Vulnerability Assessment of Transport Networks under Extreme Conditions

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SHORT SUMMARY

Climate-related hazards, operational incidents, and extreme disruptive events are increasing the exposure of transport systems to localized and systemic failures. This paper proposes a framework for assessing the vulnerability of urban road networks to major breakdowns (such as accidents, flood-related disruptions, and extreme weather conditions). We use a static traffic assignment model here, while dynamic features will be investigated at a later stage. The approach distinguishes between local effects on individual links and broader systemic impacts transmitted through rerouting and network-wide congestion. We introduce a simple composite link vulnerability indicator to capture both congestion amplification and network resilience across different demand segments. The methodology is first applied in a large complex network in the city of Minneapolis with both arterials and freeways, while other urban areas will be investigated and compared. The article situates this framework within a broader reflection on resilience, demand and supply shocks, information regimes, and traveller adaptation under extreme conditions and partial information.

Keywords: resilience; flooding; risk maps; road average speed; traffic assignment models; vulnerability; multiple scenarios

1. INTRODUCTION

The increasing frequency and intensity of disruptions affecting transport systems have created a new challenge for planners and decision-makers. Climate-related hazards, operational failures, and geopolitical tensions can destroy or impair the functioning of transport infrastructures. This can rapidly generate cascading effects across economic activities and local communities. We focus in this paper on private transport. Because transport networks connect places, markets, and daily routines, a local disruption may quickly propagate and produce congestion, delays, and accessibility losses far beyond the initially affected area. For example, in the Milano region, recurrent flooding of the Seveso and Lambro corridors created significant stress on the road network and on the local and national economy, while a bridge collapse in Minneapolis some years ago significantly influenced travel patterns and route choices in the whole network (Zhu et al., 2010). Flood scenarios are defined by combining the spatial extent of inundation with discrete water-depth thresholds, which generate speed reductions (using depth-speed relationships from the literature).

In this context, analytical tools and predictive models are essential for identifying exposed infrastructure and anticipating the functional consequences of disruptive events. Beyond the physical detection of vulnerable assets, simulation approaches allow us to understand how degraded infrastructure performance propagates through the network. They are therefore critical for the design of resilience-oriented policies, including emergency response, evacuation planning,

and ex-ante mitigation measures (Mattsson, 2015). In the long run, such studies can provide guidelines for the building of new infrastructure.
This paper develops a methodology for assessing the vulnerability of urban road networks to significant disruptions such as accidents, strikes, extreme weather conditions, and floods. The proposed framework combines hazard mapping, depth-based speed reductions, and traffic assignment modelling to evaluate both local and systemic consequences of major breakdowns. For example, in the metropolitan area of Milano, recurrent river flooding creates a particularly relevant test case for road-network resilience. The effect of total travel time is investigated as a function of capacity loss due to the disruption for different configurations (e.g. link capacity loss, number of links influenced etc.). The remainder of this paper is structured as follows. Section 2 presents the literature review. Section 3 introduces the application to the Minneapolis metropolitan areas. Section 4 defines resilience, shocks, and behavior under severe and extreme conditions. Section 5 reports the preliminary results and Section 6 concludes.

2. LITERATURE REVIEW

Literature generally defines resilience as the capacity of a system to absorb disturbances, adapt to changing conditions, and recover functionality after disruption (Hollnagel, 2011). The resilience curve introduced by McDaniels et al. (2008) represents system performance over time. It emphasizes two central dimensions: vulnerability, which captures the initial loss of performance (treated in this paper), and rapidity, which reflects the speed of recovery. Within this broader perspective, vulnerability assessment focuses more specifically on the immediate magnitude of system degradation when the network is exposed to a shock (Vugrin et al., 2011).
Three hierarchical dimensions of vulnerability are commonly distinguished. Physical vulnerability (1) refers to the structural susceptibility of infrastructure components to damage. Functional vulnerability (2) concerns operational degradation, such as lower speeds or reduced capacity following heavy rain or infrastructure malfunction. Systemic vulnerability (3) captures the wider effects generated through demand-supply interaction, including rerouting, spillback, congestion propagation, and modal substitution.
Early contributions often relied on graph-theoretic indicators such as betweenness centrality to identify structurally critical links. Although these metrics remain useful for highlighting topological importance, they do not account for congestion dynamics, behavioural adaptation, or demand-supply interaction (see, e.g., Brandes, 2001). Their explanatory power is therefore limited when disruptions are spatially distributed and involve partial link degradation rather than complete network failure, and when both policies and user behaviour matter. Reaction-diffusion models combined with macroscopic fundamental diagrams or percolation theory (Li et al., 2015) can provide a better understanding of congestion propagation for large networks (Bellocchi and Geroliminis, 2020).
System-based approaches offer a richer alternative. By combining hazard information with traffic assignment models, they simulate how a local deterioration in infrastructure performance generates route changes, congestion spillovers, and broader accessibility losses. This perspective is especially valuable for climate hazards such as flooding, where the spatial footprint of the event and the resulting decline in speeds or capacity may vary substantially across links. Demand segmentation can further improve policy relevance by revealing differentiated effects across traveller groups and trip purposes. Different network performance measures could shed light in the trade-off between capacity loss, magnitude of disruption and multimodal effects (Bellocchi et al., 2021).
European regulatory frameworks increasingly support this line of analysis. The EU regulations on climate-proofing infrastructure and on the adaptation and mitigation of economic activities identify several categories of climate-related hazards, among which flooding is one of the most

disruptive for transport systems (EURLEX 2021/5430; EURLEX 2021/2139). For example, flood events may affect a wide urban area simultaneously and generate significant losses in performance even when physical destruction remains limited (Shen and Kim, 2020).
Building on this literature and adding the key behavioural and policy dimensions, this paper proposes a scenario-based framework for assessing the vulnerability of urban road networks under major disruptions.

3. APPLICATION TO THE MINNEAPOLIS METROPOLITAN AREA

The methodology is applied to the metropolitan area of Minneapolis–Saint Paul, a major urban region located along the Upper Mississippi River and intersected by several tributaries, including Minnehaha Creek, the Minnesota River, and Bassett Creek, all of which contribute to flood exposure during episodes of intense rainfall and snowmelt. The flood-risk maps used in this study are derived from the Federal Emergency Management Agency (FEMA) and regional watershed management authorities, and are associated with different return periods of significant flood events. The transportation network is based on the Minneapolis network from the open city-scale traffic assignment dataset introduced by Xu et al. (2024). Figure 1 shows the baseline Minneapolis network together with the equilibrium link-flow pattern used as the reference state for the disruption analysis.

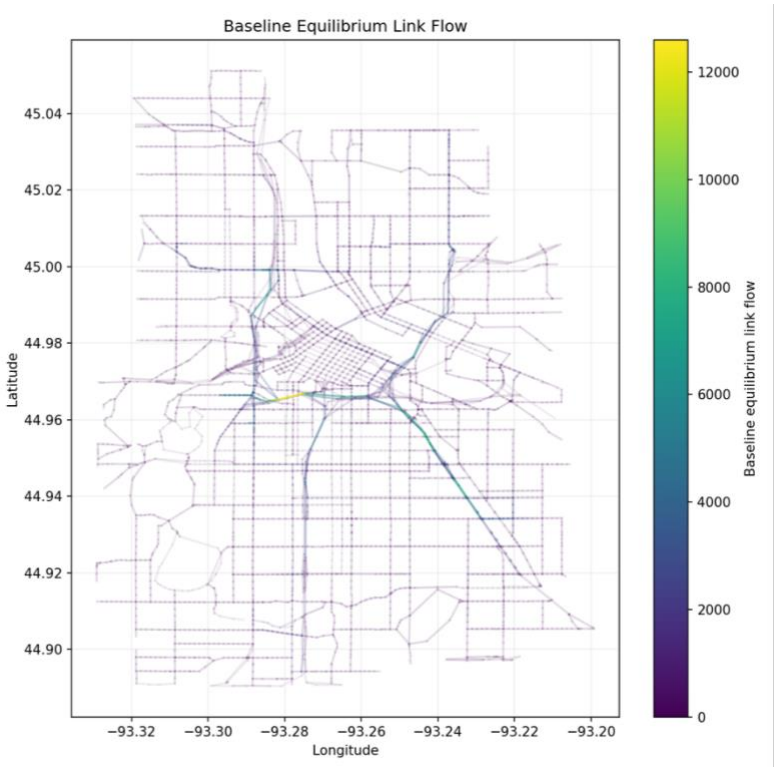


Figure 1. Illustration of Minneapolis Network

These flood-prone areas are combined with discrete water-depth assumptions, 50, 150, and 300 mm, leading to the identification of five distinct flood scenarios. For each scenario, the impact of water depth on vehicle speed is incorporated into the traffic assignment model, which simulates morning peak-hour demand and estimates the resulting changes in network flows and travel times. To improve the policy relevance of the analysis, travel demand is segmented geographically into central urban trips, commuting trips between suburban zones and the downtown core, and peripheral inter-suburban trips. This segmentation highlights heterogeneous vulnerability patterns that would remain partly concealed in an aggregated analysis. Commuting trips to and from the

downtown core are expected to experience the largest relative increases in travel time because they rely heavily on major river crossings and radial freeway corridors, notably Interstates I-94, I-35W, and I-394. Central urban trips are more exposed to localized congestion effects, while peripheral trips are likely to display substantial rerouting behaviour under more severe flood scenarios.
The simulation outputs are then used to compute a composite vulnerability index for each link and each demand segment. This index includes a direct component related to local traffic degradation on the affected link itself and an indirect component capturing the broader network impacts generated by the deterioration of that link. In this way, the framework identifies the road segments that are expected to become the most critical under flood-related disruptions.
Our approach places particular emphasis on policies, user behavior, and information provision, which are examined in greater detail in the next section.

4. RESILIENCE, SHOCKS, AND BEHAVIOR UNDER SEVERE AND EXTREME CONDITIONS

The vulnerability framework presented above can be situated within a broader analysis of resilience in transport networks. A useful distinction is between demand shocks and supply shocks, since each type of disturbance modifies traffic equilibria and system performance in a different way.

4.1 Demand shocks

Demand shocks correspond to variations - often unexpected - in travel flows. They may result from changes in modal preferences, special events, or indirect traffic reallocations caused by incidents. Public transport strikes, for example, often shift users toward private cars, thereby increasing road congestion (see Arnott, de Palma and Lindsey, 1993, for the case of a fully dynamic model with stochastic capacities and stochastic demand). Major sporting or cultural events may also temporarily alter the spatial and temporal structure of demand (Giuliano, 1989).
In modelling terms, demand shocks are represented by changes in origin-destination matrices. These changes may be aggregate, when total demand rises, or structural, when the spatial distribution of trips is modified. A special event can thus be modelled as an increase in flows toward a specific destination, with all relevant origins contributing proportionally to that destination.

4.2 Supply shocks

Supply shocks affect the capacity or functioning of transport infrastructure directly. They may be technical, planned, environmental, or extreme. Examples include signal failures, roadworks, floods, snow events, wildfires, bridge collapses, and even acts of war or attacks targeting strategic transport nodes. In each case, the physical or operational characteristics of the network are modified, with direct consequences for generalized travel costs.
Flooding of the Seine in Paris illustrates a supply shock in an urban setting, as it may require the closure of riverside roads, substantially reducing network capacity. In traffic models, such shocks are typically represented as changes in link capacities, ranging from partial degradation to full closure (Patriksson, 1994).

4.3 Emergency evacuations

Emergency evacuations constitute a specific case in which demand shocks are massive, sudden, and highly constrained. Under such conditions, usual travel patterns become irrelevant because travelers primarily seek to leave a dangerous area or reach safe locations. The demand structure must therefore be reconstructed from the current location of individuals, the zones to be evacuated, and the available shelters or refuge areas.
Dynamic models are generally better suited to this context because they explicitly capture the temporal evolution of flows, departures, route choices, and congestion. Static assignment models may still be used as approximations, but they cannot represent within-period shock timing, queue formation, spillback, or the persistence of residual congestion across subperiods. In this approach, we rely on static models (see Wardrop, 1952, and Sheffi, 1981) to allow fast and systematic comparison between cities. Outputs should therefore be interpreted as average equilibrium conditions rather than as the actual traffic state at a specific instant.

4.4 User behaviour and information regimes

Behavioural adaptation is a central component of resilience. Under disrupted conditions, travellers may adjust departure time, route, mode, activity scheduling, or even cancel trips altogether (de Palma and Rochat, 1997; Khattak and de Palma, 1997; Böcker et al., 2013; Zhou et al., 2017; Cui et al., 2024). Risk aversion also becomes more salient, since individuals face not only higher expected travel costs but also greater uncertainty regarding those costs. This supports modelling approaches that go beyond simple risk neutrality, including constant absolute risk aversion specifications (de Palma and Picard, 2005).
Information regimes matter as well. Under a full information policy, all users know the disruption before making their choices, and the equilibrium is computed on the disrupted network. Under a zero-information policy, users continue to follow pre-disruption route choices even though travel times are recalculated under reduced capacity. A partial information policy introduces heterogeneity: some users remain uninformed, while others adapt optimally given both the disruption and the residual congestion caused by those uninformed users. This yields a Stackelberg-type game in which fixed uninformed flows are taken as given (residual assignment) by the informed travellers.

4.5 Preliminary conclusions

Taken together, these elements establish a systematic and transferable methodology for identifying the most vulnerable components of an urban road network under spatially distributed hazard conditions. The framework combines hazard scenarios, traffic assignment, behavioural interpretation, and composite link indicators to connect local disruption with broader network performance.
The Minneapolis application suggests that the topology of the network (ring-road sections and radial access corridors, etc.) and the demand system are likely to play a disproportionate role in preserving mobility during major events (such as flood events). The following empirical section presents the scenario-by-scenario results, vulnerability rankings, and policy implications for mitigation, adaptation, and emergency planning for different information policies.

5. PRELIMINARY RESULTS

5.1 Experimental Setup

We evaluate network degradation through a progressive disruption experiment on the Minneapolis road network. Starting from the baseline network without any disruption, links are

cumulatively affected through a probabilistic deletion process. At each deletion step, one link is selected without replacement from the set of eligible physical links. The selection probability of link i is proportional to its baseline equilibrium flow, i.e.

$$p_i = \frac{f_i}{\sum_{j \in E_r} f_j}$$

where f_i denotes the baseline equilibrium flow on link i, and E_r is the set of candidate links that have not yet been disrupted. As a result, links carrying larger traffic volumes are more likely to be disrupted earlier in the sequence. At each disruption level, we compare different partial-capacity reduction factors, which represent the fraction of residual capacity kept on each affected link. Smaller values therefore correspond to more severe local degradation.

The analysis focuses on two benchmark behavioral regimes. In uninformed case, users remain uninformed and continue to follow pre-disruption routes, while travel times are recalculated under degraded capacities. In informed case, all users are assumed to be informed and re-optimize their routes through a new static user equilibrium. To complement travel-time effects, we also report vehicle-kilometers traveled (VKT) in the fully informed regime.

5.2 Results

Figure 2 reports total system travel time (TSTT) in the zero-information regime (uninformed case) as a function of deleted capacity. Here, residual capacity denotes the fraction of the original link capacity that remains available after disruption. For example, a residual capacity of 0.3 means that only 30% of the original capacity remains, i.e., the link has lost 70% of its capacity. Each color represents what fraction of local link capacity is lost for every disrupted link. TSTT rises sharply as the disruption level increases, especially for low residual capacity. When affected links retain only a small fraction of their original capacity, the network experiences a very large increase in congestion costs. By contrast, larger partial factors produce much flatter curves, indicating that preserving residual capacity substantially mitigates system degradation. The increase is initially steep and then gradually plateaus. This reflects the cumulative nature of the disruptions: the most influential links are affected first, while later disruptions add progressively smaller marginal damage. The contrast between the curves also shows that under uninformed behavior the system is highly sensitive to severe local capacity reductions.

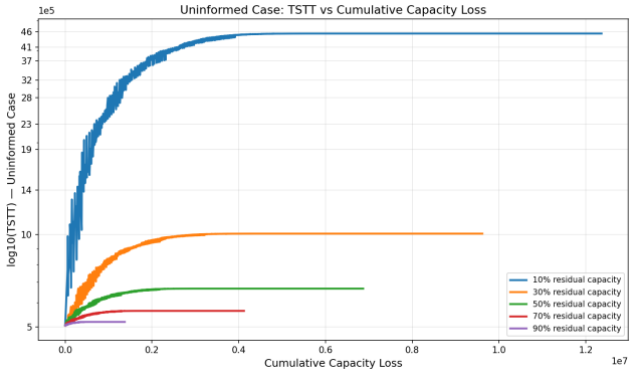


Figure 2. Uninformed Case: Total System Travel Time (TSTT) vs. Deleted Capacity

Figure 3 presents the fully informed regime (informed case) for the same other settings as in Figure 2. As expected, TSTT also increases when capacity is deleted, but the increase is much smaller than in uninformed case. This indicates that route adaptation absorbs an important part of the disruption impact. Even under severe degradation, informed users can redistribute themselves across the network and avoid part of the congestion amplification observed when no information is available. The ranking of the residual capacity remains the same as in uninformed case: lower residual capacities lead to worse system performance. However, compared with the uninformed

case, the curves are closer together. This suggests that information does not eliminate disruption effects, but it significantly reduces their system-wide consequences.

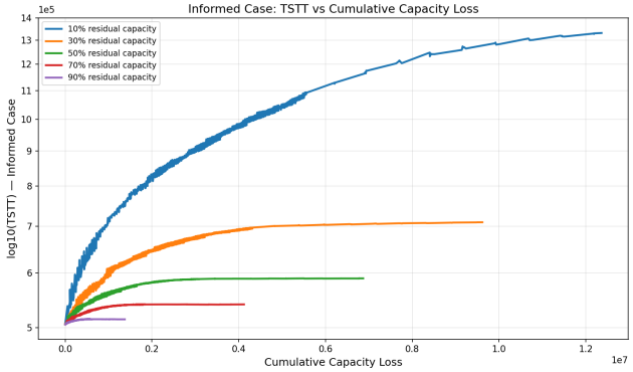


Figure 3. Informed Case: Total System Travel Time (TSTT) vs. Deleted Capacity

Figure 4 reports VKT in the fully informed regime as the number of disrupted links increases. For the 30%, 50%, 70%, and 90% residual-capacity settings, VKT remains close to its baseline value, indicating that mild and moderate degradation do not substantially change the total distance traveled. A more complex pattern appears under the most severe setting, where affected links retain only 10% of their original capacity. In that case, VKT first decreases, then rises, and finally falls sharply as additional links are degraded. This non-monotonic pattern can be understood by considering how travelers adjust their route choices when they are fully informed. In normal conditions, many users rely on high-capacity corridors such as ring roads or arterial routes. These roads may involve longer distances, but they are attractive because they are fast and uncongested. Once these main corridors lose most of their capacity, they become heavily congested and less attractive. Travelers then switch to shorter local streets or more direct paths. These alternatives reduce the total number of kilometers driven, which explains the initial decline in VKT. A simple example is a commuter crossing a city. Under normal conditions, the commuter may choose a 14 km bypass road that is fast and reliable. If that road becomes severely congested after disruption, a slower 8 km route through local streets may become preferable. Travel distance falls, even though travel time increases. As the disruption expands further, some of these local shortcuts also become saturated or disconnected, forcing users to take broader detours through the remaining network. This generates the intermediate rise in VKT. Under even more severe degradation, however, route choice becomes dominated by feasibility rather than speed. Travelers concentrate on the shortest remaining usable paths, even if these routes are extremely slow. VKT therefore declines again, while TSTT continues to rise. In this final stage, the main penalty of disruption is no longer extra distance, but severe congestion and loss of network efficiency.

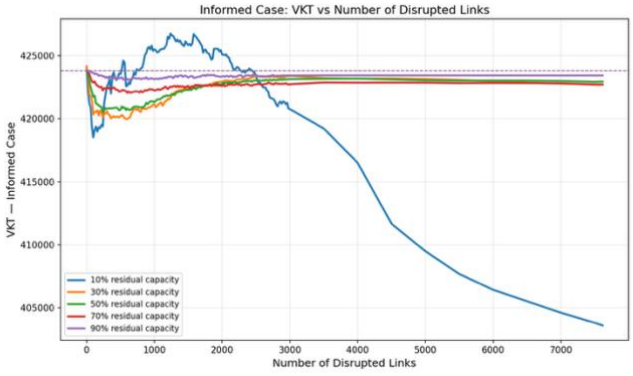


Figure 4. Informed Case: Vehicle Kilometer Traveled (VKT) vs. Number of Disrupted Links

6. CONCLUSION

This paper proposed a framework for assessing the vulnerability of urban road networks under major breakdowns, with explicit attention to supply degradation, traveller information, and demand variation. Using static traffic assignment, the analysis distinguishes between full-information, and zero-information. In our next step, we will proceed to examine the partial-information regimes, thereby linking infrastructure disruption with user adaptation. The empirical application shows that network performance deteriorates progressively as the disruption budget increases, and that the magnitude of this deterioration depends strongly on the severity of capacity loss. The proposed framework can therefore serve as a useful tool for comparing cities, evaluating disruption scenarios, and supporting resilience-oriented transport policies.

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