



HAL
open science

On the Computation of accessibility provided by shared mobility

Severin Diepolder, Andrea Araldo, Tarek Chouaki, Santa Maiti, Sebastian Hörl, Constantinos Antoniou

► **To cite this version:**

Severin Diepolder, Andrea Araldo, Tarek Chouaki, Santa Maiti, Sebastian Hörl, et al.. On the Computation of accessibility provided by shared mobility. 11th Symposium of the European Association for Research in Transportation (hEART), Sep 2023, Zurich, Switzerland. hal-04154712v3

HAL Id: hal-04154712

<https://hal.science/hal-04154712v3>

Submitted on 17 Nov 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

On the Computation of Accessibility Provided by Shared On-Demand Mobility

Severin Diepolder¹, Andrea Araldo^{2*}, Tarek Chouaki³, Santa Maiti⁴, Sebastian Hörl³, and Constantinos Antoniou⁵

¹ioki, 63322 Frankfurt, Germany

²SAMOVAR, Télécom SudParis, Institut Polytechnique de Paris, Palaiseau, 91120 Palaiseau France

³IRT System X, Palaiseau, 91120 Palaiseau France

⁴University College London, WC1E 6BT, London, United Kingdom

⁵Chair of Transportation Systems Engineering, Technical University of Munich, 80333, Munich, Germany

*andrea.araldo@telecom-sudparis.eu

+these authors contributed equally to this work

ABSTRACT

Shared Mobility Services (SMS), e.g., demand-responsive transport or ride-sharing, can improve mobility in low-density areas, often poorly served by conventional Public Transport (PT). Such improvement is mostly quantified via basic performance indicators, like wait or travel time. However, accessibility indicators, measuring the ease of reaching surrounding opportunities (e.g., jobs, schools, shops, ...), would be a more comprehensive indicator. To date, no method exists to quantify the accessibility of SMS based on empirical measurements. Indeed, accessibility is generally computed on graph representations of PT networks, but SMS are dynamic and do not follow a predefined network. We propose a spatial-temporal statistical method that takes as input observed trips of an SMS acting as a feeder for PT and summarized such trips in a graph. On such a graph, we compute classic accessibility indicators. We apply our method to a MATSim simulation study concerning demand-responsive transport in Paris-Saclay.

Keywords: Accessibility; Public Transport; Shared Mobility; Mobility On-Demand; Demand-Responsive Transport

1 Introduction

Location-based accessibility measures the ease of reaching surrounding opportunities, such as education, health, culture, shopping places, via transport (Miller [2020]). The ease is mainly measured in terms of time needed, but it can also include other factors, such as monetary cost, discomfort. Accessibility provided by conventional Public Transport (PT) is generally poor in low-demand areas, e.g., suburbs (Badeanlou et al. [2022]), because a high frequency and high coverage service in such areas would imply an unaffordable cost per passenger. Poor PT accessibility in the suburbs makes them car-dependent, which prevents urban regions from being sustainable ([Saeidizand et al., 2022, Section 2.2]), under the three pillars of sustainability: (i) Environment: 61% of European road transport comes from cars (EUF [2022]), (ii) Society: people without cars can have up to 5 times less access to jobs (Wiersma et al. [2021]) and (iii) Economy: the time spent into congestion amounts to 100 billion € in Europe (EU Commission [2020]). The lack of satisfying accessibility from PT and the car-dependency might be one of the cause of the fact that suburban population is responsible for a part of pollution that is larger than those living in the centre. Such fact has been observed by Pottier et al. [2020] (Fig. 4) in France.

Shared Mobility Services (SMS), e.g., Demand-Responsive Transit (DRT), ride-sharing, carpooling, car-sharing, are potentially more efficient than conventional PT in the suburbs (Calabrò et al. [2023]) and can contribute to reducing the gap of accessibility between suburbs and city centres Wang et al. [2024]. However, their current deployment is commonly led by private companies targeting profit maximization. This may turn SMS into a competitor of sustainable modes, such as Public Transport (PT) (Cats et al. [2022]), and an additional source of congestion and pollution (Henao and Marshall [2019], Erhardt et al. [2019]). In order to fully exploit the social benefit potential of SMS, their deployment should be overseen by public transport authorities. A large corpus of literature advocates for integrating SMS into conventional PT (Fielbaum and Alonso-Mora [2024], Wang et al. [2024], Calabrò et al. [2023]) instead of operating it separately. However, no quantification methods exist to measure the impact of such an integrated system on the distribution of accessibility in a given region.

In this paper, we devise a method to quantify the impact of SMS on accessibility, based on empirically observed trips. Developing such a method is challenging, because most accessibility definitions are based on computing shortest paths on a

graph. While a graph (in particular a time-expanded graph) can model well conventional PT (Fortin et al. [2016]) and road networks, SMS do not have a natural graph representation. Indeed, the routes of SMS are stochastic and change over time. As a consequence, it would be misleading to compute accessibility on a graph trivially composed of connections served by observed trips (for instance trips of the day before). Such a computation would just give us an idea of what opportunities people reached in the past and how easy it was for them. This violates the spirit of accessibility indicators, which aim instead to tell the *potential* of reaching opportunities, even those that have never been accessed by a particular user. Computing accessibility from SMS thus require to extract, from past observed trips, such a potential. This calls for statistical methods that can “summarize” observations over multiple days.

The novel contribution of this paper consists in developing a spatial-temporal statistical pipeline to transform a dataset of previously observed SMS trips in a graph representation, on top of which well-established accessibility computation can be performed. The observations that can be taken as input might come from real measurements or from simulation. This paper’s observations come from a MATSim simulation of a DRT, acting as feeder for main metro lines in the Paris Saclay (Chouaki et al. [2023]). Our method is thus adapted to the case of a many-to-one and one-to-many transport service acting as a feeder for conventional PT. However, our method could later be adapted to ride-hailing, carpooling, car-sharing or bike-sharing.

It is well known that SMS implies a high cost for the operator (Calabrò et al. [2023]), and thus for the communities who might consider developing it. Therefore, such communities need to know what are the benefits of SMS. However, SMS are often evaluated in terms of level of service (amount of requests that can be served, average trip time, etc.). By doing so, the benefits of SMS are understated, and are limited to the performance of SMS itself. High cost of development, together with a lack of understanding and quantification of the real benefits of SMS, are barriers to their large adoption. We believe that the real potential of SMS resides in its ability to improve accessibility in places where conventional PT cannot do it: being able to show claims such as “a certain SMS deployment gives to suburban people access to additional x thousands jobs in half an hour with respect to conventional PT only” is much more meaningful than just saying that it can guarantee a certain average trip time, and can foster adoption of SMS. In this sense, by providing a first method to quantify the accessibility of SMS on empirical observations, this work can contribute to foster adoption of SMS and to guide their deployment under the lens of accessibility.

2 Related Work

There exists multiple decades of excellent work regarding Shared Mobility Services (SMS) and regarding accessibility. Reviewing these two fields would be out of the scope of this section. A recent review on modelling and optimization of SMS, with a focus on Demand-Responsive Transit (DRT), can be found in Sec. 2 of Calabrò et al. [2023]. A short and excellent review on the concept of accessibility is provided by Miller [2020] and tools to evaluate it are presented in Silva et al. [2019]. However, work on SMS does not generally consider accessibility and work on accessibility does not generally consider SMS.

Chandra et al. [2013] study how SMS improves connection to conventional PT stops. The observation is confirmed by Calabrò et al. [2023] (Fig. 7), who show that, by deploying SMS-based feeder in the suburbs, the time to access main Public Transport (PT) corridors is reduced with respect to conventional fixed-route feeder lines. However, the “access to PT” observed in the aforementioned two papers needs not to be confused with accessibility, which expresses the potential to access opportunities, rather than the potential to access PT. When computing accessibility, PT should not be treated as the target, but as a means. This is why, in our work, accessibility is equal to the number of opportunities that can be reached in a certain time *via* SMS combined with PT.

Considerations about the impact of SMS in accessibility have been triggered by the advent of automated vehicles. Milakis et al. [2018] proposes a conceptual method, based on interviews to experts, to qualitatively evaluate the impact of automated SMS into accessibility. Eppenberger and Richter [2021] propose another conceptual method to identify the areas in which the accessibility currently provided by conventional PT is much lower than cars. Such areas are identified as the one in which the development of automated SMS could be the most beneficial. These contributions, however, are focused on qualitative considerations and do not compute accessibility of SMS. Quantification of accessibility provided by SMS is pursued by Nahmias-Biran et al. [2021], Zhou et al. [2021] and Ziemke and Bischoff [2023]. They all resort to random-utility based measures of accessibility (following the terminology of Miller [2020]). Such measures are based on utilities perceived by agents within high-detail simulations. However, the complexity of the development of such simulations limits the applicability of such methods. Moreover, the validity of the obtained accessibility measure is tightly dependent on the correctness of the model and of the calibration of the agent-based simulation, which is hard to obtain and hard to prove. For this reason, we adopt instead an isochrone-based measure of accessibility, which counts the number of opportunities that can be reached in a given amount of time. This measure is easily interpretable. It also allows us to quantify accessibility, solely based on observed SMS trip times, either from the real world or simulation, and applying an appropriately designed statistical method (Sec. 3).

We now emphasize the difference between our work and previous work of Ziemke and Bischoff [2023] and Abouelela et al. [2024]. Ziemke and Bischoff [2023] compute accessibility of a taxi-like service, with one passenger at a time, going from an origin to a destination. Abouelela et al. [2024] analyse the accessibility generated by shared e-scooters, which, obviously, can

be used by one user at a time. In both cases, there are no shared trips. In this work we compute instead the accessibility of a shared feeder service, where (i) having multiple passengers at a time is crucial for achieving the required cost-efficiency and (ii) the accessibility gained by passengers is achieved by bringing passengers to main PT hubs from which opportunities are easily reachable. The two aspects that characterize our work with respect to Ziemke and Bischoff [2023] and Abouelela et al. [2024] are thus (i) trip sharing and (ii) multimodality. These two aspects prevent us from computing travel times as simply inversely proportional to the speed of the considered mode (e.g., e-scooter speed, as in Abouelela et al. [2024]). The novel statistical approach we devise in this paper allows to naturally deal with these two aspects, by estimating resulting travel times from a dataset of observed trips.

Recent work focuses on the accessibility improvement achieved via a feeder provided by Demand-Responsive Transport (DRT), and models the travel times of DRT with analytic models, namely continuous approximation (Le Hasif et al. [2022], Wang et al. [2024]). The former builds a detailed dynamic graph representing the schedule of the conventional PT, based on real world General Transit Feed System (GTFS), and adds new “virtual links” with travel and waiting times obtained by continuous approximation. The latter does not adopt a detailed GTFS-based representation and resorts to a frequency-based graph: the core of this graph is a simplified representation of conventional PT, on top of which “DRT arcs” are added in the different regions in which DRT is deployed, weighted by the average waiting time and travel times, computed via continuous approximation. The goal of Wang et al. [2024] is to find an allocation of DRT in a metropolitan region in order to decrease the inequality in the geographic distribution of accessibility. The issue is that, since they use analytic models for computing SMS performance, Le Hasif et al. [2022], Wang et al. [2024] fail to give real insights specific to the areas under study. Our effort consists instead in estimating accessibility from empirical observations. Note that, recently, the GTFS-Flex extension allows also describing SMS (Craig and Shippy [2020]). Although our estimates could thus be fed into GTFS-Flex data, for the sake of simplicity, we use plain GTFS instead.

To summarize, to the best of our knowledge, we are the first to propose a method to compute isochrone measures of the accessibility obtained via integrating SMS with a conventional PT service. The main novel feature of our method is that it is fully data-driven, as it allows computing accessibility based on observed trips (either from real scenarios or simulations) via statistical methods, without needing to build complex models.

3 Methodology

The idea behind our method is intuitive: we aim to model Shared Mobility Services (SMS) with the same representation of conventional PT lines, so as to allow computing accessibility on a coherent model. Conventional PT is usually modelled as a time-dependent graph, this is the implicit model underlying GTFS. In this model, each PT line is represented by a set of arcs, each arc represents the passage of a bus from one stop to another. To adapt to the conventional PT model description, we wish to represent a feeder service from an area to a certain stop,¹ as a set of “virtual PT lines”, each connecting a centroid to that stop. We wish to construct such a virtual PT line as a proxy of the performance offered by SMS, i.e., in a way such that the performance of such a virtual line is similar, on average, to the performance actually experienced by SMS users.

3.1 Accessibility

As in (Biazzo et al. [2019]), the study area is tessellated in sufficiently small hexagons,² whose centres $\mathbf{u} \in \mathbb{R}^2$ are called centroids and denoted with set $\mathcal{C} \subseteq \mathbb{R}^2$. Each hexagon contains a certain set of *opportunities*, e.g., jobs, places at school, people. With $O_{\mathbf{u}}$ we denote the amount of opportunities in the hexagon around \mathbf{u} and with $T(\mathbf{u}, \mathbf{u}', t)$ the time it takes to arrive in \mathbf{u}' , when departing from \mathbf{u} at time t . According to the isochrone-based definition of Miller [2020], accessibility is the amount of opportunities that one can reach departing from \mathbf{u} at time of day t within time τ :

$$acc(\mathbf{u}, t) \equiv \sum_{\mathbf{u}' \in \mathcal{C}(\mathbf{u}, t)} O_{\mathbf{u}'}. \quad (1)$$

$\mathcal{C}(\mathbf{u}, t) = \{\mathbf{u}' \in \mathcal{C} | T(\mathbf{u}, \mathbf{u}', t) \leq \tau\}$ is the set of centroids reachable within time τ . We consider here travel times provided by PT (combining walk, fixed lines and SMS).³ Accessibility jointly depends on the spatial distribution of opportunities (which determines number $O_{\mathbf{u}}$ of opportunities around centroid \mathbf{u}) and the transport system (which determines travel times $T(\mathbf{u}, \mathbf{u}', t)$). The focus of this paper is on the transport system. By improving PT, such a set can be enlarged, which consents to reach more

¹Symmetrically, we also represent an SMS service from a stop to a surrounding area.

²The smaller the hexagons, the more precise is the accessibility computation, but the more the computational power needed.

³We deliberately make the choice of excluding other modes from our analysis, and in particular of excluding cars. It is true that people can access opportunities by car. On the other hand, in view of the urgent need of reducing car-dependency, we believe transport planners should be concerned on the ease of reaching opportunities *via sustainable modes*, in lieu of (or at least in addition to) the ease of reaching opportunities *by whichever modes*. Indeed, if planners aimed to improve accessibility by *whichever modes*, they would inevitably plan cities for cars, as cars are often the fastest way to travel. This would obviously contradict the effort of achieving sustainable cities.

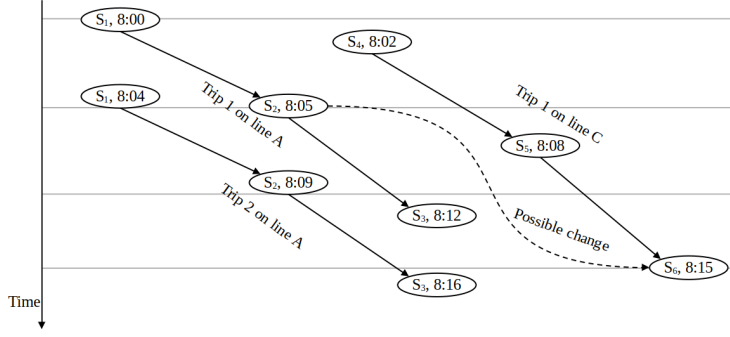


Figure 1. Time-expanded graph, representing two trips on line A and one trip on line B, as well as a potential change.

opportunities. In this work, for simplicity, the opportunities are the number of people (residents) that can be reached. We make this choice as it is sufficient to show the formalism of our method. One could easily replace the distribution of people with the distribution of other kind of opportunities to compute a more meaningful measure of accessibility. Observe that travel times $T(\mathbf{u}, \mathbf{u}', t)$ are always computed on a graph representation of the transport network. However, SMS are not based on any network, due to their dynamic and stochastic nature. Our effort is thus to build a graph representation of SMS, despite the absence of a network model. In the following subsections we describe our method to do so.

3.2 Time-Expanded Graph Model of conventional PT

We first describe the model of conventional PT. Inspired by Fortin et al. [2016] and Le Hasif et al. [2022], we model PT as a time-expanded graph \mathcal{G} , compatible with the GTFS format. The nodes of \mathcal{G} are *stoptimes*. Stoptime (s, t) indicates the arrival of a PT vehicle at a stop $s \in \mathbb{R}^2$ (modelled as a point in the plane) at time $t \in \mathbb{R}$. Different trips on a certain PT line are represented as sequences of different stoptimes, as in Figure 1. Change from a line to another is represented by a connection between stoptimes (s, t) and (s', t') , which belong to the first and the second line, respectively. This “change connection” is added if time $T_{\text{walk}}(s, s')$ between s and s' is within a maximum tolerated time and if it is possible to arrive in s' before the departure of the corresponding vehicle, i.e., if $t + T_{\text{walk}}(s, s') \leq t'$. When a user departs at time t_0 from location \mathbf{x} to location \mathbf{x}' , they can simply walk (but no more than the maximum walk time). Or they can walk to s , board a PT vehicle at t (corresponding to a stoptime (s, t)), use PT up to a stoptime (s', t') and from there walk to \mathbf{x}' . The arrival time at \mathbf{x}' will be t' plus the time for walking. Users are assumed to always choose the path with the earliest arrival time. Path computation is performed within CityChrone ([Biazzo et al., 2019, Supplementary Information]). No capacity constraints are considered.

3.3 Integration of shared mobility into the time-expanded graph

SMS is assumed to provide a feeder service to conventional PT. In a feeder area $\mathcal{F}(s) \subseteq \mathbb{R}^2$ around some selected stops s (which we call *hubs*), SMS provide connection to and from s . The set of centroids in such an area is $\mathcal{C}(s) = \mathcal{C} \cap \mathcal{F}(s)$. In this section, we will focus on access trips (from a location to a PT stop) performed via SMS. The same reasoning applies to egress trips, *mutatis mutandis*. We assume to have a set \mathcal{O} of observations. Each observation $i \in \mathcal{O}$ corresponds to an access trip and contains:

- Time of day $t_i \in \mathbb{R}$ when the user requested a trip via SMS
- Location $\mathbf{x}_i \in \mathbb{R}^2$ where the user is at time t_i
- Station s_i where the user wants to arrive via the SMS feeder service
- Duration w_i indicating the wait time before the user is served: it can be the time passed between the time of request and the time of pickup from a vehicle, in case of ride-sharing, SMS or carpooling; it can be the time to wait until a vehicle is available at the docks in a car-sharing or bike-sharing system.
- Travel time y_i : time spent in the SMS vehicle to arrive at s_i .

We interpret y_i and w_i as realizations of spatial-temporal random fields (Handcock and Wallis [1994]): for any time of day $t \in \mathbb{R}$ and physical location $\mathbf{x} \in \mathcal{F}(s)$, random variables $W^s(\mathbf{x}, t), Y^s(\mathbf{x}, t)$ represent the times experienced by a user appearing in t and \mathbf{x} , willing to go to stop s via SMS. Let $\hat{w}^s(\mathbf{u}, t), \hat{y}^s(\mathbf{u}, t)$ estimations of expected values $\mathbb{E}[W^s(\mathbf{u}, t)], \mathbb{E}[Y^s(\mathbf{u}, t)]$, respectively, at centroids $\mathbf{u} \in \mathcal{C}(s)$. We defer the computation of such estimation to the next subsection, and we now instead explain how we use such estimations to calculate “virtual PT lines”, which we then add as additional arcs to the time-expanded graph of PT.

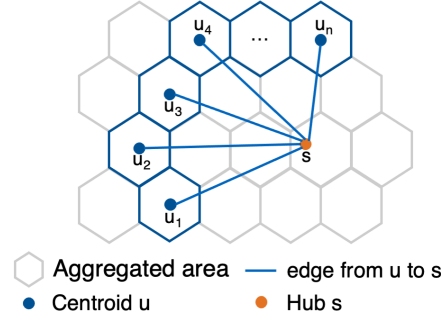


Figure 2. Hub and virtual trips provided by SMS

The virtual PT line that we will use as a proxy of SMS between centroid $\mathbf{u} \in \mathcal{C}(\mathbf{s})$ and hub \mathbf{s} (Figure 2) is a sequence of “virtual trips”. Such trips are “virtual” in the sense that they have not necessarily been observed in the past (although they should statistically summarize observed trips). We make all virtual trips start at \mathbf{u} and end at \mathbf{s} , and we assign to them departure times $t_j, j = 1, 2, \dots$ spaced by a headway $\hat{h}^s(\mathbf{u}, t_j)$, i.e. $t_j = t_{j-1} + \hat{h}^s(\mathbf{u}, t_j)$. We use the common approximation from [Cascetta, 2009, (2.4.28)], to approximate the headway as double the waiting time: $\hat{h}^s(\mathbf{u}, t) = 2 \cdot \hat{w}^s(\mathbf{u}, t)$. For each virtual SMS trip, we add a time-dependent arc to the overall graph \mathcal{G} . We associate to that arc the trip time of the virtual SMS trip, which we set equal to $\hat{y}^s(\mathbf{u}, t_j)$. The origin of each arc above is stoptime (\mathbf{u}, t_j) . Before generating stoptimes, we first fix an instant t_0 (selected uniformly at random in the interval $[00 : 00, 24 : 00]$), and then we add stoptimes before and after t_0 , all spaced by $\hat{h}^s(\mathbf{u}, t_j) = 2 \cdot \hat{w}^s(\mathbf{u}, t_j)$:

$$\begin{aligned}
 &(\mathbf{u}, t_0), \\
 &(\mathbf{u}, t_j) \quad \text{where } t_j = t_{j-1} + 2 \cdot \hat{w}^s(\mathbf{u}, t_{j-1}) \text{ for } j = 1, 2, \dots, \quad \text{until 11:59 pm,} \\
 &(\mathbf{u}, t_j) \quad \text{where } t_j = t_{j+1} - 2 \cdot \hat{w}^s(\mathbf{u}, t_{j+1}) \text{ for } j = -1, -2, \dots, \quad \text{until 00:00 am.}
 \end{aligned} \tag{2}$$

Correspondent stoptimes are also added to represent the arrival of the virtual SMS trips $(\mathbf{s}, t_j + \hat{y}^s(\mathbf{u}, t_j))$, so that the time-expanded arcs representing virtual SMS trips connect a corresponding departure stoptime and the corresponding arrival stoptime. A similar process is applied for egress trips, *mutatis mutandis*. At the end of the described process, time-expanded graph \mathcal{G} will have been enriched with stoptimes and time-expanded arcs representing SMS trips. Having done so, it is possible to reuse accessibility calculation methods for time-expanded graphs, such as CityChrono Biazzo et al. [2019], with no modifications required.

3.4 Estimation of Waiting and Travel Times

In the previous subsection, we have explained how, given estimations $\hat{w}^s(\mathbf{u}, t)$ and $\hat{y}^s(\mathbf{u}, t)$, we can enrich the overall graph with time-expanded arcs representing SMS. We now explain how we construct such estimations. For simplicity, we give our explanation only for waiting times $\hat{w}^s(\mathbf{u}, t)$ of access SMS trips only. Similar reasoning is applied to trip times $\hat{y}^s(\mathbf{u}, t)$ and egress trips. We assume random field $W^s(\mathbf{x}, t)$ is approximately temporally stationary within each timeslot:

$$W^s(\mathbf{x}, t) = W^s(\mathbf{x}, t_k), \quad \forall \mathbf{x} \in \mathbb{R}^2, \forall t \in [t_k, t_{k+1}[, \forall \text{ station } \mathbf{s} \tag{3}$$

For any timeslot, we thus just need to find estimation $\hat{w}_{t_k}^s(\mathbf{u})$ of the expected values of random field $W_{t_k}^s(\mathbf{x}) \equiv W^s(\mathbf{x}, t_k)$. First, we collect the observations \mathcal{O} that fall onto time-slot $[t_k, t_{k+1}[$:

$$\mathcal{O}_{t_k}^s \equiv \{\text{observation } i = (\mathbf{x}_i, w_i, y_i) \mid i \in \mathcal{O}, t \in [t_k, t_{k+1}[, i \text{ is related to an access trip to } \mathbf{s}\} \tag{4}$$

Estimation $\hat{w}_{t_k}^s(\mathbf{u})$ is computed by Ordinary Kriging (Sagar et al. [2018]) on the observations $\mathcal{O}_{t_k}^s$ as a convex combination of observations w_i :

$$\hat{w}_{t_k}^s(\mathbf{x}) = \sum_{i \in \mathcal{O}_{t_k}^s} \lambda_i \cdot w_i \tag{5}$$

In short (details can be found in [Chilès and Desassis, 2018, Sec. 19.4]), coefficients λ_i are computed based on a *semivariogram* function $\gamma_{t_k}^s(d)$, which obtained as a linear regression model, with predictors $d_{i,j}$ (distances between all pair of observations) and labels $\gamma_{i,j}$, which are called *experimental semivariances*:

$$\gamma_{i,j} \equiv \frac{1}{2} \cdot (w_i - w_j)^2 \tag{6}$$

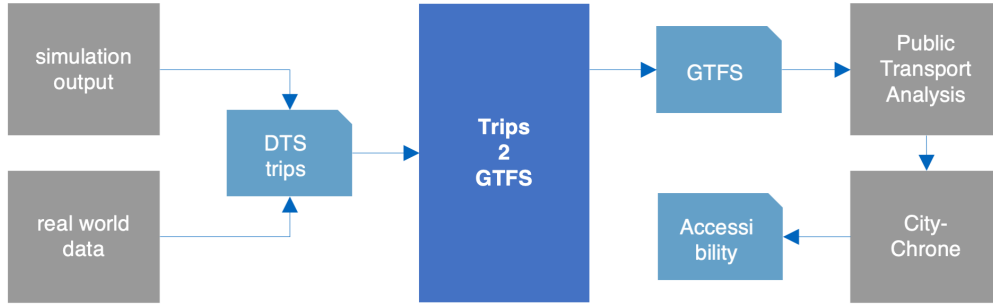


Figure 3. Implementation pipeline. Note that input data can come either from simulation or a real scenario. CityChrono is the tool developed by [Biazzo et al. \[2019\]](#).

The underlying assumption here is that correlation between wait times in two different locations vanishes with the distance between such locations.⁴ The semivariogram gives the “shape” of this vanishing slope. Formula (5) implicitly implies that different observations w_i contributes differently to the estimation of waiting time in location \mathbf{x} , and the contribution of observations closer to \mathbf{x} is given higher weight λ_i . Under hypothesis on spatial stationarity and uniformity in all directions ([Col \[2023\]](#)), Theorem 2.3 of [Yakowitz and Szidarovsky \[1985\]](#) proves that Kriging is an asymptotically biased estimator: as the number of observations goes to infinite, $\hat{w}_{t_k}^s(\mathbf{x})$ tends to the “true” $\mathbb{E}[W_{t_k}^s(\mathbf{x})]$.

Note that, by means of interpolation on a limited set of observed trips, the method described here allows inferring the potential to access opportunities, also via trips that may not have been observed yet.

4 Implementation

The methodology of Section 3 is implemented in a Python pipeline, which we release as open source ([Diepolder \[2023\]](#)) and is depicted in Figure 3.

1. We first get centroids and cells performing the tessellation via CityChrono software [[Biazzo et al., 2019, Fig. 1](#)].
2. We read the file containing the observations (SMS trips). Such a file can be a simulation output or measurements of real SMS. Each observation includes the information listed in Sec. 3.3. Observations are stored in a dataframe.
3. We assume SMS is deployed as feeder (as it is the case for the MATSim simulation on which we perform our analysis). Therefore, we can classify every SMS trip as either access or egress, depending on whether the origin or the destination is a conventional PT stop.
4. To establish feeder area $\mathcal{F}(\mathbf{s})$ around any stop \mathbf{s} , we find among the observations \mathcal{O} the furthest cell from \mathbf{s} in which a trip to/from \mathbf{s} has occurred. All cells within such a distance are assumed to be in $\mathcal{F}(\mathbf{s})$. Observe that feeder areas of different hubs may overlap.
5. We group observations in timeslots (Figure 9).
6. In each time slot $[t_k, t_{k+1}[$ and each centroid \mathbf{u} in $\mathcal{F}(\mathbf{s})$, we perform Kriging (Sec. 3.4) via library `pyInterpolate` ([Moliński \[2022\]](#)) to obtain estimations $\hat{w}_{t_k}^s(\mathbf{u})$ and $\hat{y}_{t_k}^s(\mathbf{u})$.
7. We create stoptimes and time-dependent arcs using the estimations above, as specified in (2). We add stoptimes and time-dependent arcs to the GTFS data of conventional PT, following the specifications in [gtf \[2023\]](#).
8. We give the obtained GTFS file as input to CityChrono, which will give us accessibility scores in all the centroids.

Table 1. Parameters used for the numerical results.

Parameter	Value	Reference
Side of a hexagon (tessellation)	1 km	Badeanlou et al. [2022]
τ (Equation (1))	1 hour	Badeanlou et al. [2022]
Total number of SMS trips	14700	Chouaki et al. [2023]
- as access towards PT	5289	Chouaki et al. [2023]
- as egress from PT	9412	Chouaki et al. [2023]
Maximum tolerated walk time	15 minutes	
Total number of hubs	16	
Walk times		Computed via OpenStreetMap
Travellers in the considered area	76k travellers	From the simulation of Chouaki et al. [2023]
Average request rate served by SMS in the entire region	XX requests / minute	Chouaki et al. [2023]
SMS fleet size (calculated in order to minimize rejections)	1600	Chouaki et al. [2023]
Frequencies of rail and tramway lines	1/2.4 minutes	Chouaki et al. [2023] and SGP [2015]

5 Results and discussion

5.1 Data Source of the observations

The dataset of observed trips used in this study was obtained from a MATSim simulation. The considered simulation scenario was presented in [Chouaki et al. \[2023\]](#). The simulation includes the future rail infrastructure, consisting in new automated subway lines and tramway lines, which will be deployed within the Grand-Paris Express project, in the Paris-Saclay area. An SMS service, provided via a fleet of minibuses (Demand-Responsive Transport - DRT), is simulated, operating as a feeder for rail-based public transport. The SMS service serves door-to-rail-stop and rail-stop-to-door trips. The area in which SMS is deployed is depicted in Figure 4.

This simulation is obtained starting from a synthetic population of the Île-de-France region, generated exclusively from open data, and a MATSim simulation for this population ([Hörl and Balac \[2021\]](#)). Four future subway lines planned for the region in the scope Grand-Paris Express project are added to this simulation, as well as the tramway line T12, which was under construction in the Paris-Saclay area at the time of the study. The region wide simulation after these modifications on the PT offer is performed to identify a preliminary impact of these lines on traveller decisions. Afterwards, for the simulation of the SMS service, a focus is performed on the Paris-Saclay area by cutting the road and PT network around it and leaving only agents that travel in this area. The SMS service is simulated in competition to the other modes (walk, car, bike, PT). This means that the identified trips that are used later on reflect the attractiveness of the service.

Scenario parameters are show Table 1. While absolute results may change when changing parameters such as the side of the hexagon and the time threshold τ , the method (which is the focus of this paper) would remain valid.

5.2 Analysis of Temporal and Spatial Patterns of Shared Mobility Service trips

Figure 5 clearly shows morning peak [7 : 00, 10 : 00], evening peak [16 : 00, 19 : 00] and off-peak (all the other intervals).

The following figures concern SMS trips toward/from all hubs, without distinguishing between hubs. Figure 6 is a negative result: travel times (figures on the right) do not appear to be spatially stationary (the distribution of values measured close to the related PT stops is different from further). Therefore, our estimations are not guaranteed to be asymptotically unbiased (Sec. 3.4). In our future work, we will explore indirect estimation of travel times through other indicators, e.g., the detour factor of SMS, which respect the requirements for the unbiasedness of Kriging. As for waiting time instead, there is no clear correlation with the distance (Figure 7).

Figure 8 shows that wait time follows expected peak/off-peak patterns. Values are generally low, since the simulation is configured so that an SMS trip is accepted only if the dispatcher predicts it is possible to serve it within 10 minutes. All wait times exceeding this limit are likely due to the dispatcher not taking traffic correctly into account.

5.3 Estimation of Waiting and Travel Times

Figure 9 shows that timeslots of 1h preserve the temporal pattern of trips, so 1h should be preferred to smaller timeslots, so as to perform Kriging within each timeslot with as many observations as possible.

⁴Note that we talk here about the correlation between the waiting time of observation i and the waiting time of observation j and we are assuming that such a correlation vanishes with their mutual distance $d_{i,j}$. This is not to be confused with the dependence between the wait time of observations and the distance to the hub, which may not exist, as later shown in Fig. 7

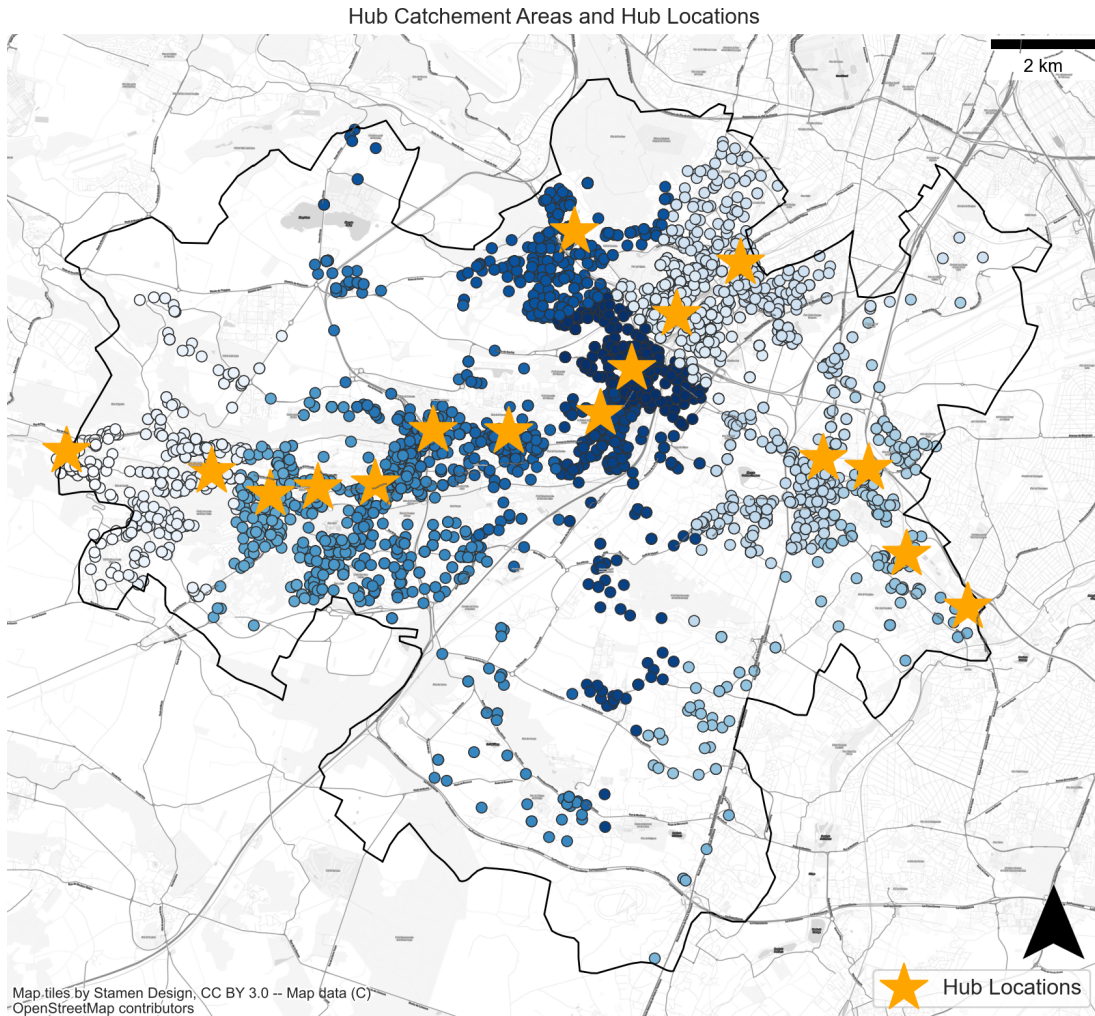


Figure 4. Hub Catchment Areas and Hub Locations. Each dot corresponds to the origin of one trip observed during the simulation. The differentiation in colour of the observed trip origins indicates the catchment by different hubs

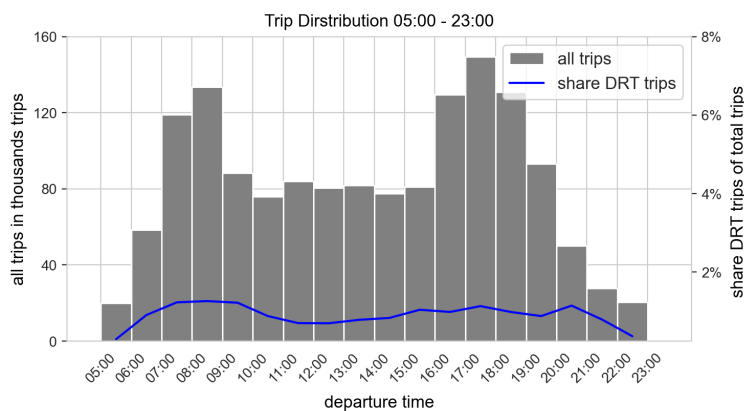


Figure 5. Trips over time. One trip is defined by the departure within the study area of Paris Saclay. A trip consisting out of multiple legs (e.g. walk + SMS + PT is considered as one trip)

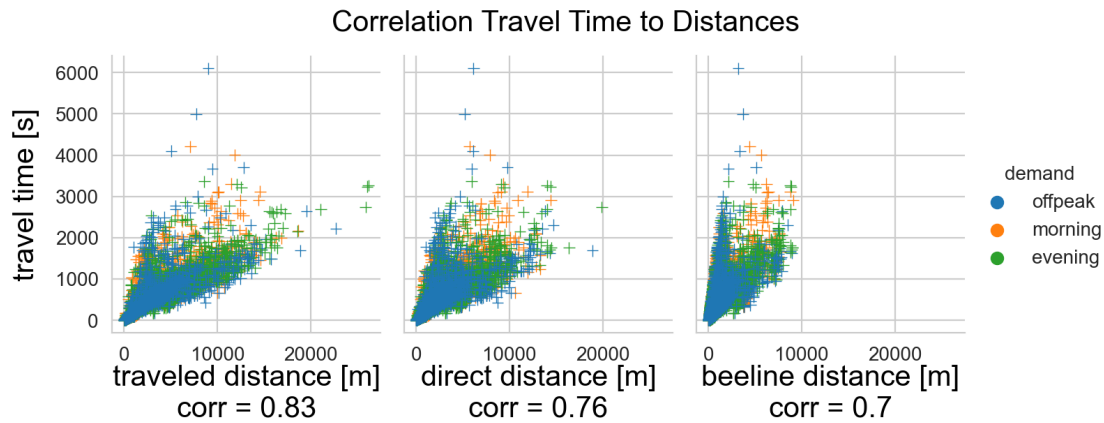


Figure 6. Relation between travel time and distance measures. Travelled distance is the actual Km travelled by the user inside the SMS vehicle. Direct distance is the one from the shortest road network road from the origin centroid to the hub. Beeline is the Euclidean distance.

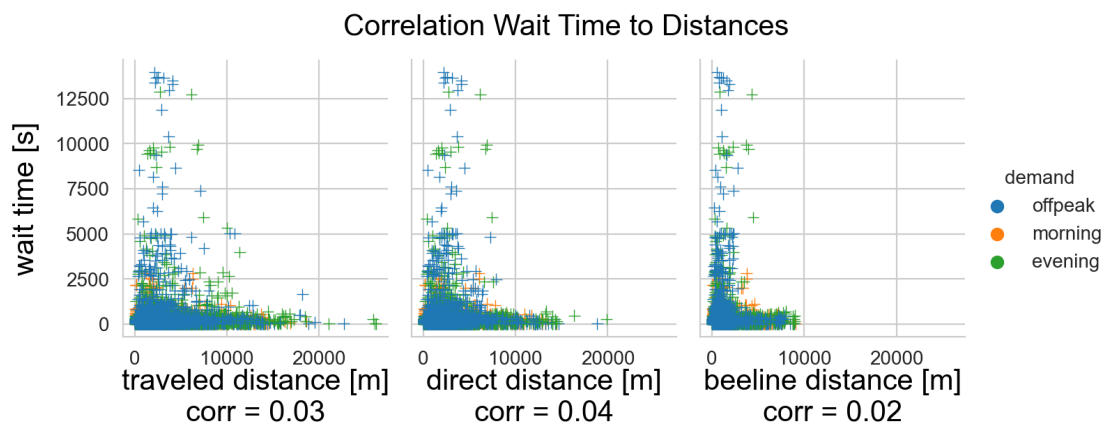


Figure 7. Relation between wait time and distance measures.

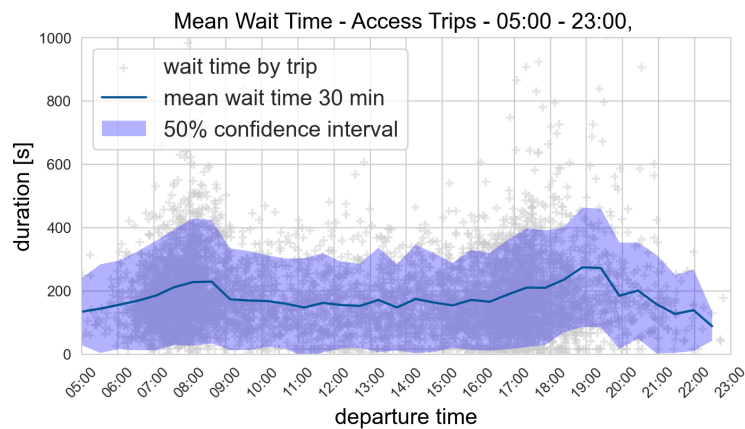


Figure 8. Mean Wait Time: A moving average of wait time during one day

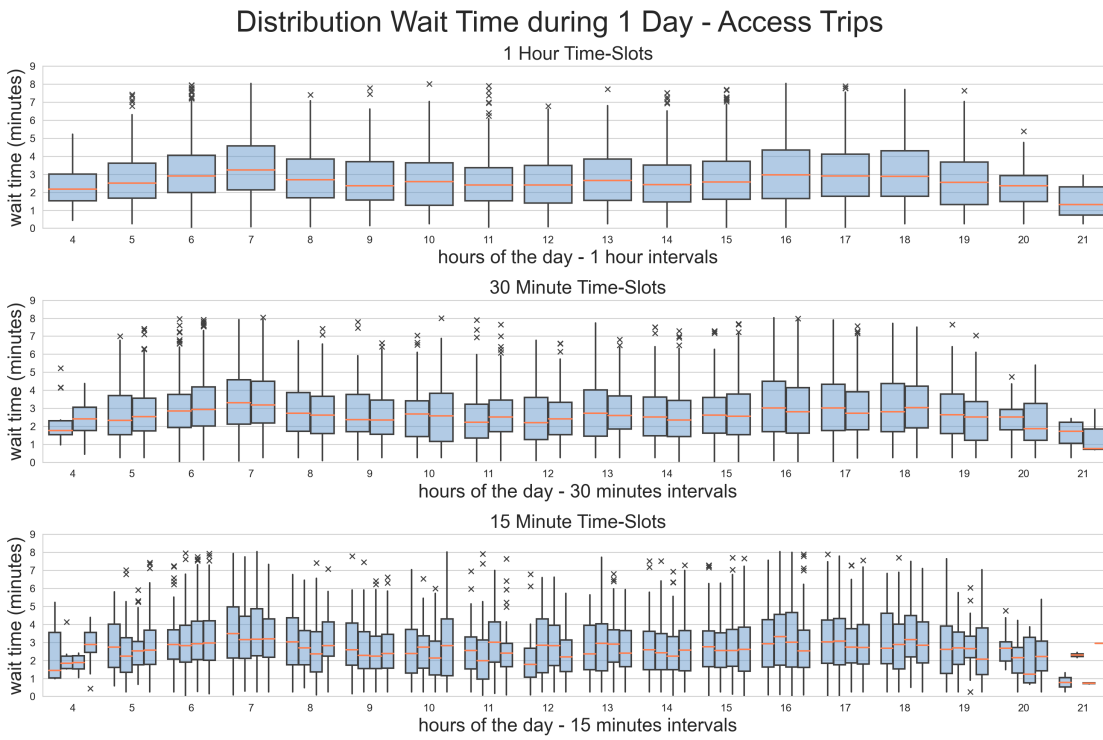


Figure 9. Comparison of different timeslot sizes. Values exceeding 10 minutes are not depicted, as they are due to simulation events unpredictable for the SMS dispatcher

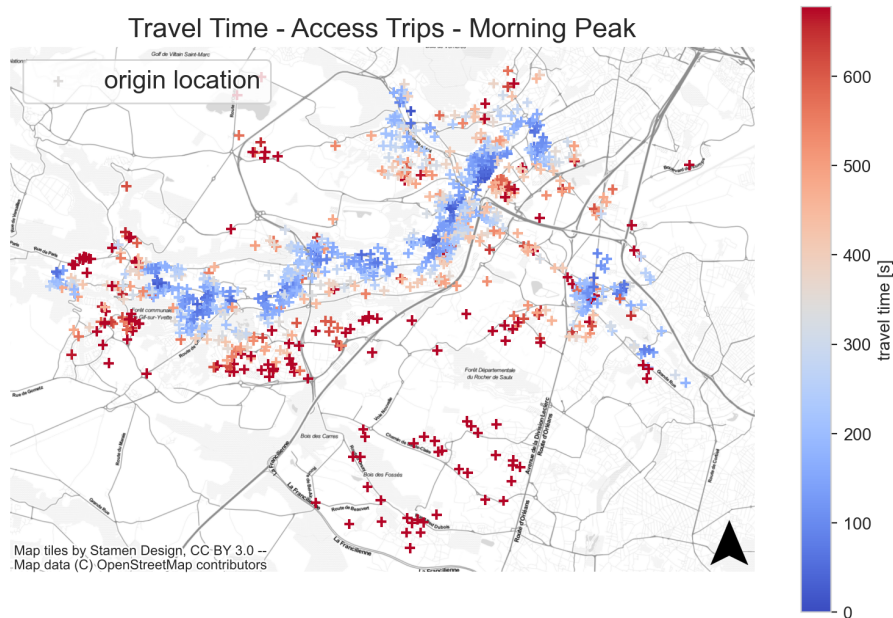


Figure 10. Spatial Trend Travel Time for access time, morning peak (evening and off-peak show similar trends).

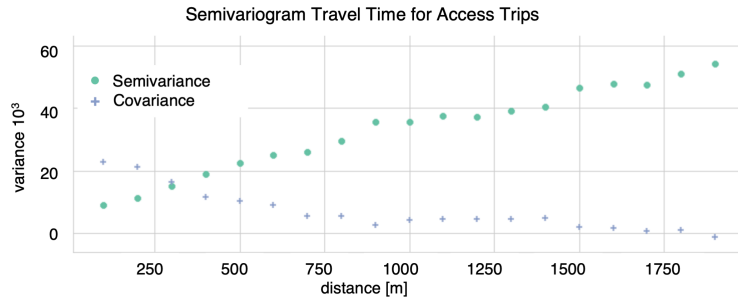


Figure 11. Spatial correlation of travel time observations

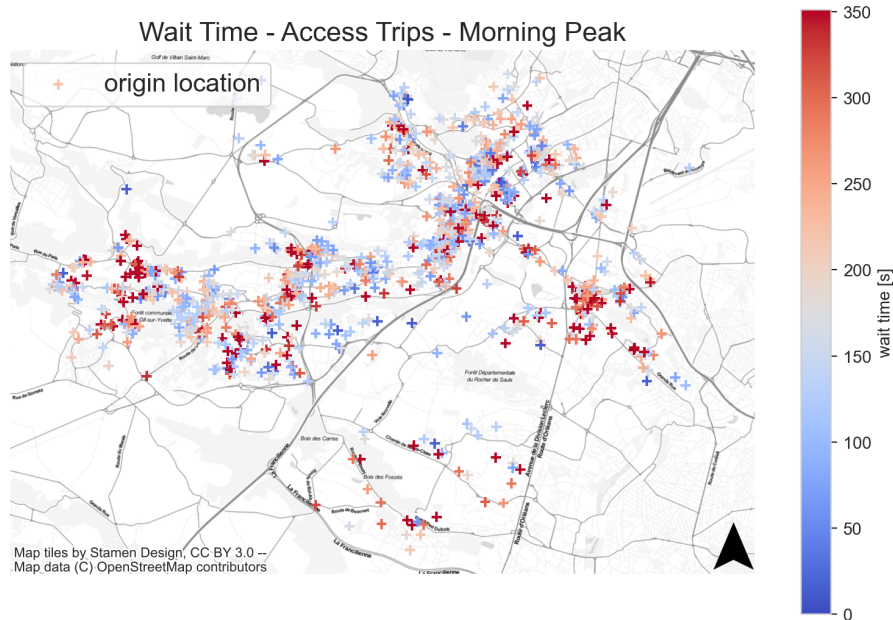


Figure 12. Spatial Trend Wait Time: No clear pattern can be identified, indicating low spatial autocorrelation

Figure 10 clearly shows that there is spatial correlation between observations, i.e., the closer the observations, the similar the values of observed travel times, which is favourable to the use of Kriging. This spatial correlation is confirmed by the experimental semivariance in Figure 11, i.e., the $\gamma_{i,j}$ between pair of observation i, j (Equation (6)) increases with the spatial distance between the observations.

Such trends are not as evident for wait times (Figure 12) although similarity between observations still decay with their mutual distance (Figure 13).

5.4 Improvement of Accessibility Brought by Shared Mobility Services

Figure 14 shows headway and travel times of the virtual SMS trips added to PT graph \mathcal{G} . We can then compute accessibility on this graph. Note that accessibility varies with the time of day (1). However, in the following figures, we show averages over the time periods mentioned.

First, we study a system with SMS access services only (no egress). Figure 15 shows that the catchment area is expanded, especially in the south: hexagons with no access to PT within the maximum tolerated walk time (15 minutes), i.e., white hexagons in Figure 15-left, can now use PT (Figure 15-right). Figure 16 shows more clearly the improvement in accessibility brought by SMS. As only access SMS feeder is added in Paris Saclay to obtain this figure, the areas outside Saclay do not show any changes, except slight improvement in some locations, for instant south of Versailles, possibly due to the possibility for travellers starting from there to make changes in Saclay, which are enhanced by SMS.

Accessibility improvements are even greater in off-peak hours (Figures 17 and 18, as SMS compensates for the low frequency of conventional PT).

Figure 19 shows the improvement in accessibility when both access and egress SMS trips are added, averaged over the

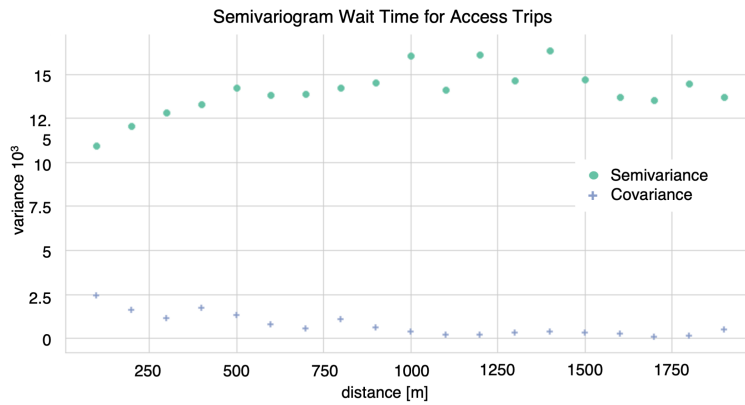


Figure 13. Spatial correlation of wait time observations

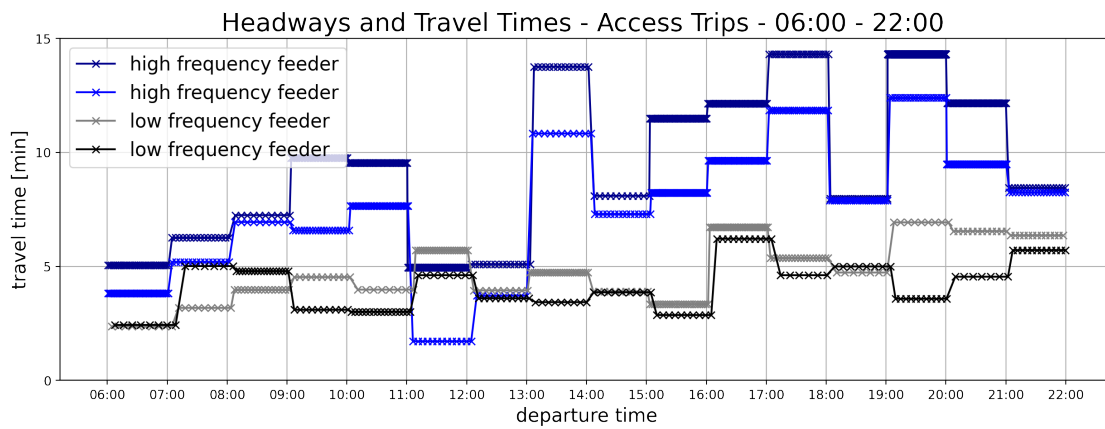


Figure 14. Headway and Travel Times of some examples of virtual SMS trips. Each departure time of a virtual SMS trip is indicated by a cross. Therefore, the distance between cross is the estimated headway. The respective travel time is indicated by the y-axis value.

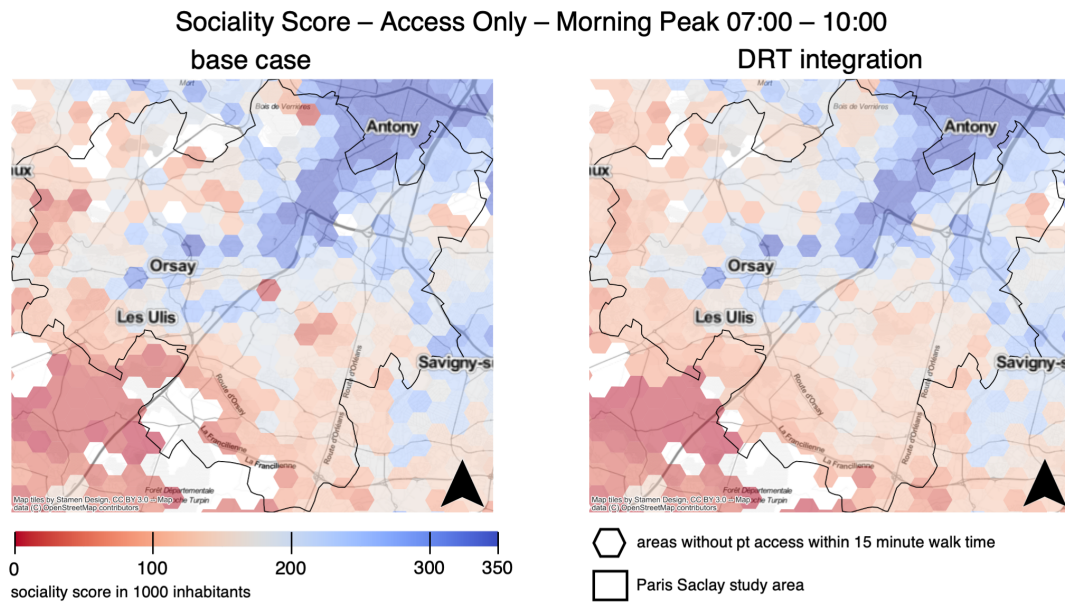


Figure 15. Sociality Score - Access Only - Morning Peak 07:00–10:00

Sociality Score Improvement – Access Only – Morning Peak 07:00 – 10:00

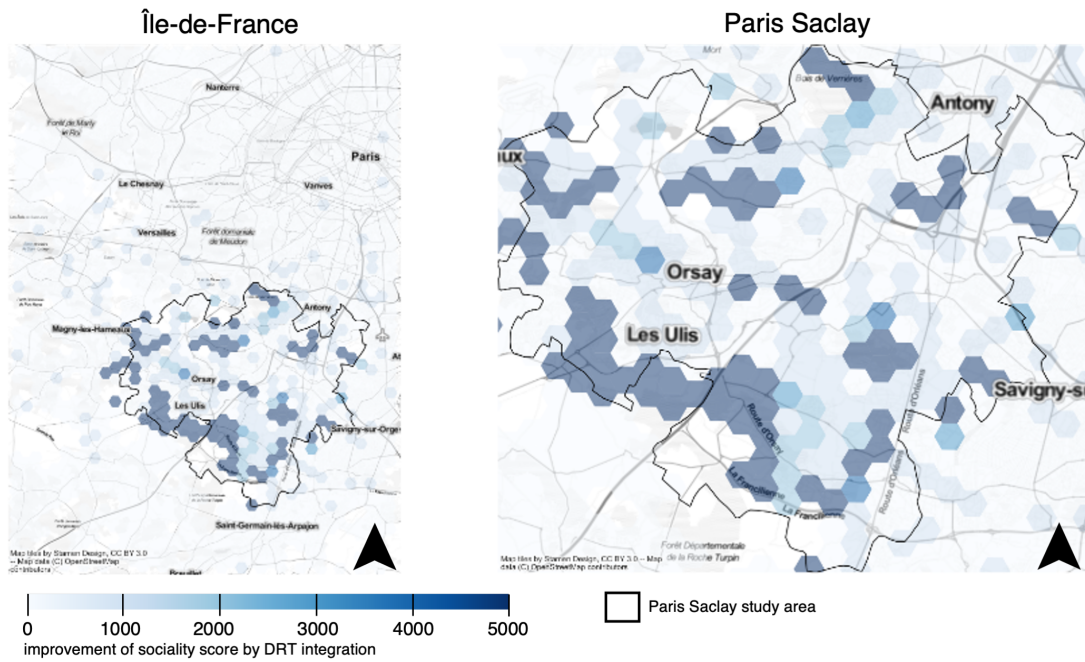


Figure 16. Sociality Score Improvement - Access Only - Morning Peak 07:00–10:00

Sociality Score – Access Only – Off Peak 10:00 – 16:00

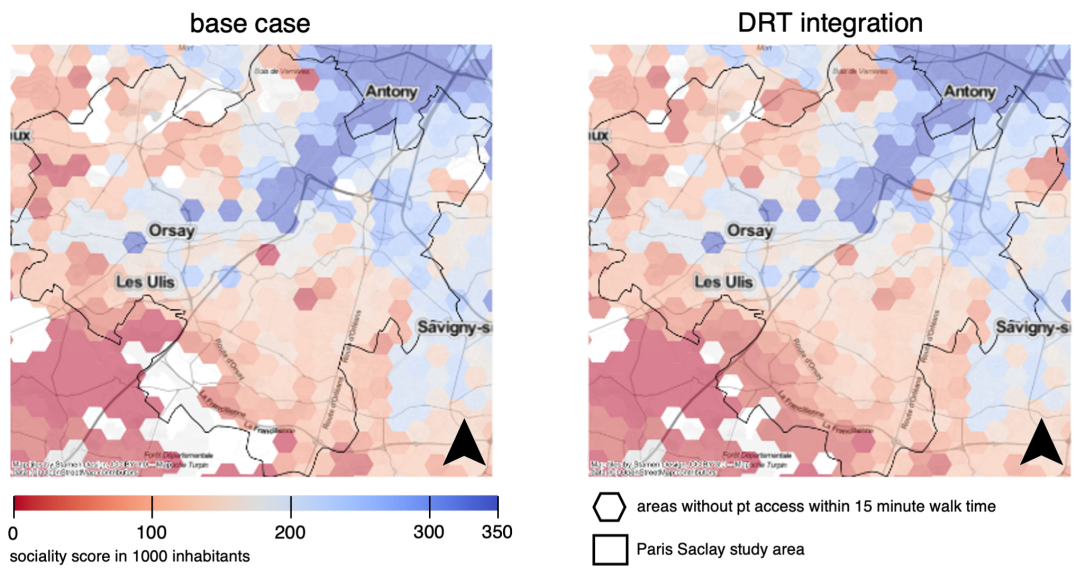


Figure 17. Sociality Score - Access Only - Off Peak 10:00–16:00

Sociality Score Improvement – Access Only – Off Peak 10:00 – 16:00

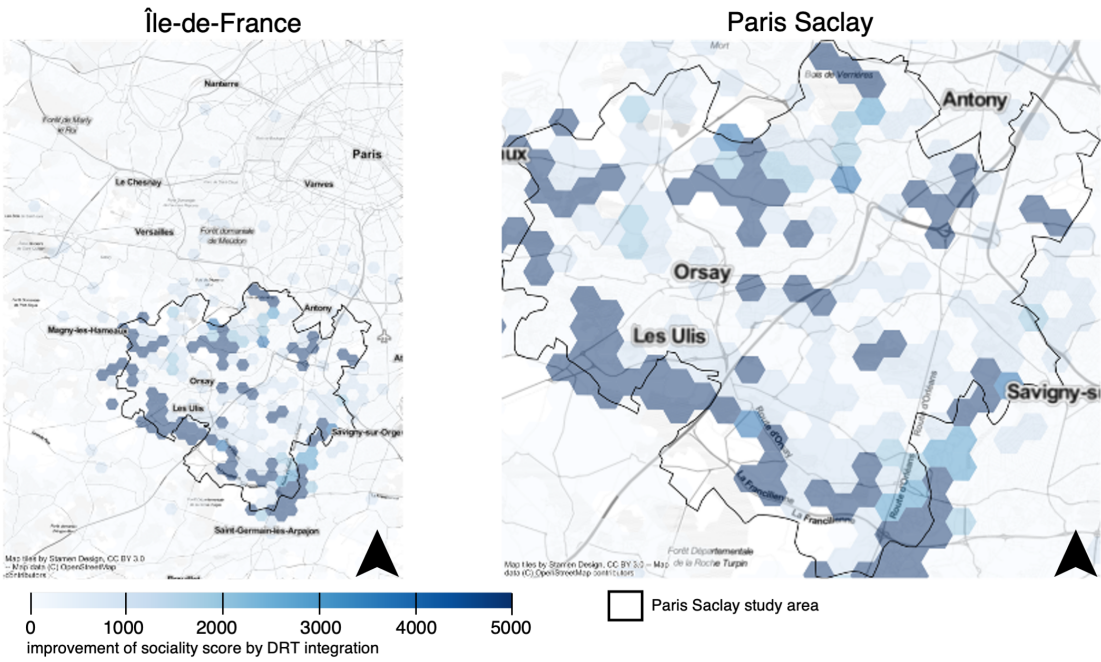


Figure 18. Sociality Score Improvement - Access Only - Off Peak 10:00–16:00

Sociality Score Improvement – Access & Egress – Full Day 05:00 – 23:00

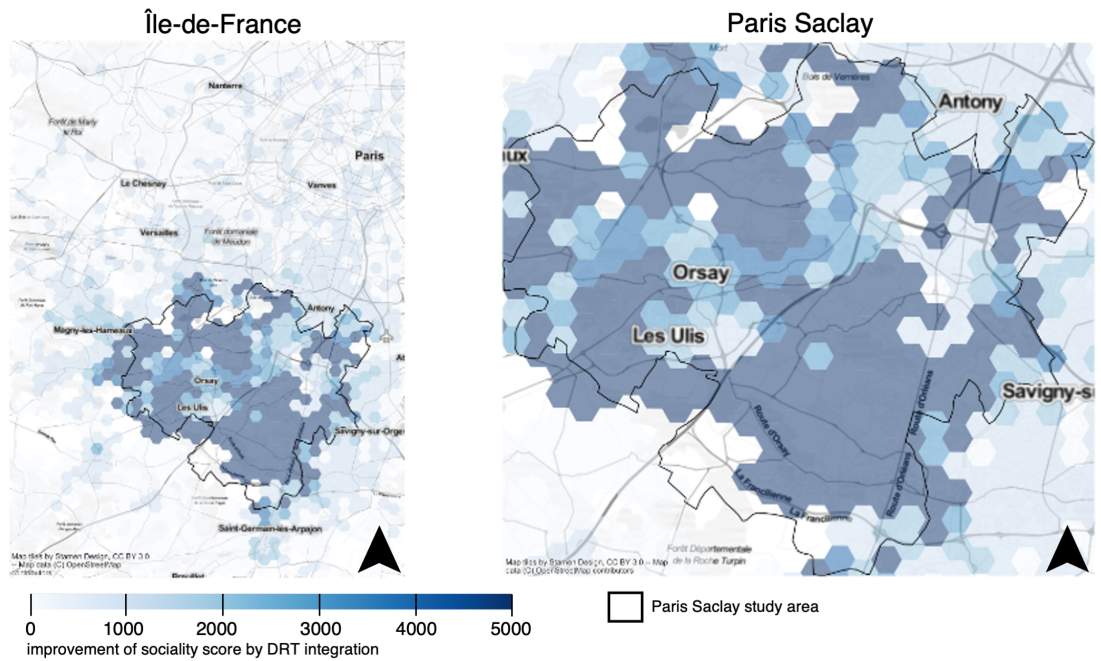


Figure 19. Sociality Score Improvement - Access & Egress - Full Day 05:00–23:00

entire day. Improvement is much greater than the access-SMS only case. It is interesting to observe that improvement is also visible outside the Saclay area, even if no SMS is deployed outside: users from everywhere can now reach opportunities in Saclay faster, thanks to SMS egress connections.

6 Conclusions

We proposed a method to compute the impact of SMS on accessibility, based on empirical observations of SMS trips. Our method can support transport agencies and authorities in future deployment of SMS, to decide in which areas SMS is more beneficial and how many resources is beneficial to invest. We believe that being able to quantitatively support claims such as “if SMS is deployed in a certain community, the number of people that can be reached by that community within 1h increases by 500 thousands” is extremely important to encourage the deployment of SMS by such communities, much more important than just estimating expected travel times or waiting times. Therefore, by devising a method that can compute accessibility improvement brought by SMS, this method contributes to accelerate their adoption. On the contrary, in some cases, our method could be used to assess the uselessness of SMS in a certain region, if it does not considerably improve accessibility over the already deployed conventional PT, which can also prevent the emergence of an undesirable competition between conventional PT and SMS.

References

- CO2 emissions from cars: facts and figures. Technical report, The European Parliament, 2022. URL <https://www.europarl.europa.eu/news/en/headlines/priorities/climate-change/20190313STO31218/co2-emissions-from-cars-facts-and-figures-infographics>.
- Kriging interpolation, 2023. URL <https://www.publichealth.columbia.edu/research/population-health-methods/kriging-interpolation>.
- GTFS Reference Document, 2023. URL <https://developers.google.com/transit/gtfs/reference?hl=en>.
- Mohamed Abouelela, David Durán-Rodas, and Constantinos Antoniou. Do we all need shared e-scooters? an accessibility-centered spatial equity evaluation approach. *Transportation Research Part A: Policy and Practice*, 181:103985, 2024.
- Amirhesam Badeanlou, Andrea Araldo, and Marco Diana. Assessing transportation accessibility equity via open data. *hEART*, 2022.
- Indaco Biazzo, Bernardo Monechi, and Vittorio Loreto. General scores for accessibility and inequality measures in urban areas. *Royal Society open science*, 2019.
- G. Calabrò, A. Araldo, M. Ben-Akiva, et al. Adaptive Transit Design: Optimizing Fixed and Demand Responsive Multi-Modal Transport via Continuous Approximation. In *Transportation Research Part A*, 2023.
- Ennio Cascetta. *Transportation systems analysis: models and applications*. Springer Science & Business Media, 2009.
- Oded Cats, Rafal Kucharski, Santosh Rao Danda, and Menno Yap. Beyond the dichotomy: How ride-hailing competes with and complements public transport. *Plos one*, 17(1):e0262496, 2022.
- Shailesh Chandra, Muhammad Ehsanul Bari, Prem Chand Devarasetty, and Sharada Vadali. Accessibility evaluations of feeder transit services. *Transportation Research Part A*, 2013.
- Jean-Paul Chilès and Nicolas Desassis. *Fifty Years of Kriging*, chapter 29. Springer International Publishing, 2018.
- Tarek Chouaki, Sebastian Hörl, and Jakob Puchinger. Towards reproducible simulations of the grand paris express and on-demand feeder services. In *TRB*, 2023.
- Thomas Craig and Weston Shippy. Gtfs flex—what is it and how is it used? *National Center for Applied Transit Technology*, 2020.
- Severin Diepolder. Accessibility of dynamic transport, 2023. URL <https://github.com/severindiepolder/AccessibilityOfDynamicTransport>.
- Norman Eppenberger and Maximilian Alexander Richter. The opportunity of shared autonomous vehicles to improve spatial equity in accessibility and socio-economic developments in european urban areas. *European transport research review*, 13(1):32, 2021.
- Gregory D. Erhardt, Sneha Roy, Drew Cooper, Bhargava Sana, Mei Chen, and Joe Castiglione. Do transportation network companies decrease or increase congestion? *Science Advances*, (5), 2019. ISSN 23752548.
- EU Commission. Mobility and transport, 2020. URL https://ec.europa.eu/transport/themes/urban/urban_mobility.
- Andres Fielbaum and Javier Alonso-Mora. Design of mixed fixed-flexible bus public transport networks by tracking the paths of on-demand vehicles. *Transportation Research Part C: Emerging Technologies*, page 104580, 2024. ISSN 0968-090X.

- doi: <https://doi.org/10.1016/j.trc.2024.104580>. URL <https://www.sciencedirect.com/science/article/pii/S0968090X24001013>.
- Philippe Fortin, Catherine Morency, and Martin Trépanier. Innovative gtfs data application for transit network analysis using a graph-oriented method. *Journal of Public Transportation*, 2016.
- Mark S. Handcock and James R. Wallis. An approach to statistical spatial-temporal modeling of meteorological fields. *Journal of the American Statistical Association*, (426), 1994.
- Alejandro Henao and Wesley E. Marshall. The impact of ride-hailing on vehicle miles traveled. *Transportation*, (6), 2019. ISSN 15729435.
- Sebastian Hörl and Milos Balac. Synthetic population and travel demand for Paris and Île-de-France based on open and publicly available data. *Transportation Research Part C: Emerging Technologies*, 130:103291, September 2021. ISSN 0968-090X. doi: 10.1016/j.trc.2021.103291. URL <https://www.sciencedirect.com/science/article/pii/S0968090X21003016>.
- Cathia Le Hasif, Andrea Araldo, Stefania Dumbrava, and Dimitri Watel. A graph-database approach to assess the impact of demand-responsive services on public transit accessibility. In *15th ACM SIGSPATIAL International Workshop on Computational Transportation Science*, 2022.
- Dimitris Milakis, Maarten Kroesen, and Bert van Wee. Implications of automated vehicles for accessibility and location choices: Evidence from an expert-based experiment. *Journal of Transport Geography*, 68:142–148, 2018. ISSN 0966-6923. doi: <https://doi.org/10.1016/j.jtrangeo.2018.03.010>. URL <https://www.sciencedirect.com/science/article/pii/S0966692317308098>.
- Eric J Miller. Measuring accessibility: Methods and issues. In *Roundtable on Accessibility and Transport Appraisal*. International Transport Forum, 2020.
- Szymon Moliński. Pyinterpolate: Spatial interpolation in python for point measurements and aggregated datasets. *Journal of Open Source Software*, 2022.
- Bat-hen Nahmias-Biran, Jimi B Oke, Nishant Kumar, Carlos Lima Azevedo, and Moshe Ben-Akiva. Evaluating the impacts of shared automated mobility on-demand services: An activity-based accessibility approach. *Transportation*, 2021.
- Antonin Pottier, Emmanuel Combet, Jean-Michel Cayla, Simona de Lauretis, and Franck Nadaud. Qui emet du co2? panorama critique des inégalités écologiques en france. *Revue de l'OFCE*, (5):73–132, 2020.
- Pedram Saeidizand, Koos Franssen, and Kobe Boussauw. Revisiting car dependency: A worldwide analysis of car travel in global metropolitan areas. *Cities*, 2022.
- B. S. Daya Sagar, Qiuming Cheng, and Frits Agterberg, editors. *Advances in Sensitivity Analysis of Uncertainty to Changes in Sampling Density When Modeling Spatially Correlated Attributes*, chapter 19. Springer Open, 2018. ISBN 9783319789989.
- SGP. Fréquences prévisionnelles des trains aux heures de pointe du matin - Société du Grand Paris, 2015. URL <https://www.data.gouv.fr/fr/datasets/frequences-previsionnelles-des-trains-aux-heures-de-pointe-du-matin/>.
- Cecilia Silva, Nuno Pinto, and Luca Bertolini. *Designing accessibility instruments: Lessons on their usability for integrated land use and transport planning practices*. Routledge, 2019.
- Duo Wang, Andrea Araldo, and Mounim A El Yacoubi. Aceq-drt: Planning demand-responsive transit to reduce inequality of accessibility. In *Transportation Research Board (TRB) 103rd Annual Meeting*, 2024.
- J. K. Wiersma, L. Bertolini, and L. Harms. Spatial conditions for car dependency in mid-sized European city regions. *European Planning Studies*, 29(7):1314–1330, 2021. ISSN 14695944. doi: 10.1080/09654313.2020.1854691. URL <https://doi.org/10.1080/09654313.2020.1854691>.
- S. J. Yakowitz and F. Szidarovsky. A comparison of kriging with nonparametric regression methods. *Journal of Multivariate Analysis*, 1985.
- Meng Zhou, Diem-Trinh Le, Duy Quy Nguyen-Phuoc, P Christopher Zegras, and Joseph Ferreira Jr. Simulating impacts of automated mobility-on-demand on accessibility and residential relocation. *Cities*, 2021.
- Dominik Ziemke and Joschka Bischoff. Accessibilities by shared autonomous vehicles under different regulatory scenarios. *Procedia Computer Science*, 220:747–754, 2023.

Acknowledgements

This work has been supported by The French ANR research project MuTAS (ANR-21-CE22-0025-01) and by BayFrance (FK-14-2021). It has also been supported by the European Union’s Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement no. 899987 Data were provided by the Anthropolis research project at the SystemX Technological Research Institute, supported by the French government under the “France 2030” program.

Author contributions statement

A. A., S. D., C. A., S.M.: conceptualization

A.A.: theoretical development

S. D.: code development, implementation, results

S. D., A. A., S. M.: data analysis, writing, discussion

T. C., S. H.: simulation

All authors reviewed the manuscript.