Evaluating flood impact for improving the resilience of urban multi-modal transportation networks

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SHORT SUMMARY

Urban multi-modal transportation networks, such as subway and tram, are essential for socioeconomic development but vulnerable to climate change-induced floods. This research focuses on Amsterdam's subway and tram networks, assessing flood impacts on multi-modal transport functionality and resilience. Travel patterns for 524 origin-destination pairs were analyzed under normal and flooded conditions using Dijkstra's shortest-path algorithm. Results show that tram stations are more vulnerable to flooding than subway stations, causing greater accessibility losses. However, intermodal transfers mitigate these impacts by reducing the number of inaccessible routes by 4%-8% when both stations are affected. Despite intensified flooding reducing network connectivity, the increased usage of critical transfer stations emphasizes their vital role in maintaining functionality. Additionally, the indirect impacts on unflooded stations highlight the importance of interdependencies in multi-modal systems. This research provides critical insights into flood-induced impacts and supports the further formulation of strategies to enhance the resilience of urban transportation system.

Keywords: urban flooding, multi-modal transport, network modelling, impact assessment

1. INTRODUCTION

Extreme weather events, particularly floods caused by extreme precipitation, storms, and hurricanes, are increasing due to climate change, posing severe threats to urban areas (Forero-Ortiz et al., 2020; Yadav et al., 2020). Events such as Hurricanes Irene and Sandy in the United States caused significant damage and economic losses to transportation networks (Zhu et al., 2017). In July 2021, extreme precipitation caused severe flooding in subway networks of London, UK, and Zhengzhou, China, resulting in devastating impacts (Bi et al., 2024; Xie et al., 2022). Damage to these critical transportation infrastructures not only disrupts service but also triggers cascading effects that affect society, the economy, and environmental sustainability (Bi et al., 2023). To address these challenges, it is crucial to systematically assess impact losses and explore the resilience of urban multi-modal transportation networks under flood hazards.

Urban transportation systems are highly interconnected and complex (Xu & Chopra, 2023). However, most studies focus on a single mode, such as roads, trains, or subways (Bi et al., 2024; Henke et al., 2024), neglecting the cascading disruptions in multi-modal systems caused by interdependencies. Failure in one mode can propagate across the entire urban transportation system, leading to extensive damage losses(Zhang et al., 2016). Comprehensive impact assessments based on historical flood scenarios are needed to address these cascading failures.

Complex network theory effectively captures the topological structure, connectivity, and importance of components within transportation networks (Ding et al., 2019; Háznagy et al., 2015). However, challenges remain in simulating flood impacts with complex network theory and models on urban multi-modal transport. Current flood impact assessments often rely on random or targeted failure simulations, which fail to reflect real-world flood exposure and dynamics, leading to overly abstract results (Bi et al., 2023). Misalignment between simulation network models and geo-spatial realities can overlook critical weaknesses in transportation systems. Additionally, most studies focus on physical infrastructure losses, including damage to roads, tracks, and stations(Bi et al., 2024; Henke et al., 2024; Li et al., 2018; Wang et al., 2019), but neglecting service functionality, such as disruptions to mobility and travel demand changes(Wang et al., 2023).

Based on these challenges and limitations, this research assesses flood impacts on urban multimodal transportation networks amid climate change, focusing on system functionality loss, critical components under flood scenarios, and providing a foundation for exploring prevention strategies to enhance network resilience. Using Amsterdam's subway and tram systems as a case study, we develop an integrated network model, evaluate flood impacts, and propose recommendations to strengthen urban transportation resilience.

2. METHODOLOGY

The methodological framework consists of four key steps. In brief, the methods work as follows. First, a fully connected, undirected baseline transportation network is constructed utilizing geographical data from OpenStreetMap (OSM). Second, we simulate the travel demand by creating origin-destination (OD) pairs to model urban residents' travel patterns. Third, four hypothetical flood events from the Klimaateffectatlas are generated, providing possible water depths in the area. These events are overlaid on the baseline transportation network to identify flood-prone stations and their removal from the network. Finally, changes in OD pairs and realizable travel demand under altered topological structures are calculated to evaluate accessibility loss under each flood scenario.

2.1 Baseline network construction

We utilize OSM data(extracted in 17 April, 2023) to construct a multi-modal transportation network model for Amsterdam, focusing on subway and tram systems. OSM's geographic data, including stations, platforms, rail tracks, enables the simulation of real-world transportation network topologies and the identification of transfer points between modes.

Initially, we retrieve and categorize subway and tram data stored under OSM's "railway" tag and distinguished by the "subway" and "tram" sub-tags. Nodes, stations, links, and routes are extracted and pre-processed to ensure a fully connected network, including adding endpoints, standardizing station names, and correcting station IDs and link directions. Besides, attributes such as average speed, distance, and travel time are added to the sequenced links. Additionally, the correctly ordered station dictionary and links Dataframe enable the application of Dijkstra’s algorithm(Edsger W., 1959) to construct a bidirectional graph capturing outbound and return trips. Next, the bidirectional graph is simplified into an undirected network where geographic coordinates of return-route stations serve as platform points, connected by straight-line links between consecutive platforms. To simulate intra- and inter-layer connectivity, virtual links are added between transfer platforms within specified distances and transfer times. Transfer penalties, equivalent to 16.5 minutes of subway travel time, are incorporated as the weights of virtual links based on prior studies(Garcia-Martinez et al., 2018). In summary, key assumptions for transfer links to construct the connected network include: (i) Transfer platforms with identical names are treated as equivalent; (ii) Intra-network transfers occur within 500 meters and inter-layer transfers within 300 meters, both modelled with bidirectional virtual links; (iii) Virtual links are weighted based on the transfer penalty.

This network construction approach result in a fully connected, undirected, weighted baseline network suitable for flood impact analysis.

2.2 Travel demand simulation based on OD pairs

Travel demand is represented by the journeys of passengers from the start (or end) stations of each line to the the start and end stations of all other lines, with the set of all OD pairs covering every station in the entire urban transportation network. To simulate the travel demand under normal situation, we apply Dijkstra's shortest path algorithm to the weighted baseline network constructed in section 2.1 to find the shortest paths between each OD pair.

2.3 Hypothetical flood scenario generation and impact assessment

Figure 1 illustrates flood depth maps for river and coastal flooding in the Amsterdam region under four hypothetical scenarios from the Klimaateffectatlas(*Climate Impact Atlas Netherlands - Climate Impact Atlas*, n.d.), showing progressively larger affected areas from panels (A) to (D). After importing these raster maps into QGIS, we integrate them with baseline network vector data (section 2.1) by aligning their coordinate reference systems. This allows us to intersect the datasets spatially, as shown in Figure 2. Using QGIS, we sample flood depth values from the raster data into the attribute table of the baseline network, generating an enhanced vector layer. This new layer retains all geographical data from section 2.1 while adding flood depth values for each station.

Using the travel demand network from section 2.2, we analyse the impacts of affected stations on OD accessibility, travel times, and station utilization. For each scenario, we identify affected stations (flood depths > 30 cm), remove these stations and associated edges to update the network topology, and apply the shortest path algorithm to evaluate changes in OD travel times. OD pairs with infinite travel times are marked as unreachable, enabling comparisons of reachable/unreachable pairs and increases in travel times across scenarios. Additionally, we analyze differences in the number and usage frequency of unaffected stations to assess flooding's indirect impacts on overall system.

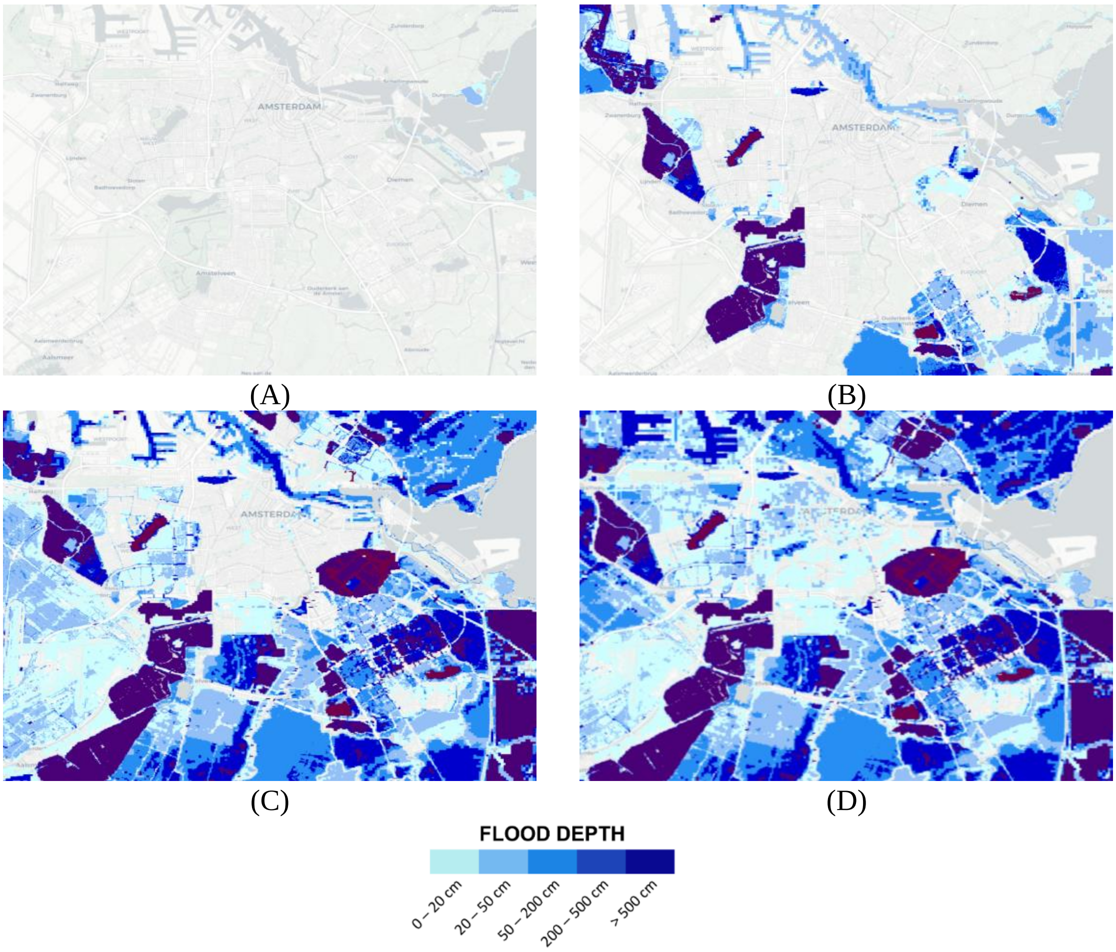


Figure 1: Flood maps of four hypothetical scenarios from the Klimaateffectatlas. Panel A to D shows that the four flood scenarios progressively affect larger areas in Amsterdam.

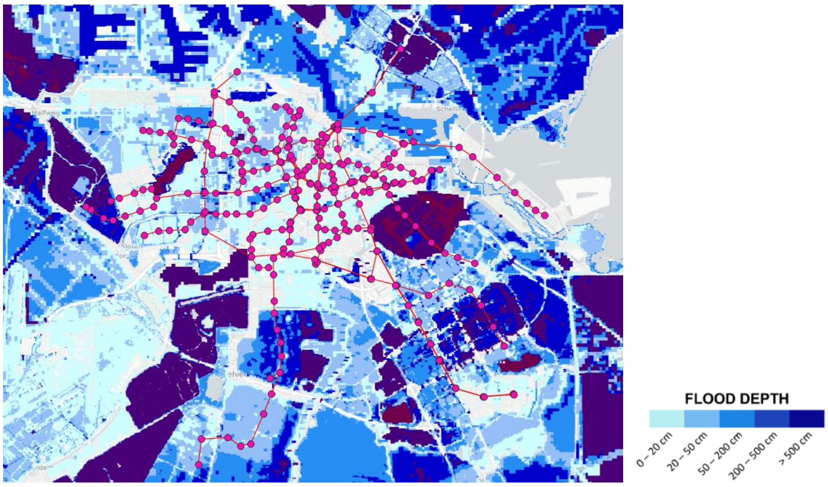
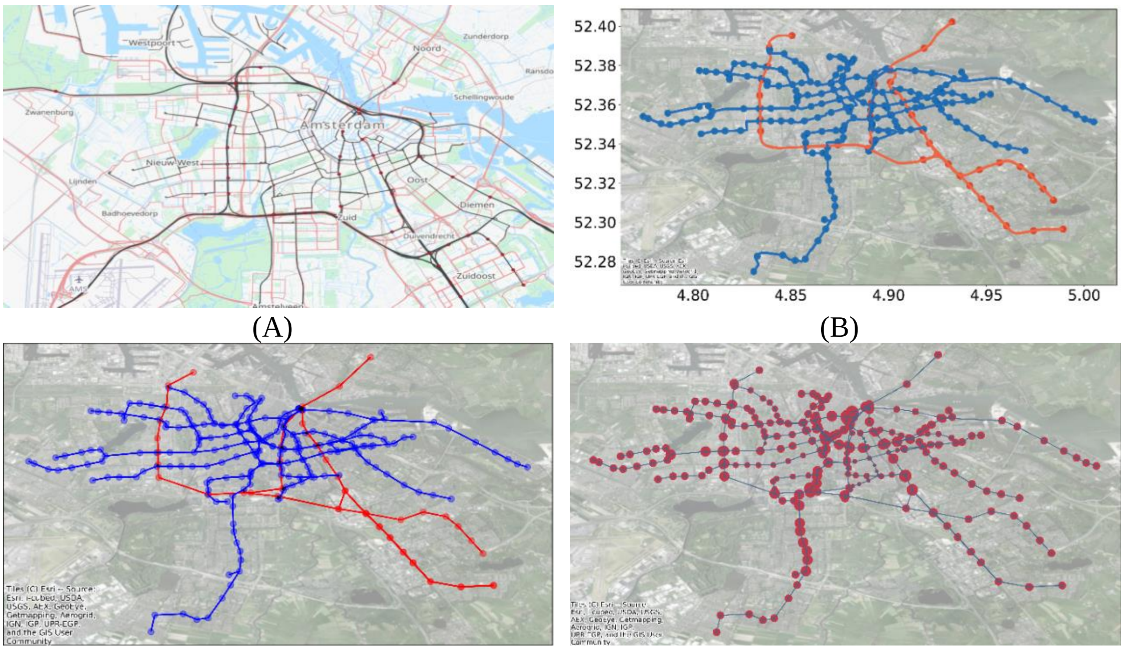


Figure 2: Flood map D interconnected with baseline network

3. RESULTS AND DISCUSSION

3.1 The baseline and travel demand network of Amsterdam

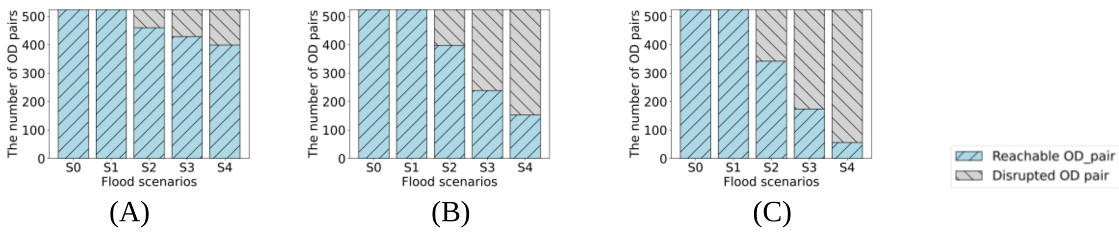
Amsterdam's urban area includes five subway lines and fourteen tram lines, with station and track coordinates available from OpenStreetMap (Figure 3A). Using methods from Section 2.1, we construct a bidirectional network reflecting real-world operations (Figure 3B), which is then simplified to create a baseline network. This network includes 52 subway stations, 50 subway links, 14 virtual subway links; 239 tram stations, 239 tram links, 68 virtual tram links; and 38 virtual links connecting subway and tram stations (Figure 3C). From this baseline, we generate a transport demand network of 524 OD pairs, pairing stations across all lines. Under the normal condition, all OD pairs are reachable, when the travel demand is fully satisfied. At the same time, every station is used at least once with red circle sizes indicating the the station's usage frequency in Figure 3D.



(C) (D)

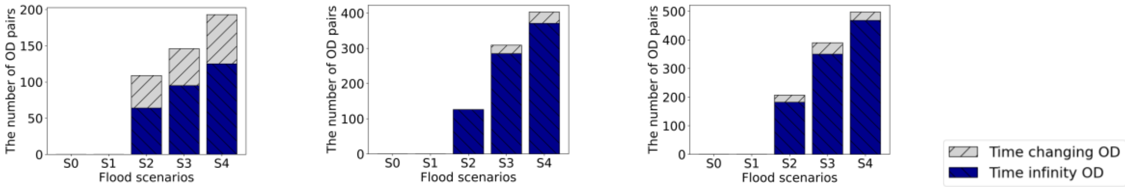
Figure 3: Process of constructing baseline network and simulating travel demand of Amsterdam subway and tram. Panel A shows OSM datasets of Amsterdam subway and tram. Panel B shows the bidirectional network. Panel C shows baseline network. Panel D shows station use frequency to satisfy travel demand of all OD pairs in scenario 1(no flood).

3.2 Flood impact assessment results



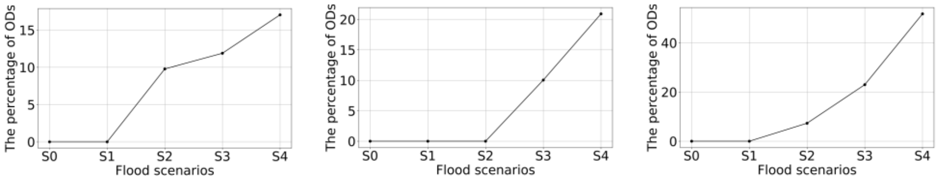
(A) (B) (C)

Figure 4: Changes in the number of connected OD pairs.



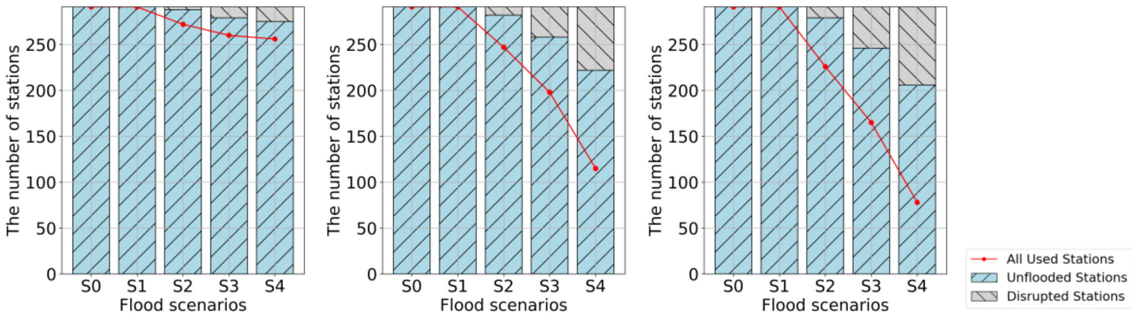
(A) (B) (C)

Figure 5: Comparison of the number of OD pair with time changing and time infinity.



(A) (B) (C)

Figure 6: Percentage of OD pairs with time changing to all OD pairs that can be connected.



(A) (B) (C)

Figure 7: Changes in the number of used stations, unflooded stations and disrupted stations.

This paper considers three station failure conditions under each scenario: (A) subway stations affected, (B) tram stations affected, and (C) both affected, as they shown in above figure 4,5,6 and 7. Flood scenario 1 shows identical results to the scenario 0 (normal conditions without flooding), indicating no impact on the network. However, the accessibility of OD pairs declined as the flood impact expanded across scenario 2, 3, and 4, as shown in Figure 4. While comparing panels (A), (B), and (C) in Figure 4, it reveals that subway station failures (A) have the least impact on accessibility, tram station failures (B) cause significant disruptions, and simultaneous failures (C) have the greatest impact. But the affected OD pairs in (C) are fewer than the combined total amount of (A) and (B) which suggests intermodal transfers provide alternative routes during flooding. As shown in Figure 5, the number of OD pairs with increased travel time (including those that become inaccessible) rises as the flood impact expands. Figure 6 further demonstrates that the percentage of OD pairs with increased travel times also grows among all accessible OD pairs. As the affected area expanded shown in figure 7, the proportion of operational stations in use decreases, causing the degradation of network structure and seriously reducing the connectivity(Ma et al., 2019).

In Figure 8, red circles represent station usage frequency, and yellow arrows mark locations of affected stations. For each scenario(sub-figures Ⅰ Ⅱ Ⅲ Ⅳ), we still consider three failure conditions as explained in above paragraph. Comparing all panel A in all sub-figures, more subway stations are damaged, their usage frequencies decline, except for a slight increase in Nieuwmarkt, Waterlooplein, and Weesperplein in scenario 4 compared to scenario 3. At the same time, some tram station usage declines but does not reach zero; even over 43% of tram stations experiences increased usage frequencies as the flood impact expands. Specially, In scenario 2 shown in subfigure Ⅱ, while only two subway stations (Lelylaan and Bullewijk) are flooded, over 36% of subway stations become unused due to inaccessibility, highlighting the cascading effects due to the flood through the station coupling(Ma et al., 2019). Under tram station failure conditions (all panel B), all tram stations experiences reduced usage as the flood impact expands. However, 16 subway stations on lines 50, 51 (Sloterdijk to Overamstel) and 53, 54 (Central Station to Sparklerweg), including Nieuwmarkt, Waterlooplein, and Weesperplein, see slight increases in usage in scenario 4 compared to scenario 3. When both station types fail simultaneously (all panel C), station usage frequencies generally decline, but the same three subway stations show slight increases in scenario 4. In summary, these three subway stations are key elements that affect the multimodal transportation network, and defense should be strengthened to ensure the connectivity of the system under flood scenarios. Additionally, the importance of each station can be evaluated in turn to find feasible and effective strategies to improve system resilience in the future studies.

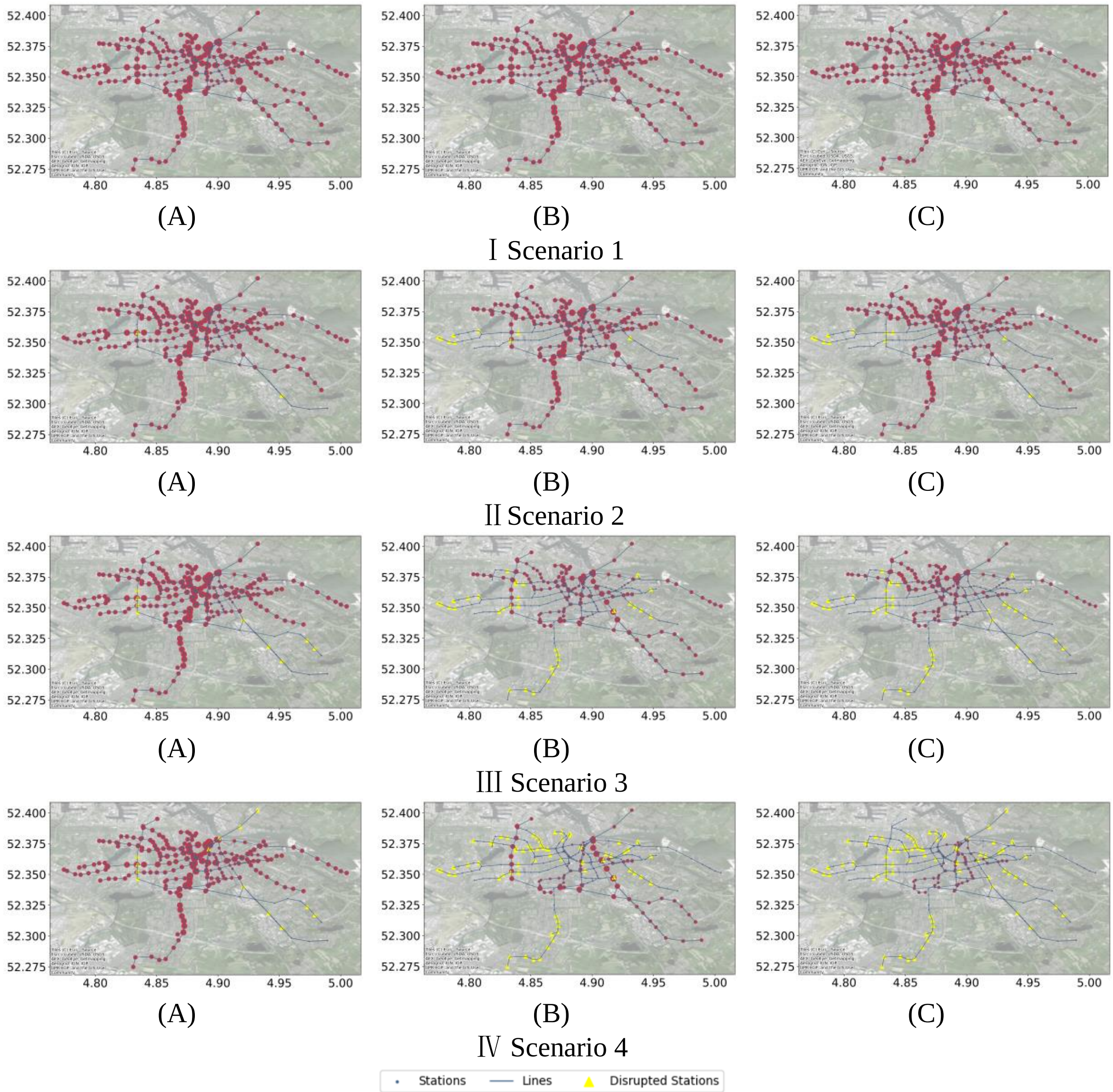


Figure 8 Failed station and use frequency graph of each station in each scenario

4. CONCLUSIONS

The results demonstrate that the number of stations actually utilized under flood conditions, while meeting accessible OD travel demand, is fewer than the stations unaffected by flooding. This phenomenon highlights the indirect physical impacts of flooding on urban multi-modal transportation networks(Markolf et al., 2019) and emphasizes the critical locations of key stations. These findings provide actionable directions for implementing flood defence measures. However, the current assumptions do not account for the elevation relationships between station platforms, entrances, and surrounding roadways. In practice, if the platform is higher than the entrance or surrounding roads, stations could still function as intermediate stops for transferring passengers to the nearest unaffected station. Future research will consider this situation into the model to simulate more realistic emergency alternatives.

The findings also show that OD travel demand can be satisfied through longer alternative routes enabled by intermodal transfers under flood conditions, emphasis the importance of interdependency in the multi-modal networks(Xu & Chopra, 2023). While abnormal increases in subway and tram station usage confirm the reliance on these transfer stations in alternative routes, this paper does not delve into which OD pairs specifically change travel paths or which transfer links are crucial. Further investigation will focus on identifying critical transfer edges to enhance the system's adaptability and resilience to flooding.

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