily commute is along these routes, this effect may result in saving more than 1.5 hours every day. The caveat is, of course, that people are able to access and make full use of the micromobility system given their economic and safety considerations.

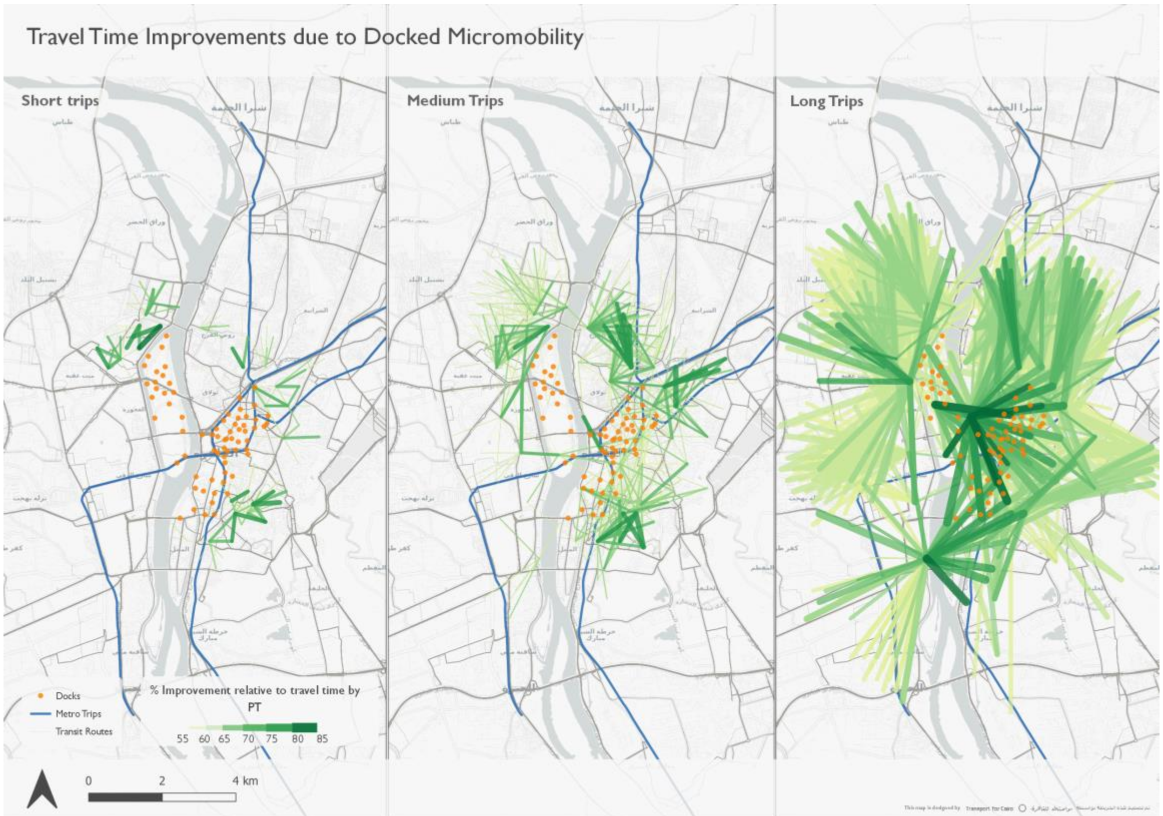


Figure 18: OD Pairs that with highest improvement in travel times (Cairo)

## 4.2 Mexico City

### 4.2.1 Accessibility by car

Compared to Cairo, accessibility by car is not affected by congestion as much in Mexico City. Figure 19 shows that congestion has the largest effect on accessibility within a 15-minute travel time threshold, but as the travel time threshold goes up accessibility is comparable between free flow and congested speeds. This does not mean that travel times are the same, but that the same destinations can be reached within a 30 minute or more cut-off time. The results may be partially attributed to the fact that the Federal District being analysed is not as big as Cairo, approximately 87% of Cairo size, and the relatively regular shape of the city's footprint which makes travel distances shorter.

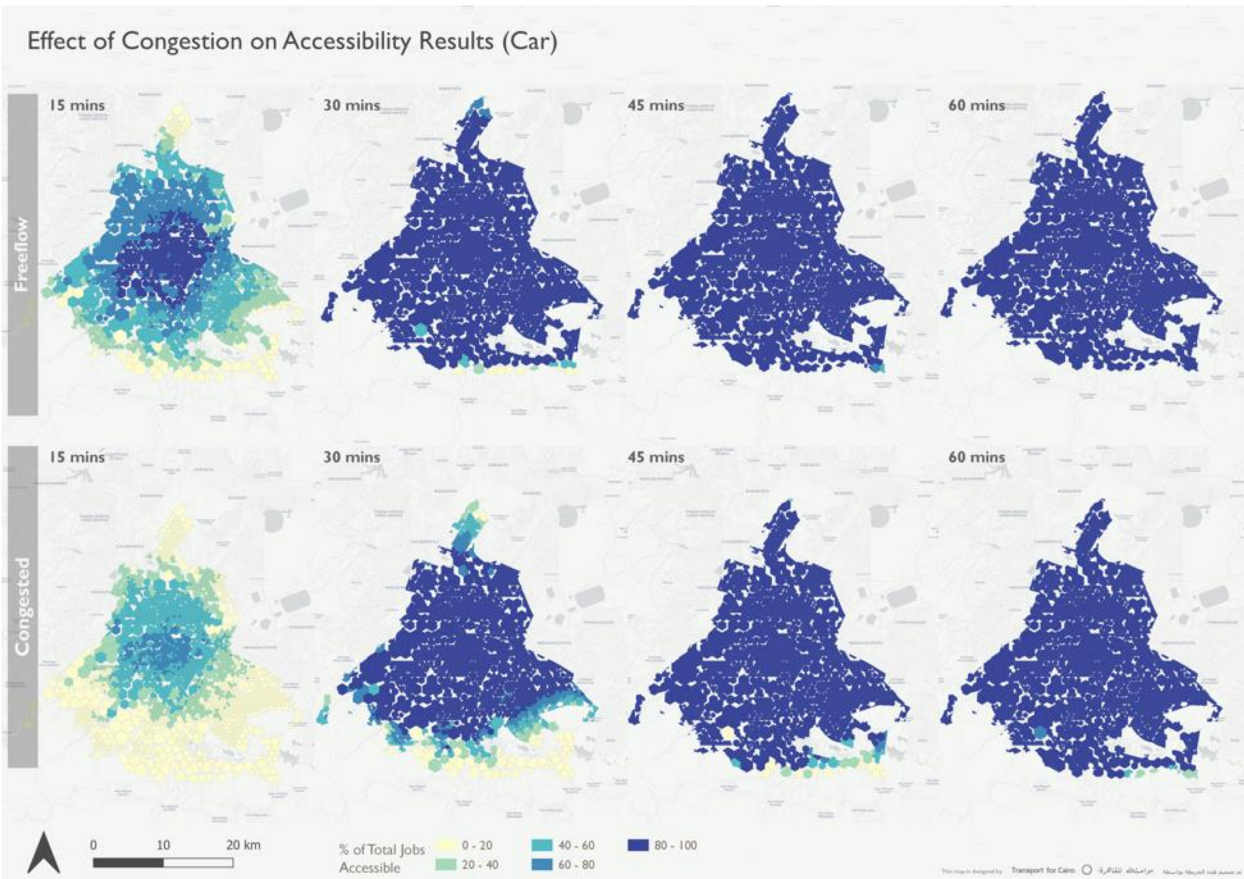


Figure 19: Effect of Congestion on Accessibility Results. (Top Row) Accessibility at Different Time Thresholds under Free flow Conditions. (Bottom Row) Accessibility at Different Time Thresholds under Congested Conditions – Mexico City

Adding parking and access/egress times noticeably decreases accessibility at the periphery of the city (Figure 20). One can observe that the peripheries are always critical accessibility points due to their lower connectivity to the transportation system of the city. Most of the jobs are in the west and center of the city, which explains why accessibility at the center remains good.

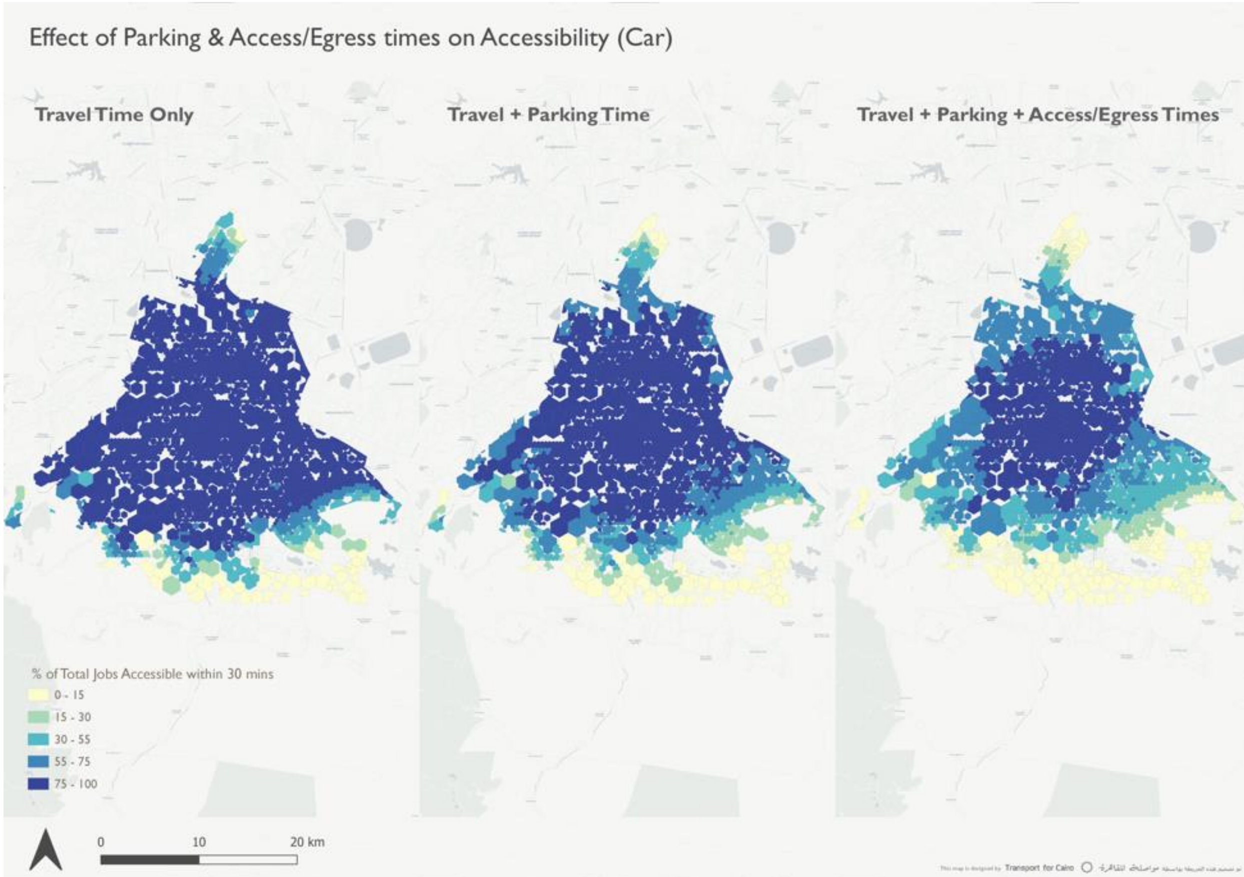


Figure 20: The Effect of Parking & Access/Egress times on Accessibility (30-minutes). (Left) Travel Time Only. (Right) Travel + Parking Time. (Right) Travel + Parking +Access/Egress Times (Mexico City)

### 4.2.2 Multimodal and Intermodal accessibility

Accessibility by car is much higher than that by any other mode, especially for travel time thresholds of 30 minutes or higher (Figure 21). However, at 15 minutes, cars do not seem to provide substantial gains over other modes of transport. Micromobility improves accessibility by public transport for all travel time thresholds. The improvement is marginal, but this is to be expected since micromobility only operates in a subset of the city.

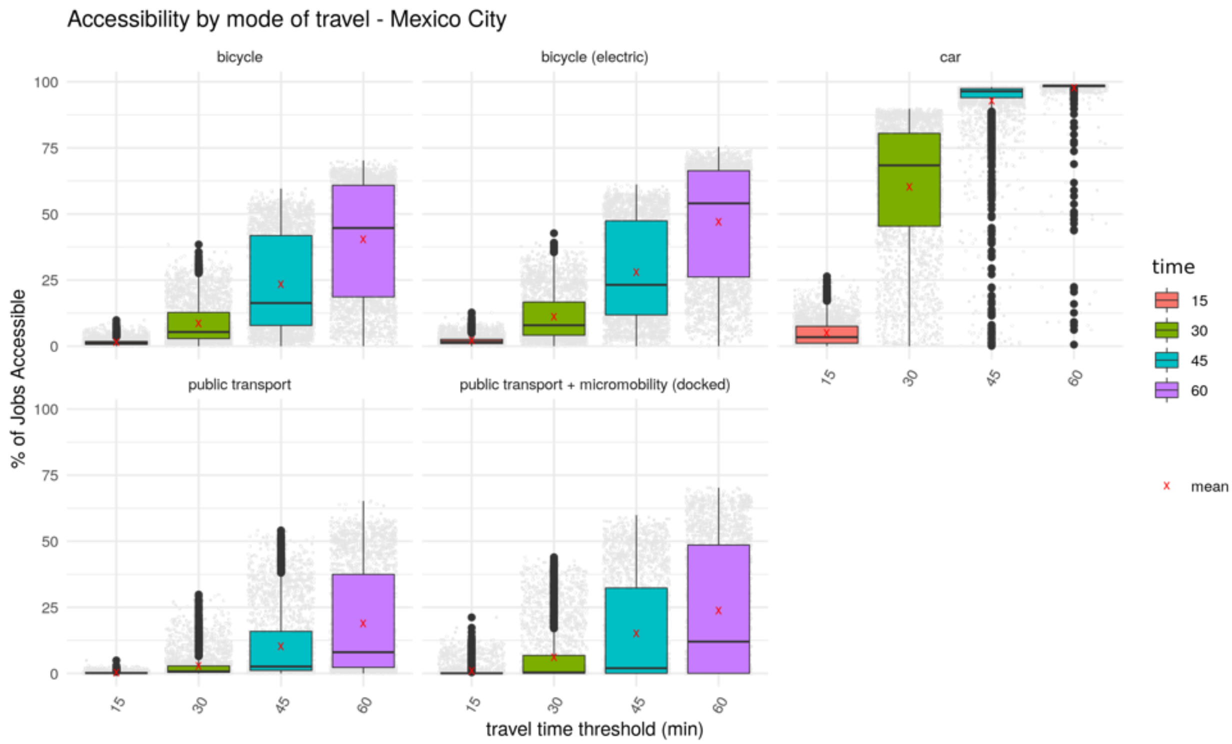


Figure 21: Distribution of accessibility for each mode (Mexico City)

Figure 22 and Figure 23 show the spatial distribution of accessibility by public transport and the improvement in accessibility resulting from the availability of micromobility. At a 15-minute threshold, accessibility by public transport is low throughout the city, but this accessibility improves gradually as the travel time threshold increases. The improvement is most noticeable in the center of the city, and some areas at the periphery have poor accessibility by public transport even at a travel time threshold of 60-minutes.

The effect of micromobility on accessibility is apparent even at a travel time threshold of 15-minutes, emphasizing the value of micromobility for short trips. As the travel time threshold increases, the improvement begins to show further out, expanding radially outwards. The improvements outside the service geography of the bikeshare network are due to micromobility being used as a last-mile solution to access jobs in the center of the city, and parts of the improvement inside the service geography of the bikeshare network are due to micromobility being used as a first-mile option to access the public transport network.

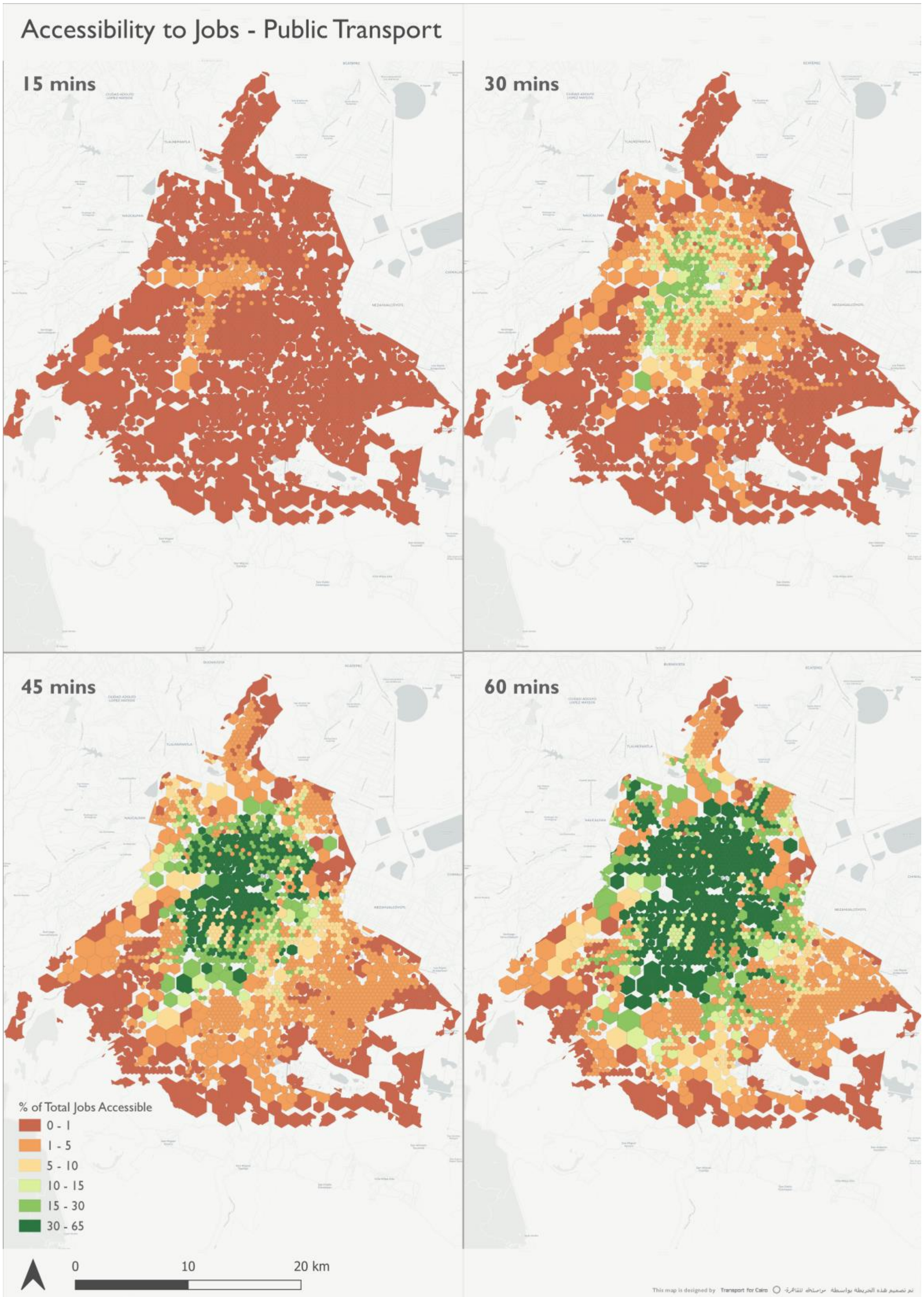


Figure 22: Accessibility by PT for different travel time thresholds (Mexico City)

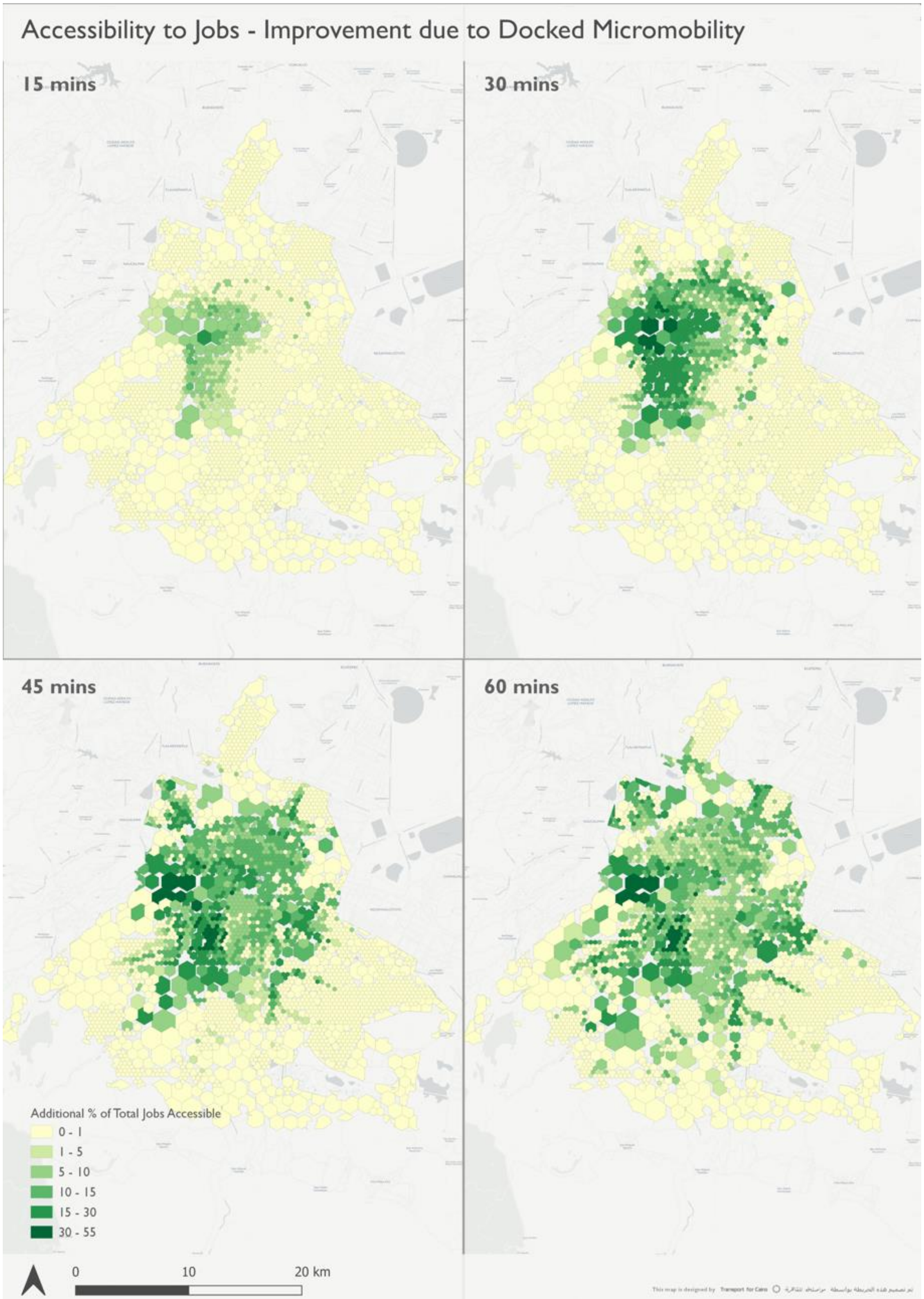


Figure 23: Accessibility gain due to micromobility (Mexico City)

Figure 24 shows box plots with the distributions of improvement in accessibility in each travel time threshold. Interestingly, the mean and maximum improvement increase with increased travel time until the 45-minute threshold, where the mean stops increasing while the maximum increases further at 60 minutes. This indicates that although more zones witness improved accessibility at higher travel time thresholds, the improvement per zone plateaus or decreases relative to public transport.

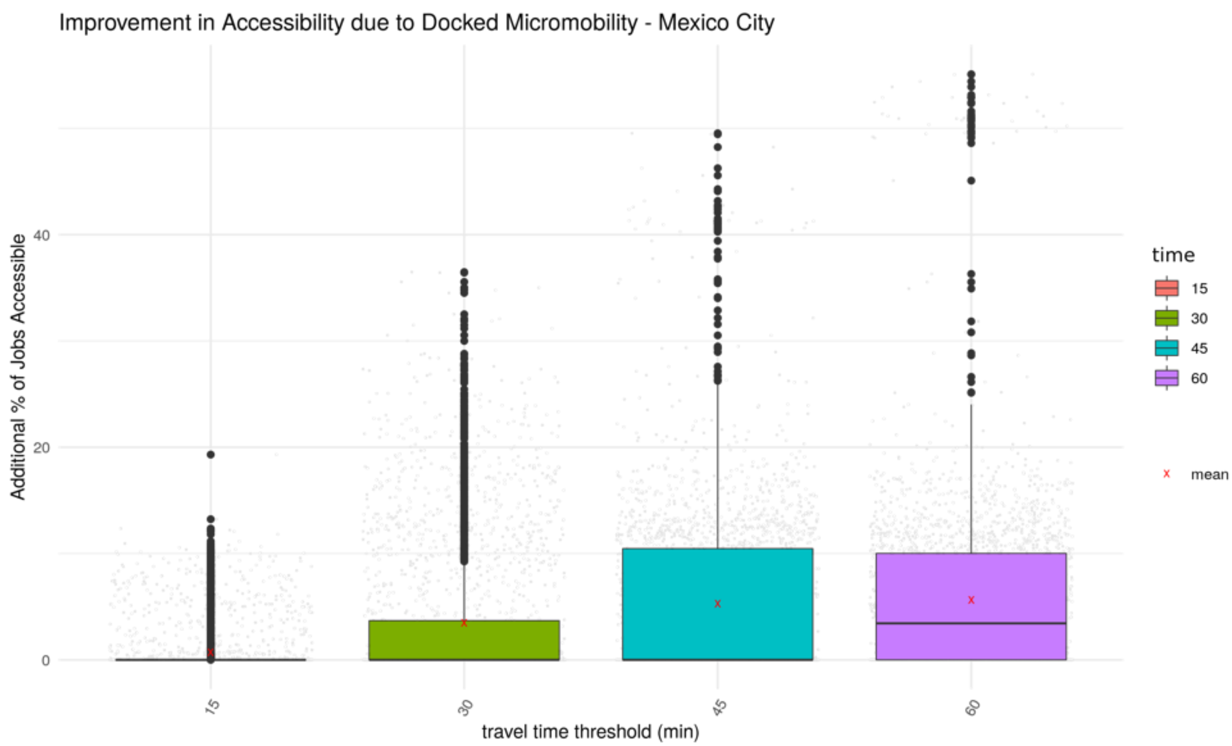


Figure 24: Improvement in accessibility due to docked systems for different travel time thresholds – Mexico City

Similar to Cairo, there are many pairs of ODs in Mexico city that witness a significant improvement in travel time due to micromobility, as shown in Figure 25. These trips, shown in green lines with hue and thickness indicating the extent of the improvement, offer a benefit to commuters that is obfuscated in the COM accessibility calculation. For short (< 20 mins) and medium trips (20-40 mins), these improvements are contained within neighborhoods in the northwest, northeast, and south of the city. While for long trips (> 40 mins) the entire city witnesses improvements in travel time due to micromobility.

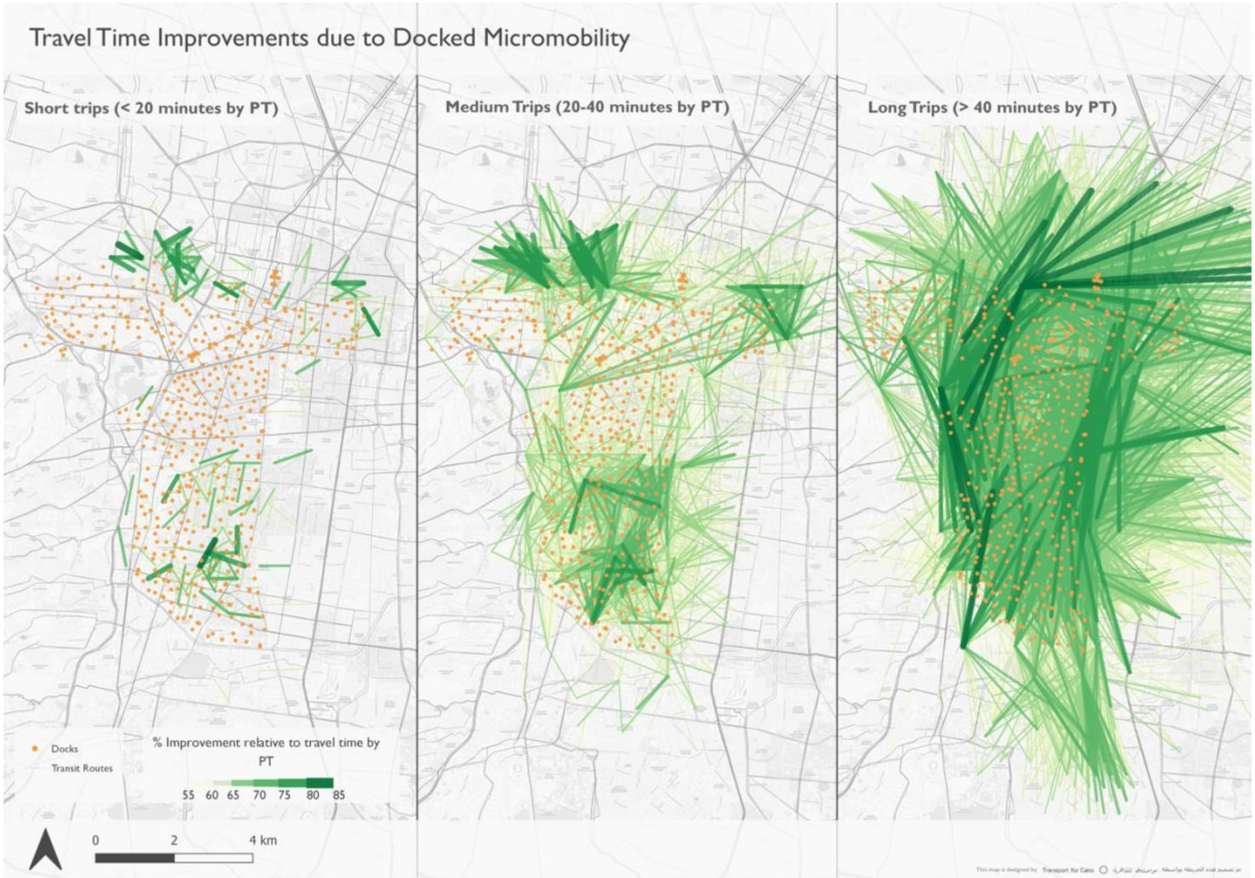


Figure 25: OD Pairs that with highest improvement in travel times (Mexico City)

## 4.3 Minneapolis-Saint Paul

### 4.3.1 Accessibility by car

Accessibility by car in Minneapolis-Saint Paul is, unsurprisingly, very good. We were not able to obtain real speeds for the roads of the city, so congestion was not taken into effect in our analysis. However, the effect of parking and access/egress is significant when applied to a 30-minute COM accessibility in Figure 26. Since jobs are distributed evenly across the suburban counties, apart from a small concertation in the downtowns of Minneapolis and Saint Paul, accessibility by car is a function of distance with the core having the highest levels of accessibility. Whereas a large central area reaches accessibility greater than 75% if only travel time is considered, only 55% of jobs are accessible from the center when parking and access and egress times are considered.

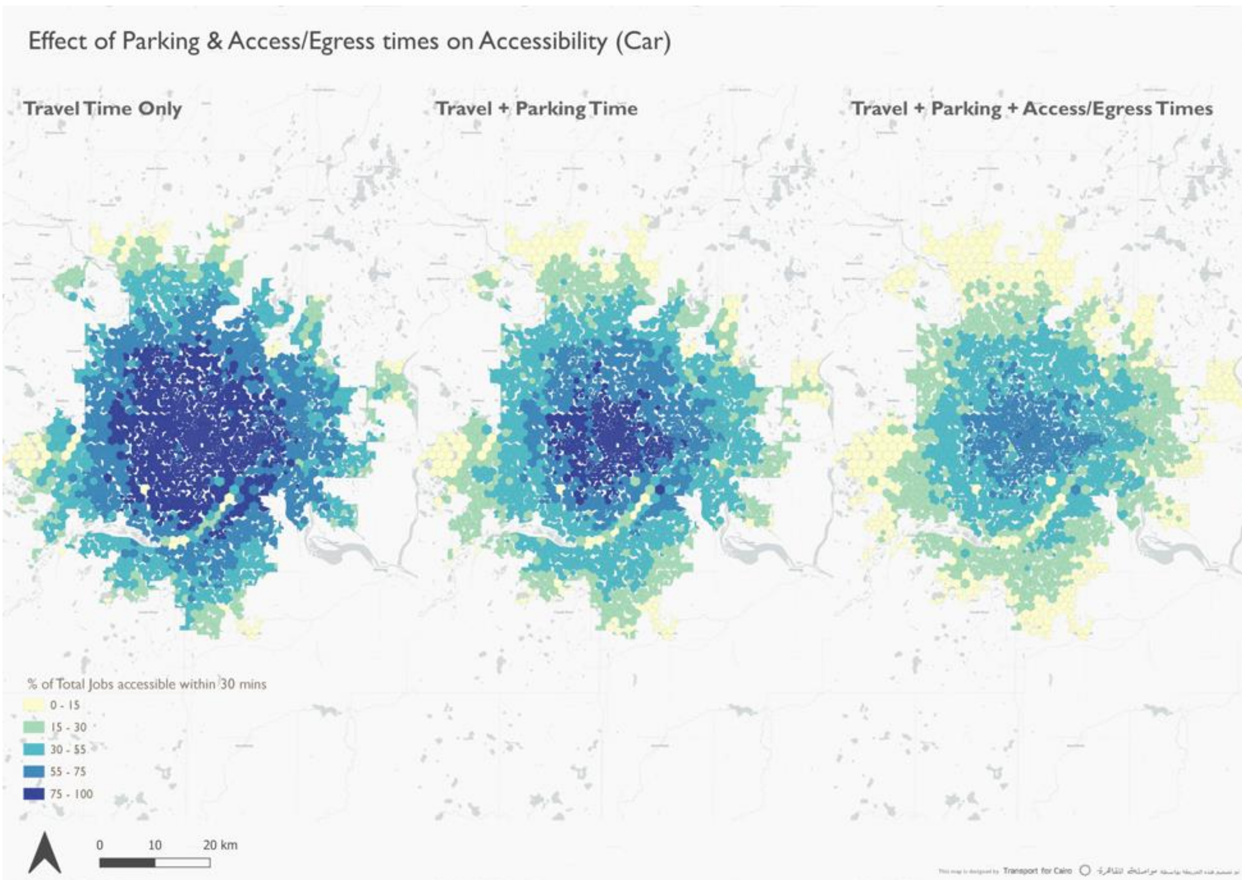


Figure 26: The Effect of Parking & Access/Egress times on Accessibility (30-minutes). (Left) Travel Time Only. (Right) Travel + Parking Time. (Right) Travel + Parking +Access/Egress Times (Minneapolis)

### 4.3.2 Multimodal and Intermodal accessibility

Accessibility by car is again much higher than that by other modes. This can in part be explained by the large size of the city; the longer the travel distances, the more likely it is that car trips are more efficient. Accessibility by other modes is competitive with accessibility by car at a travel time threshold of 15 minutes. In fact, there are many zones where accessibility by private bicycle or shared micromobility is better than that by car.

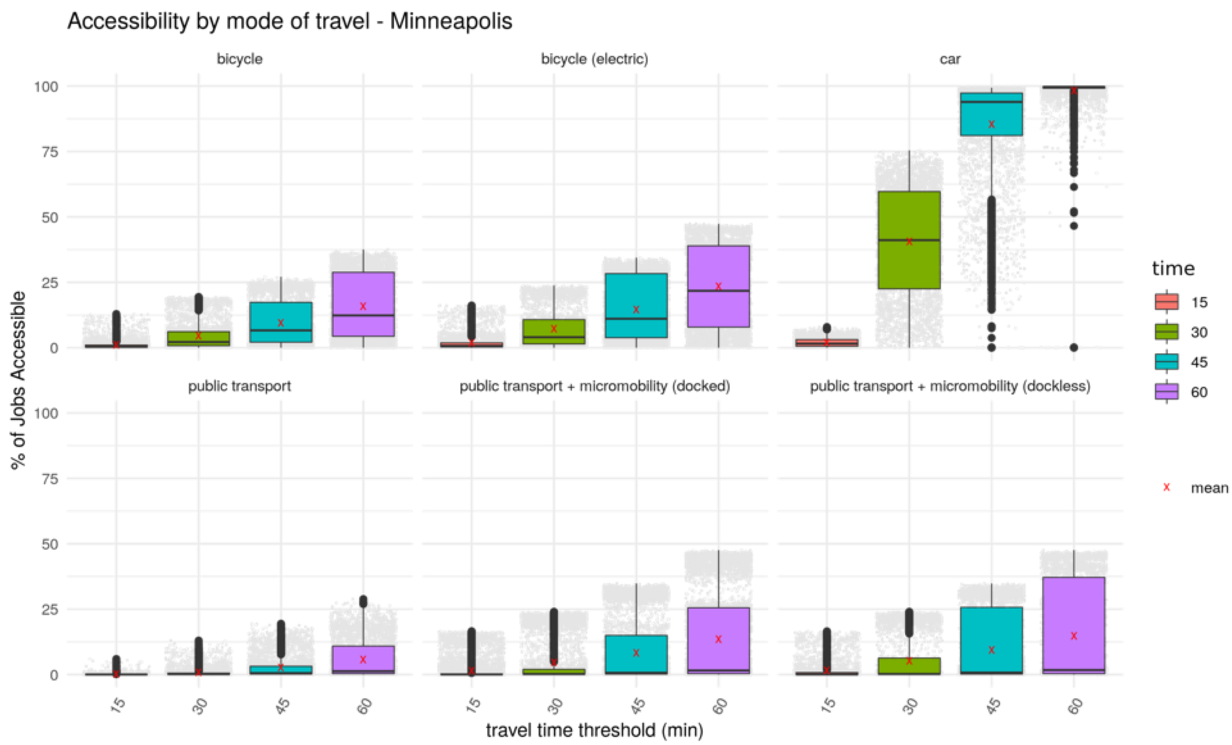


Figure 27: Distribution of accessibility for each mode (Minneapolis)

Figure 28 and Figure 29 show the spatial distribution of accessibility by public transport and the improvement in accessibility resulting from the availability of micromobility. Accessibility by public transport is very low in Minneapolis; it is only at travel times thresholds above 45-minutes that we begin to see accessibility over 15% for some zones in the center of the city. This could be attributed to the large size of the city, and to the poor coverage of public transport in it.

Both docked and dockless micromobility improve access to opportunities significantly, as shown in Figure 29. The effect is predominantly inside the coverage zones of the micromobility providers, but improvements outside of this geographic boundary can be seen at a 60-minute travel time threshold. The improvements due to the dockless network is slightly more spread out than that of the docked network. This is to be expected since dockless networks are not constrained by the geographic location of docking stations.

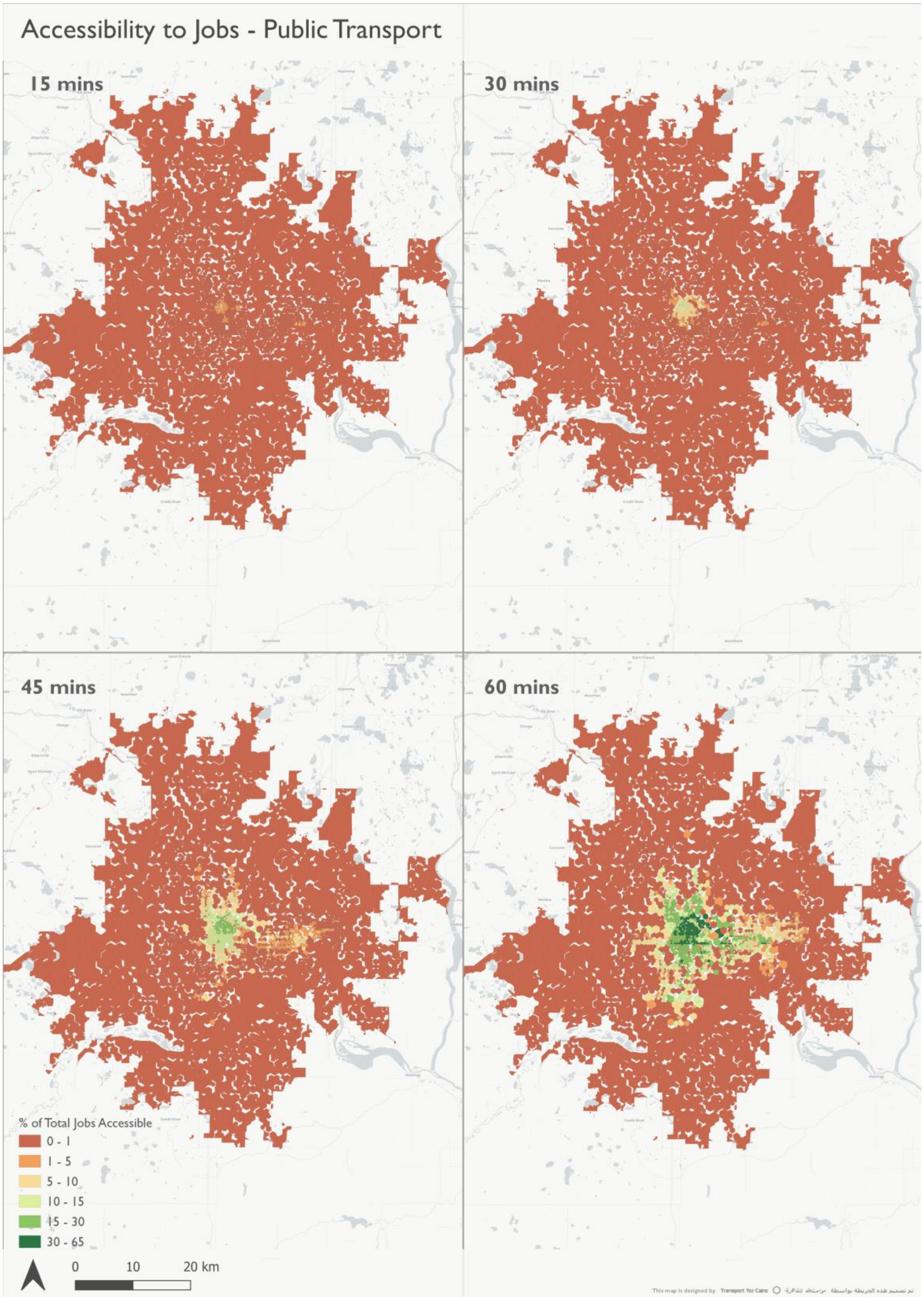


Figure 28: Accessibility by PT for different travel time thresholds (Minneapolis)

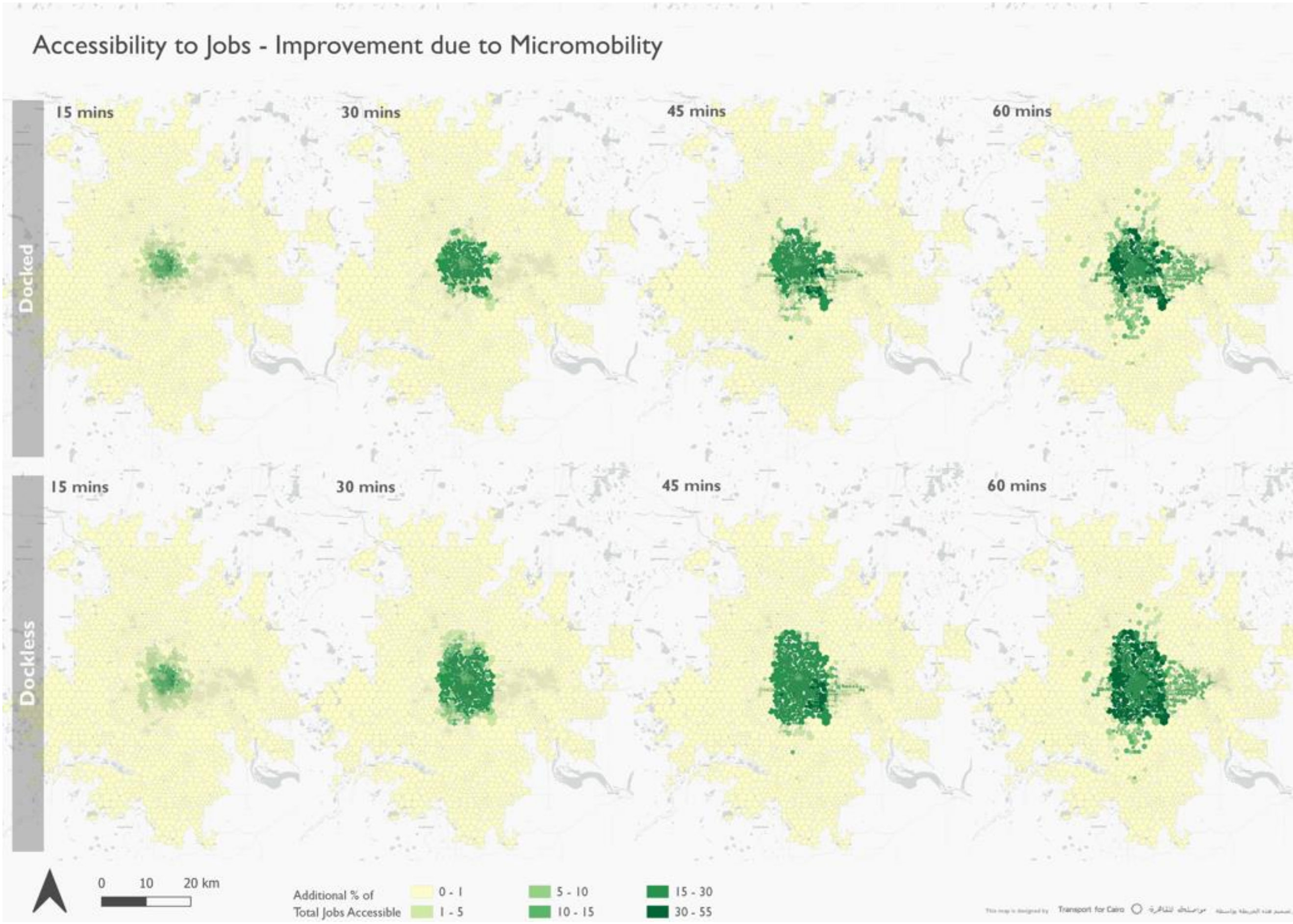


Figure 29: Accessibility gain due to micromobility (Minneapolis)

The variance and mean of improvement due to dockless micromobility is higher than that of docked micromobility at all travel time thresholds in Minneapolis, as seen in Figure 30. The phenomenon of the mean improvement plateauing after a certain time threshold is not seen within 60 minutes of travel in Minneapolis. This indicates that even for 60-minute trips by public transport, micromobility offers a significant improvement when used as access, egress, or the main mode of travel. This is likely due to the infrequency of public transport bus routes in Minneapolis compared to other cities in our study.

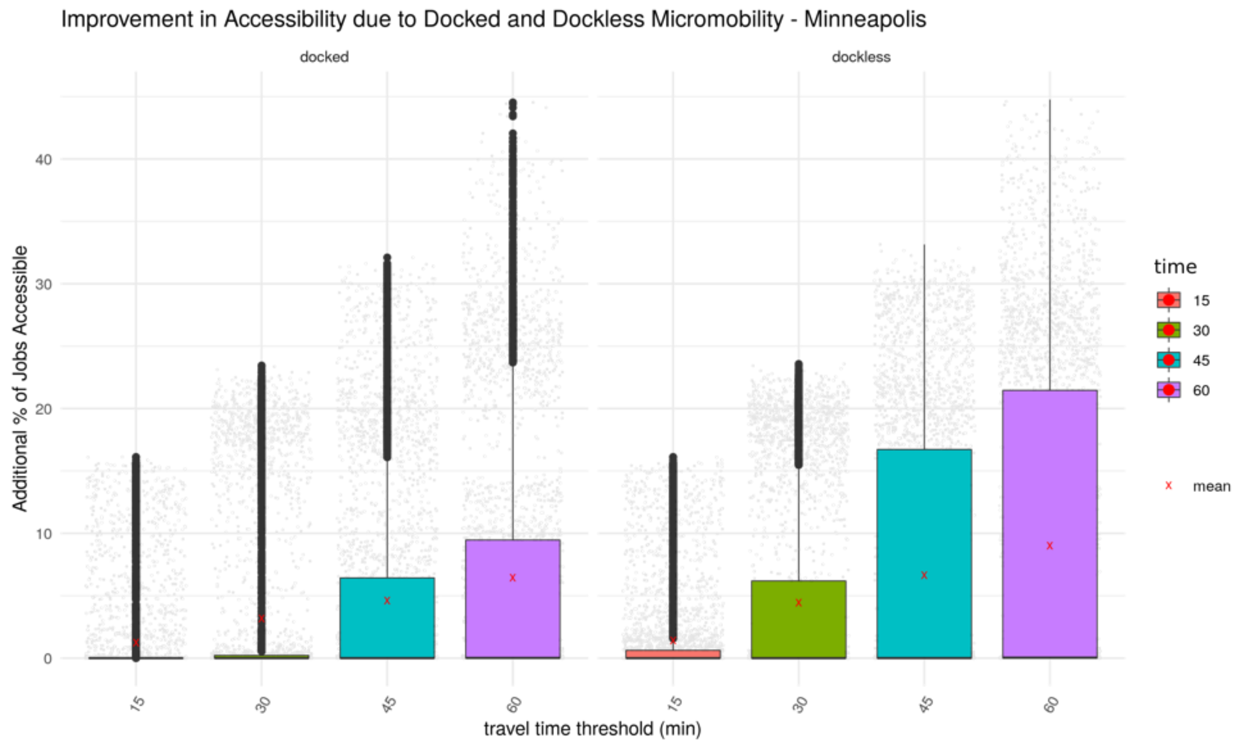


Figure 30: Improvement in accessibility due to docked and dockless systems for different travel time thresholds – Minneapolis

## 4.4 San Francisco

### 4.4.1 Accessibility by car

Incorporating real travel times due to congestion has a significant effect on accessibility by car, as can be seen in Figure 31. Under free flow conditions, almost all zones have greater than 80% accesibility within 45 minutes of travel by car. Whereas 46% of zones would reach more than 80% of jobs within 30 minutes under freeflow conditions, not a single zone would reach more than 60% of jobs within 30 minutes under realistic congested conditions. A similar pattern can be observed for accessibility levels within 60 minutes of travel by car. Under freeflow condtions, 99% of zones would reach more than 80% of jobs but only 33% of zones would reach that many jobs under congested conditions. This result highlights the benefit of including realtime speeds for driving in accessibility analysis.

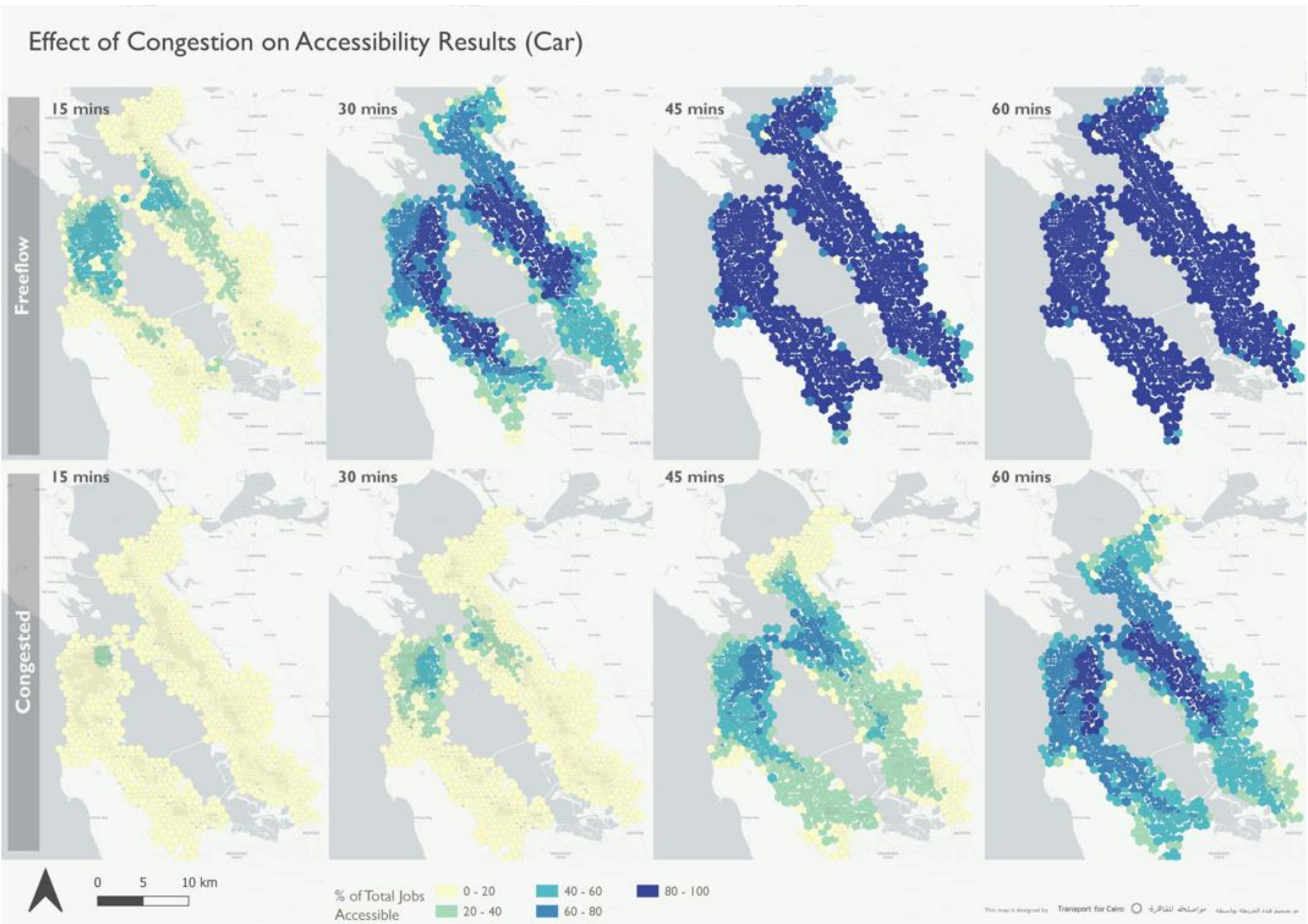


Figure 31: Effect of Congestion on Accessibility Results. (Top Row) Accessibility at Different Time Thresholds under Freeflow Conditions. (Bottom Row) Accessibility at Different Time Thresholds under Congested Conditions – San Francisco

The effects of parking time as well as access and egress time are shown in Figure 32 to be similarly significant in reducing the realistic accessibility of personal car drivers. The parking component in the first leg of a tour, and then accessing the parked car at the end of it are not usually considered within individuals' decision-making processes on mode choice. Apart from the brief note on availability of on-site parking, navigation apps or routing engines do not automatically add that extra time to car-based trips. This is not the case in public transport trips, whereas walking to your final destination from the station is always added for public transit modes. This discrepancy in the comparison falsely encourages people to prefer driving over other more sustainable modes.

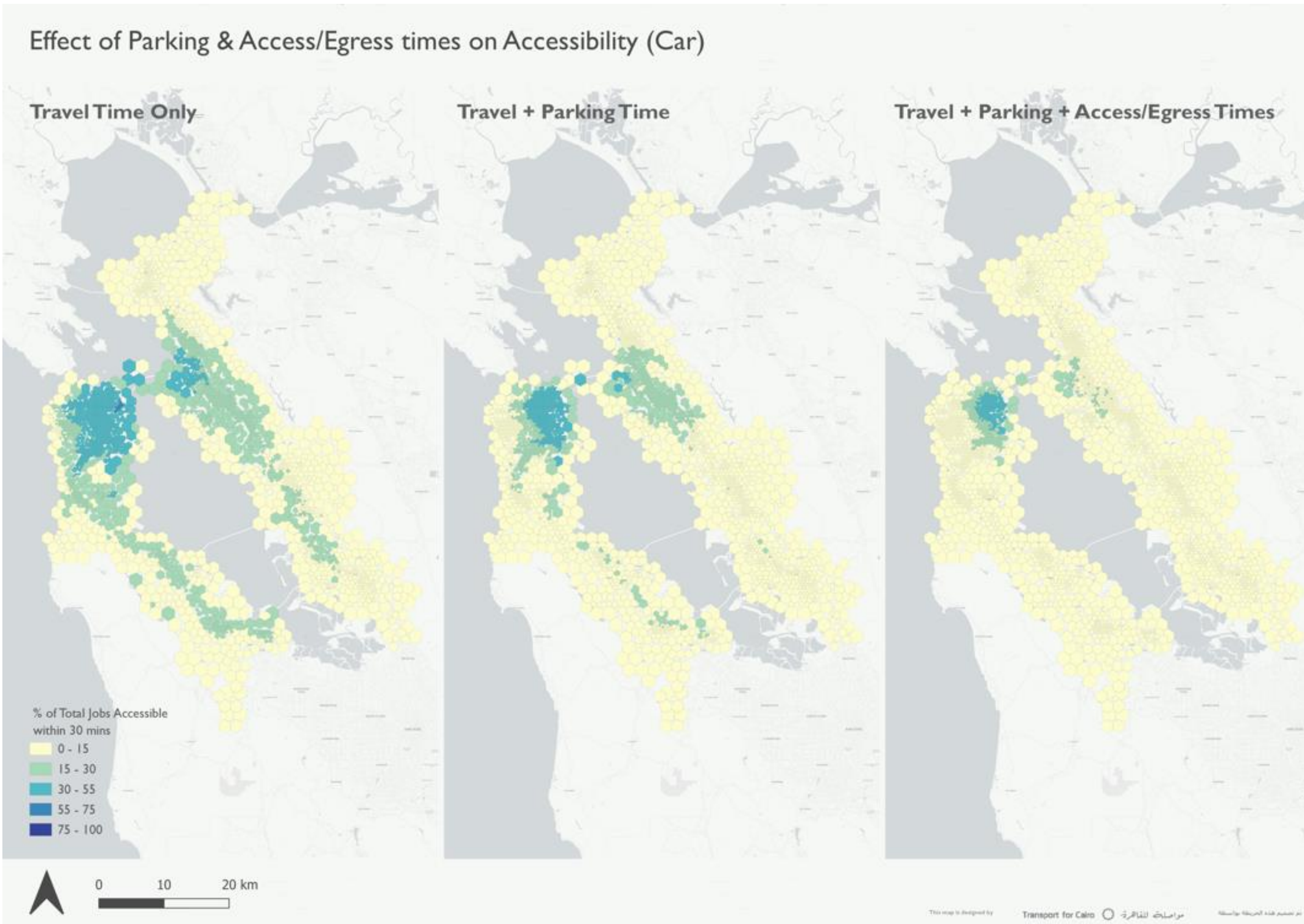


Figure 32: The Effect of Parking & Access/Egress times on Accessibility (30-minutes). (Left) Travel Time Only. (Right) Travel + Parking Time. (Right) Travel + Parking +Access/Egress Times (San Francisco)

### 4.4.2 Multimodal and Intermodal accessibility

Accessibility by car is generally higher than the ones by other modes, as shown in the zone-level accessibility for each mode combination (Figure 33). We can see that the car is superior to other modes for most zones, especially at higher travel time thresholds. However, at lower travel time thresholds, bicycles offer a competitive alternative. This can be attributed to the parking and access/egress times affecting car travel time. While public transport accessibility is low, the addition of micromobility as a possible mode to be combined with it increases accessibility significantly. This can be seen clearly for the 30- and 45-minute thresholds, where public transport and micromobility inter-modal accessibility becomes competitive with respect to car accessibility. For micromobility, one can observe higher variance in the accessibility improvement results that can be seen in the large difference between the mean (red X in Figure 33) and median (centerline of boxplot in Figure 33). This is due to micromobility services improving travel times significantly for the zones in which they are coupled with transit services. This should also draw attention to the importance of accounting for the availability of micromobility services when analysing their impact on accessibility. Service availability will be further discussed in the next section (Section 4.4.3).

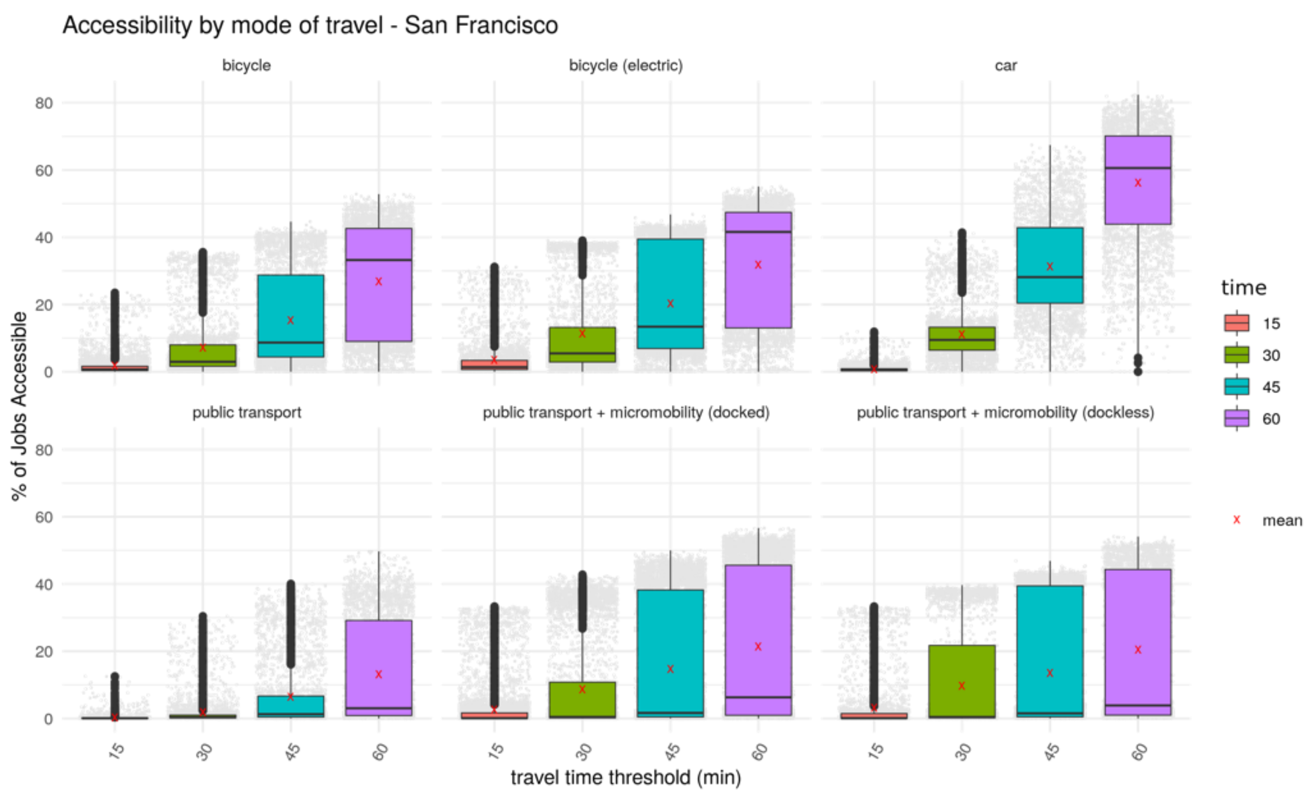


Figure 33: Distribution of accessibility for each mode – San Francisco. (Top Right) (Top Middle) (Top Left) (Bottom Left) (Bottom Middle)

Figure 34 and Figure 35 show the spatial distribution of accessibility by PT and the improvement in accessibility due to both docked and dockless micromobility services. Accessibility by public transport is very low within the 15, and 30 travel time thresholds, but both docked and dockless services remarkably improve the accessibility around their service areas.

Improvements due to micromobility spreads to more zones at higher travel time thresholds, and this can be attributed to quicker access to public transport, and the ease of coupling both modes within a more flexible time window. The improvement along the East side of the bay area, from Oakland towards the South, is due to quicker access to BART services.

Improvements due to micromobility tend to decrease in some zones as the travel time threshold is increased. One should notice that the accessibility is also constrained by the public transport schedule and frequency. If the public transport services do not provide good access, then improving accessibility to their stations using micromobility has a limited effect on accessibility improvements.

Comparing the top and bottom row in Figure 35, we see that dockless micromobility offers higher improvement than its docked counterpart at all travel time thresholds. This improvement is more pronounced in the 30-minute time threshold, as can be seen in Figure 36. We assume that dockless micromobility can be found anywhere inside its service area, whereas docked micromobility availability is a function of station locations. The assumed prevalence of dockless micromobility means that access and egress times are shorter. This is a legitimate scenario due to the flexibility of dockless services, yet it is optimistic as micromobility is subject to availability constraints. Again, we explore and elaborate on the service availability and supply constraints in Section 4.4.3.

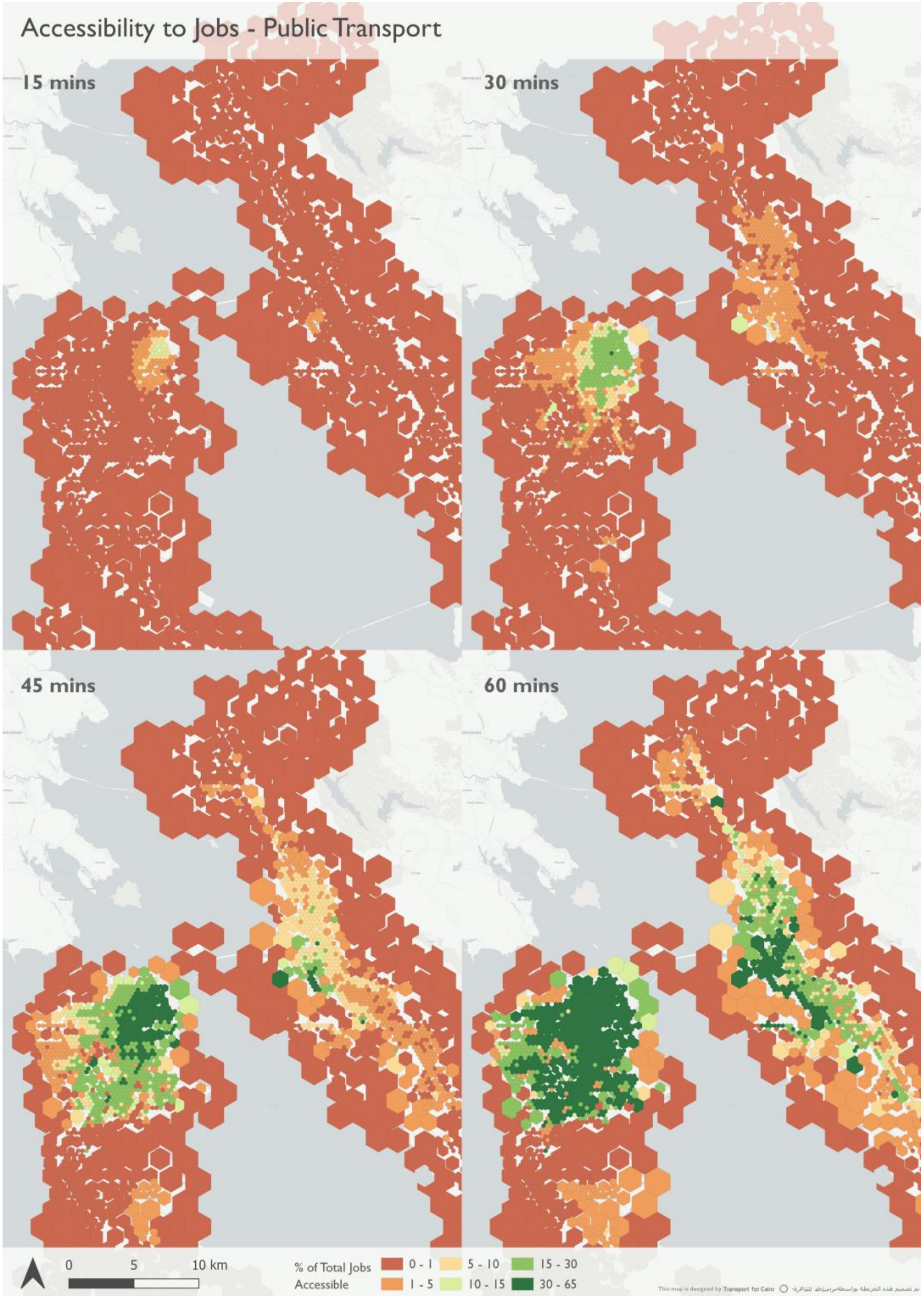


Figure 34: Accessibility by PT for different travel time thresholds (San Francisco)

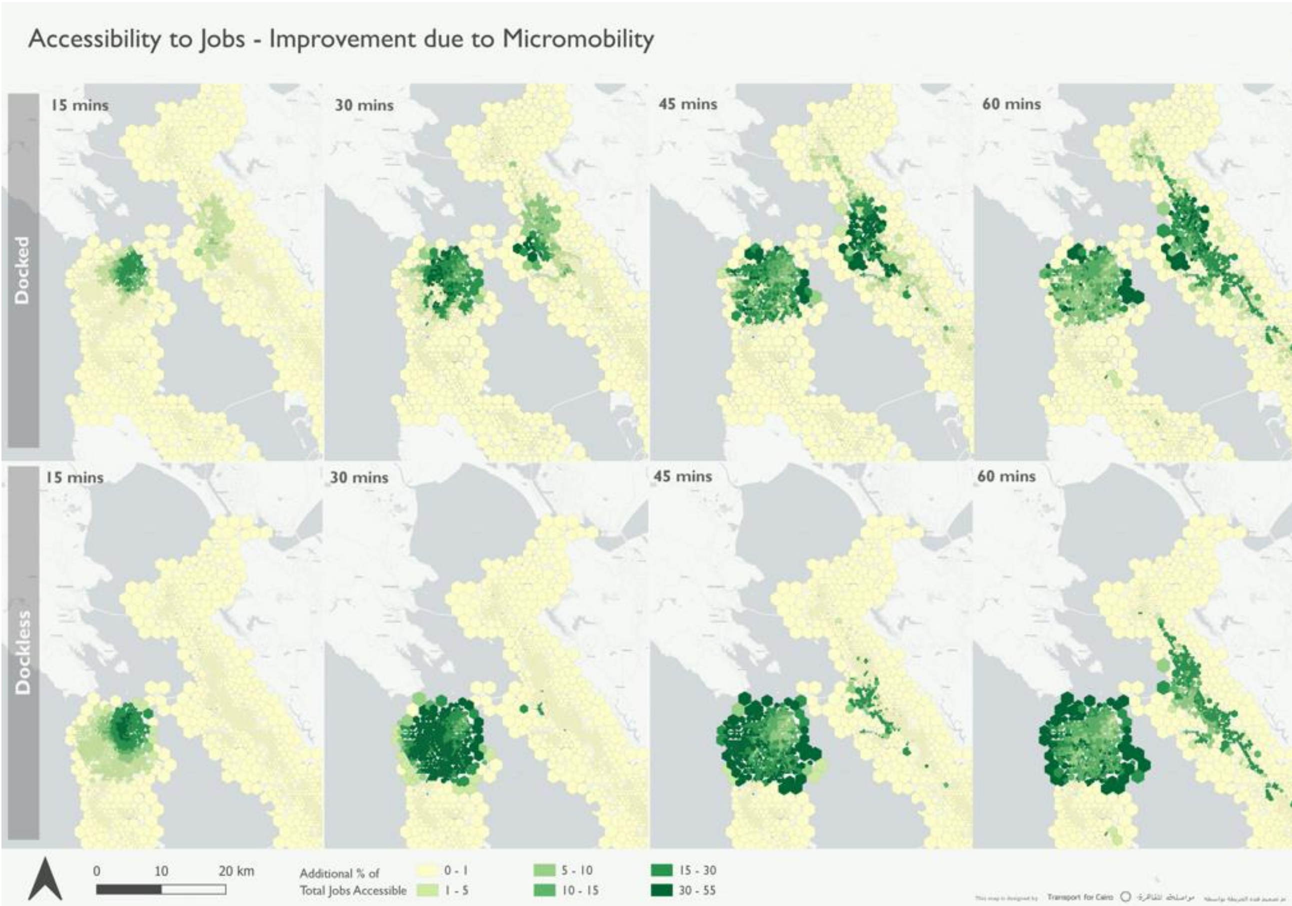

Figure 35: Accessibility gain due to micromobility (San Francisco)

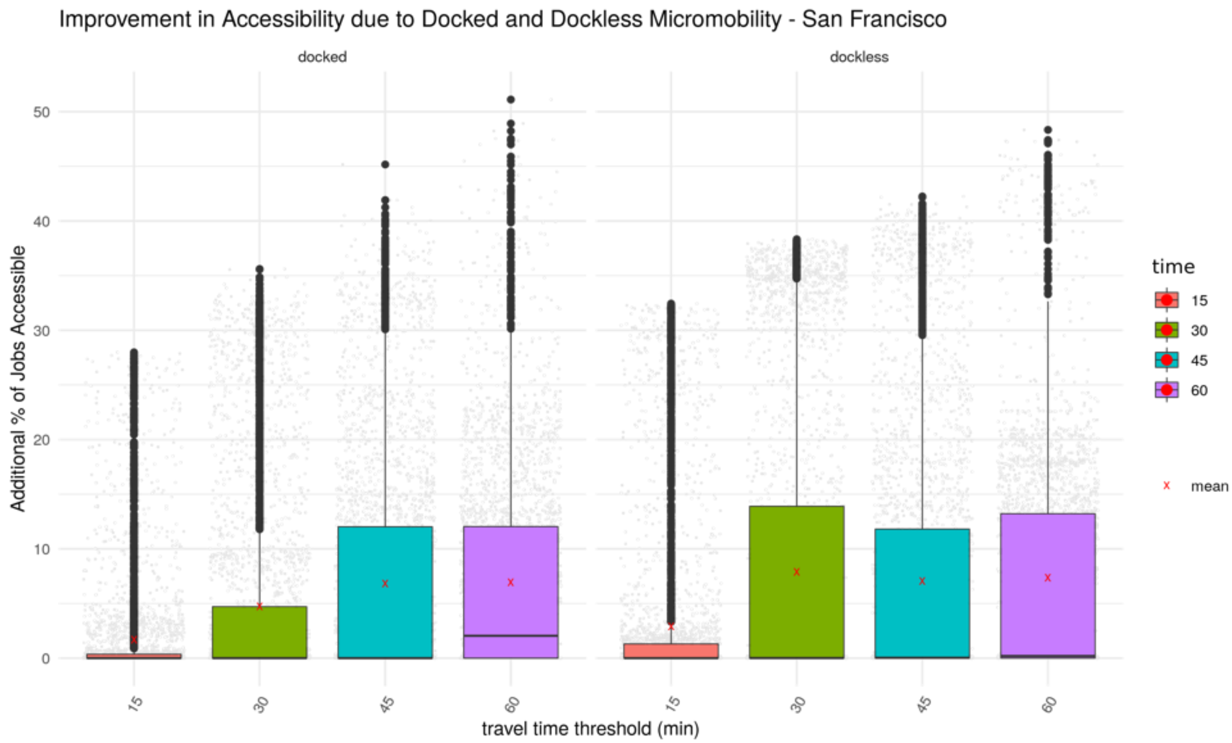


Figure 36: Improvement in accessibility due to docked and dockless systems for different travel time thresholds - San Francisco

### 4.4.3 Supply Constraints

While our results show that micromobility can have a significant impact on accessibility, they are based on the assumption that micromobility vehicles are always readily available within their service geographies. In reality, there is a limited number of vehicles, and assuming that anyone who wishes to find a vehicle is actually successful (at a docking station or within the dockless service geography) would lead to optimistic results.

Figure 37 shows an estimate of the impact of supply constraints on improvements in accessibility (the reader is referred to Section 2.4.2 for an explanation of the calculations). The map on the left shows the probability of finding a bike, while the 2nd and 3rd maps show the improvement due to micromobility ($\boldsymbol{A_{i,3-1}}$), expressed as the additional % of total jobs reachable, with and without supply constraints, respectively. The estimated effect of micromobility on accessibility is reduced to some extent when we account for supply constraints, especially in the zones inside the micromobility service geography (Figure 37). The mean reduction in jobs is around 8.5% (of total jobs). However, the zonal distribution of this reduction is long-tailed, in which, the vast majority of zones have a reduction less than the county-level mean (Figure 38). The calculations only take into account San Francisco county; looking at the entire Bay Area would have watered down the effect of supply constraints significantly given that most zones in the Bay Area are not serviced by micromobility.

It should be noted that this model assumes that demand is fixed at the figures supplied to us by the micromobility service providers. In reality, demand may change for several reasons (micromobility becomes cheaper, PT or gas becomes more expensive). If demand increases, then that would affect availability of vehicles. Since supply constraints are a function of both supply and demand, a deeper dive into the effect of micromobility supply on accessibility would require demand modelling. This is a limitation of our current approach.

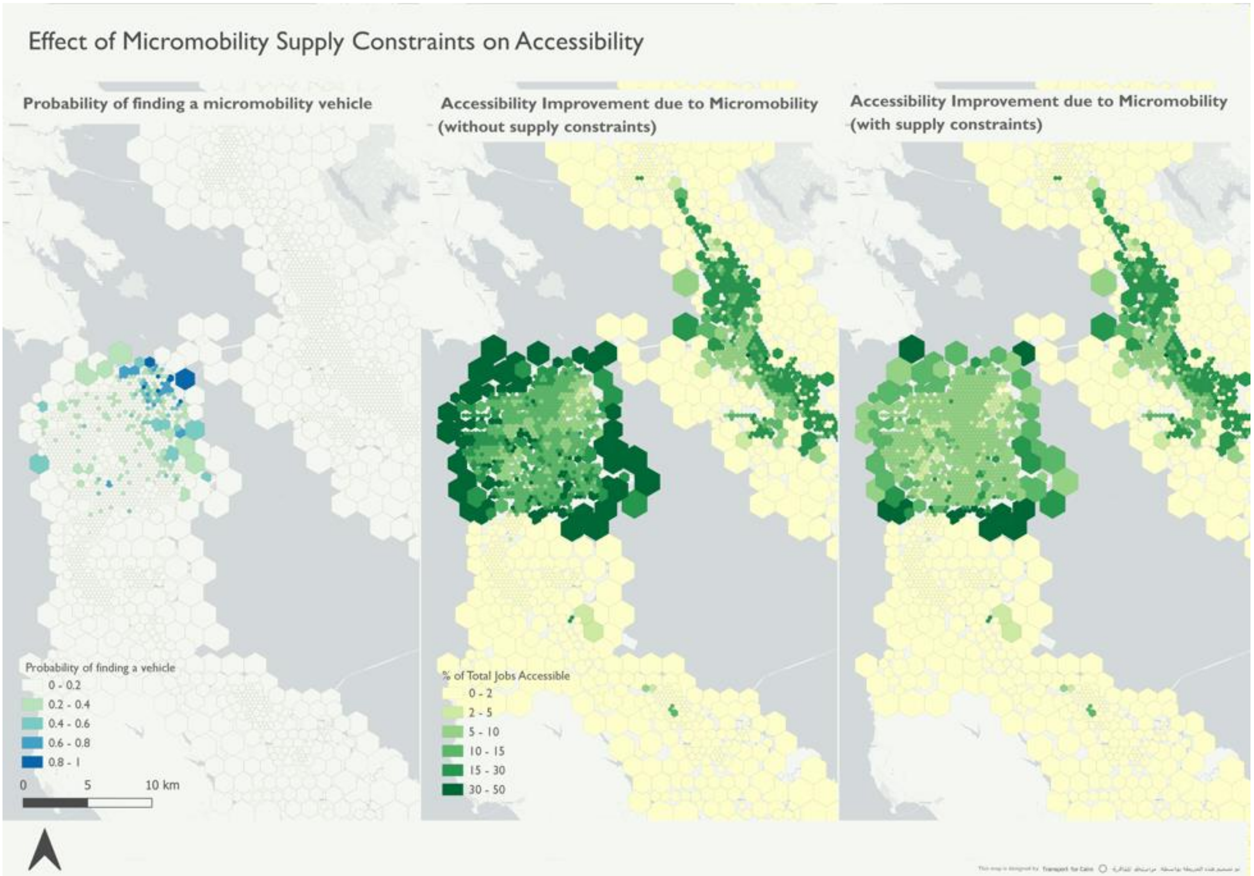


Figure 37: Effect of micromobility supply constraints on accessibility.

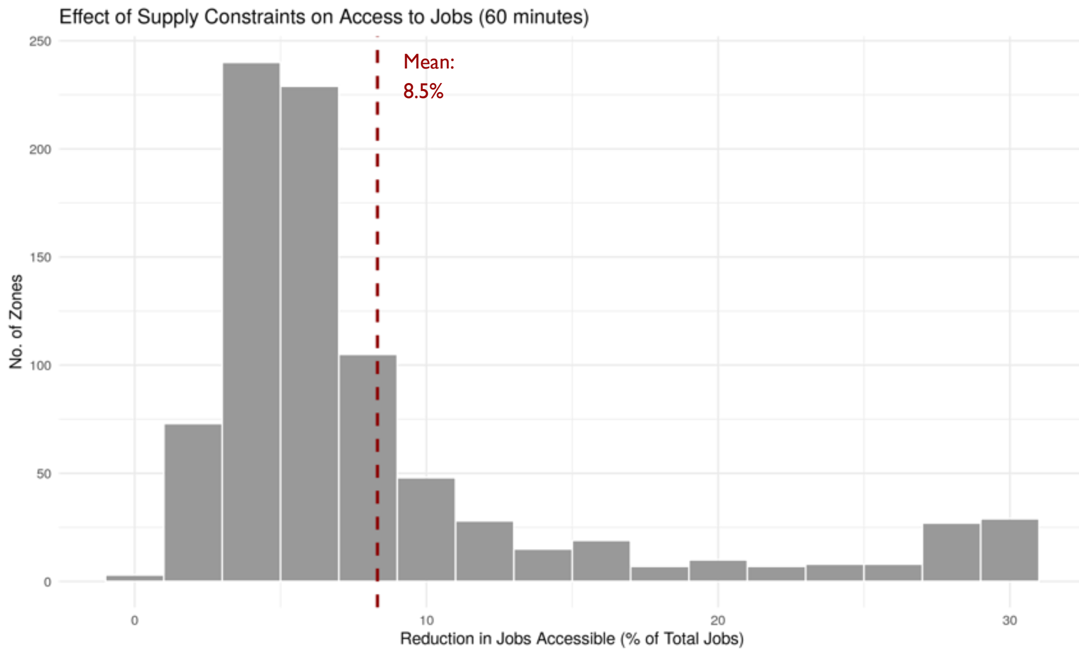


Figure 38: Reduction in jobs accessible due to supply constraints

## 4.5 Equity of Access to Opportunities

### 4.5.1 San Francisco, California

#### 4.5.1.1 Visualizing the variation in access to opportunities

Figure 39 shows the improvement in accessibility gained by having access to micromobility over the public transit system (without considering supply constraints). It also shows the spatial distribution of the racial groups across the zones in the area being studied using a racial dot map. The improvements are clustered in San Francisco in the West and in Oakland, Berkeley, and Richmond along the BART lines in the East Bay. These areas serve a diverse group of residents with White, Hispanic, and Black residents heavily represented in the improved zones. In slight contrast, there is a large agglomeration of Asian- majority population zones in the Southeast of the study region that have little to no improvement in accessibility due to micromobility.

The spatial distribution of race groups and improvements will serve as a reference to the following sections where we compute more precisely the effects of micromobility on the different groups residing in the study area.

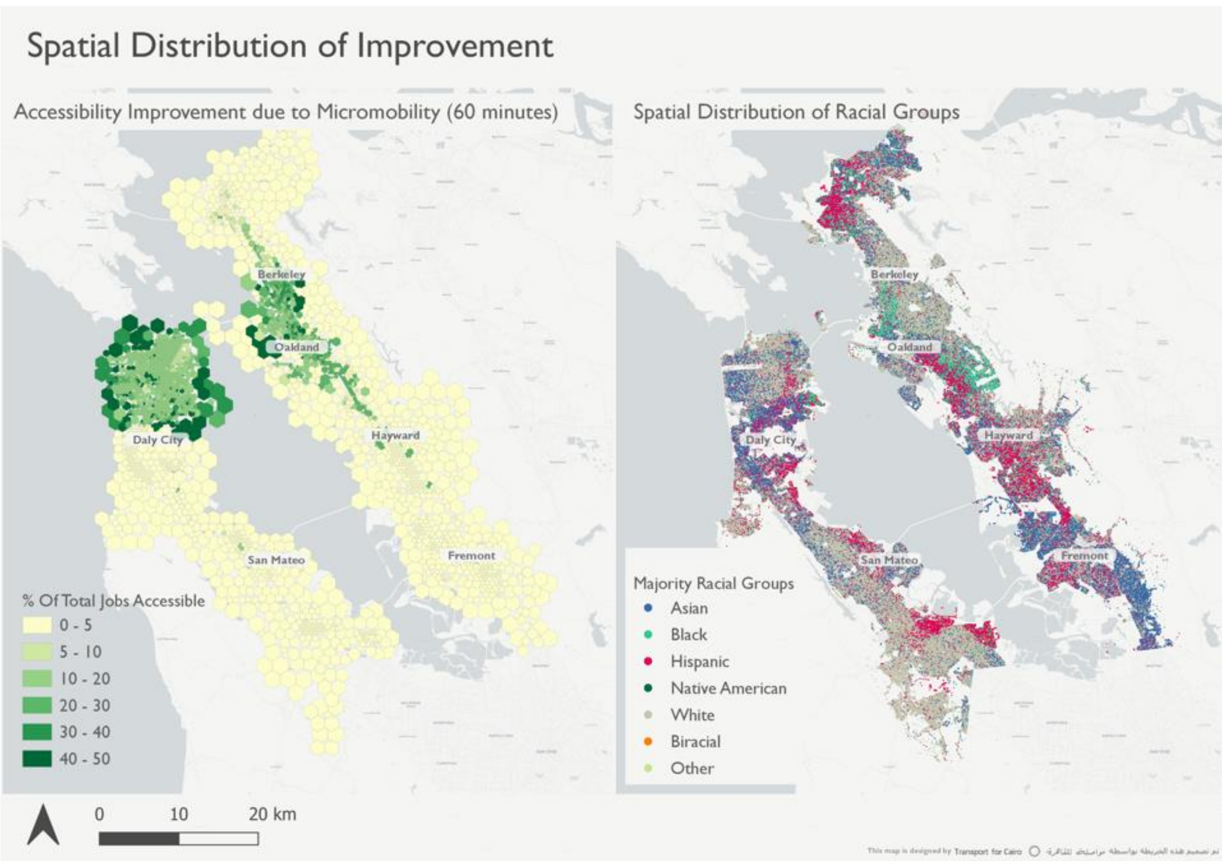


Figure 39: Spatial Distribution of Improvement in Accessibility. (Left) Accessibility Improvement due to Micromobility (60-minutes). (Right) Spatial Distribution of Majority Racial Group by Zone – San Francisco

#### 4.5.1.2 Measuring the variation in access to opportunities

The Gini coefficient and Lorenz curve are used to quantify the level of inequality in access to opportunities using different modes. In the plot in Figure 40 below, we see the curve of each mode and its distance from the ideal diagonal line. As expected, we see that the highest level of inequality is observed for the public transit mode and the mode closest to the diagonal is the best of the micromobility options. The Gini Coefficient approaches 0 for perfect equality and 1 for perfect inequality. Therefore, a Gini coefficient closer to 0 represents a more equitably distributed accessibility. The Gini coefficients of each mode are presented in Table 2.

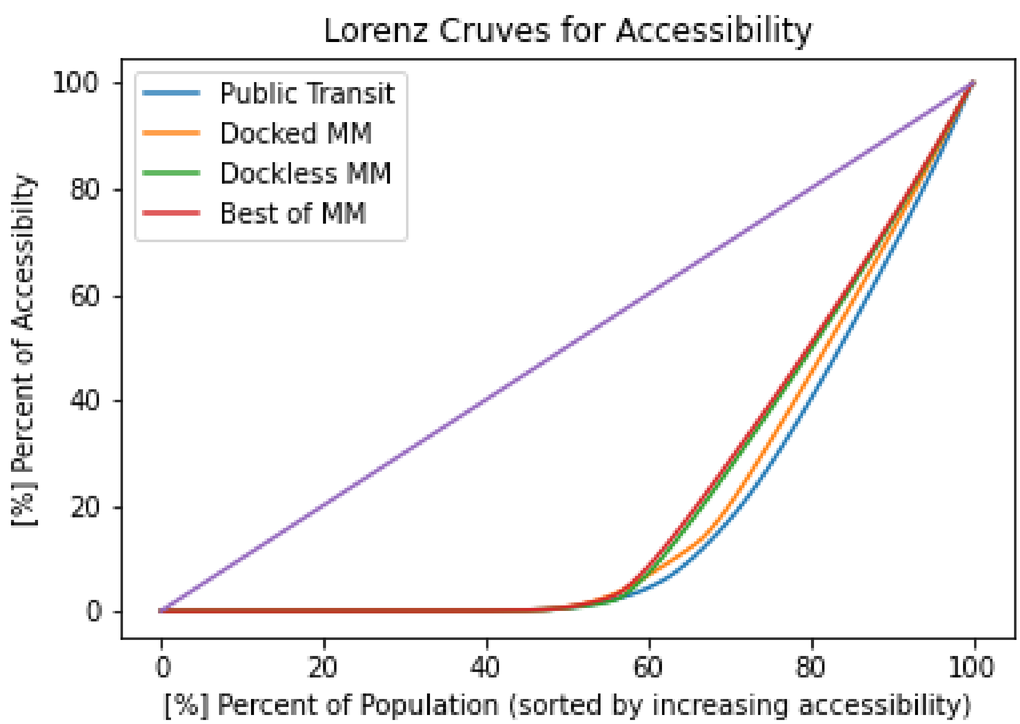


Figure 40: Lorenz Curve for Accessibility of Different Modes – San Francisco

The Gini coefficient gets closer to 0 as we go down the table as seen in Table 2. This indicates that the addition of micromobility improves the equitable distribution of accessibility to jobs across the city. In addition, dockless micromobility, since it can be taken up to the doorstep of the desired destination, has a larger positive impact on accessibility and equity in accessibility. However, given the unhindered choice between docked and dockless micromobility, the model shows that if the correct choice is made, the best of both types can lead to an even higher accessibility and equity in accessibility. Although the improvement is between 3 and 6% only, this represents a significant improvement given the vast number of zones included in the analysis.

Table 2: Gini Coefficient of Different Modes and Types of Micromobility in San Francisco

| Mode | Gini Coefficient |
|---|---|
| Public Transit | 0.6449 |
| Public Transit + Docked Micromobility | 0.6167 |
| Public Transit + Dockless Micromobility | 0.5894 |
| Public Transit + Best Micromobility | 0.5802 |

The Lorenz curves and Gini Coefficients are aggregate metrics that do not show the variation in accessibility across different demographic groups. To measure that we compute the Weighted Average Accessibility (WAA) by race across the entire study area. Comparing each race's WAA with that of the entire population will give us an idea about the gap in accessibility between races. In addition, the WAA for each race is computed for the public transit scenario without Micromobility, mode combination 1, and for public transit with micromobility, mode combination 3, to quantify the effect of micromobility on improving accessibility for each race. These metrics are shown in Table 2 below.

Table 3: Weighted Average Accessibility by Race in San Francisco Bay Area

| Racial Group | WAA without Micromobility [jobs] | WAA with Micromobility [jobs] | Improvement in WAA [jobs] |
|---|---|---|---|
| Total Population | 214008 | 287789 | 73781 |
| White | 223224 | 295050 | 71826 |
| Black | 222528 | 330235 | 107707 |
| American Indian | 232499 | 326263 | 93764 |
| Asian | 214003 | 279718 | 65715 |
| Hawaiian | 94150 | 136677 | 42527 |
| Other Race | 183070 | 260222 | 77152 |
| Other Two Races | 206923 | 285471 | 78548 |

The results tell an interesting story about the distribution of both accessibility by public transit and accessibility gain from micromobility across the races. White, Black, and American Indian residents of the Bay Area have WAA scores higher than the that of the total population while Asian residents are at the average and Hawaiian, Other Race and Other Two Races are below the average. The highest accessibility is achieved by American Indian residents which is a small minority group in the area. Asian and Hawaiian residents' improvement was less than that of the total population and their WAA considering micromobility is less than the total population WAA. On the other hand, while improvement in WAA for Other Race and Other Two Races was higher than that of the total population, the resulting WAA considering micromobility is still lower than that of the total population.

From the last column in Table 2, we can observe the effect of micromobility on the accessibility of the groups. For most minority race groups, like Black, American Indian, Other Race and Other Two Races, the improved WAA is higher than the average improvement for the total population. A different aspect of the equity story was observed when the population groups chosen were income groups.

Table 4 shows the WAA by income group in the San Francisco Bay Area with and without micromobility and the difference between them. The first row shows the total population average. Compared to the average, only the lowest income groups, below 40K, and the highest group, above 200K, have better WAA than that of the total population. With micromobility, this improves slightly to include the income group up to 45K. Interestingly, while the most affluent group had a WAA higher than the average before micromobility, its WAA after micromobility is slightly below that of the total population. Given San Francisco Bay Area's spatial distribution of income groups where the city proper has extreme wealth and poverty, it is unsurprising that most middle-income families live outside the city and have WAA scores lower than the average. Micromobility pushes the needle in the right direction, giving more low-income groups better access to jobs in the city.

Table 4 Weighted Average Accessibility by Income Group in San Francisco Bay Area

| Income Group | WAA without Micromobility [jobs] | WAA with Micromobility [jobs] | Improvement in WAA [jobs] |
|---|---|---|---|
| Total Population | 256616 | 410737 | 154121 |
| Less than 9K | 330644 | 526181 | 195537 |
| Between 10K and 15K | 379876 | 570451 | 190575 |
| Between 15K and 20K | 318255 | 498516 | 180260 |
| Between 20K and 25K | 298315 | 477357 | 179042 |
| Between 25K and 30K | 278960 | 445045 | 166084 |
| Between 30K and 35K | 267539 | 433724 | 166185 |
| Between 35K and 40K | 248914 | 405492 | 156579 |
| Between 40K and 45K | 253547 | 412989 | 159442 |

| Income Group | WAA without Micromobility [jobs] | WAA with Micromobility [jobs] | Improvement in WAA [jobs] |
|---|---|---|---|
| Between 45K and 50K | 239830 | 406654 | 166823 |
| Between 50K and 60K | 235358 | 387763 | 152405 |
| Between 60K and 75K | 237561 | 393302 | 155741 |
| Between 75K and 100K | 224932 | 372173 | 147241 |
| Between 100K and 125K | 234168 | 376634 | 142466 |
| Between 125K and 150K | 232182 | 374756 | 142575 |
| Between 150K and 200K | 237700 | 380887 | 143187 |
| More than 200K | 261186 | 407729 | 146543 |

Jobs in our model are overwhelmingly concentrated in downtown San Francisco and Oakland. While all population groups see an improvement in accessibility due to micromobility being available as a last-mile option near the downtowns, the population groups that reside where there is micromobility see an improvement from both the first mile and the last mile usage of micromobility. An example of this is Oakland's Black residents who live Northwest and Southeast of downtown Oakland in areas served by micromobility. They can utilize the service as a first-mile access mode and can benefit from micromobility services in downtown San Francisco for the last mile as well. Their accessibility gain is higher than the total population gain in WAA.

## 4.5.2 Minneapolis, Minnesota

### 4.5.2.1 Visualizing the variation in access to opportunities

Figure 41 shows the spatial distribution of improvement in accessibility which is concentrated in the center of the city where the service geography of the micromobility is. On the right of the same figure, we can see the spatial distribution of the races in the city in a racial dot map. The map shows that White residents occupy the outskirts of the city, far from the zones of improvement due to micromobility; Asian residents are in between the outskirts and downtown and the South and East of the city; Black residents as well as Hispanic residents, which may be in any race category, occupy the center where most of the improvement can be observed.

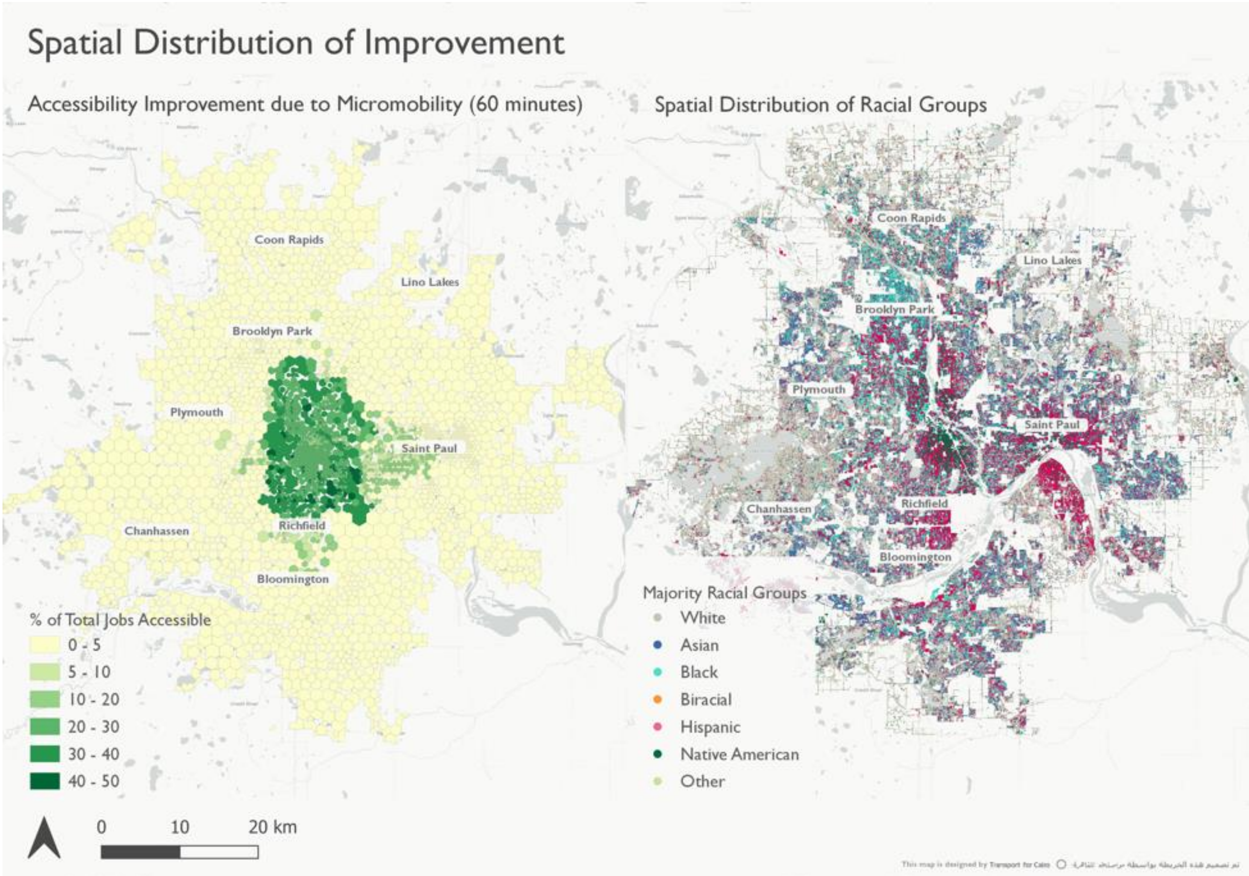


Figure 41: Spatial Distribution of Improvement in Accessibility. (Left) Accessibility Improvement due to Micromobility (60-minutes). (Right) Spatial Distribution of Majority Racial Group by Zone - Minneapolis

#### 4.5.2.2 Measuring the variation in access to opportunities

The Lorenz curve in Figure 42 tells an interesting story about the effect of the different kinds of micromobility on the distribution of accessibility across the zones in Minneapolis. Compared to Public Transit alone (PT), Docked micromobility does not improve the equitable distribution of improvement due to micromobility and Dockless micromobility is practically the same as PT alone. However, when they are combined and the best of either Docked or Dockless is chosen, the overall Gini coefficient improves by only 0.6% as shown in Table 5. Looking at the red curve (Best micromobility) compared to the blue curve (PT), we see that the distribution gets less equitable for zones in the lower 70th percentile, and improves only for the zones in the top 30th percentile of accessibility. Micromobility effectively evens out the high accessibility enjoyed by areas with relatively high PT connectivity, further increasing the gap in their accessibility from areas with relatively low accessibility by PT.

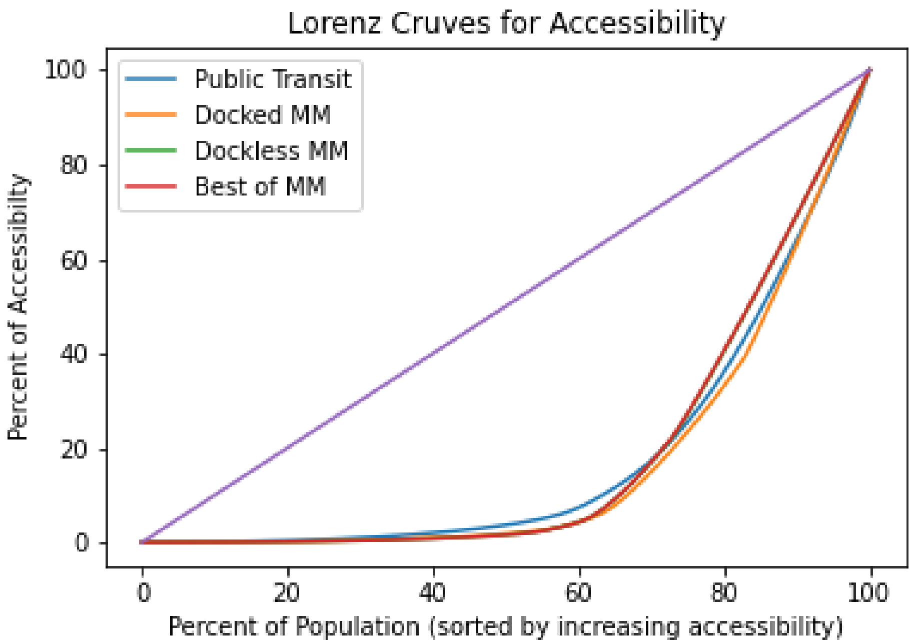


Figure 42: Lorenz Curve for Accessibility of Different Modes – Minneapolis

Table 5: Gini Coefficient of Different Modes and Types of Micromobility in Minneapolis

| Mode | Gini Coefficient |
|---|---|
| Public Transit | 0.6431 |
| Public Transit + Docked Micromobility | 0.6692 |
| Public Transit + Dockless Micromobility | 0.6378 |
| Public Transit + Best Micromobility | 0.6371 |

Although overall equity in the distribution of the improvements in accessibility due to micromobility may be unchanged, the improvement to the level of accessibility of the zones is significant in Minneapolis. Table 6 shows the WAA of each population group without micromobility and then with it. As can be expected, White and Asian residents' improvements are less than that of the total population since they benefit from micromobility services only in the last mile of their trips to jobs. On the other hand, Black, American Indian, and Other Race groups benefit from micromobility services at the first and last miles of their trips thus improving their accessibility by more than that of the total population.

Table 6: Weighted Average Accessibility by Racial Group in Minneapolis

| Racial Group | WAA without Micromobility [jobs] | WAA with Micromobility [jobs] | Improvement in WAA [jobs] |
|---|---|---|---|
| Total Population | 59189 | 156837 | 97774 |
| White | 49726 | 137086 | 87477 |
| Black | 104792 | 260828 | 156175 |
| American Indian | 126607 | 315632 | 189137 |
| Asian | 60684 | 140749 | 80235 |
| Hawaiian | 62482 | 159330 | 96856 |
| Other Race | 112277 | 280312 | 168200 |
| Other Two Races | 72855 | 190385 | 117692 |

In Table 7, we see the WAA by income group instead of race. This shows that lower income groups, from Less than 9K to 75K, witness improvements higher than that of the total population. Conversely, higher income groups, from 75K upwards, witness improvements in WAA lower than that of the total population. The most affluent residents of the city live in the Western outskirts of the city which has very little improvement in accessibility due to micromobility. From an equity perspective, this result shows that those who may need the most assistance in getting to jobs are served well by the current spatial distribution of micromobility services.

Table 7: Weighted Average Accessibility by Income Group in Minneapolis

| Income Group | WAA without Micromobility [jobs] | WAA with Micromobility [jobs] | Improvement in WAA [jobs] |
|---|---|---|---|
| Total Population | 63519 | 168359 | 104951 |
| Less than 9K | 118991 | 290249 | 171400 |
| Between 10K and 15K | 113913 | 273950 | 160139 |
| Between 15K and 20K | 95809 | 236966 | 141310 |
| Between 20K and 25K | 87412 | 216434 | 129166 |
| Between 25K and 30K | 82676 | 206347 | 123792 |

| Income Group | WAA without Micromobility [jobs] | WAA with Micromobility [jobs] | Improvement in WAA [jobs] |
|---|---|---|---|
| Between 30K and 35K | 78850 | 198707 | 119999 |
| Between 35K and 40K | 77059 | 195456 | 118525 |
| Between 40K and 45K | 68714 | 181645 | 113042 |
| Between 45K and 50K | 68807 | 178823 | 110181 |
| Between 50K and 60K | 66593 | 172198 | 105729 |
| Between 60K and 75K | 64190 | 169119 | 105042 |
| Between 75K and 100K | 56575 | 152180 | 95700 |
| Between 100K and 125K | 48367 | 133793 | 85511 |
| Between 125K and 150K | 47035 | 133186 | 86253 |
| Between 150K and 200K | 44888 | 128001 | 83223 |
| More than 200K | 43144 | 133657 | 90597 |

### 4.5.3 Caveats of the Equity Calculations

For most cities in the world, the downtown core is likely to have the highest levels of accessibility due to the concertation of jobs and the interconnectedness of transit lines. In addition, the city core typically has the highest density with vibrant land use, and therefore it is the area most likely to have micromobility infrastructure. Therefore, residents of the inner city benefit from micromobility in the first mile as well as the last mile as they take multimodal trips to jobs.

However, this belies the fact that minority populations may not be able to access micromobility services for economic reasons. For example, in Minneapolis, most black and Hispanic residents of the city live in the city center where most jobs and micromobility services are located. However, the per capita income of the inner city is below 42K for most zones. Populations with less disposable income have less access to credit cards needed for the micromobility systems and lower feelings of safety using the system and moving around the city. The analysis of these other factors falls outside the scope of our current study but is not of less importance.

# 5 Conclusion

The aim of this research is to develop a methodology for incorporating micromobility into traditional accessibility measures and, in doing so, get a better understanding of the effect of micromobility on access to opportunities.

To ensure a fair comparison, travel times used are as realistic as possible. For private vehicles, we find that using real speed data from Uber/Mapbox has a significant effect on car-based accessibility compared to using free flow speeds. Parking and access/egress times also has an effect on car-based accessibility, but this effect is more noticeable for shorter travel time thresholds (15 and 30 minutes) where the time to park or walk to or from the car represents a bigger proportion of the total trip time.

However, even after accounting for congestion, parking, and access/egress times, private cars still have better accessibility than public transport or public transport and micromobility in all the cities in our study. For shorter travel time thresholds, micromobility, where it is available, is a competitive alternative to car-based transport. Micromobility can also be competitive with private cars for travel time thresholds of 30 minutes in San Francisco due to high public transport accessibility which allows micromobility to be useful as a first or last-mile solution for public transport trips. So, while micromobility on its own can provide similar accessibility to cars inside a 15-minute threshold, good public transport and micromobility are required together to provide accessibility similar to that of cars for larger travel time thresholds.

The spatial distribution of improvements of accessibility due to micromobility also varies depending on the travel time threshold considered. For short travel time thresholds, the improvement is mostly focused inside the service geography of the micromobility providers. As the travel time threshold increases, improvements in accessibility extend outwards to zones bordering the service geography and beyond as micromobility acts as a last-mile option for trips from these zones into the center of the city. Improvements at short travel time thresholds can decrease as the threshold increases, and this is due to the schedule constraints of public transport serving these zones. It could be useful to focus on peripheral zones that show increasing improvement with increasing thresholds as well as zones that show no improvement even at small thresholds. The former benefit from micromobility as a last-mile option but accessibility may be limited by the time needed to access public transport. The latter are probably in inaccessible zones and would benefit from micromobility as an access mode to public transport as well.

Dockless micromobility shows better improvement in accessibility than its docked counterpart since it is not restricted by specific docking station locations.

We applied a novel methodology to account for the supply constraints of micromobility since an individual is not guaranteed to always find a micromobility vehicle at the docking station. Our results showed that accounting for supply constraints reduces the accessibility gains of micromobility. The average reduction in improvement in accessibility per zone is around 8.5% of total jobs. This methodology is experimental, and it assumes that demand is fixed at the figures supplied to us by the micromobility service providers. Since supply constraints are a function of both supply and demand, a deeper dive into the effect of micromobility supply on accessibility would require demand modelling, which is outside the scope of this study.

Equity considerations have become an essential part of transport appraisal. In this work we operationalized equity parameters into the analysis framework. The Gini coefficient and Lorenz curves were used to quantify the level of inequality in access to opportunities using different modes. The analysis focused on the two US cities: San Francisco Bay Area and Minneapolis-Saint Paul.

For San Francisco the use of micromobility is associated with a decrease in the Gini coefficient, indicating that the addition of micromobility improves the equitable distribution of accessibility to jobs across the city. Dockless micromobility results are better than those of docked micromobility. Although the improvement is between 3 and 6% only, this represents a significant improvement given the vast number of zones included in the analysis.

For Minneapolis, the results were not as positive. Neither docked nor dockless micromobility improve the equitable distribution of improvement in accessibility. When the best of either docked or dockless micromobility is chosen, the overall Gini coefficient improves by only 0.6%. Improvements in accessibility are focused on areas that already have high accessibility due to high public transport connectivity, further increasing the gap between areas with high and low accessibility.

Another perspective of equity is the effect of micromobility on the different racial and socioeconomic groups. To quantify this effect, we look at the Weighted Average Accessibility (WAA). For both cities, we see that lower income groups witness improvements higher than that of the total population. Conversely, higher income groups witness improvements in WAA lower than that of the total population. This relatively equitable distribution of the gains due to micromobility is due to its use as a first and last-mile mode as well as main mode for populations living in the center. On the other hand, population groups outside the center can benefit from micromobility only in the last mile after using public transport to get into the service geography of micromobility.

A high positive effect of micromobility is only achievable in tandem with a robust public transport system. Since the highest density of job opportunities is in central downtown areas, outer zones need better connectivity to the center with more frequent public transport services. Micromobility combined with frequent public transport service would lead to significant improvements in accessibility in outer zones. Its mean improvement increases as travel time increases until it reaches a plateau. This plateau varies for the cities studied (30 minutes for dockless micromobility in SF; 45 for micromobility in Cairo, Mexico, and docked micromobility in SF, and 60 for Minneapolis) and is due to the interplay with public transport schedules. The better the connectivity of zones with public transport alone, the lower the travel time threshold where the improvement plateaus are reached.

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