BEYOND TRAFFIC PERFORMANCE: ASSESSING TRANSPORT NETWORK RESILIENCE THROUGH ACCESS AND EQUITY

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Abstract

Weather disruptions endanger transport network operations and accessibility, hindering people's possibilities to reach opportunities and services. While most research focuses on infrastructure impacts, few studies have examined how different socioeconomic groups experience such disruptions. This paper introduces a comprehensive method for assessing transport resilience to extreme weather and includes a case study highlighting social disparities in access to healthcare services. The case study reveals that access to essential city services varies by socioeconomic strata and that extreme weather events can exacerbate inequalities.

Introduction

Maintaining physical connection between distant places has been fundamental to the functioning of societies and economies throughout history. Transport networks enable the movement of people and goods, serving as the backbone of economic activity and societal development (Zhang and Cheng, 2023). In recent decades, these infrastructure systems have faced significant challenges due to the increasing intensity and frequency of extreme weather events (Kurth et al, 2020). The disruptions caused by these events have had several implications, including economic losses, casualties, and physical and psychological health issues among affected populations (European Environment Agency, 2024).

Research on transport infrastructure resilience to extreme weather constantly operationalises resilience as a time-dependent property of service that combines (i) the ability to withstand or absorb a disruption, (ii) the capacity to adapt to new settings, and (iii) the ability to recover within acceptable time and cost envelopes (Bruneau et al., 2003; Li et al., 2020; Wassmer et al., 2024). Hence, resilience metrics are described in operational terms (e.g., speed, delays), network-topology terms (e.g., efficiency under link removal), accessibility terms (e.g., reachable opportunities), or monetised socioeconomic impacts (e.g., wage loss) (Afrin and Yodo, 2020; Faturechi and Miller-Hooks, 2014; Hadjidemetriou et al., 2022). As a consequence of this approach, the role of social disparities among affected communities is often overlooked.

For example, the operational approach to resilience treats performance metrics, such as time delays, as both the primary measure of impact and diagnostic tool for inferring management priorities. From operational approaches, a resilient transport network is resistant to disturbances and can recover rapidly in case of occurrence, ensuring traffic flow and reducing congestion (Ganin et al., 2017; Zhang et al., 2017). In this line, Rebally et al. (2026) assess the impact on traffic of the 2013 flood in Calgary (Canada) using HEC-RAS for flood modelling and SUMO for micro-scale traffic simulation, and demonstrate the extent to which the flooding event causes longer travel times and distances, and how the disruption leads to cascading impacts. Likewise, Liu et al. (2026) integrate the effects of flooding, reduced visibility, and traffic signal failures during extreme rainfall to evaluate network performance by estimating the average delay per time slice and a delay-based resilience index in a case study of Greater London. In these and similar studies, transport resilience is measured by observing or simulating operational degradation and recovery in traffic or service variables under specified meteorological conditions. This stance treats disruption impact as a departure from the original “steady-state”, and resilience as the shape of the performance-time profile, frequently summarised into a scalar “resilience index” for comparison across different scenarios (Achillopoulou et al., 2020; Zhang et al., 2024).

Scholars across fields and perspectives do not deny the importance of societies' ability to withstand shocks, but call for awareness of how that goal is pursued (Cutter, 2016). Uncritically applied, resilience may imply short-term stability at the cost of long-term vulnerability. However, if conceived critically, resilience can be aligned with transformative adaptation and social justice, thereby making communities safer and more equitable. In this line, a significant share of research in transport resilience has shifted from “traffic loss” to “activity loss”.

A major stream of research treats resilience and vulnerability to extreme weather events as changes in access (to opportunities, locations, services, etc.) rather than as changes in traffic speed, flow or time delays. In this approach, the impact of weather-related disruption is translated into the extent to which it elongates or interrupts effective connections between people and destinations, and resilience is evaluated by how rapidly and unevenly accessibility is restored or substituted (Martín et al., 2021). Accessibility metrics are frequently integrated with link-removal experiments and hazard overlays. For example, Martín et al. (2021) compare how territorial accessibility is reduced under the cumulative exclusion of transport links through random removal, removal by criticality, and targeted removal in high-flood-risk areas. Other studies, like Farahmand et al. (2024) focus on metrics such as agency costs, user costs, and environmental costs to enable targeted investment through benefit-cost analysis. Overall, the methodological importance lies in integrating climate change factors and effectively coupling network criticality with hazard-informed failure mechanisms (Martín et al., 2021).

Further critical perspectives serve a crucial function in prompting the question: 'Resilience for whom and to what end?' (Cretney, 2014; Cutter, 2016). For example, little is said about prioritising emergency vehicles when recovering the level of service (Wassmer et al., 2024; Wu and Chen, 2023), or trips by road users trying to reach healthcare facilities.

A critical gap exists in leveraging existing methodologies to account for social disparities in access to essential services through the existing infrastructure, particularly in the context of weather-related disruptions. For this reason, this paper leverages transport modelling principles to investigate the effect of weather-related disruptions on trips to healthcare facilities across users from households with different socioeconomic strata. To achieve this, the proposed workflow, the required data and preprocessing procedures, model specifications, and the disruption experiment design are presented in the Methodology chapter. Then, a case study of a real midsize city in Colombia is presented, highlighting pre-existing disparities among households categorised as low-, mid-, and high-socioeconomic stratum households in access to healthcare services and how a flooding disruption can deepen these disparities.

Methodology

This paper leverages transport planning tools and data from Origin-Destination (OD) surveys to develop a reproducible workflow for estimating the impact of extreme-weather-related disruptions on groups of people with different income levels and trip purposes. The main steps in the workflow are (i) the construction of the model in Geographical Information Systems (GIS) of the city's road network, (ii) the simulation of the OD demand matrix distribution over the network under static traffic assignment, and (iii) the quantification of network performance and travel times for groups of interest for a baseline "as-is" scenario and a disrupted scenario.

Data and tools

The proposed workflow requires: (i) geographical network and zoning data; (ii) the demand OD matrices for the established zoning; and (iii) the disruption layer (i.e., flooding risk map). The network can be assembled from GIS vector layers representing nodes (i.e., intersections and connections between origins and destinations), links (i.e., roads), and zones (i.e., Transport Analysis Zones). This study employs AequilibraE for modelling and aligns data requirements with this tool (Camargo, 2015). However, other software can be used to build the model. Overall, network data can be accessed using OpenStreetMap (OSM), obtained from local transport authorities, or built from a basic geometric representation of the network. Table 1 summarises the network attributes that must be specified.

Table 1: Network attributes specification

Data	Format	Source(s)
Nodes (N)	Geometry	OSM
N_ID	ID number of node	
N_IsCentroid	1: is a centroid 0: is not a centroid	Computed
Links (L)	Geometry	OSM
L_NodeA	ID number of node A	
L_NodeB	ID number of node B	
L_Direction	1: from A to B 0: both ways -1: from B to A	
L_Distance	Length [m]	
L_Lanes (AB & BA)	Number of lanes	
L_Speed (AB & BA)	Speed [km/h]	Observed/ Estimated
L_Type	'Default' or 'Connector'	Computed
L_TravelTime (AB & BA)	Travel time [s]	Computed
L_Capacity (AB & BA)	Total capacity [PCU/h]	Computed
Zones (Z)	Geometry	OD survey – Transport Analysis Zones (TAZs)
Z_ID	ID number of zone	

OD demand matrices must be provided, including the origin zone (i), destination zone (j), and number of trips (from i to j). For this study, the static traffic assignment approach assumes a single network for Passenger Car Unit (PCU) assignment, so trips are computed by assigning 1.0 PCU to car trips and 0.4 PCU to motorcycle trips. Table 2 lists the fields required for the OD matrices.

Table 2: Fields required for OD matrices

Field	Format	Source(s)
Origin	ID number of zone	OD survey (individuals)
Destination	ID number of zone	
Trips	PCU/h	
Mode	'car' or 'motorcycle'	OD survey (households)
Others (e.g., income level, trip purpose, etc.)	-	OD survey

The preprocessing procedure includes verifying network connectivity (i.e., every link has a start and an end node; no nodes or links are isolated from the network; each zone has a centroid node; and each centroid node is associated with a connector link to the network). Also, some network attributes are either observed or computed from the available OSM data. Speed (free-flow) on links can be observed or estimated from the link road class (e.g., highway, local, collector, etc.), the topology of the network, and the traffic management systems (e.g., heavy signalling cities with many intersections and pedestrian crosswalks require a lower speed than metropolitan areas connected by major roads or highways). Travel time is computed based on link speed and distance, and capacity is assumed to be the standard value per lane (1800 PCU/h/lane).

The simulation requires that the OD matrices be balanced with the Production-Attraction (P-A) vectors (i.e., the total number of trips produced equals the total number of trips attracted). Trips from OD surveys are converted to PCUs using assigned mode-specific values and aggregated across fields of interest based on the available data (e.g., trip purpose, income level, etc.).

Model specification

The model follows the principles of a 4-step transport model for an urban setting (Ortuzar and Willumsen, 2024). However, the first three steps (i) trip generation, (ii) distribution, and (iii) mode choice are intentionally fixed to isolate the effects of the weather-related disruption on (iv) the assignment step. The network is represented as a graph for the car mode (or PCU), where the supply representation and cost function are given via the congested travel time on the links, which is computed post-assignment using the Bureau of Public Roads (BPR) as Volume-Delay Function (VDF) (Bureau of Public Roads, 1964):

$$t = t_0\left(1 + \alpha\left(\frac{v}{c}\right)^{\beta}\right) \quad (1)$$

Where for each link, t0 is the initial travel time defined using estimated/observed free-flow speed, v is the assigned flow, c is the capacity, and α and β are parameters of the BPR function that define how early and sharply congestion starts.

The model employs two different assignment steps. The initial assignment is made using the methodology All-or-Nothing (AoN) (Bureau of Public Roads, 1964) to ensure network connectivity. This is done by loading the entire demand onto a single least-cost path computed using the initial travel time (i.e., there is no feedback from congestion, as the paths are defined by the static cost). Once the model implements the AoN assignment, the model moves to the User Equilibrium (UE) assignment (Patriksson, 1994), which operationalises Wardrop's principle: no traveller can reduce their travel time by unilaterally changing routes, given the congestion created by everyone else. The UE assignment is an iterative procedure in which each iteration takes the current estimate of travel times on the network's links, finds the shortest path, assigns flows, updates travel times using the previously defined VDF function, and then repeats until the convergence criterion is met.

Modelling outputs

Once the OD matrix trips are assigned to the network, traffic flow (PCU/h) and travel times are obtained for each used link. Then, instead of determining resilience in terms of operational variables that average the experience across all the road users in the network, the travel time for every group defined by the previously chosen fields of interest (e.g., income level, trip purpose) can be computed using the initial OD trips matrix and the OD congested times matrix, as:

$$\bar{T}^{(g)} = \frac{\Sigma_i \Sigma_j D_{ij}^{(g)} T_{ij}}{\Sigma_i \Sigma_j D_{ij}^{(g)}} \quad (2)$$

Where g is the index for the groups made of chosen fields (e.g., higher income level travelling for work), Dij(g) is the demand for group g from the origin i to the destination j, and Tij is the congested time from i to j. Obtaining travel times for different user types is not only useful for acknowledging disparities between groups but also for understanding whether these disparities are exacerbated under disruption scenarios.

Disruption experiment design (flood scenario)

The disruption input is a polygon layer delineating high-risk areas for disruption (e.g., flooding). The disruption mechanism reduces link capacities in proportion to the length share of each link intersecting the risk areas, scaled by a scenario severity parameter. Flood share in links is computed as the percentage of the link's length that overlaps the flooding area. The capacity reduction rule induced, and the corresponding parameters are as follows:

$$cap_{flood} = cap_0(1 - severity \cdot flood_{share}) \quad (3)$$

Where cap_{flood} is the new capacity of the link to be used for the trip assignment, cap0 is the initial capacity considered for the baseline scenario, and the severity is a parameter that determines how the link's capacity is affected by the portion affected by the flood. However, a capacity floor is required to prevent convergence issues caused by ODs that are 4disconnected and cannot be assigned.

Case study

To test the proposed workflow, the case study compares a baseline assignment with a flooding scenario for Villavicencio, a mid-sized city of approximately 600.000 inhabitants and an urban centre spanning up to 70 km2, located in the eastern plains of Colombia. Using data from the Origin-Destination Survey conducted in the city in

2022, travel times for people from households in lower-, middle-, and higher socioeconomic strata whose purpose of travel is "health" are obtained. The results of the baseline scenario show the extent to which times differ across socioeconomic strata and how they change during a flooding-induced disruption across the network.

Figures 1 and 2 display the network (links only) and zoning (TAZs) of Villavicencio, highlighting flood-prone areas along the city's rivers, as well as the density of "health" trips production (Figure 1) and attraction (Figure 2).

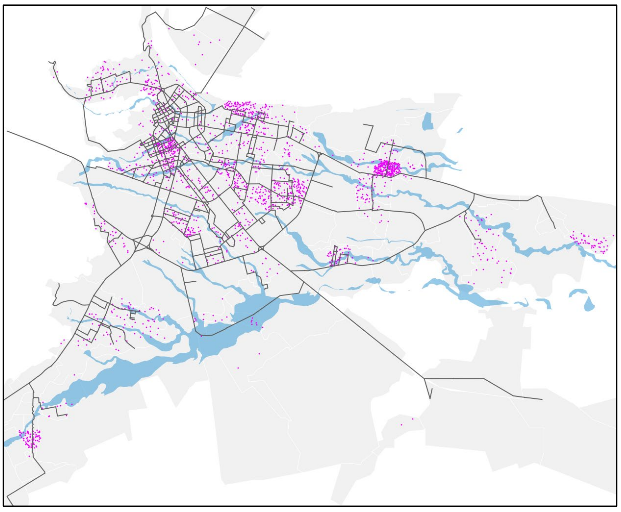

Figure 1: Villavicencio's network, flood-prone areas and "healthcare" trips production

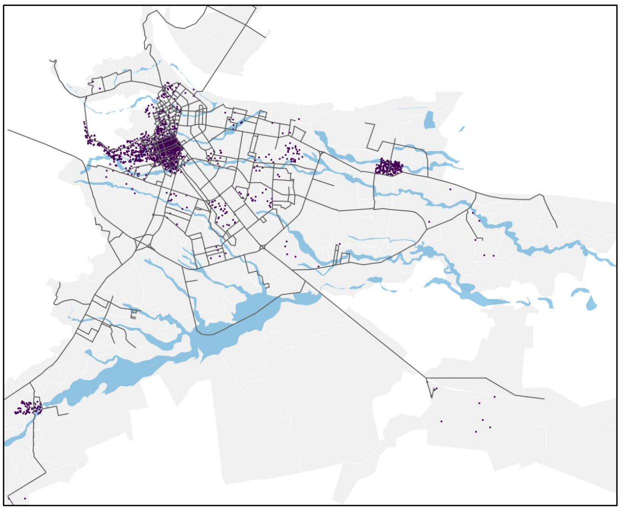

Figure 2: Villavicencio's network, flood-prone areas and "healthcare" trips attraction

The OD survey gathers information on approximately 11.500 trips that, after applying expansion factors, account for approximately 880,000 trips, of which 300,000 are by car or motorcycle (as driver or taxi user). Of the total number of trips, around 23.000 are made to access healthcare. However, despite the provision of health centres at each of the three corners of the triangular urban area, access remains unequally distributed across the population. In Colombia, households are classified in six socioeconomic strata based on their location, surrounding infrastructure, and access to public services (e.g., water and energy supply) (DANE, 2021). Table 3 shows the number of "health" trips by stratum (of the household) and mode during a day.

Table 3: Number of "health" trips by mode and level of income

Socioeconomic strata	Trips by car	Trips by motorcycle	Other modes
Low (1 & 2)	2786	1601	10244
Middle (3 & 4)	4125	1036	2870
High (4 & 6)	248	29	129

Since the methodology is based on static traffic assignment, using only trips observed during the highest-demand hour would produce a sparse OD matrix and exclude a substantial number of "health" trips. Therefore, the OD pattern was determined from a 3-hour period with the highest demand, which provides better spatial coverage of trips.

To ensure consistency with the static assignment framework, in which network capacities are represented on an hourly basis, the 3-hour OD matrix is converted into an equivalent peak-hour matrix using the expression:

$$T_{ij} = \frac{T_{1h,max}}{T_{3h,max}} \cdot T_{ij,3h} \tag{4}$$

The resultant OD matrix is converted to PCU by assigning 1.0 PCU to cars and 0.4 PCU to motorcycles. Along with the network properties, topology and scenario settings, traffic assignment is conducted to obtain congested travel times for every OD pair. The UE assignment is conducted using $\alpha = 0.3$ and $\beta = 2.0$. This procedure is carried out for the baseline and disruption scenarios, in which the link segments that intersect the flood-prone area (highlighted in Figure 3) are used to reduce capacity accordingly.

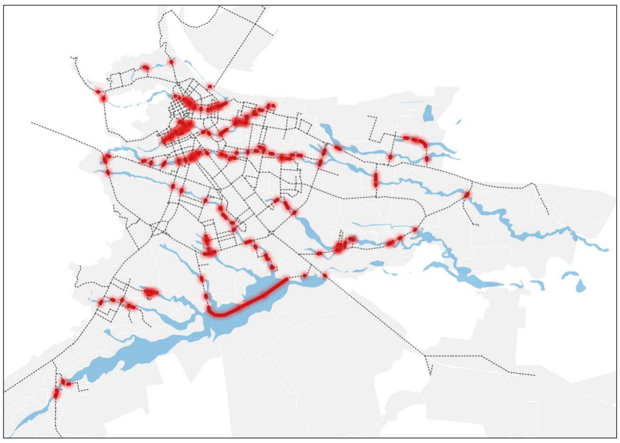

Figure 3: Network links intersecting flood-prone areas

Table 4 presents the number of health trips considered in the modelling period, and the estimated travel time across the three socioeconomic strata groups and simulated scenarios.

Table 4: Travel time by scenario, socioeconomic stratum for "health" trips on the 3-hour peak period

Scenario	Socio-economic stratum	Health trips	Health trips avg travel time, min
Baseline	Low	1049	29.9
	Middle	950	17.9
	High	67	13.4
Disruption	Low	1049	31.8
	Middle	950	18.6
	High	67	13.9

The results of the baseline scenario show that access to health services in the city is not equally distributed among people across different socioeconomic strata. Even in the absence of disruption, the network topology and urban setting make it more difficult for most of the people in the city, who live in lower socioeconomic stratum households, to access health services in the city. People in this stratum experience travel times up to 67% longer than those in middle-stratum households and 123% longer than those in higher-stratum households.

In the flooding scenario, travel times are generally longer for all trips because congestion from reduced capacity on affected links impacts everyone. Nevertheless, the results show that the flooding does not have the same effect on everyone in the city. Travel time for trips by people in lower stratum households to access health services increases by 6.5%, by 3.9% for middle stratum households, and by 3.8% for high stratum households. Thus, the urban setting and transport network not only provide reduced access to healthcare services for people in less favourable conditions but also allow for this gap to be stretched during flooding-related disruptions.

Conclusions

This paper presents a methodology that leverages transport demand modelling tools and OD survey data to assess the impact of weather-related disruptions beyond traffic metrics. Although transport modelling is a valuable tool for understanding the observable effects of disruptions on transport operations, it is crucial to continue developing methodologies that translate traffic performance assessments into a more comprehensive resilience assessment of transport networks.

The main contribution of this paper is to advance this line by proposing a workflow that accounts for social disparities in the context of transport network disruptions. Further research can improve the methodology by incorporating tools that enable dynamic analysis of the disruption over time (e.g., agent-based modelling), while still examining the impact of these events on people rather than on assets or operations. Other disruptions can also be considered, as the methodology allows for the implementation of additional event types that ultimately affect the network's capacity.

The findings of the case study are inherently shaped by the specific socioeconomic conditions, land-use configuration, and transport network topology of Villavicencio. Accordingly, they should not be interpreted as evidence that weather-related disruptions intensify social disparities in the same way across all cities. Nevertheless, the proposed methodology is broadly transferable, as it can be implemented in many urban contexts where the input data typically used in demand estimation studies are available. Furthermore, rather than seeking to predict real-world conditions, the case study is intended to illustrate the potential of the proposed methodology to bring social disparities in accessibility to the forefront. In doing so, the methodology supports a more nuanced understanding of how inequalities influence access to vital urban services in normal conditions and how they may be amplified during disruptions such as flooding.

Finally, the policy implications for Villavicencio point to the need for further investigation into how residents from lower socioeconomic strata access healthcare facilities using modes other than private vehicles, particularly public transport, as these groups appear to depend more heavily on such modes for this type of trip. In this context, a prudent priority would be to strengthen transport connectivity under baseline conditions, since access to healthcare already appears more difficult for populations in less favourable circumstances, even in the absence of disruption. This suggests the value of complementing the city's efforts to expand the spatial provision of healthcare facilities across the urban area with a closer assessment of the transport connections serving those locations, as well as of healthcare-related services that remain concentrated in the city centre.

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References

Achillopoulou, D. V., Mitoulis, S.A., Argyroudis, S.A., Wang, Y., 2020. Monitoring of transport infrastructure exposed to multiple hazards: a roadmap for building resilience. Science of the Total Environment. https://doi.org/10.1016/j.scitotenv.2020.141001

Afrin, T., Yodo, N., 2020. A survey of road traffic congestion measures towards a sustainable and resilient transportation system. Sustainability (Switzerland). https://doi.org/10.3390/su12114660

Bruneau, M., Chang, S., Eguchi, R., Lee, G., Rourke, T., Reinhorn, A., Shinozuka, M., Tierney, K., Wallace, W., von Winterfeldt, D., 2003. A Framework to Quantitatively Assess and Enhance the Seismic

Resilience of Communities | Enhanced Reader. Earthquake Spectra 19, 733–752.

Bureau of Public Roads, U.D. of C., 1964. Traffic Assignment Manual.

Camargo, P., 2015. AequilibraE: A free QGIS add-on for transportation modeling. Foss4g North America.

Cretney, R., 2014. Resilience for whom? Emerging critical geographies of socio-ecological resilience. Geogr. Compass 8, 627–640. https://doi.org/10.1111/GEC3.12154

Cutter, S.L., 2016. Resilience to What? Resilience for Whom? Geogr. J. 182, 110–113.

DANE, 2021. Mesa de expertos de estratificación socioeconómica.

European Environment Agency, 2024. Economic losses from weather- and climate-related extremes in Europe [WWW Document].

Farahmand, H., Yin, K., Hsu, C.W., Savadogo, I., Espinet Alegre, X., Mostafavi, A., 2024. Integrating climate projections and probabilistic network analysis into regional transport resilience planning. Transp. Res. D Transp. Environ. 133. https://doi.org/10.1016/j.trd.2024.104229

Faturechi, R., Miller-Hooks, E., 2014. Measuring the Performance of Transportation Infrastructure Systems in Disasters: A Comprehensive Review. https://doi.org/10.1061/(ASCE)IS.1943

Ganin, A.A., Kitsak, M., Marchese, D., Keisler, J.M., Seager, T., Linkov, I., 2017. Resilience and efficiency in transportation networks. Sci. Adv. 3. https://doi.org/10.1126/SCIADV.1701079

Hadjidemetriou, G.M., Herrera, M., Parlikad, A.K., 2022. Planning road network layout based on connectivity assessment of critical assets. Proceedings of the Institution of Civil Engineers: Smart Infrastructure and Construction 175, 181–189. https://doi.org/10.1680/jsmic.21.00034

Li, C., Fang, Q., Ding, L., Cho, Y.K., Chen, K., 2020. Time-dependent resilience analysis of a road network in an extreme environment. Transp. Res. D Transp. Environ. 85. https://doi.org/10.1016/j.trd.2020.102395

Liu, J., Xu, Z., Wan, L., MacAskill, K., 2026. Road transport resilience under extreme rainfall: Integrating multiple impact factors and delay propagation. International Journal of Disaster Risk Reduction 134. https://doi.org/10.1016/j.ijdrr.2026.106024

Martín, B., Ortega, E., Cuevas-Wizner, R., Ledda, A., De Montis, A., 2021. Assessing road network resilience: An accessibility comparative analysis. Transp. Res. D Transp. Environ. 95. https://doi.org/10.1016/j.trd.2021.102851

Ortuzar, J. de D., Willumsen, L.G., 2024. Modelling Transport.

Patriksson, P., 1994. The traffic assignment problem: models and methods.

Rebally, A., Valeo, C., Saidi, S., He, J. (Jennifer), 2026. Assessing the temporal qualities of indirect impacts of flooding on traffic. International Journal of Disaster Risk Reduction 135, 106035. https://doi.org/10.1016/j.ijdrr.2026.106035

Wassmer, J., Merz, B., Marwan, N., 2024. Resilience of transportation infrastructure networks to road failures. Chaos 34. https://doi.org/10.1063/5.0165839

Wu, Y., Chen, S., 2023. Traffic resilience modeling for post-earthquake emergency medical response and planning considering disrupted infrastructure and dislocated residents. International Journal of Disaster Risk Reduction 93. https://doi.org/10.1016/J.IJDRR.2023.103754

Zhang, W., Wang, N., Nicholson, C., 2017. Resilience-based post-disaster recovery strategies for road-bridge networks. Structure and Infrastructure Engineering 13, 1404–1413. https://doi.org/10.1080/15732479.2016.1271813

Zhang, X., Lu, Y., Wang, J., Qi, Y., 2024. Enhancing highway transportation safety resilience during emergencies: A network-based analysis and assessment. PLoS One 19. https://doi.org/10.1371/journal.pone.0307233

Zhang, Y., Cheng, L., 2023. The role of transport infrastructure in economic growth: Empirical evidence in the UK. Transp. Policy (Oxf). 133, 223–233. https://doi.org/10.1016/J.TRANPOL.2023.01.017