An Accessibility-based Approach to Characterize the Dynamic Vulnerabilities of Multi-modal Urban Transport Networks

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1 Introduction

Although crucial in our society, transportation networks suffer from numerous disruptions that continually jeopardize their operations. Therefore, the quantification of their vulnerabilities and the enhancement of their resilience, i.e., the capability to face disruptions, is paramount. However, there is currently no strong consensus on how transport network vulnerability should be characterized [1]. Indeed, two major type of approaches are present in the literature [2], i.e.: a static one, leveraging graph-based methodologies to analyze network topology; and a dynamic one, based on the analysis of traffic variables (i.e., speed, flow and density) at different scales (e.g., links, zones, whole city, etc.) and different scenarios. Both kinds of approaches have traditionally been separately studied in the research about transport network resilience, but, recently, a growing interest towards fusing them has emerged [3]: it is nowadays possible to collect data on traffic states from pervasive sensors, project them on the transport network topology as edge/nodes attributes, and analyze the resulting temporally evolving weighted graph via complex network tools, such as centrality indicators [3, 4] or other metrics to retrieve insights and even predict transport network dynamics and associated vulnerabilities.

In this paper, we continue building upon this research thread by proposing a novel approach based on a simplified version of an accessibility metric from the literature [5]. Our approach allows to characterize network vulnerabilities in a novel original dynamic and multi-modal fashion, by taking into account: *i)* the underlying topology of the multi-modal transport network, and *ii)* information on travel times (which could be retrieved dynamically from various data sources), thus allowing to compute weighted shortest paths on a multi-modal urban network to monitor the variations of accessibility in both time and space. The main idea is that such variations could be a (real-time) indicator of disruptions and dynamic vulnerabilities that could be notified to a traffic operator in order to enact prompt intervention for preserving an acceptable level of performance, thus improving the global resilience of the transport system.

Accessibility represents the ultimate goal of most transportation activity [6], i.e., the ease of reaching a destination [7] from different areas of a city. Accessibility is strongly influenced by several mobility characteristics, such as the travel demand, transport mode or travel time, but also depends on network topology. It thus appears as a relevant candidate to consider the two major existing approaches for resilience/vulnerability analysis. In the literature, different indices are provided to compute *accessibility*, including travel cost. Most of them are derived from the Hansen integral index [7], which defines *accessibility* on a per-origin basis, by considering the distances of destination zones from the given city area origin, weighted by the attractiveness of the destination areas, measured in terms of presence of Points of Interest (POIs).

A large majority of works focuses on the computation of the *accessibility* for a specific transport mode. Chen et al. [1] propose a method for evaluating the impact of link failure on the road network. The used metric depends on the random utility of the different alternative paths, which is consistent with the combined travel demand based on utility maximization with budget constraints. They conclude that their metric can quantify the consequences of both demand and supply changes due to the presence of a disruption. In [8], an *accessibility* and remoteness index, called ARIA, is proposed for studying the impact of degradation on some vulnerable sections of the Australian highway network. The ARIA index is based on the computation of road distance measurements from populated locations. Lu et al. [9] focus instead on the accessibility of the urban rail transit network. Their accessibility metric is defined on a per-station basis, by measuring the impact of disruptions as the capability to provide an alternative mode (e.g., additional buses with a specific capacity) to reach the destinations from the disrupted station. Nonetheless, the study is limited because it focuses only on the computation of *accessibility* per one single transport mode (i.e., metro transit system).

In 2015, Chen et al. [10] modified this index to consider the impact of floods on different travel modes. The authors compare the Hansen index [7] with their proposed metric. Similarly, Miao et al. [5] focus on the multi-modal accessibility of a city. They analyze the impact of disruption over the intercity transportation network of Yangtze River Delta, which includes bus, car and train alternatives. The disrupted scenarios consist in removing one or two road nodes or rail stations. In [5], *accessibility* is defined as follows (Eq. 1):

$$A_s = \omega_s^a \sum_{\substack{r \in Z \\ r \neq s}} \omega_r^g \left[(1-\beta) \sum_{l \in M} \left(p_{lrs} \frac{c'_{lrs}}{c_{lrs}} \right) + \beta \frac{s_{lrs}}{s'_{lrs}} \right]^{-\alpha} \tag{1}$$

where ω_r^g (resp. ω_s^a) represents the travel generation weights of the departure area r (resp. travel attraction weights of the destination area s) and Z the set of areas; β ($0 \leq \beta \leq 1$) is a coefficient weighting the impact of the level of service; p_{lrs} is the probability to choose transport mode l to travel from r to s and M is the set of all the transport mode; c_{lrs} (resp. c'_{lrs}) is the travel cost from r to s with transport mode l under normal conditions (resp. disturbed conditions); s_{lrs} (resp. s'_{lrs}) is the level of service of transport mode l when travelling from r to s under normal conditions (resp. disturbed conditions); and α represents a travel cost decay parameter, greater than zero, allowing to control the weight of the travel cost ratio.

At the network scale, the *accessibility*, called global *accessibility* in the following results, is defined as the sum of all the *accessibility* of the areas composing the network.

$$A = \sum_{s \in Z} A_s \tag{2}$$

This methodology could be easily adapted to monitoring the time-varying accessibility of a specific area in a city, by considering e.g., the variations of (average) travel cost over time (based on observed measures of travel time in specific moments of the day over the links in the area). One major advantage of the application of such measure on an urban transport network is the simplicity through which it permits to consider the multi-modal aspect in vulnerability characterization in presence of disruption.

2 Methodology and Hypotheses

The proposed study aims at characterizing the spatio-temporal evolution of the *accessibility* (Eq. 1) for an urban multi-modal transport network to quantify the impact of a disruption both in time and space.

The area generation weights ω_r^g and the area attraction ones ω_s^a are defined by counting the number of POIs included in the areas and their nature. We assume that a touristic point attracts and generates more travel demand than e.g., a school, which interests a smaller part of the population.

In this paper, for simplicity reasons, we fix the parameter β equal to 0. The metric does not include therefore the disruption impacts on the level of transportation service s_{lrs} caused by the reduction of available travel alternatives. This choice is motivated by our simplistic emulation of disruptions on public transports which will be more accurate in future works, possibly based on public transport data.

Based on such assumptions, the accessibility metric only depends on travel cost dynamics, expressed via *i)* travel cost under normal conditions c_{lrs} and *ii)* in presence of disruption c'_{lrs} for each available transport mode l, from departure area r to the arrival one s. As in previous studies [5, 10], we fix the travel cost decay α equal to 1. Concerning modal shares, we consider fixed probabilities p_{lrs} of choosing a specific mode l to travel into the whole urban network based on household survey data available for the city of Lyon, France, the region of interest in this work [11]. Specifically, 45% of people use a personal car to travel, while public transport is selected by the remaining share, with a 25% probability to select subways, more efficient for long distance movements, and an equal 15% probability for both bus and tramway.

We define the travel costs c_{lrs} and c'_{lrs} as the average shortest paths travel time (tt) between nodes included in the departure area r and nodes in the arrival area s. As described in detail in Sec. 3, the computation of such costs for private vehicles is based on a large dataset available for the region of interest. In case a specific transport mode sub-graph has no node in a given area, we consider the shortest walking path between the closest transport mode graph node and the area centroid. Such walking travel time is then added to the shortest path travel time of the specific mode. In this work, for simplicity reasons, paths have to be realized according to a unique transport mode, combined with walking mode when no single travel mode allows joining the origin and destination areas.

The final simplified definition of accessibility, based on Eq. 1 is the following:

$$A_s = \omega_s^a \sum_{\substack{r \in Z \\ r \neq s}} \omega_r^g \frac{1}{\sum_{l \in M} p_{lrs} \frac{tt'_{lrs}}{tt_{lrs}}} \tag{3}$$

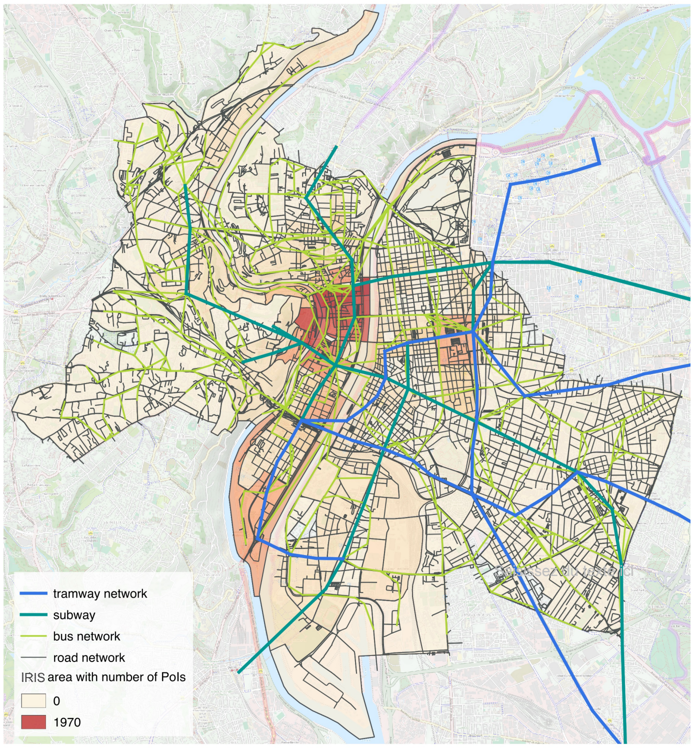
Based on the accessibility formula of Eq. 3, it is worth remarking that, by ignoring the contribution related to the level of service from Eq. 1, the suppression of a specific transport mode, modeled as an infinite travel cost ratio, inevitably implies a zero value of *accessibility* for the given area s. In such disrupted scenarios, we assume people will realize their path by walk, which implies a travel time increase of $speed_{mode}/speed_{walk}$, i.e., proportional to the initial transport mode speed. Assuming humans have a walking speed equal to 4km/h [12], we obtained travel time ratios equal to 5 for buses, 7.5 for tramways and 10 for subways.

3 Case study

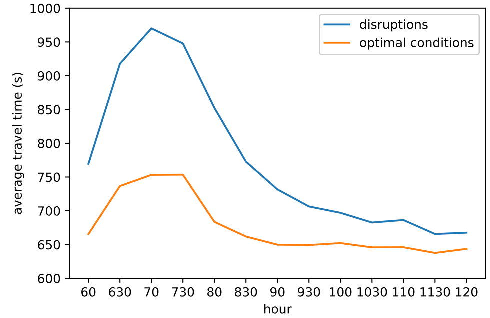
Our study focuses on the multi-modal network of Lyon, which includes road, bus, subway and tramway sub-networks. In order to reproduce realistic traffic dynamics, we consider multiple, timestamped weighted snapshots of the graph, by relying on travel time as the notion of cost for each transport mode.

Firstly, we compute travel cost under normal conditions. For personal cars, the corresponding graph is weighted via average travel time information, computed from probe data and available with a 30-minutes periodicity. These data were recorded over one year, from October 2017 to September 2018, in the Rhônes-Alpes region, France. Regarding public transport modes (bus, subway and tramway), we do not have access to actual travel time data. Although travel times for buses could be inferred from the same GPS data used for private cars, plenty of dedicated bus lanes exist in Lyon. For this reason and because the waiting time at each bus stop is hardly quantifiable, we weight the graph with a fixed travel time computed according to an average bus speed of 20km/h. This average speed is supposed to take into account the waiting time at bus stop as well. For the tramway and the subway sub-networks, we adopt a similar approach, by considering a fixed travel time [12] with average speeds equal to 30km/h and 40km/h, respectively. These speeds are assumed to be higher because such modes are composed of completely dedicated lanes and a lower number of stops exists compared to buses. Finally, we consider a walking graph, composed of non-directed road network edges, connecting all the remaining areas of the city. The corresponding edges are weighted according to a travel time issued from a speed equal to 4 km/h.

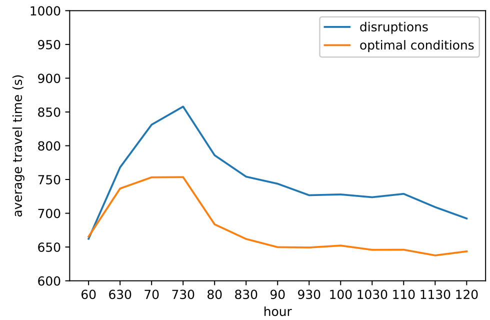
To compute travel costs in presence of disruptions, we target two specific events that occurred during the period in which GPS probe data are available. On Monday, December 18$^{\text{th}}$, 2017 (Fig.1b), the network was disrupted because of a heavy snowfall. Regarding public transport, we emulate the potential impact of this disruption due to the lack of available data. During this first event, bus and tramway services were stopped because of the snowfall, whereas subways stayed operational all day long. We modify the probabilities reported in Sec. 2 for each of the two disrupted public transport modes (both buses and tramways), i.e., from 15% to 10%, assuming that such 10% of people would carry out their travels by walk (because of the tram and bus blockages), while the remaining 5% would prefer the subway system. In our emulation, we assume therefore subways attracted more people due to the lack of alternative public transport choices, thus implying an increase of waiting time at subway stops. Hence, the probability of taking the subway globally increases from 25% to 35%. Finally, we add a 5 minutes delay to each subway shortest path travel time, to emulate the need to wait more to get in a subway train due to higher demand.



(a) Lyon's transport networks



(b) Average shortest path travel time: December 18th



(c) Average shortest path travel time: December 19th

Figure 1: Case study: Lyon divided in Iris areas colored by the number of included the number of points of interest with road, bus, tramway and subways networks.

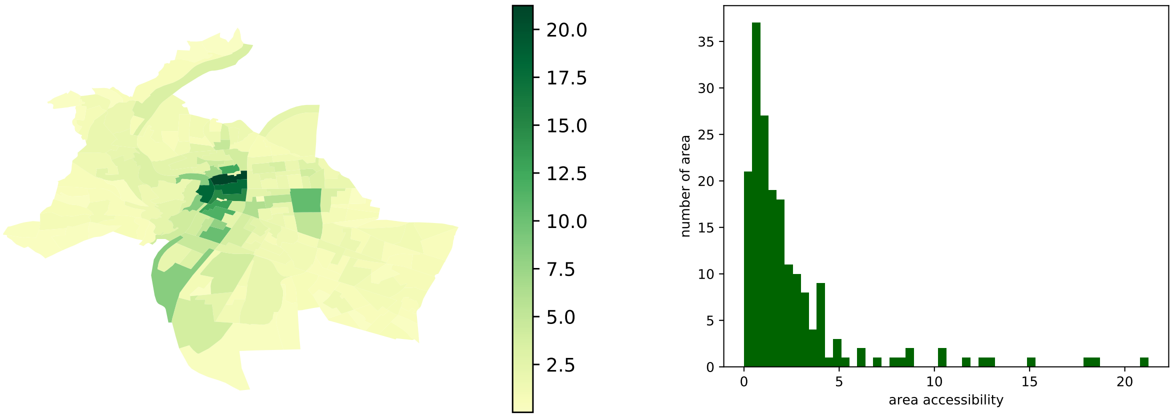
On Tuesday, December 19th, 2017 (Fig.1c), the subway system was blocked during the day because of the presence of an undefined smoke development in the subway tunnel. For this second event, we emulate the impact of the disruption on the subway system by removing all the five subway lines of Lyon from our graph. This is a simplification because, during the real event, only two lines were affected. For the tramway and the bus sub-networks, we increase the associated waiting time because of the modal shift from subway users. At the end, we assume only 10% of people maintain the initial choice of taking the subway for their travel (which is performed by walk because of the disruption), while 55% of the people are at the end equally distributed between the tramway and the bus, against 30% under normal conditions.

It is worth remarking that, despite the presence of several assumptions that introduce a rather simplistic modelling of transport disruptions, the approach adopted in this paper remains general enough to achieve the main objective of this paper, i.e., assessing the capability of the accessibility metric to respond, in a dynamic fashion, to occurred (or partially emulated) disruptions of the multi-modal transport network. Increasing the realism of our disruption model and removing some assumptions related to the weights of the multi-modal network remains matter of future work.

4 Results

By computing the *accessibility* (Eq. 3) over the network under normal conditions and in the presence of two different disruptions, we want to observe the ability of the studied metric to capture the vulnerability of the urban multi-modal transport network. The temporary subway disruption provides insights about the ability of the metric to follow the recovery phase, after the disruption.

Without disruption, under normal conditions, the *accessibility* only depends on the area's attraction and



(a) Optimal accessibility

(b) Accessibility distribution

Figure 2: Accessibility under optimal traffic conditions without disruption.

generation weights. Indeed, in such conditions, the ratio of travel costs is equal to one for every transport mode. With such definition, the central area presents the highest *accessibility* because of the presence of many points of interests (Fig. 2a). The distribution of areas' accessibility (Fig. 2b) shows that most of the zones possess a relatively low *accessibility* (> 1), meaning that their generation and attraction weights, equals in our study, are generally low. These areas do not significantly generate or attract people due to the limited presence of POIs. Under normal conditions, the global *accessibility*, which is the sum of all areas *accessibility* (Eq. 2), is equal to 451.31. Based on such reference value, we can study the temporal evolution (i.e., reductions) of global *accessibility* in time in presence of disruption, thus providing insights on the network state.

4.1 Case study 1: disruption on 18$^{\text{th}}$ December 2017

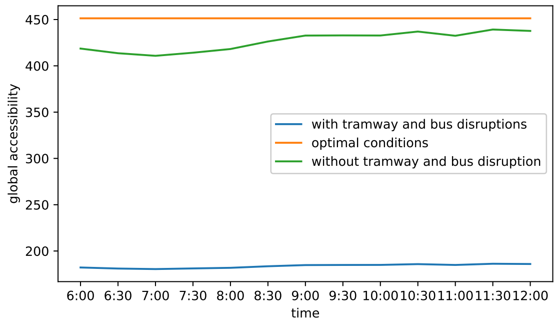
On December 18$^{\text{th}}$ 2017, a heavy snowfall occurred in Lyon and impacted most of the transport system with the exception of its subway lines. The disruption of surface transport is clearly manifested in the GPS probe data related to this day: reported travel times present a huge difference compared to the ones recorded under normal conditions (Fig. 1b).

For this specific day, we compute the global *accessibility* when the public transport system is not impacted by the snowfall (i.e., green curve) and when the surface public transport networks (i.e., tramway and bus networks) is disturbed (i.e., blue curve), as detailed in the previous section.

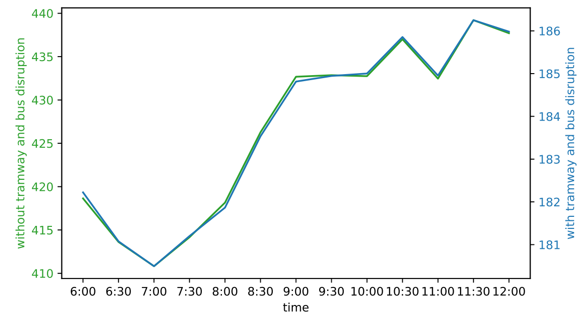
Both with and without the public transport disturbance (Fig. 3b), we notice that *accessibility* strictly follows the variations of travel times. The more travel time increases in presence of disruption, compared to normal conditions, the lower *accessibility* is. The spatial distribution of the metric shows that the central areas are the most impacted by the snowfall (Fig. 3e-3f). Nonetheless, by analyzing the spatial distribution of the *accessibility*, the evolution of the metric is more evident without the public transport disruption (Fig. 3c and Fig. 3d). The public transport disruption during the whole simulation time (from 6:00am to 12:00pm) heavily impacts the measure, thus smoothing the dynamic disruption affecting the car travel times.

4.2 Case study 2: disruption on 19$^{\text{th}}$ December 2017

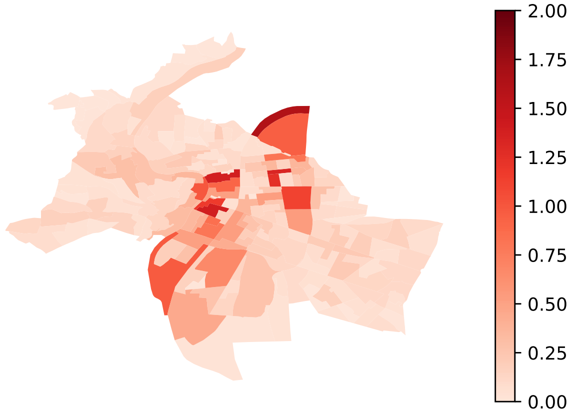
Fig. 4 presents the impact of the disruption on December 19$^{\text{th}}$, 2017 on *accessibility*. We analyze the impact of the disruption in two cases (Fig. 4a): *i)* as observed via recorded probe data only (green curve) and *ii)* as a consequence of subway closure (blue curve). The temporal evolution of global *accessibility* in the two cases is similar (Fig. 4b). Nonetheless, the changes in time, only due to the car mode, are more evident



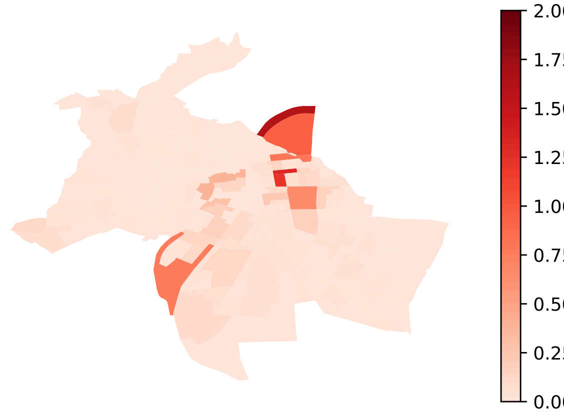
(a) Global accessibility



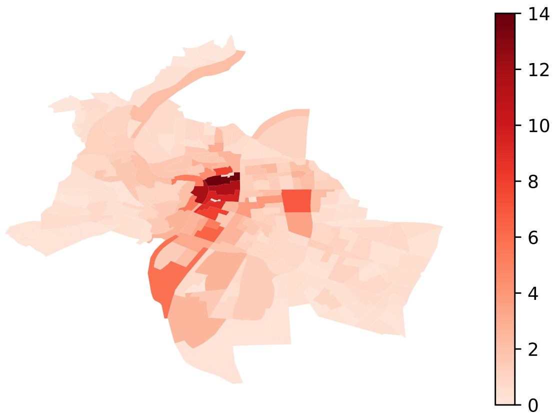
(b) Global accessibility



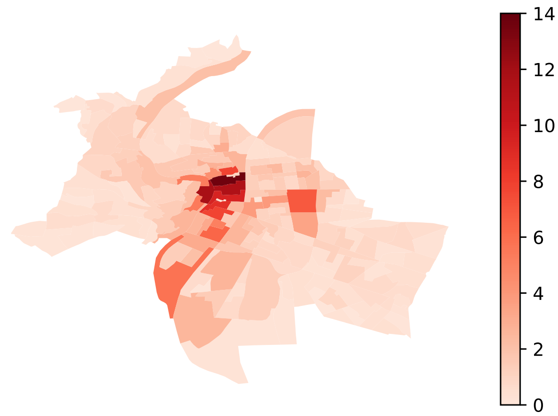
(c) Loss of accessibility at 7 : 00am
without the tramway and bus disruptions



(d) Loss of accessibility at 11 : 30am
without the tramway and bus disruptions



(e) Loss of accessibility at 7 : 00am
with the tramway and bus disruptions

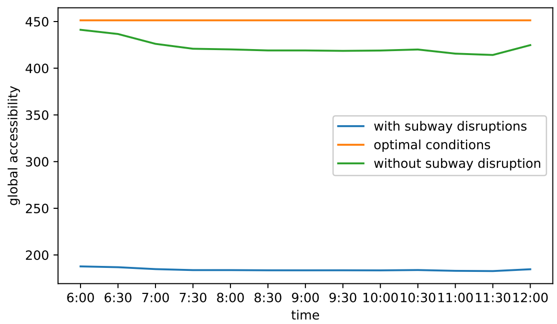


(f) Loss of accessibility at 11 : 30am
with the tramway and bus disruptions

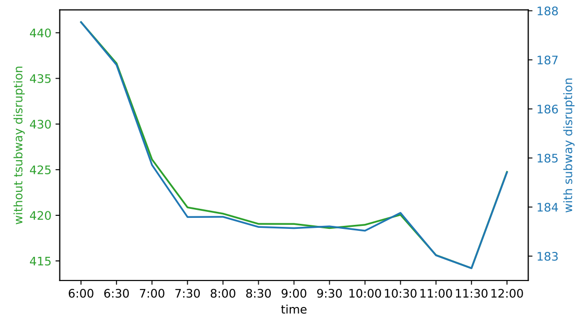
Figure 3: Impact of the travel time increase on 18$^{\text{th}}$ December, 2017, with and without the tramway and bus closures impact 3a in time and spatially without the subway closure (i.e, only the car impact recorded by the probe data) (resp. with) at 7 : 00am 3c (resp. 3e) and at 11 : 30am 3d (resp. 3f).

without the subway disruption. This transport mode closure is emulated during the whole temporal window and tends to smooth the global *accessibility* variations.

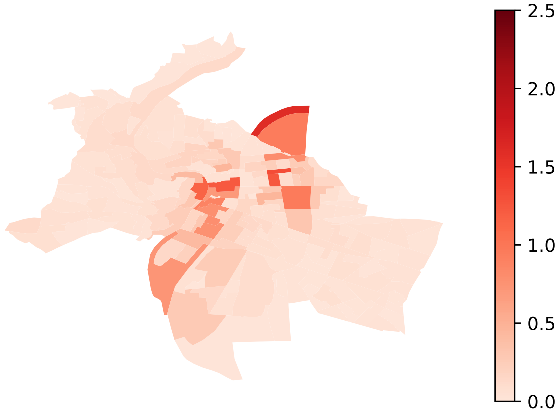
In Fig. 4c and Fig. 4d, we analyze the spatial distribution of the loss of *accessibility* induced only by



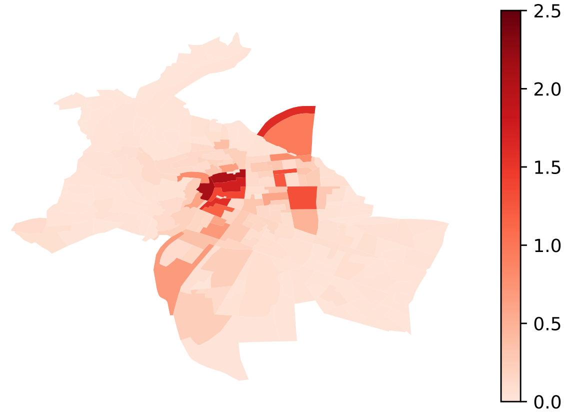
(a) Global accessibility



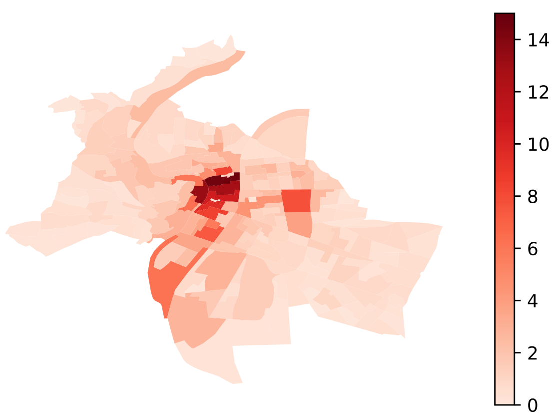
(b) Global accessibility



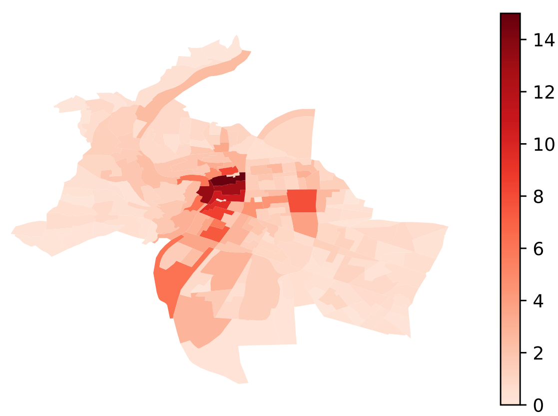
(c) Loss of accessibility at 8 : 00am without the subway disruption



(d) Loss of accessibility at 11 : 30am without the subway disruption



(e) Loss of accessibility at 8 : 00am with the subway disruption



(f) Loss of accessibility at 11 : 30am with the subway disruption

Figure 4: Impact of the travel time increase on 19^{th} December, 2017, with and without the subway closure impact 4a in time and spatially without the subway closure (i.e, only the car impact recorded by the probe data) (resp. with) at 8 : 00am 4c (resp. 4e) and at 11 : 30am 4d (resp. 4f).

the car travel time increase. The reduction per area is stronger at 11:30am as recorded in Fig. 4b and in accordance with the travel times evolution under normal conditions and in presence of disruption (Fig. 1c). The loss of *accessibility* is higher for the central areas.

The subway closure impact is taken into account in Fig. 4e and Fig. 4f. Globally the loss of *accessibility* is much more evident with these disruptions. As concerning the temporal evolution, we notice a mitigation of the variations of *accessibility* in time because of the static nature and the strong impact of the subway disruption.

5 Conclusion and future works

The results comfort the idea that *accessibility* provides interesting insights on network vulnerability in the presence of daily or heavy disruptions that cause slowdowns or public transport delays. The measure depends on traffic conditions and appears thus to be sensitive to the dynamic nature of the disruption. Nonetheless, *accessibility* presents two major limits. Such measure is not appropriate to capture the impact caused by the total removal of a public transport mode without supposing people will realize their path by walk (or other slower mode), which is a strong assumption. Otherwise, area *accessibility* will be equal to 0 whereas other transport modes still allow moving in the network. Another limit results in the negative impact of the boarding effect on the measure. Indeed, we notice a huge reduction of *accessibility* for the bordering areas because of the weak presence of paths going to them. It is thus not possible to study the areas at the extremities of the graph, implying the necessity to broaden the study perimeter.

For our future work, we aim at better exploring the impact of disruptions on the level of service, caused by the reduction of available travel alternatives. To characterize the level of service for the different transport modes a qualitative study needs to be lead merged with a risk analysis defining the reliability of each mode for the different paths. Moreover the transport mode probability coefficient could be refined depending on the itinerary. In the city center, where public transport is more capillary, the probability of taking these modes is higher than in the outskirts, where the service is typically less present and efficient.

Finally, we aim to compare accessibility to other metrics such as the degree heterogeneity, studied in our previous work [13].

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