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Measuring urban road network vulnerability to extreme events: An application for urban floods

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A B S T R A C T

This paper aims to propose a convenient metric to evaluate the vulnerability of road networks to extreme events in small to medium-sized cities. We present the efficiency of alternative metric, which centers on how obstructions caused by a disaster tends to increase path lengths in the system. A case study was conducted as proof of concept to evaluate the impact of floods on individual modes of transportation in São Carlos, a medium-sized city in Brazil. The results show that walking and cycling tend to be more robust modes in the city while motorized individual transport tends to be more vulnerable and show that longer trips tend to be more vulnerable to floods, evidencing that car-oriented policy can worsen the network's vulnerabilities. In contrast, compact city planning that encourages walking or cycling for relatively short distances may be more resilient to flooding.

1. Introduction

Extreme natural phenomena are an uncomfortable reality of urban regions worldwide, and climate change is predicted to increase both the frequency and the intensity of extreme precipitation (Tabari, 2020). Additionally, there is also evidence that developing countries might be in a difficult position to deal with floods due to the challenges that arise from rapid urbanization processes (Chen et al., 2015; Singh & Singh, 2011; Stevaux et al., 2009). This reality constantly reminds transport planners that systems have to be not only efficient but also resilient. Resilience is a system's capacity to adapt when exposed to adverse situations, avoiding potential losses (Westrum, 2012). In transportation, it is usually described as the capacity to timely recover the level of service in the operations (Ganin et al., 2017). Nevertheless, vulnerabilities can hide in the complexity of large networks. Considering the diversity of ways a transportation system can fail, building a single model to cover all planning for resilient transportation systems becomes a challenge. Due to this diversity, researchers have developed a variety of methods for measuring risk and planning for adverse events: some measuring the overall capacity of systems to absorb impacts (Ip & Wang, 2011; Leu et al., 2010; Morelli & Cunha, 2019); and others focusing on specific events such as an oil supply crisis (Azolin et al., 2020; Martins et al., 2019; Newman et al., 2009), hurricanes (Beheshtian et al., 2018; Chan & Schofer, 2016; Litman, 2006) or floods (Gil & Steinbach, 2008; Ortega et al., 2020; Tsang & Scott, 2020; Wiśniewski et al., 2020). However, there is little consensus between the various types of analysis, making the integration of models a highly complex process.

The problem becomes particularly noticeable in medium-sized cities in developing countries where natural phenomena are

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increasingly destructive due to a mixture of fast urbanization and climate change. Still, the scarcity of resources and data creates barriers to preemptive planning for disaster. This reality highlights the need for comprehensive methods that can be easily integrated with other established urban planning methods, relying on data already available. This paper's main primary goal is to propose a simple yet useful analysis to assess vulnerabilities to natural phenomena in road systems, using as an example the case of flooding in São Carlos, a medium-sized city of Brazil. The method relies only on network topology, geometry, and travel distribution data to assess how efficient a system is in creating alternatives to paths disrupted by flooding, making it a valuable tool to orient policy and strategies to develop more robust and resilient cities in the face of disaster. Moreover, while there is vast consensus on how motorized vehicles and car-oriented infrastructure contribute to pollution and climate change (Banister, 2011; Moriarty & Honnery, 2008). The study of how natural phenomena have distinct impacts on different modes of transportation is still in its infancy, particularly in regards to active versus motorized modes in urban regions. There is some evidence that pedestrian movements are more resilient due to the greater density of edges in pedestrian networks (Boeing, 2019). However, there still are questions about how differences in travel behavior play in this regard. This paper bridges this gap by exploring how planning for compact cities and active modes of transport can lead to more resilient transportation in the face of disasters.

2. Literature review

Detecting vulnerabilities is one of the cornerstones of resilience design in transport systems (Mattsson & Jenelius, 2015). Since the weakest links in a network are generally the ones that require the most attention and timely action to reduce the magnitude of crises and the system's recovery time, hence the need for a good preliminary estimate for the vulnerabilities. Vulnerability analysis is very diverse in scope since different types of crises affect the network differently. In the next sections, we introduce a brief review of the conventional methods devised in research by category.

2.1. Graph analytical approaches

Network vulnerabilities is a topic that goes beyond transportation planning and has its roots in graph theory and complex networks research. Therefore, numerous studies analyze road networks through this lens (Appert & Laurent, 2013; Berche et al., 2009; Gil & Steinbach, 2008; Ip & Wang, 2011; Leu et al., 2010). The most common measure used to find vulnerabilities is the *Betweenness Centrality* of nodes or edges of the network, which measures the tendency of paths in a given network to pass through the element. This parameter implies that nodes or edges with high *Betweenness Centrality* tend to concentrate on more trips and be more critical in a network (Barthélemy, 2004). This property has led researchers to look for vulnerabilities in networks through strategies involving this metric (Appert & Laurent, 2013; Berche et al., 2009; Boeing, 2020; Ip & Wang, 2011). Other centralities from graph theory speculated to provide insight into the vulnerability of a network are the *Node Degree* (Berche et al., 2009), which expresses how many connections a given intersection have, and *Closeness Centrality* (Berche et al., 2009) describing how central (closer to all others) an element is. These approaches have the advantage of having low data requirements since the only aspect evaluated is network structure; but the disadvantage of not taking into account land use or trip distribution, which may create distorted results. *Betweenness Centrality*, although the most promising of the metrics, will give higher importance to edges near regions with high intersection density since all network nodes have equal weight. Rodríguez-Núñez and García-Palomares (2014) avoid this problem by assigning actual passenger loads in a metro network.

2.2. Trip substitution approaches

Some researchers study events that do not change the structure of a network but change the viability of motorized transportation modes. That is the case for studies in oil supply crises, that may force some users to abandon individual motorized modes in favor of active modes (Martins et al., 2019) or public transit for more efficient use of the scarce oil (Azolin et al., 2020). The problem in these scenarios shifts from the vulnerability in the network elements to the vulnerability of the trips. The analysis focuses on how long the distances favor substitution by active modes or how the transit network is structured to provide alternatives.

2.3. Traffic allocation approaches

More recent research also focuses on traffic allocation algorithms to assess networks' vulnerabilities (Ganin et al., 2017; Kasmalkar et al., 2020; Wiśniewski et al., 2020), leaning towards the level of service or the increase in delays caused by problems in the network. This method targeted towards the degradation of the network by removing connections or loss in capacity with further traffic analysis. Ganin et al. (2017) focus on how random degradation of network links affects traffic in 40 cities in the United States, while Kasmalkar et al. (2020) and Wiśniewski et al. (2020) focus on specific flood scenarios. The strong point of these approaches is that they give a more traditional metric to traffic analytics. Nevertheless, their weakness is the analysis's car-oriented nature, which makes them unsuitable for comparative analysis between modes.

3. Proposed method

We propose the metric efficiency of alternative to express how detours on the network affect the usual trip lengths of the city given a network disruption. Only two datasets are required to evaluate this metric: network structure and travel distribution. This simplicity allows for the strategy to be applicable in small to medium cities, usually with data restrictions. Moreover, this metric does not evaluate the system in terms of traffic delays as usual in recent research (Ganin et al., 2017; Tsang & Scott, 2020; Wiśniewski et al., 2020) makes it flexible enough to also be applicable for active modes of transportation.

3.1. Network disruption

Network disruption might occur for various reasons, but its effect on network structures can be reduced to a simple phenomenon: an event acts to limit or prevent movement on a road element or a series of them. This way, an event that prevents movement along some segment will impact an individual route in one of three ways:

- Not affect the route (Fig. 1(a));
- Divert a route (Fig. 1(b)), increasing its length;
- Affect the route and all its alternatives (Fig. 1(c)) rendering the path impossible.

In these cases, we assume the user will always follow the shortest path connecting two points so that a damaging event can never decrease route lengths. This way, route efficiency can be inferred from the variation on average minimum distances between points. When a network element is removed, routes that previously depended on that element must be diverted, increasing the total path length. This way, the efficiency of alternative for a single route can be defined as:

$$\boldsymbol{\eta}(\boldsymbol{s},\boldsymbol{t}) = \frac{\boldsymbol{d}_0(\boldsymbol{s},\boldsymbol{t})}{\boldsymbol{d}_i(\boldsymbol{s},\boldsymbol{t})} \tag{1}$$

where: $\eta(s,t)$: efficiency of the alternative route from s to t;
s and t: Nodes belonging to the network;
$d_0(s,t)$: Length of the shortest path between nodes before the impact;
$d_i(s,t)$: Length of the shortest path between nodes after the impact.

However, this approach leads to problems in the case denoted in Fig. 1(c) since there is no path between the two points after the impact on the network. To manage this, we consider the length between two disconnected nodes on the network as tending to infinity, hence leading the efficiency on Equation (1) to tend to zero.

3.2. Network model

In this paper, we represent the road network as a primal directed graph, but, since the infrastructure available to each mode of transportation can vary, we use different graphs for evaluating different modes. One example of the difference in the graphs' structure for different modes can be observed comparing car and pedestrian infrastructure since vehicles usually have a regulated direction of flow on each link and pedestrians can walk in both directions. This difference can lead to situations where traffic of cars is blocked due to a disruption, but pedestrian movements still have an alternative, as shown in Fig. 2. To account for these differences, we use distinct graphs for different modes using the OSMnx library (Boeing, 2017) to extract the "walk", "drive" and "bike" networks directly from OpenStreetMap and convert them to nonplanar graphs. This representation is also useful to simulate the impact scenarios. The prevention of movement along an impacted road segment can be achieved by removing the referred edge from the graph, so the minimum paths generated in the disrupted network ignore the blocked road.

3.3. Impact between traffic zones

Most travel behavior surveys describe trips as movements between traffic zones in origin–destination (OD) matrices. Each zone

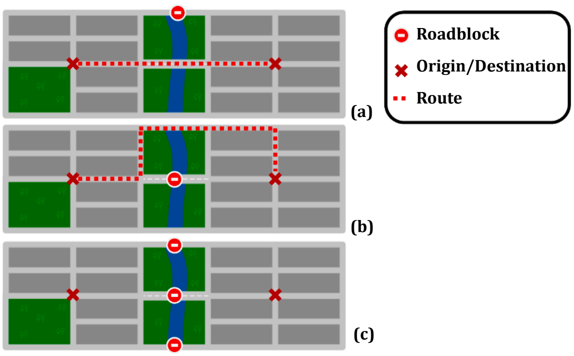

Fig. 1. Types of impact for a single route. A set of blocked segments can: (a) not impact a route; (b) force a detour increasing the route's length; and (c) render the route impossible.

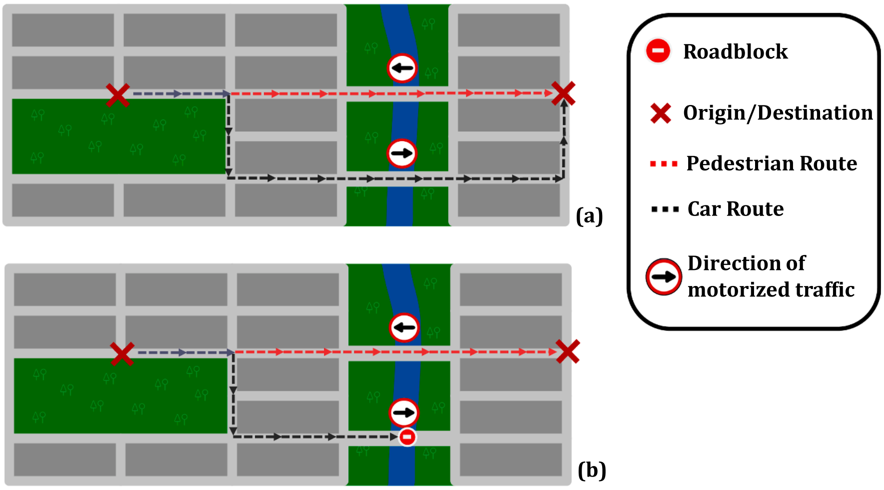

Fig. 2. Pedestrian and motorized vehicle travel examples - (a) A pedestrian path could be shorter than a car route; (b) some events may block movements of one mode of transportation but not all.

encompasses a set of intersections and road segments, as shown in Fig. 3 that have the traffic zones for São Carlos, the city studied in this paper. Therefore, the network distance between two zones is not defined by a single route, but as an average of the distances between the points belonging to each zone which is usually estimated as the network length between centroids of traffic zones, as represented in Fig. 4(a). We chose not to use this approach since it estimates the length as solely dependent on links used for the path between centroids, neglecting changes outside of it. A better measure of how lengths change when degradation occurs needs to account for a more diverse set of routes (Fig. 4(b)) In this case, we propose a sample of routes that start in a random node of zone A and end in a random node of zone B to represent the impact on the OD pair A/B, such as represented in Fig. 4(b). This sample has to be large enough to capture the pair's properties, but not too large to limit the computational load. For the case study in this paper, as we evaluate a medium city with only 41 traffic zones, we decided to consider all possible pairs between zones, but larger urban areas may require downsampling. The paths were calculated through Dijkstra's algorithm (Dijkstra, 1959) using the iGraph library (YU et al., 2009).

Equation (1) measures the efficiency of a single route in absorbing impacts on the network, but since the length between zones is an average, the efficiency between zones must also be defined as such. Therefore, the most direct way to express this efficiency would be dividing the average length before by the average length after the impact. Nevertheless, this approach would lead to problems when pairs of disconnected nodes appear between the zones since one such pair would drag the average length between zones to infinity (since we consider unconnected routes as having infinite length). Therefore, the approach we chose is to average the efficiency –

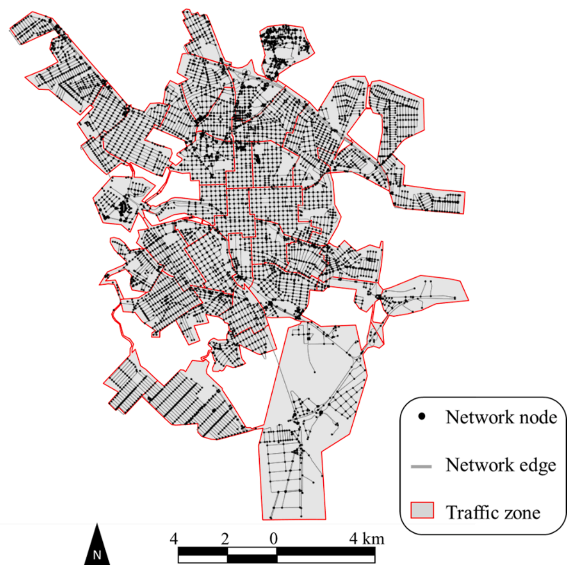

Fig. 3. Network of São Carlos with demarked traffic zones.

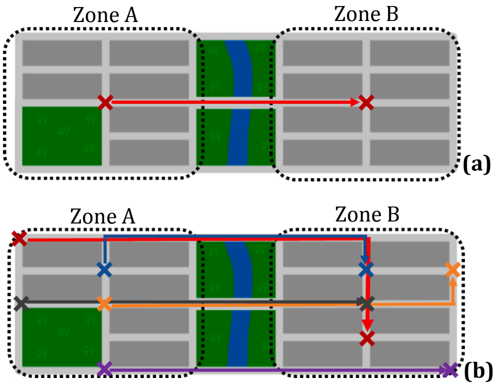

Fig. 4. Travel analyzes – (a) centroid approach; (b) random sampling approach.

constraining the range between zero and one – of each path sampled between the zones. Therefore, the efficiency of the routes between zones A and B after a network degradation is:

$$\eta(A,B) = \sum_{s\in A}\sum_{t\in B}\frac{\eta(s,t)}{N_A \cdot N_B} \tag{2}$$

where: $\eta(A,B)$: network efficiency between zones A and B;

A and B: Traffic zones;

N_i: Number of nodes sampled in zone i.

Equation (2) can also be used when A is the same as B, in such case denoting the efficiency of trips that start and end in the same zone. This is useful since internal routes can be significantly impacted, mainly when the zones are large. It should also be noted that the efficiency from zone $\boldsymbol{A}$ to zone $\boldsymbol{B}$ is not necessarily equal to the efficiency from $\boldsymbol{B}$ to $\boldsymbol{A}$ and the existence of a route from nodes $\boldsymbol{s}$ to $\boldsymbol{t}$ does not imply the presence of a route from $\boldsymbol{t}$ to $\boldsymbol{s}$ given the directed nature of the graphs.

3.4. Effects of trip distribution

If two zones have relatively few trips occurring between them, they do not impact the system in a significant way, independent of how efficient the connection between the zones is. Likewise, the relative vulnerability of a system depends not only on the network efficiency between zones but also on each pair's volume of trips. An overall index can be devised as the mean efficiency between zones weighted by the number of trips between each pair of zones:

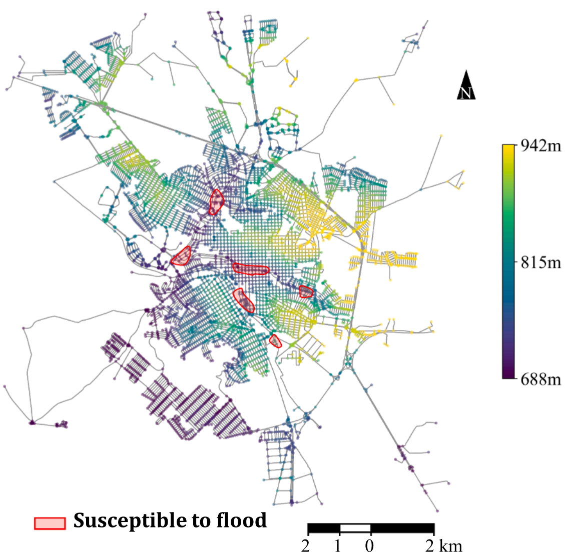

Fig. 5. Node elevation and regions susceptible to floods as defined in São Carlos's masterplan of 2005.

$$E_m = \frac{\sum_{A\in Z}\sum_{B\in Z}[\eta(A,B)\cdot trips_m(A,B)]}{\sum_{A\in Z}\sum_{B\in Z}trips_m(A,B)} \tag{3}$$

where: E_m: Overall efficiency of alternative index for trips with the mode m;

Z: Set of all traffic zones;

$trips_m(A,B)$: Number of trips from A to B with the mode m.

Equation (3) is calculated separately for each mode, which allows for the comparison of impacts between them. E_m varies from 0 to 1 with the lowest value corresponding to the total collapse of the system – no trips are possible during the impact – and the highest corresponding to perfect redundancy when the system can provide equally good paths in the face of degradation.

3.5. Flood scenarios

For the case study, we simulate flooding scenarios in the urban area of São Carlos. The city is in the Southeast of Brazil crossed by river valleys that occasionally suffer from flooding due to the region's topography, as shown in Fig. 5 which has the graph of the city with the nodes colored according to their elevation. The Master Plan of the town, created in 2005 and still in effect, delineates the areas at greater risk of flooding and is also marked in Fig. 5. Since then and in the future, the effects of climate change, urbanization, and poor drainage may cause the expansion of flood risk areas.

In this case study, we aim to simulate an increase in flooding intensity by gradually expanding the risk zones through fixed rises in water level, by first defining a baseline scenario as a flood affecting the risk areas defined in the Master Plan of 2005 and increasing the water level (Δy) in steps of 10 cm from the baseline up until 1.5 m. As this process unfolds, areas at higher elevations begin to flood and further block the traffic through the edges connected to the flooded nodes. To simulate this process, we consider the topography of the region (elevation of each node in the graph) obtained through the Google Maps API. Some of these flooding scenarios are in Fig. 6.

3.6. Trip distribution

The trip distribution in the city is given by the OD survey conducted by Rodrigues da Silva (2008) for the municipality, with the division of the territory into 41 traffic zones. In the universe of interviewees, an average of just over 6,000 trips per day was recorded in the two days of the survey, distributed among walking, cycling, individual motorized, bus, and other modes. For this paper, only walking, cycling, and individual motorized trips are considered. Also, we consider only the most essential trips, disregarding those with leisure motives.

4. Application and discussion

The impacts of flooding scenarios in São Carlos are evaluated in this session. We calculated the system's efficiency through Equation (3) for each water level for the different modes, and the curves are in Fig. 7. We observe that pedestrian movements tend to be less impacted, with the efficiency of the mode hitting levels close to 80% in the most critical scenario. The characteristics of pedestrian movements may justify this trend. First, the network for pedestrians tends denser and more flexible, with all links in the system allowing for two-way movements leading not only to more redundancy in the system but also to a tendency for alternative paths to have a closer length to the original since there are more paths to choose from. This difference between the "walk" and "drive" networks

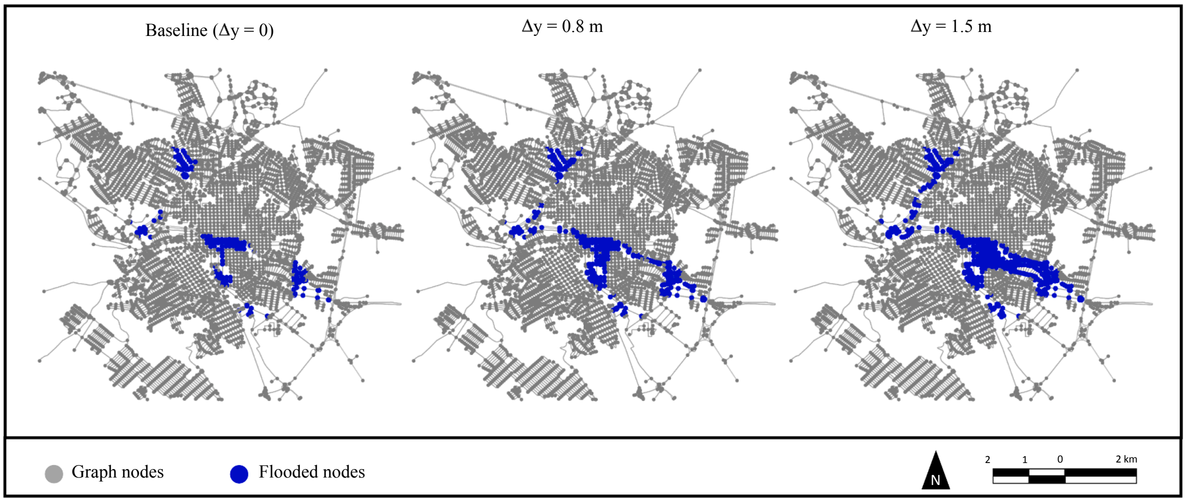

Fig. 6. Flooding scenarios in the city of São Carlos. The baseline is the region of greater risk of flooding as defined in the city's masterplan and the further scenarios are defined through an increase in water level from the baseline (Δy).

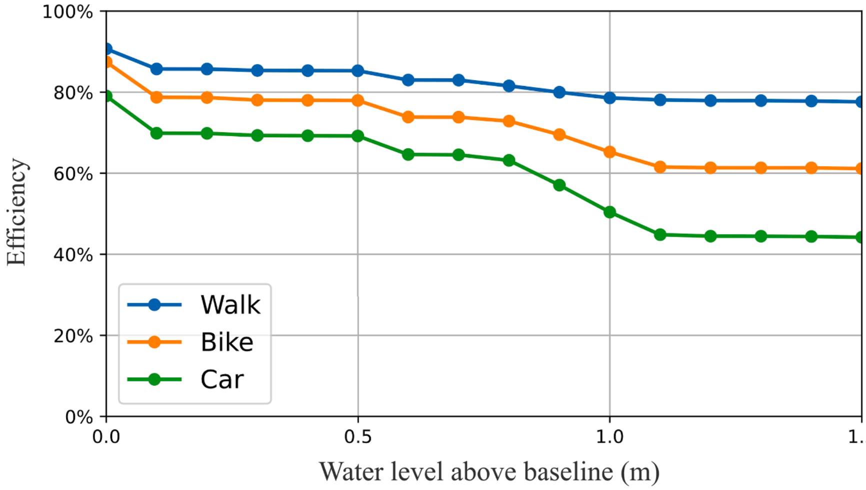

Fig. 7. Efficiency of different modes of transport. Driving is the most vulnerable mode of transportation, with its efficiency dropping below 50% for rises above 1.0 m.

has been consistently observed by other researchers in the USA and Cambodia (Boeing, 2019; Yen et al., 2019). The average length of trips may also have an impact on the vulnerability of the route, since shorter trips tend to be restricted to a small section of the city, reducing the probability of it being impacted by a flood, and, while other authors found that walking networks have lower circuity resulting in shorter distances traveled (Boeing, 2019; Yen et al., 2019), walking trips tend to be shorter mostly because users avoid large walking distances. Fig. 8 shows the distribution of trip lengths in the undisturbed network. Table 1 brings the average statistics of trip lengths,indicating that walking tends to be constrained to shorter movements.

Nevertheless, bikes and cars share the same niche in the system, with length distributions very similar. The network for bicycles is also mostly the same as for motor vehicles, with predefined directions for movement. Yet, bicycle movements, although more vulnerable than walking, are considerably less vulnerable than motorized vehicles. We hypothesize that the difference in vulnerability between cars and bicycles is mostly due to the nature of infrastructure along the river basin. Large marginal avenues with high traffic speeds along the rivers are typical in São Carlos. These avenues are car-oriented and, although there are cycling lanes along some of them, they are not densely connected to the rest of the system disincentivizing their use by commute cyclists. Another characteristic of the city that may impact cyclist's choice is the river valleys with intense slopes near the flooding regions in movements perpendicular to the river flow. This formation may cause cyclists to avoid these regions of the city and making their trips more resilient to floods.

Fig. 9 shows the vulnerability curves divided by trip length range to further evaluate the effect of length on vulnerability. The trend indicates that longer trips tend to be more affected by flooding. Walking is less vulnerable to floods mostly because most of the trips made by this mode are under 1.5 km (60.5%). This behavior shows that one way to reduce the impacts of natural phenomena in the city is to incentivize compact regions where trips are relatively short and diluted throughout the network. Nevertheless, the impact is different depending on the mode used for the trip. Car trips are more vulnerable than other modes, even for relatively small routes, while bike trips tend to show less vulnerability than other modes for trips ranging from 1.5 km to 4.5 km. This trend may be linked to the car-oriented nature of the regions with higher risks for flooding and cyclists' tendency to avoid these regions.

Fig. 10 shows the maps of efficiency where the color of a traffic zone becomes darker as the efficiency of trips originated in that zone falls. We observe that, as expected, the areas next to the flooding event are heavily impacted in all modes yet, for pedestrians, the impact tends to be constrained to the flooded region. In contrast, for bikes and particularly for cars, the consequences are noticeable

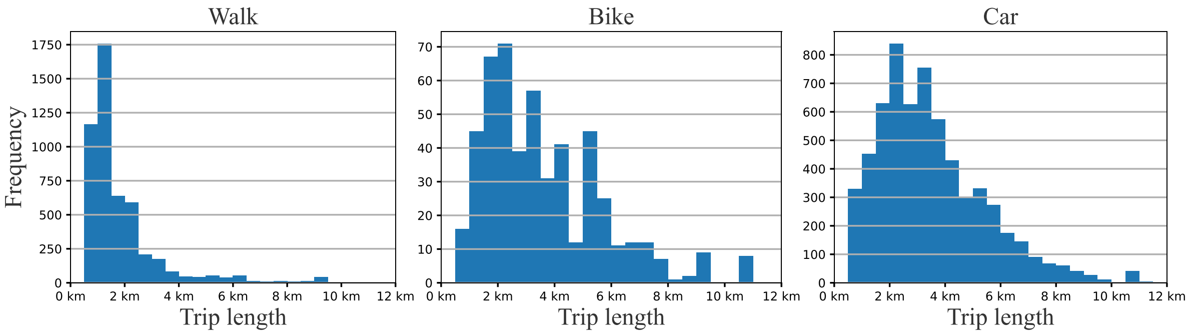

Fig. 8. Distributions of trip length per mode. While walking tends to be centered on shorter distances, cycling, and driving seem to occupy the same niche.

Table 1
statistics of length per mode.

Mode	Trips	Percentile		
		25%	50%	75%
Walk	4953	1 004 m	1 327 m	2 101 m
Bike	511	1 995 m	3 224 m	5 048 m
Car	6201	2 062 m	3 185 m	4 515 m

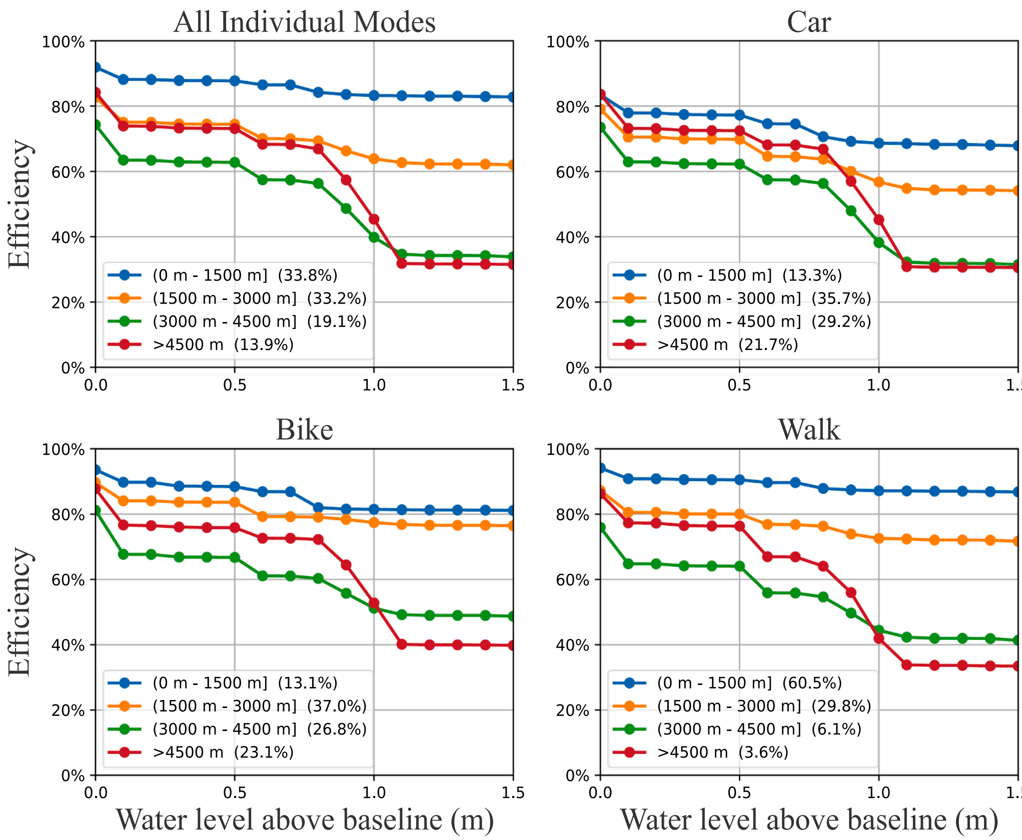

Fig. 9. Efficiency grouped by length. Shorter trips tend to be less vulnerable in general.

throughout the system. This behavior is another evidence that incentivizing short routes – through mixed-use development – can improve the resilience of a system by constraining the impacts of natural phenomena to smaller regions, decreasing the overall impacts of disasters.

5. Conclusion

We proposed a novel method for measuring transportation vulnerability to extreme events in urban road networks based on travel distribution. The databases required for the analysis are the road network and the OD matrix, both already common in urban planning, which facilitates the integration of this method in decision-making processes for planning resilience in transportation networks of different modes. We propose the metric *efficiency of alternative* which is indicative of the average increase in route lengths, and the proportion of isolated nodes after an impact on the road network and can be measured for active modes as well as for motorized vehicles. As a case study, the method was applied to measure the impact of flooding in São Carlos, a mid-sized city in the state of São Paulo in Brazil. The overall impact for pedestrians was significantly smaller than that of motorized vehicles, mostly due to the average length of the trips being larger for vehicles and the car-oriented nature of the avenues closest to rivers in this city. This evidence is an indicator that shorter trips tend to be more robust to these extreme events. This points to the conclusion that providing proper density to cities and incentivizing residential development in biking or walking distance to services and job opportunities may limit the problems caused by events of this nature. Furthermore, bicycle routes also show less vulnerability to flooding than cars, although having a similar distribution on distance traveled indicates that bicycle users tend to avoid marginal avenues.

The case study is an example of the applicability of these metrics in other research to evaluate the impacts of extreme events of

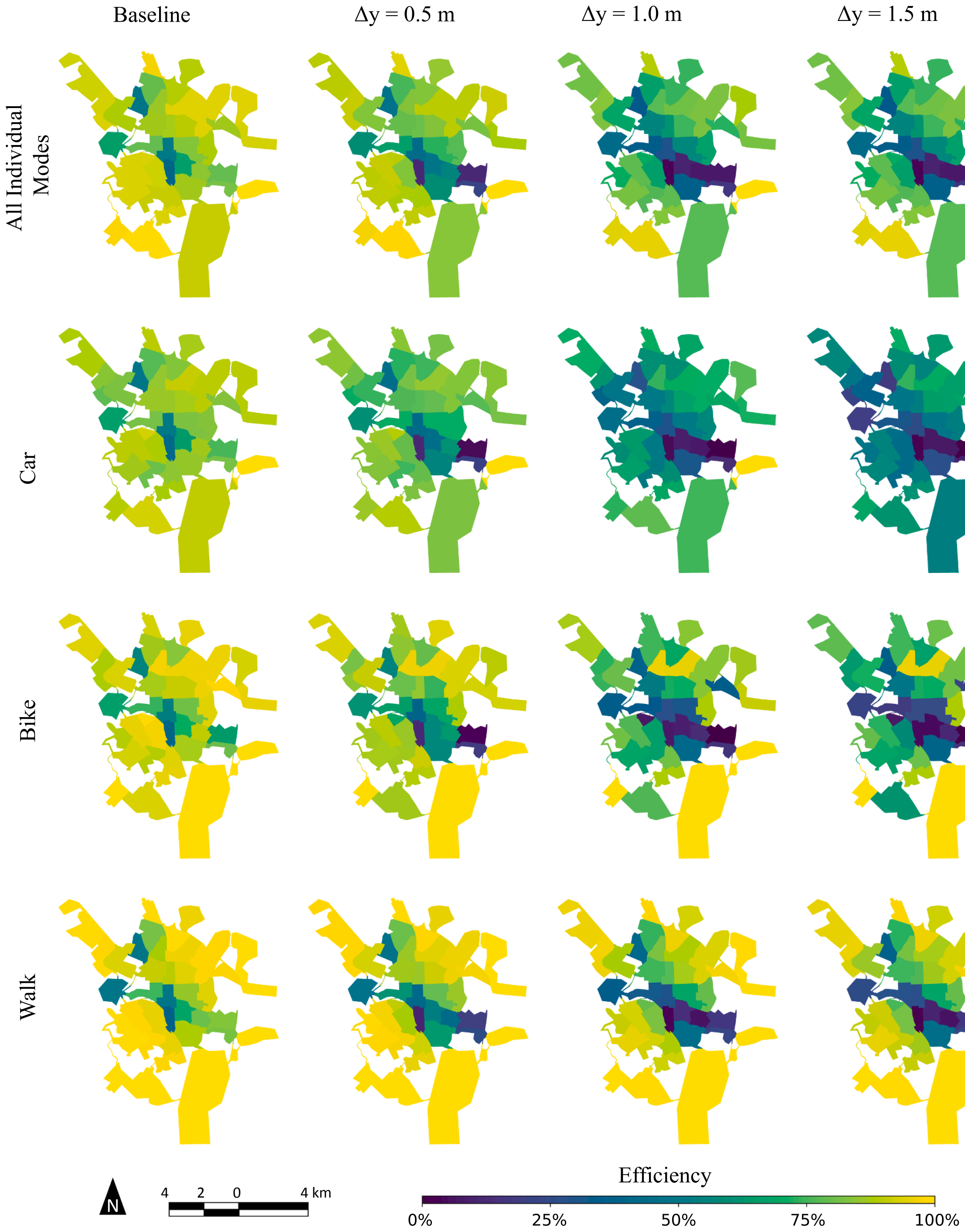

Fig. 10. Impact on trips originated in each zone of traffic where darker the zones are more impacted by the floods. While walking and cycling tend to concentrate the impacts close to the floods, driving is heavily impacted even in zones distant to the occurrence.

various natures in different cities in a relatively simple way, setting a framework for further research on transport network's resilience. Also, as the data needed for this analysis are relatively common in mid- to large-sized cities, these metrics may prove to be useful guides to decision-makers. Planning for emergency action during floods, for example, might be one direct application of the metric, as authorities can evaluate the extent to which emergency vehicles can reach the population and plan for the location of facilities. This type of action should also be coupled with regulations to guide urban development more robustly, like avoiding the creation of densely populated areas separated from jobs, services, and emergency facilities by a flood risk zone. On the network side, this metric can show potential vulnerabilities on the system, like over-dependence on few critical infrastructures, as the metric may not only be applied for floods and disasters, but also for evaluating scenarios where one particular road is removed from the system, potentially guiding the project of well-placed redundancies. This flexibility highlights other potential uses for the metric, like evaluating more damaging and lasting events, such as earthquakes and landslides. Finally, to facilitate these applications, we also make the code created for this analysis open-source, for researchers and practitioners to use or remodel for their needs.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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