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A NETWORK MODELLING-BASED APPROACH FOR QUANTIFYING FLOOD RESILIENCE OF URBAN RAIL TRANSIT SYSTEMS

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Abstract

While the trend towards building resilience in transport infrastructure systems in the face of extreme flooding is accelerating, scant attention has been paid to assessing the flood resilience of urban rail transit systems (URTSs). This paper develops an approach to quantitatively assess the URTS flood resilience by integrating the system performance-based resilience triangle curve, complex network modelling, and scenario analysis. A case study of the London URTS has been demonstrated to test its feasibility. This approach is novel in capturing the structural topology, operational performance, and engineering features of the URTS to comprehensively assess its resilience under flooding.

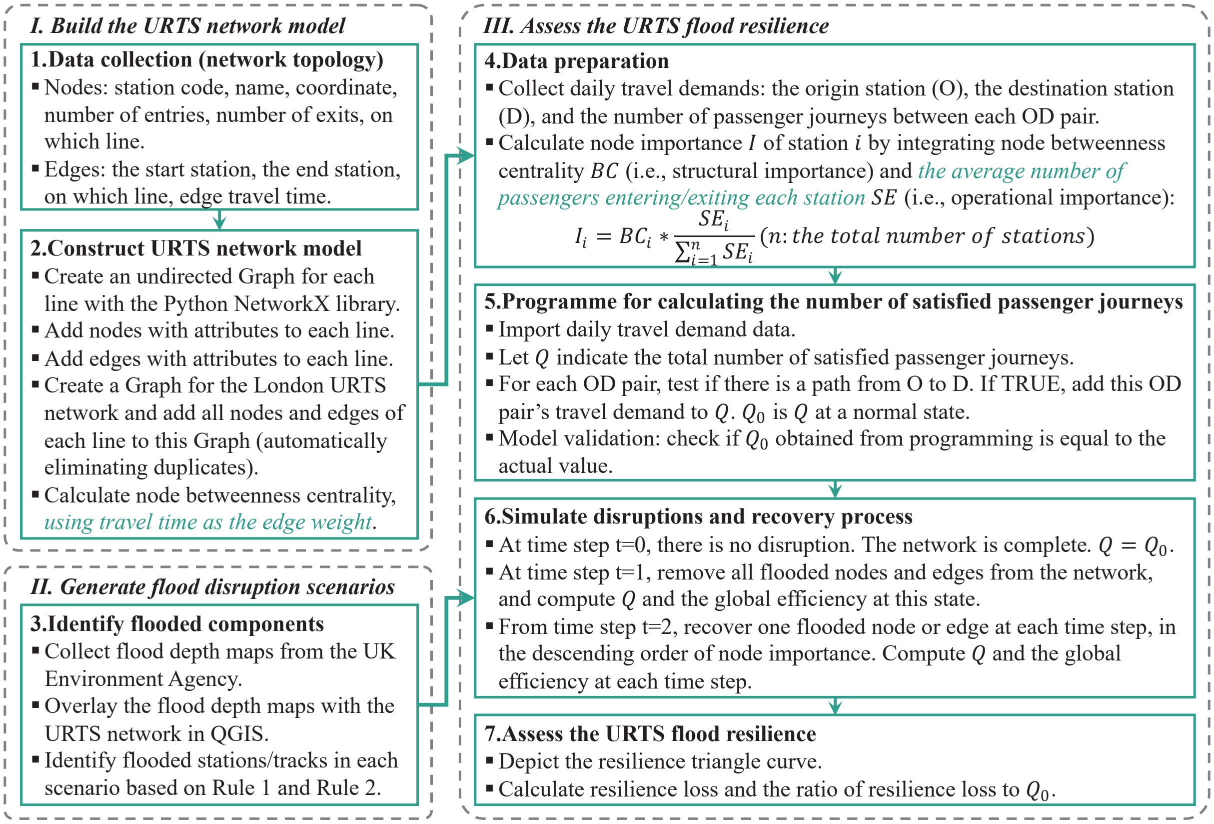
Introduction

Urban rail transit systems (URTSs), such as metros, light rail, and trams, are critical infrastructure for efficient and sustainable mobility in cities worldwide, providing safe, reliable, and accessible passenger service within and around urban and suburban areas. While the dependence on URTSs keeps growing in response to environmental challenges, continuing urbanisation, and aspirations for a better quality of life, the increasing complexity and connectivity of these networked systems make them susceptible to disruption. A local failure of one network component could incur cascading failures in others. Such vulnerability has been exposed by the continued effects of climate change, which have enhanced the frequency and intensity of observed extreme flooding. Compelling evidence is the near-simultaneous heavy precipitation events in the summer of 2021 in Europe, the United States, and China: flooded metro stations were closed in London and New York (Matthew, 2021), and 14 people died in a flooded metro tunnel in Zhengzhou (Gan and Wang, 2021).

Ongoing extreme flooding reminds us that it is impossible to prevent all disruptions. A recent investigation of the flooding that occurred across London in July 2021 confirms that the scale of this flooding, which exceeded a 30-year rainfall event, far exceeds design standards for the current sewer system (which combines sewage with surface water runoff), and it may not be economical or practicable to invest in eliminating the risk of a similar event (Wilcockson, 2022), not to mention the estimated 1000-year flood event occurred in Australia in early 2022 (Morton and Readfearn, 2022). Under such circumstances, the concept of resilience has grown in popularity as a mechanism for infrastructure systems to survive uncertain extreme events outside traditional design boundaries and plan for safe-to-fail. Resilience emerges as a new way of thinking that goes beyond prevention and protection-centred mindsets to emphasise the multi-faceted abilities of infrastructure systems to (a) withstand the impact of disruptions and continue to operate with acceptable function degradation, (b) restore the normal system performance level in a timely manner, and (c) adapt to future disruptions (Cutter et al., 2013; Department for Transport, 2014; Bruneau et al., 2003).

Despite the necessity of dealing with extreme flooding in URTSs and the popularity of building resilience in infrastructure systems, a review of research on the flood resilience of URTSs reveals that this topic has received scant attention. The query string "TS = (flood OR flooding OR rainfall OR storm OR (weather event) OR (extreme weather)) AND (metro OR subway OR underground OR (rail transit) OR (rapid transit)) AND (resilience OR resilient OR resiliency)" was searched in the Web of Science and Scopus. A total of 228 articles were obtained after removing duplicates and only 8 papers were found to be relevant to the flood resilience of URTSs after examining the title, abstracts, and keywords (see Sun et al. (2022), Zhang and Ng (2021), Yadav et al. (2020), Martello et al. (2021), Chan and Schofer (2016), Jiao et al. (2021), Liu et al. (2020), and Zhu et al. (2017)). The focus of these papers is on the flood resilience assessment of metro systems by using network modelling, where metro systems are abstracted as a network with stations as nodes and tracks as edges. However, the current methodology designed for assessing the URTS flood resilience shows a phenomenon of oversimplification.

First of all, these papers generally assess resilience by indicating system performance purely with topological network attributes (e.g., network efficiency or the giant connected components). Such an approach can capture the resilience of the physical URTS network but ignores the impacts of its operational performance, such as the number of passengers served at each station and the number of passenger journeys completed per day. How the physical and operational aspects can be combined to



Note: Italics in colour show the capture of operational attributes.

Figure 1 Procedure for the URTS flood resilience assessment

achieve a comprehensive resilience assessment is still under development. Second, the simulation of flood disruption scenarios has not been considered in detail. As infrastructure resilience is set up on the prerequisite that not all disruptions can be avoided, we need to understand how the system is affected by a range of scenarios and, through simulations, gain the capacity to manage a more effective response and recovery. Scenario analysis or stress testing of disruptions is an indispensable step of resilience assessment. In the extant network modelling for infrastructure resilience assessment, random failures are usually used to simulate disruptions caused by natural hazards, with the assumption that all nodes in the infrastructure network have the same failure probability and fail sequentially in a random manner. However, flooding presents more significant risks to certain parts of the network due to their physical construction and geographical locations – segments located in flood zones are more likely to be inundated and the severity of inundation varies with influential factors such as flood depth and velocity. As such, applying random failures at individual stations across the network is unrealistic for stress testing of certain disturbances such as flooding caused by weather events.

Motivated by addressing the growing flash flooding challenges facing URTSs through resilience management and bridging the extant limitations, this paper proposes a network modelling-based approach for quantifying the URTS flood resilience under three realistic flood scenarios, namely 30-year, 100-year and 1,000-year floods. It makes the first step towards incorporating practical engineering features of the URTS into its resilience assessment and combining topological and operational properties in complex network modelling. This paper takes the London metro as a case study. The assessment results visualise how the system is affected by flooding and provide insights into how resilient the system is in its current state.

Methodology

The methodology designed for quantifying URTS flood resilience has three components, including the construction of the URTS network model, the generation of flood disruption scenarios, and the assessment of URTS flood resilience through the system performance-based resilience triangle curve. Figure 1 illustrates the procedure for the URTS flood resilience assessment.

Building the URTS network model

To capture its network topology, the URTS can be abstracted as an undirected graph based on complex network theory. Complex network theory focuses on observations of real-world networks and ad hoc mathematical concepts to quantify them (Iñiguez et al., 2020). Let $G = (V, E)$ denote a URTS network, where V is a set of nodes representing locations such as metro stations and E is a set of edges that link these nodes to represent routes such as rail tracks. Adjacency matrices are used to represent how nodes are connected by edges. For instance, a metro network can be represented by an unweighted adjacency matrix A where a value of 1 means that two stations are connected and a value of 0 denotes no such connection (see Eq. (1)).

$$A = \{a_{ij}\} = \begin{cases} 1, if\ station\ i\ and\ j\ are\ directly\ connected \\ 0, if\ station\ i\ and\ j\ are\ not\ directly\ connected \end{cases} \quad (1)$$

The URTS network model is considered undirected (i.e., if there is an edge between node A and node B, it is possible to travel from A to B and from B to A), because URTS trains usually run in both directions between two stations. In addition, operational features are assigned to nodes and edges as weights to reflect a more realistic picture. The node weight is the average number of passengers entering/exiting the station, which is used to assess node importance (see Figure 1 III-4). The weight of the edges is the realistic travel time of each edge, which is used to calculate the length of the shortest path when measuring node betweenness centrality (see Figure 1 I-2). The NetworkX library of Python is used to build the network model and calculate network attributes such as node betweenness centrality for further use in the assessment process.

Generating flood disruption scenarios

The process of generating flood disruption scenarios takes into account basic engineering features of URTSs, including geographical location and the type of station. First of all, flood disruption scenarios are generated by overlaying the URTS network with flood depth maps in ArcGIS to evaluate the location-specific flood exposure of stations and tracks. 0.9m is selected in this case as a conservative initial scenario for determining if stations and tracks are inundated. It is assumed that flood water with a depth over 0.9m at ground level is very likely to cause structural damage and disable property-level flood resilience measures (Environment Agency, 2019):

- Rule 1: If the station has entrances/exits or platforms where flood depth is over 0.9 m, the node representing this station is considered inundated.
- Rule 2: If the two stations at the end of a track are not inundated but a flooded area with flood depth over 0.9m blocks the track, the edge representing this track is considered inundated.

Furthermore, URTS stations and tracks are usually located underground, at grade, or elevated. When determining the components to be flooded, the type of station and track should be considered to differentiate the possibility of inundation. For example, elevated stations and tracks are less susceptible to flooding because they are high above the ground and do not easily hold water. Besides, if no water flows through the at-grade entrance into the station, the underground track is also less likely to be flooded because there is no water source. Considering this practical context, the following principles are used for identifying flooded components for different types of stations and tracks.

- If the station entrance/exit is located at grade and the tracks connected to the station are underground or elevated, use Rule 1 to check if the node is flooded. If YES, the node is removed and the connected edges will be removed automatically.
- If both the station entrance/exit and the connected tracks are located at grade, first use Rule 1 to check if the node is flooded. If YES, the node is removed, and the connected edge will be removed automatically. If NO, use Rule 2 to check if the edge is flooded.
- If both the station entrance/exit and the connected tracks are elevated, there is no need to check – neither node nor edge will be flooded.

Assessing the URTS flood resilience

The guiding philosophy behind network-based resilience assessment approaches is the system performance-based resilience triangle curve proposed by Bruneau et al. (2003). As presented in Figure 2(a), system performance $Q(t)$ is an objective measure of system function with a range from 0 to 100%. It can be evaluated by indicators such as the number of services delivered, the number of people served, and the level of economic activity, depending on the type of system and resilience scope (Ouyang et al., 2012). Disruption occurs at t_o and $Q(t)$ decreases before returning to its normal state at t_1. The shaded area in Figure 2(a) depicts resilience loss (RL), which is the difference between the performance curve of the degraded infrastructure system and the as-planned performance curve. A lower RL value indicates higher resilience as this means that the system is less affected by the disruption, while a larger RL implies lower resilience. Figure 2(b) shows another way to measure the resilience value R, which uses the ratio of the areas between the actual system performance curve to the as-planned system performance over the disruption duration (Reed et al., 2009). The resilience obtained in this way is a normalised percentage of the remaining performance, which enables the comparison of the resilience of different systems under different disruptions.

The resilience triangle curve was originally proposed to measure community seismic resilience but has since been more widely adopted to assess infrastructure resilience under disruptions. Infrastructure resilience generally refers to the ability of infrastructure systems to withstand, recover from, and adapt to disruptions. As demonstrated in Figure 3 (adapted from McDaniels et al. (2008)), the three capacities emerge sequentially as the disruption progresses. Withstanding refers to the ability of a system to absorb and/or resist the adverse impacts of disruptions and continue to operate even with function degradation) in order to minimize consequences. Recovery indicates the ability to repair and restore service. Adaptation is the ability to adjust to changing internal demands and external disturbances. Adaptation studies usually provide insights for decision-making by analysing strategies to help the system better prepare for future disruptions, which is out of the scope of this paper. This paper adopts the measurement of R, which covers the abilities to withstand and recover.

Table 1 illustrates the system performance indicator selected in this paper. The fundamental purpose of URTSs

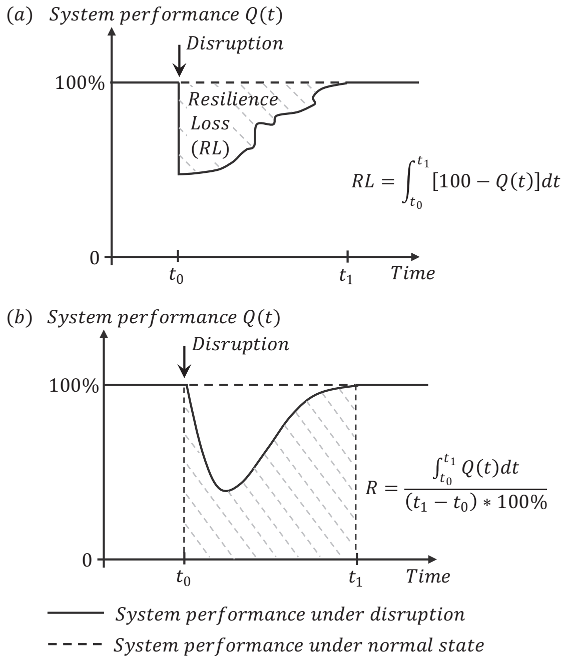


Figure 2 Resilience triangle curve

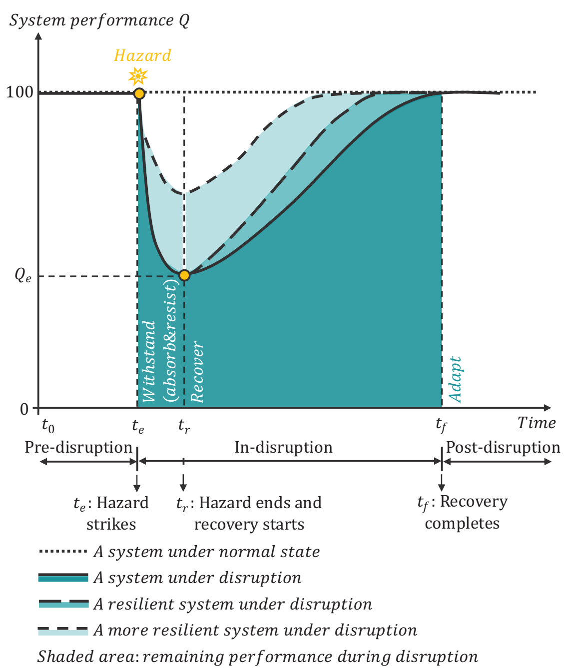


Figure 3 Adapted resilience triangle curve

is to carry passengers from their origin stations to destination stations. Hence, the number of satisfied passenger journeys is selected as the indicator of system performance because it can signal to what extent this purpose is fulfilled under disruption. The widely adopted network attribute – global efficiency – is used as a comparison. The assessment equations Eq. (2) and Eq. (3) follow the principle illustrated in Figure 2(b). The detailed assessment procedure is demonstrated in Figure 1 III. In carrying out the assessment, we have assumed that:

Table 1 Explanation of system performance indicators

Indicator	Explanation
The number of satisfied passenger journeys	Every day, passengers commute between their targeted origin stations (O) and destination stations (D) in the URTS. A daily average number of passengers journeys between each OD pair can indicate the system performance under the normal state. For each OD pair, if the URTS network has a path from O to D, the passenger journeys on this OD pair can be satisfied. Passenger journeys on all OD pairs can be met when the network is intact. However, when the network is disrupted by flooding, passenger journeys on some OD pairs are not expected to be satisfied due to the absence of an available path. Resilience (R) is assessed by the ratio: $$R = \frac{\int_{t_e}^{t_f} Q_t dt}{Q_0(t_f - t_e)} \quad (2)$$ where Q_t is the number of satisfied passenger journeys at time t, Q_0 is the initial number of satisfied passenger journeys at the normal state, and $(t_f - t_e)$ is the time interval between the occurrence of the disruption and the full recovery of the system (see Figure 3).
Global efficiency	The efficiency of a pair of nodes in a network is the inverse of the shortest path distance between the nodes. That is, the shorter the shortest path between a pair of nodes, the more efficiently the information is transferred between them. The global efficiency of a network is the average efficiency of all pairs of nodes. In the context of a URTS network, global efficiency indicates the ability of a URTS to efficiently move passengers between different stations and measures how well it is functioning. Resilience (R) is assessed by the ratio: $$R = \frac{\int_{t_e}^{t_f} E_t dt}{E_0(t_f - t_e)} \quad (3)$$ where E_t and E_0 is the network global efficiency at time t and the normal state, respectively.

- As shown in Figure 1 III-4, the node importance I is determined by its betweenness centrality BC and the average number of passengers entering/exiting each station SE. BC is the number of times a node lies in the shortest path between other nodes, representing the degree to which a node stands between others. A node with a higher BC has more significance in influencing network performance, and thus BC is suitable to indicate the importance of a node in the network structure. SE indicates how many passengers are served at each station on a typical autumn weekday, which captures the operational importance of each station. To integrate structural and operational importance, we assume that the node importance of station i is the weighted BC_i, where the weight is the ratio of SE_i to the SE of all.

- When the flood occurs at time step $t = 1$, all predefined flooded nodes and edges are disabled.
- During the recovery phase, recover one network component (either nodes or edges) at each time step. The recovery sequence is set in the descending order of the node importance. The time step is arbitrary at this stage and is a current major assumption. It is presented here to demonstrate the concept. The development of recovery profiles is part of future planned stages for the model development.
- The maximum acceptable delay time for passengers is half an hour. In the recovery phase, if a feasible path exists between the origin and destination stations but takes half an hour more than the shortest path under the normal state, we assume that this is not practical for passengers and that these journeys cannot be fulfilled. This time is estimated based on the delay refund of Transport for London (TfL) – passengers can claim a refund if their journey was delayed for 15 minutes or more on the London Underground (LU) lines and the Docklands Light Railway (DLR) line or 30 minutes or more on the London Overground (LO) line and the Elizabeth line. Although delays caused by bad weather are not covered by the refund claim, the time can be used to approximate the maximum acceptable delay time for passengers. Thirty minutes is adopted to accommodate extreme conditions.

Results and discussion

Study case – the London URTS

London is a metropolis with over 5 million daily travel demands on its URTS, which is a highly connected and complex network with a long history of operation. However, built on the River Thames, London is vulnerable to flooding. It is estimated that 4% of the LU and the DLR stations and 9% of the lines are at risk of a 30-year tidal/fluvial and/or surface water flooding (Greater London Authority, 2018).

The London URTS studied in this paper covers 11 lines of the LU, the LO line, the Elizabeth line, and the DLR line. Figure 4(a) presents the 14 lines modelled for this paper, and Table 2 describes the data. Geographical location is used to overlay the true geography of London URTS with flood maps to generate flood disruption scenarios. In terms of engineering features, the metro route map is used to identify station connections for network model construction, and the types of stations and tracks are used to differentiate the possibility of inundation, as previously stated. Among the operational features, passenger entering/exiting data and travel time are used to assign weights to nodes and edges, respectively. Passenger journey is used to indicate system performance and assess resilience. The passenger journey data is acquired from an open access dataset from TfL, representing the travel demand on a typical weekday (Monday-Thursday), Friday, Saturday, and Sunday at all stations and lines in 2019. As depicted in Figure 4(b), this paper studies 5,343,049 passenger journeys travelling between 51,917 origin-destination (OD) pairs on a typical weekday in London in 2019, with the number of passenger journeys indicated by stroke width and the number of lines where the starting station is located indicated by colour. It should be noted that part of the new Elizabeth line (i.e., from Reading to West Drayton) is not involved in modelling due to no 2019 data.

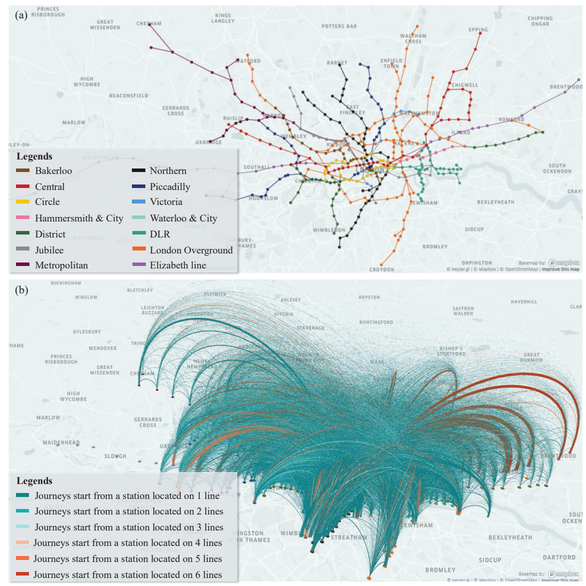


Figure 4 Schematic of the London URTS: (a) 14 lines studied in this study; (b) passenger journeys on a typical weekday in the autumn of 2019

Table 2 Data description

Data Type	Data detail	Data source
Geographical location	Shapefiles of the London URTS, including latitude and longitude of stations and tracks.	Transport for London; OpenStreetMap
Engineering features	Metro route map, including 406 nodes and 483 edges.	Transport for London (2022)
	Station and track type (i.e., underground, at grade, or elevated).	Transport for London; Google Street View
Operational features	• The number of passengers entering and exiting each station.	Transport for London (2020)
	• The number of daily passenger journeys between each OD pair.	
	Travel time between two adjacent stations.	Transport for London (2013)

To analyse the flood resilience of the London URTS with potentially realistic flood disruption scenarios, this paper adopts flood depth maps of 30-year, 100-year and 1,000-year floods generated by the UK environment Agency. Developed based on up-to-date data and advanced techniques (e.g., hydrological/hydraulic modelling and digital terrain model), the maps simulate the flooding taking place from the "surface runoff" generated by rainwater which is on the surface of the ground (whether or not it is moving) and has not yet entered a watercourse, drainage system or public sewer (Environment Agency, 2019). This matches well with the flash flooding studied in this paper. Moreover, the maps are with a high horizontal grid resolution of 2m, which enables the identification of flooded metro components with excellent detail, though this will be reviewed in further detail later in the project as local asset managers have indicated some limitations to the extent to which these maps capture local drainage capacities.

Results

Following the aforementioned methodology, the London URTS network model is constructed through Python and three flood disruption scenarios are identified (see Table 3). The results of the URTS flood resilience assessment are depicted in Figure 5, showing the overall trend of passenger journey-based and global efficiency-based resilience triangle curves. The curves indicate how the London URTS is affected by flooding of different intensities and how much the recovery of one flooded component contributes to the recovery of the system performance at each time step. Table 4 presents the URTS flood resilience value calculated by Eq. (2) and Eq. (3).

Table 3 Flood disruption scenarios, using a conservative 0.9m flood depth threshold

Flood scenario	The number of flooded nodes	The number of flooded edges
30-year flood	11	10
100-year flood	32	11
1,000-year flood	76	14

Table 4 URTS flood resilience assessment results

Flood scenarios	Resilience assessed by passenger journeys	Resilience assessed by global efficiency
30-year flood	96%	95%
100-year flood	91%	89%
1,000-year flood	83%	82%

Two insights can be drawn from these initial results. Firstly, although the resilience assessed based on passenger journeys and global efficiency is similar in each scenario, this does not necessarily mean that global efficiency can be a reasonable predictor of URTS flood resilience. One reason is that a station's loss of service (i.e., the number of passengers served) is not necessarily in line with the network's loss of global efficiency. For instance, the overall trends of passenger journey-based and global efficiency-based curves in Figure 5 are similar, but the rates of change are not consistent at certain stages. An example is that the recovery at time step t=8 in the 30-year scenario sees a significant rise in system performance but a gentle change in global efficiency, indicating the impact of operational features – the number of passengers served at each station. The more such examples there are, the greater the difference in the results will be. The results in Table 4 are somewhat similar across two measures, as the majority of metro stations serving large numbers of passengers in London are not flooded in these scenarios. Another reason is that global efficiency does not always grow with the recovery of nodes and edges. It is observed from the results that when the node to be recovered in the next step is at a very marginal location in the network or takes a relatively longer time to other stations (e.g., some LO stations), the global efficiency decreases instead. This is because adding such a node could increase the average shortest path length (which is weighted by travel time) of the network. However, this does not make sense for assessing system resilience, as the more is recovered, the more resilient the system is. This may be obvious to an asset manager, but this practical interpretation of the network modelling parameters is often missing from existing academic literature.

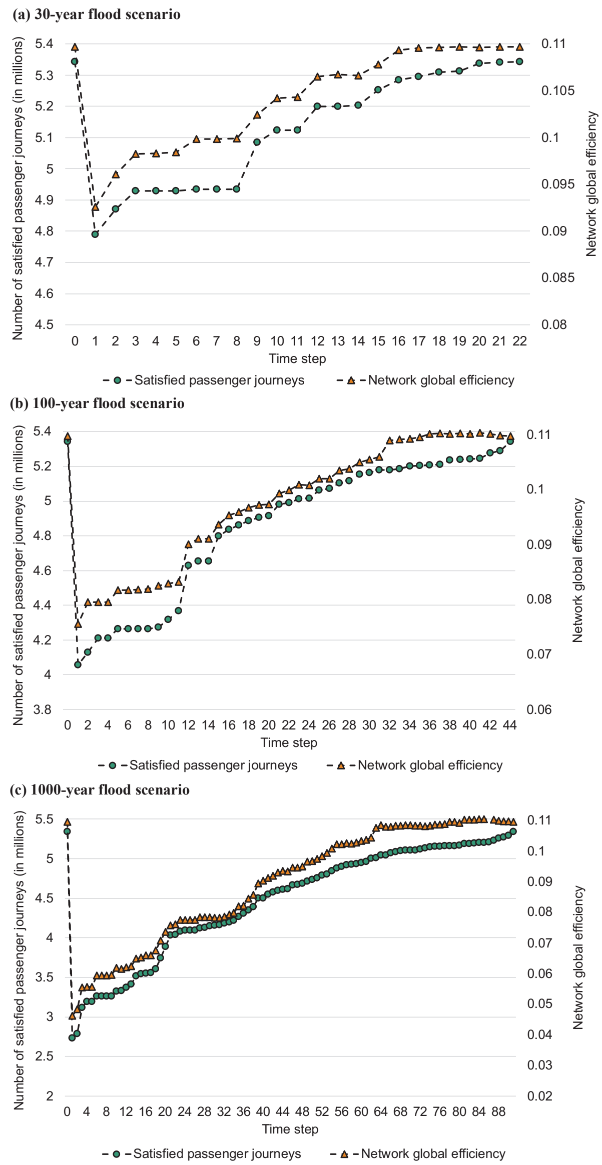


Figure 5 Flood resilience curves of the London URTS under 30-year, 100-year, and 1,000-year floods

Secondly, the more extreme the flood, the greater the impact on system performance – which may become practically unaffordable and unacceptable. For example, the URTS flood resilience is only 83% in the 1,000-year flood scenario outlined in this paper and considerable economic loss would be expected as a result. While the recovery regime adopted remains highly theoretical (affecting the practicality of the results achieved at this point in development), what is demonstrated in this paper is the ability to explore possible tipping points in the network operation by testing out less probable but possible scenarios. It provides the starting point to think about what actions can be taken to reduce the impact and restore services in a timely manner. The methodology proposed in this paper can also be used to test the effectiveness of potential actions.

Discussion

The case study is conducted to test the feasibility of a resilience assessment approach that builds on existing network modelling approaches but with more practical applications for decision-making in mind. It captures engineering features of URTSs and tests the resilience quality under a range of potentially realistic scenarios. However, this demo assessment has some limitations and needs further work on modelling details.

First, although the normalised percentage R can indicate the value of system resilience, we do not know what the threshold for a resilient system is and thus cannot tell if the current system is resilient based on the value of R. To address this limitation, the economic impacts can be further measured to signal the acceptable level of system resilience value in operation, because the URTS operator invests a lot of money and effort to keep URTSs running and flood disruptions can incur high economic impacts (e.g., revenue loss and average delay). We suggest that if the economic loss is acceptable to the operator, the system can be considered resilient.

Secondly, the 0.9m flood level threshold is a level set by the UK Environment Agency for houses, which normally have entrances with steps above the ground level. However, considering that a large part of the tracks and station entrances of URTSs are at ground level, the 0.9m flood level threshold is a very conservative starting point for URTS flood inundation analysis. Alternative thresholds will be explored in future analysis. Table 5 illustrates an example. To facilitate this work, a tool could be developed on the ArcGIS platform to automatically identify flooded components at different flood levels (this is currently a manual process).

Finally, the assumption of recovering one network component at each time step underestimates the actual recovery capacity of the URTS operational team. A more sensible recovery profile needs to be informed by practical assumptions, such as the extent to which there is the capacity to deploy resources across multiple stations to bring the assets back online.

Table 5 Possible traffic-light system for differentiating the impacts of flood depths

Flood depth	Category	Impact
< 0.3m	Green: no flood	No impacts.
0.3-0.6m	Yellow: might be flooded	Low level impacts that can be eliminated by emergency measures (e.g., sandbags).
0.6-0.9m	Amber: may be flooded	Medium level impacts that could potentially disrupt operations.
> 0.9m	Red: definitely will be flooded	High level impacts and operations will be totally disrupted.

Conclusions

While the trend towards building resilience in transport systems in the face of extreme flooding is accelerating, the flood resilience assessment of URTSs has received scant attention. This paper is novel in proposing an approach to quantitatively assess the URTS flood resilience by using complex network modelling and scenario analysis. Taking the London URTS as a case study, this paper assesses the current level of resilience of the London URTS under scenarios of 30-year, 100-year, and 1,000-year floods. Results show that global efficiency is not necessarily a quality indicator as good as passenger journeys and the London URTS may not be resilient to extreme flooding at the 1,000-year flood level.

This approach captures the structural topology and operational performance of the URTS to comprehensively assess its resilience level under flood disruptions, which is reflected by the way the node importance and the resilience value is measured. The flood disruptions are generated based on potentially realistic flood scenarios with considering the type of stations and tracks and location-specific flood risk exposure, which advances infrastructure resilience assessment under specific types of disturbance and provides informative insights for disaster risk reduction decisions in the face of future extreme situations. Finally, the designed methodology can be widely applied to measure the resilience of other single or interdependent infrastructure networks.

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