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Evaluating the flooding level impacts on urban metro networks and travel demand: behavioral analyses, agent-based simulation, and large-scale case study

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ABSTRACT

With urban residents' increasing reliance on metro systems for commuting and other daily activities, extreme weather events such as heavy rainfall and flooding impacting the metro system services are becoming increasingly of concern. Plans for such emergency interruptions require a thorough understanding of the potential outcomes on both the system and individual component scales. However, due to the complex dynamics, constraints, and interactions of the elements involved (e.g., disaster, infrastructure, service operation, and travel behavior), there is still no framework that comprehensively evaluates the system performance across different spatiotemporal scales and is flexible enough to handle increasingly detailed travel behavior, transit service, and disaster information data. Built on an agent-based model (ABM) framework, this study adopts a data-driven ABM simulation approach informed by actual metro operation and travel demand data to investigate the impact of flood-induced station closures on travelers as well as the overall system response. A before-after comparison is conducted where the traveler behaviors in disaster scenarios are obtained from a discrete choice model of alternative stations and routes. A case study of the Shanghai Metro is used to demonstrate the ability of the proposed approach in evaluating the impacts of flood-induced station closures on individual traveler behavior under normal operation and a series of water level rise scenarios of up to 5m. It was found that, when the flood-induced station closures only affect a few river-side stations in the city center, the travelers experience only minor disruptions to their trips due to the availability of unaffected stations nearby as a backup. However, as the water level increases and more stations (mainly in the suburban area) are affected, up to 25% of trips are no longer being fulfilled due to the loss of entrances, exits, or transfer links. The system experiences overall less crowdedness in terms of passenger volume and platform waiting time with a few exceptions of increased passenger load due to concentrations of passenger flows to alternative stations under flooding-induced station closures. The proposed approach can be adapted to other disaster scenarios to reveal the disaster impacts on both aggregated and disaggregated levels and guide the design of more spatio- and temporally-targeted emergency plans for metro systems.

1. Introduction

Water-related disasters such as floods and extreme rainfalls represent a large proportion of natural catastrophes, and they are expected to continue to grow in scale and frequency due to climate change, urbanization, and degradation of the natural environments [1,2]. In cities, due to the impermeable concrete surface covering large areas of development, the run-off water frequently overloads the sewage system and inundates streets and subways. Past research indicates that subway systems are less resilient than roadway systems [3]; roads can recover in days, while it takes months for the subway network to recover fully. During the events of Hurricane Irene (Year 2011), Hurricane Sandy (Year 2012) and Hurricane Ida (Year 2021), the New York Metropolitan Transportation Authority (MTA)'s subway network was closed in preparation for the heavy storms [4]. The disruptions and infrastructure damages caused great impacts on the city's roadway and metro transportation systems, and the estimated losses or costs of strengthening range from 65 million to 5 billion dollars for the three events [5–7]. Other subway systems in major cities such as London and Paris face a similar challenge: aging subway drainage systems and excessive climate-driven extreme rainfalls. Even for new subway/metro systems in Shanghai and Zhengzhou, their drainage was not designed for the extreme floods seen in the past few

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years. The 2021 inundation of the metro system in Zhengzhou [8] has signaled a warning message.

As subways are more frequently influenced by water penetration related disturbances or disasters, understanding and managing the metro network as well as mitigating the impacts to the passengers under various flooding events are key tasks for planners, asset managers, and decision makers to undertake. The system's capability of restoring after a disaster is described by resilience, which was first used in ecology but was widely adopted in many other systems [9–11]. The resilience of metro systems can thus be defined as the ability to maintain its designed level of service or restore itself in a specific timeframe. The evaluation of resilience can be decomposed into calculating the loss, as well as the recovery time of serviceability. For highly dynamic systems and disaster events such as metro flooding, more specific considerations are needed, such as the interactions of the passengers, the infrastructures, and the service providers, the congestion and crowding, the peak and off-peak hours as well as the passenger behavior dynamics [12–16].

The resilience of urban underground transportation has been studied in different aspects. For example, Huang et al. (2022) [17] investigated the multi-hazard impacts of the infrastructure and analyzed the network performance. A few studies have been on quantifying and modeling metro disruptions, mainly focusing on the demand changes and the schedule design after disruptions. Demand changes are considered by predicting passenger behaviors responding to a metro disruption. In this direction, smart cards and other real data sources are frequently adopted for analyzing and predicting passenger demand patterns. For example, Zhu et al. (2016) [3] provided an observational analysis of the recovery of trip patterns after Hurricanes Irene and Sandy based on a ridership dataset obtained from the New York MTA. A recovery model was developed and calibrated against the data, enabling the quantification of the resilience of the MTA system. Sun et al. (2016) [18] developed a Bayesian method and utilized smartcard data to assess the effects of common disruptions and identify the delay times in urban rail transit by arbitrarily selecting specific station closures. Yap et al. (2018) [13] investigated the impact of disturbances on passengers on the Hague public transport network. Rahimi et al. (2019) [19] employed a stated-preference method to estimate passengers' waiting time tolerance to unplanned transit service disruptions and found trip variables such as distance and times are influential in the passengers' behavior on waiting tolerance. Tan et al. (2020) [20] investigated the heterogeneous risk-taking behaviors of the affected metro passengers. They conducted a case study based on a real-world network in Wuhan. Wang et al. (2020) [21] developed a regret theory-based decision-making method to manage the rainstorm disaster in urban rail systems capturing the passengers' utility and costs. Zhang et al. (2021) [22] explored the metro passengers of both inbound and outbound flows and evaluated the metro network's vulnerability, and found that there exists a linear relationship between the shortest paths passing the nodes and edge. These studies tried to figure out the influence and the outcomes of the metro disruptions, therefore preparing the countermeasures to reduce the negative impacts.

On the other hand, some researchers studied the timetable and schedule design of the metro services after disruptions. Gao et al. (2016) [23] incorporated the constraints imposed by the disruption at hand: the limited train capacity, over-crowded conditions, and time-dependent passenger arrivals, into optimizing the timetable. Veelenturf et al. (2017) [24] integrated the rolling stock and the timetable rescheduling by considering the passenger demand changes. Several studies also consider multimodal disruption management involving urban rail transit and bus services [12,25]. As bus service efficiently bridges the metro passengers once disruption occurs, more and more attention has been paid to this issue. For instance, Gu et al. (2020) [26] proposed a two-stage approach to allocating buses to predefined bridging routes after a metro disruption to minimize the bridging time and total passenger delay. The model was formulated in a rolling horizon framework and applied to two case studies in Shanghai. They find it is necessary and helpful to plan for the urban metro disruptions, mostly concerning timetable adjustments, rolling stock and crew rescheduling, as well as contracting bridging buses. While the majority of previous studies focused on the operation and supply side, research involving complex dynamics between the system performance and individual response patterns is still emerging, especially under certain natural disasters such as the metro traveler's behavior when facing a flood.

Apart from the dynamic demand changes and interactions with the service schedules, the uniqueness of the events and systems also needs to be acknowledged in studying metro resilience. Miao et al., (2018) [27] surveyed various US transit agencies to investigate their preparedness for dealing with extreme weather. They found that extreme weather is typical in many areas, yet the events and scales can be varied. While previous literature mainly focused on regional effects or local effects of disruptions with selected stations and fixed disruption levels for natural flood disasters, assessment of urban rail transit networks at both disaggregated and aggregated levels are still valuable for flooding management in metro systems. In addition, many previous studies focus on a topological approach without considering the travel demand and service conditions [22]. For those that consider the service schedule and travel demand characteristics, only coarse time step or traveler groups are used and generated aggregated metrics [13,24], which inevitably overlooks the dynamics that can only be captured at a finer spatiotemporal scale, such as platform waiting time. For planners and asset managers, a more generalized approach is needed, where the uniqueness of the events and the complex interactions of system components at different spatial and temporal scales are more thoroughly modeled and validated to generate forecasts of emergent outcomes.

This study proposes an agent-based model (ABM) framework to quantify the impacts of flood levels on metro networks, including station closures, demand pattern changes, and trip pattern and time changes. Traffic modeling has been a powerful tool for forecasting traffic patterns under different situations. Hence, they are widely employed for studying the dynamics of traffic systems at various spatial and temporal scales [9,11,28]. In particular, the ABM has received widespread popularity in recent years for traffic and transport system modeling, where the inclusion and validation of fine-grained analysis of passenger behavior are possible [8,29–32]. The agent is often defined as a "single cognitive entity", and in the case of transport planning, often represents the passengers, vehicles, etc. ABM in transport planning applications is used to capture the emergent behaviors of agents resulting from their interactions with other agents in the system as well as the interactions with the environment [33]. Specifically, evacuation simulation has become one of the most attractive applications of the ABM category due to its ability to incorporate complex system interactions and model a diverse range of scenarios [34–36, 30, 37]. In developing an ABM framework for metro flooding resilience, the locations of stations and the topology of a metro network can be created with real data. The passenger demand is informed by real-world smart card data and modeled by agents who can interact with each other and the metro system. The agent-based framework allows the integration of (1) disaster scenarios, (2) individual human decisions, as well as (3) infrastructure schedule and operations into the analysis of the system.

The rest of the paper is organized as follows. Section 2 introduces the problem and system settings of urban rail transit with natural flood disasters. Section 3 develops the agent-based simulation framework with behavioral models for assessing and quantifying the flood level impacts, whereas Section 4 conducts a case study with large-scale metro networks and demand data. Section 5 validates and compares the system performance and demand patterns before and after the floods. Section 6 concludes and discusses future research avenues.

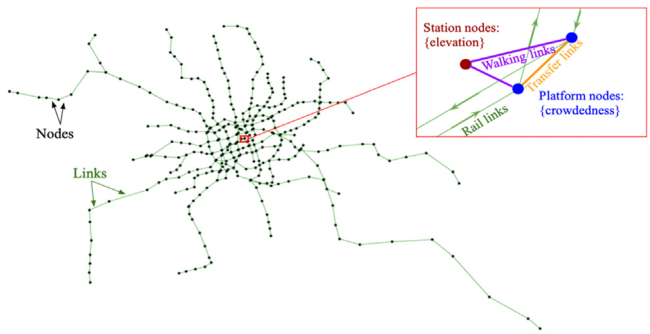


Fig. 1. Network representation of a metro system.

2. Problem and system settings of flooding in an urban rail transit system

Consider a directed metro network graph $G = (Z, A)$ with a finite set of nodes Z and a finite set of directed links A, as shown in Fig. 1. Each node represents a metro platform or a station, and each link represents either a rail linkage between two platforms, a walking path connecting the entrance/exit to the platform, or the walking path to transfer platforms at interchange stations.

Each station also has an elevation attribute representing the height of the station above sea level. During heavy rainstorms, the metro stations will be affected depending on the flooding level and the elevation height. Potential outcomes include station closures, vehicle rerouting, timetable adjustments, line closures, or system shutdowns. Station closure is the most common among these emergency operation measures during extreme weather and natural disasters. When the flooding level induces a station closure, passengers who enter, exit, or transfer at the closed station may change their origin or destination stations or routes. Some passengers may be unable to complete their trips in the metro system if there are no alternative stations or routes, which are called "unfulfilled trips." As the flooding level rises, the number of station closures increases, leading to a higher number of impacted passengers and other network effects such as accessibility, congestion, queuing, and travel times.

This study considers station closure in the metro network based on the flooding levels. It develops a general framework of quantitative and qualitative methods with agent-based simulations to evaluate the impacts of flooding levels on metro network congestion and queuing. The framework is portable to another city given standard transit study inputs without deteriorations in computational speed. The following section describes the evaluation framework with agent-based simulation.

3. Evaluating flooding level impacts with agent-based simulation

In the proposed evaluation framework, the impact of station closures due to water level rises or localized flooding is studied by integrating the traveler behavior model and a dynamic agent-based transit simulation, as shown in Fig. 2. The behavior model informs how travelers' origin, destination, and departure times will change. The transit simulation is used to derive key performance metrics, such as the impacted trips, increase in travel time, and critical platforms. The evaluation outputs will yield the impacts of the flooding levels at the individual passenger, station, and network levels, including the number of station closures, the number of unfulfilled trips, the origin-destination pattern changes and the network congestion and queuing trends after the station closures. The rest of this section explains the behavioral models and agent-based simulations developed for the evaluation framework.

3.1. Travel pattern analyses with discrete choice models

Following the assumptions made by Zhang et al. (2019) [38], it is assumed that the station entrance is 0.45m higher than the ground elevation. Once the flooding level is above the station entrance, the corresponding station will be closed while the rail transit operation maintains the same. Therefore, changes in travel patterns (i.e., new entrance, exit, or transfer stations) will be expected for passengers with original entrance, exit, or transfer stations associated with the closed stations. The changes in user behaviors with station closures are captured by two dimensions: 1) the change in the origin-destination patterns and 2) new routes, jointly determined through the discrete route choice model.

Upon a station closure, we assume passengers whose origins or destinations are associated with the closed station will use one of the nearby alternative stations within walking distance w (e.g., w = 1km). Therefore, in city centers where stations are relatively densely located, a passenger may have multiple alternative choices of origin, destination, or both. The choice sets are all available entrance and exit station pairs $(o_i^p,\ d_i^q)$ for passenger i when either one or both original entrance and exit stations $(o_i^0,\ d_i^0)$ are closed. We denote the alternative origin stations for passenger i as $O_i = \{o_i^1, o_i^2, \dots o_i^p\}$ and the alternative destination stations as $D_i = \{d_i^1, d_i^2, \dots d_i^q\}$. In this case, the passenger i has a set of discrete route choices denoted by $f_i = \{f_{i,1}, f_{i,2}, \dots, f_{i,k}\}$, where $f_{i,k}$ is one of the routes connecting the origin-destination pair $(o_i^p,\ d_i^q)$.

The passenger' route choice is modeled based on the random utility function (Ben-Akiva and Bierlaire, 2003):

$$U_{ik} = V_{ik} + \varepsilon_{ik} \tag{1}$$

$$V_{ik} = wt_o^{ik} + tt_{od}^{ik} + wt_d^{ik} + t_s^{ik} \tag{2}$$

where U_{ik} is the passenger's utility of choosing route $f_{i,k}$ including a systematic component V_{ik} representing deterministic utility and a random component ε_k capturing the uncertainty or disturbances of the utility. In the function of V_{ik}, both wt_o^{ik} and wt_d^{ik} are the walking times, from the original entrance/exit to the new entrance/exit. If the original entrance/exit is not affected by the local water level rise, the walking time is 0. tt_{od}^{ik} is the in-transit time from the new entrance to the new exit station and is estimated using the train schedules. t_s^{ik} is the transfer time for route $f_{i,k}$ (e.g., 90s for each transfer).

The probability that a traveler will choose a route $f_{i,k}$ is modeled based on the multinominal logit model where the random component ε_k is assumed to be independent and identically distributed with Gumbel distribution. The probability of choosing a route $f_{i,k}$ is expressed as

$$\begin{aligned} P_{ik} &= P\left(U_{ik} \geq U_{im}, \forall m \in f_i, m \neq k\right) \\ &= P\left(V_{ik} + \varepsilon_{ik} \geq V_{im} + \varepsilon_{im}, \forall m \in f_i, m \neq k\right) \\ &= \frac{e^{-\mu V_{ik}}}{\sum_{m \in f_i} e^{-\mu V_{im}}} \end{aligned} \tag{3}$$

where μ is the scaling parameter related to the common standard deviation of the Gumbel distribution. Without loss of generality, we set it arbitrarily to a convenient value 1, as commonly used in literature.

Therefore, the probability a passenger i will choose a route f_{ik} is expressed as:

$$P_{ik} = \frac{e^{-\left(wt_o^{ik} + tt_{od}^{ik} + wt_d^{ik} + t_s^{ik}\right)}}{\sum_{m \in f_i} e^{-\left(wt_o^{im} + tt_{od}^{im} + wt_d^{im} + t_s^{im}\right)}} \tag{4}$$

In the entire urban rail transit network, the demand for each route f is expressed as:

$$E_f = \sum_{j \in J} P_{jk} \tag{5}$$

where J is the set of the passenger who has alternative route f in their route sets.

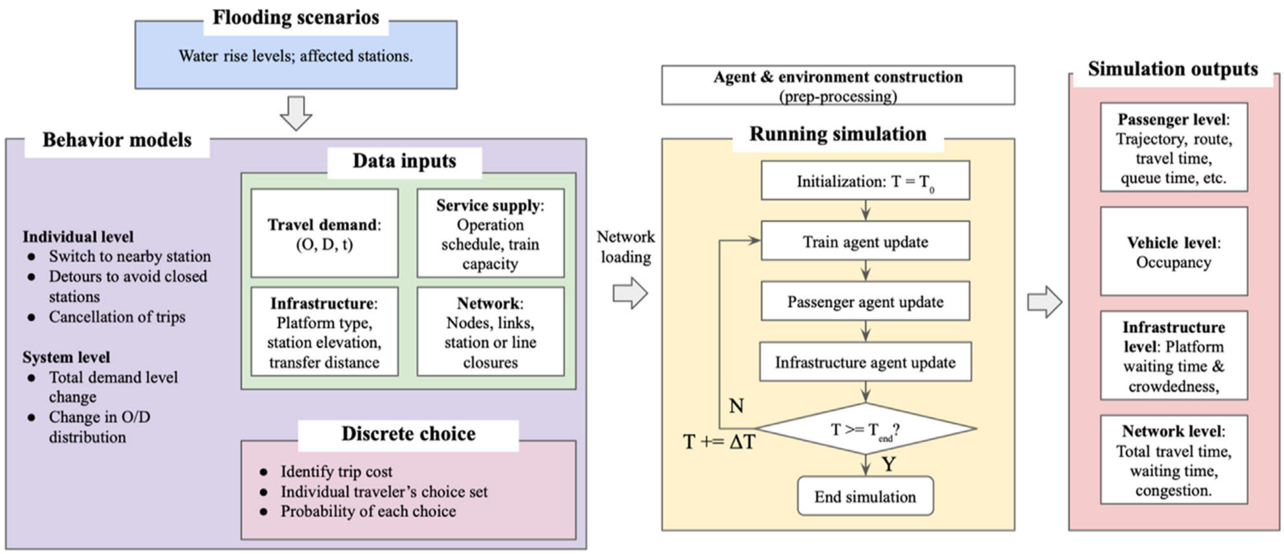


Fig. 2. Conceptual framework to evaluate flooding level on urban rail transit networks.

3.2. Data-driven ABM simulation

The overall framework is comprised of three key procedures (Fig. 2), including 1) behavior modeling, which handles and adjusts the inputs (travel demand patterns, network connectivity, etc.) to the simulation according to the flooding scenarios; 2) an agent-based simulation module capturing the spatiotemporal interactions of different categories of agents, such as the train arrival, departure, passenger walking, queueing, boarding, platform crowdedness, and vehicle occupancy; and 3) an output module that generates passenger, train, infrastructure, and network-level outputs for post-processing and validation. Specifically, the framework is considered data-driven for two reasons: first, the inputs directly utilize state-of-the-art highly disaggregated behavior data from smartcard users, as well as the standardized and widely available General Transit Feed Specifications (GTFS) data. This feature benefits from the increasing availability of disaggregated or standardized data inputs and overcomes previous barriers where inputs need to be generated from aggregated sources (e.g., zonal level travel demand or stated preference surveys). Second, it is also possible for the framework to support data-driven model calibration. As briefly demonstrated in the later Section 5.1, certain parameters such as service intervals and train capacity parameters can be tuned in an iterative manner to minimize the differences in the simulation results and the data-revealed travel time metrics. These are the characteristics of the current data-driven ABM framework.

The behavior modeling is the first step to generate the relevant inputs for the subsequent agent-based subway traffic simulation. The overall goal is to capture the individual- and system-level changes in passenger origin, destination, departure time, routes, etc., given the relevant flooding scenario and network damage data. Specifically, the individual-level behavior changes reflect various levels of interruptions including entrance/exit stations, routes and cancellation of trips. On the system-level, the goal of conducting behavior modeling is to capture system-level changes particularly on the demand side, such as the overall reduction in numbers of trips and the new spatial distribution of the trip origins and destinations. Four categories of data are utilized in the behavior model, including i) the baseline passenger-level travel information (e.g., from the smartcard data), such as the departure time, the origin and destination stations; ii) metro service schedules such as the initial departure time and interval of the trains; iii) infrastructure for the static environments for the urban rail transit system, such as the capacity of the platform and the elevation of the station entrance; iv) network for the connectivity of the key infrastructure pieces, such as the link between platforms, the walking path, and the routes. The flooding scenarios (exogenous inputs to the ABM framework) will alter the availability of some stations and transfer options underneath the water level, including the changes in passengers' origins, destinations, departure times, and routes. The distributions of the demand on route choices within each OD pair are then obtained through the discrete choice model as introduced in Section 3.1. For example, upon the closure of a station, passengers seek to utilize a nearby station within 1km and may have multiple station and route choices. For each option, the probability that a passenger will choose can be derived by Eq. (4) based on the trip costs of each option, Hence the distributions of the total demand on these choices will be based on the probabilities derived in the discrete choice model as indicated in Eq. (5). Through the behavioral models, updated origin, destination, departure time, and route information for each passenger will be generated and used in subsequent simulations. In a more disruptive scenario, the flooding scenario inputs also affect the metro service schedule if water enters the subway tunnel. However, such severe flooding scenarios are less common and would require drastic changes in travel demand patterns and thus are not the focus of this study.

Three types of agents are used in the data-driven ABM simulation, and they are the platform agents, the passenger agents, and the vehicle (service run) agents, respectively. Each agent has various static and dynamic attributes, such as the capacity of the train (static), passenger location (dynamic), or the number of passengers on a platform (dynamic). At each simulation time step (usually no longer than 20 seconds), the train location is first updated according to the metro schedule inputs. A train or service run can either be running between two stations or dwell at a platform for boarding and alighting. When a train dwells at a platform, passengers who have reached the destination station or transfer station will leave the train and move to the platform, while those who are waiting at the platform can board the train on a first-come-first-serve basis. Passengers will not be able to board the train if the capacity of the train has already been reached. The simulation continues until all passengers have reached their destination or the end time has been reached. At each step, the dynamic attributes of the platform, train, and passenger agents will be updated. Detailed as well as aggregated outputs, such as the platform crowdedness at every time step, or passenger locations at every 5 min, are saved for postprocessing analysis.

The output module can generate results at different aggregation levels, from travel times for individual travelers and crowdedness at each

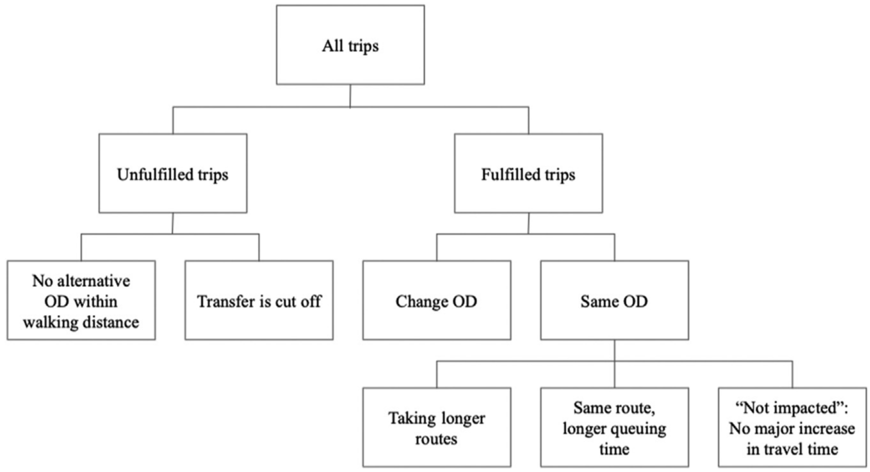


Fig. 3. Categorization of impacts of metro station closure on passengers' travel outcomes.

platform to the overall system-level trip completion rate under flooding disruptions. This varied level of resolution is one advantage of agent-based models. The individual-level travel times output can be compared with smart card tap-out times for validation purposes. Specifically, we focused on the mean and standard deviations of travel time differences to verify the consistency and quantify the discrepancy between the simulation results and real-world observations.

3.3. The impacts of flooding levels on urban rail transit networks

To analyze the flooding level impacts, the system performance of the metro networks will be compared at different flooding levels using the developed ABM as described above, including a benchmark case with normal station access, and a number of flooding cases. Each case represents a separate ABM simulation run. Specifically, we focused on the performance at passenger and system levels as follows:

3.3.1. Impacts on passengers' trips

Quantifying the changes to passengers' travels is fundamental to understanding the flooding impacts. The impacts of flooding levels on passengers' travels are categorized using the tree-like structure in Fig. 3. Specifically, we define the "not impacted" category as those whose travel times increase by no more than 10%, or 10 min, compared to the base travel times (e.g., no flooding-induced station closures). Other types of impacts include: trips unfulfilled due to the lack of alternative entrance, exit, or transfer stations; trips that are fulfilled but require walking to a new entrance or exit stations, trips taking a longer detour, or longer time queuing on the platform.

3.3.2. Impacts on system operations

Apart from individual passengers' travel outcomes, the ABM will also capture the changing interactions and dynamics between the passenger, service run, and platform agents, which are crucial to derive the system operation performance from evaluating flooding impacts on the metro system. Specifically, we focused on:

Affected stations: number of stations that are closed due to certain flooding levels. The affected stations depend on the difference in station elevation height and flooding levels. Depending on the geography and city planning, the affected stations may increase exponentially with the flooding level.

Passenger volume on service line segments: number of travelers passing through each service line segment (between two stations). This indicates the changes in traffic distribution on a network level due to the inaccessibility of some stations due to flooding-induced closures.

Platform crowdedness and waiting time: the total number of passengers or time spent waiting at each platform during the examined periods. This reflects the changes in passenger loads to be handled by other stations due to the flooding station closures.

3.4. Applications of the ABM framework to other common disruptions and disasters

The proposed ABM framework is also applicable to other disasters or scenarios involving the metros or other types of public transport operating on rather fixed routes and schedules. Closely related to flooding, coastal cities also suffer from strong winds from typhoons or hurricanes, when the surface and elevated portions of the networks are impacted the most. In such disaster scenarios, the surface and elevated portion of the network will be closed, and the service runs will be shortened to only cover the underground part. The resulting passenger volume and trip fulfillment ratio can thus be obtained under the same framework.

Depending on the magnitudes of the disaster, the modeling considerations are also different. First, the disaster impacts are reflected in the behavior model in Fig. 2. For example, for smaller disruptions and disasters (e.g., flooding, wind incidents), it is believed that the overall travel demand patterns only need localized modifications, such as switching to a nearby station or rerouting. For major disasters (e.g., catastrophic earthquakes), the travel demand pattern will be drastically different, as people's daily lives will be greatly affected. An estimation of travel demand patterns in emergency scenarios is thus needed. The agent-based transit passenger simulation logic can be regarded as generally applicable. The proposed framework can be combined with optimization framework to identify the most suitable schedule and stop locations as a disaster response tool.

4. Case study

The proposed methodology is applied to the metro network of Shanghai to analyze the system outcomes and impacts on travelers under heavy rainfall-induced metro station closing scenarios. Like many large cities, Shanghai heavily depends on the metros for passenger transport. According to the smartcard data used for this study (Section 4.2), in 2015, the system carried nearly 5 million trips daily. On the other hand, as a coastal city subjected to land subsidence, Shanghai is also vulnerable to inland flooding under adverse weather events. Extreme weather events affect the metro system in various ways, such as the closure of the elevated sections under typhoon weather or service interruption if water accumulates in the subway tunnels. Here we choose to explore the impacts of flooding-induced station closures. Compared to major flooding events that require a whole system shutdown for days (such as Hurricanes in New York), station closures represent a moderate flooding

Table 1
Network and service-related inputs.

Category	Item	Source	Usage
Network topology	Network connectivity	2015 map of Shanghai Metro	Construction of the network environment
	Station coordinates	Gaode Map geocoding API	Convert into stop information with GTFS format; used for route planning, visualization, distance calculation
Train operation schedules	Between-station travel time Service frequency	Bendibao Shanghai metro timetable	Convert into stop and route information with GTFS format; used for construction and simulation of the service run agent.
Train capacity	# carriages	Wikipedia	Used for populating the service run agent properties.
Station elevation	Elevation by meter	Zhang et al., 2019	Determine closed stations under different water level scenarios.

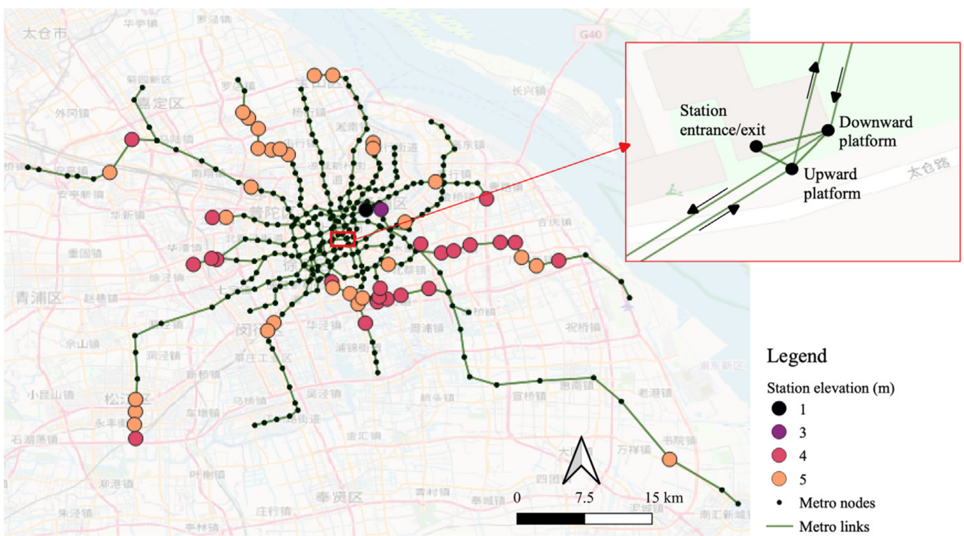


Fig. 4. Metro network and elevation data, with a zoomed-in view of station and platform representations.

scenario where the service runs are not significantly impacted. Nevertheless, it is worth investigating as such scenarios are more commonly seen in real cases, and it is reasonable to assume the normal travel demand (e.g., commuting trips) still holds. Due to data availability, the case study scenarios are mostly built on the 2015 metro network and travel demand data. The preparation of the case study data will be introduced in the next two subsections.

4.1. Supply-side data inputs: metro network and service timetable

The ABM simulator requires basic inputs for building and running the agent-based simulation for the metro network. These include the metro network topology and train operation schedules in the format of The General Transit Feed Specification (GTFS) [39]. In addition, some optional inputs are also needed for the flooding analysis of this study, including the station entrance elevation and train capacity. These data inputs are sourced from various open data sources and summarized in Table 1 below.

First, a list of all lines and stations is obtained based on a 2015 map of the Shanghai Metro. The station coordinates are subsequently queried from the GaoDe Map Geocoding API [40]. This information is processed into the stop information with GTFS format, which is a required input by ABM for the network environment construction, as well as for distance calculation and Geographical Information System (GIS) visualization related tasks in pre- and post-processing of the analysis. The network has 303 stations, 742 platform nodes, and 3,772 links connecting the platforms and stations. The network map is shown in Fig. 4.

Built on the base map of network topology, the service run-related inputs are sourced from a local information website, including the time for the first trains at each station and the service intervals [41]. During the morning peak hours, the service interval is mostly 2.5-4 min, with the maximum being 9 min for the suburban sections of Line 10. While for off-peak hours, the service interval is between 4-12 min. To simplify the data processing, a metro line with bifurcations (or the circle line) or differences in service intervals is broken into sub-line segments. Each segment is a simple line without branches and has uniform service intervals. The timetable-related inputs are converted into the stop information and route information with GTFS format They are the required inputs for ABM to construct and simulate the train movements in the network, such as dwelling on a platform or running between two stations.

Furthermore, the number of carriages for each metro line is obtained and used to calculate the design capacity based on the line planning. For most of the lines, six carriages are used, and each train has a design capacity of 1,470 passengers per service run. Lines 1, 2, and 14 use eight carriages per train, leading to a capacity of 1,960 passengers per service run. Line 6 uses four carriages per train, giving it a slightly lower capacity of 980 passengers per service run. As shown in a recent validation effort of ABM, the inclusion of accurate capacity information helps to better capture the crowding phenomenon on the platforms [32,42].

An additional piece of information needed in this study is the elevation data. Visual inspection shows that elevation data obtained from open sources such as Google Maps are not accurate. As a result, we manually add the station entrance elevation, referring to the figures in Zhang et al. (2019) [38]. The elevation data reveals that, except for two stations near the inner-city Huangpu River in lower-lying areas, most other stations affected by the water rise scenario for up to 5m are in the suburban areas. It indicates that the passenger journeys in the city center may be less impacted under a uniform water level increase. The elevation map is shown together with the network map in Fig. 4.

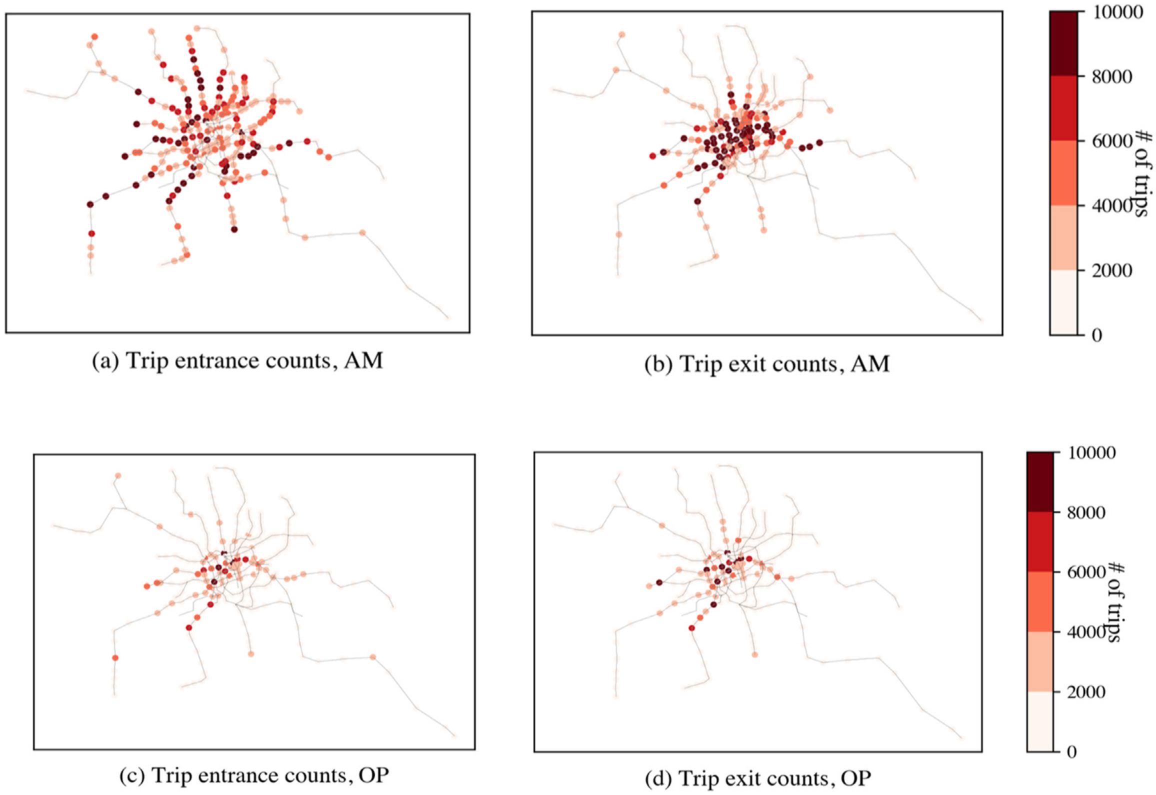


Fig. 5. Numbers of entrance and exit trips by station and analysis time periods.

4.2. Demand-side inputs: traveler origin, destination, and departure time

The trip information inputs for running ABM agent-based simulation can come from multiple sources, such as behavior models informed by travel surveys, or smartcard data. For the Shanghai metro, anonymized traveler data for April 2015 have been made open through the 2015 Shanghai Open Data Applications (SODA) competition. This smartcard data is chosen to be used in this case study.

The smartcard data contains transaction information for the metro and buses, taxis, ferries, and park-and-ride parking. In general, nearly 10 million trip transaction records are available on a typical weekday associated with the metro system. The estimated daily metro trips are 5 million, as each trip consists of two transactions (tap-in at the entrance, tap-out at the exit). The transactions for a typical working day, April 3, 2015, are extracted for further analysis. Trip entrance and exit data are re-organized as a list of (origin, destination, departure time) format required by ABM. There are 1.3 million OD trips from 7:00-9:00 (labeled as the “AM” analysis period in the subsequent analysis) and 0.47 million trips from 12:00-14:00 (labeled as the “OP,” or off-peak, analysis period). The stations colored by the numbers of passenger entrances and exits are shown in Fig. 5 for the AM and OP analysis periods. It is clearly visualized that in the morning peak, trips come from the suburban area toward the city center. Comparatively, in the off-peak period, the demand is significantly less and does not have a clear spatial pattern of movement.

4.3. Study scenarios

Based on a survey in the news, expert opinions, and previous studies, it is understood that the metro system is impacted differently during extreme weather. In typhoon weather, the surface and elevated portions of the network are at the most significant risk, and trains usually stop running. However, if water accumulates from the extreme rainfall and cannot be drained fast enough, one or several stations may be flooded and closed. Trains normally won’t stop running but usually, skip boarding and alighting at the affected stations. Under extreme cases, the flooding into the station cannot be pumped out and would enter the subway tunnel, in which case the metro will stop operating for safety reasons. Each scenario is worth further exploration, but this study focuses on the more common scenario where stations are closed, but the metro operations are not affected. Apart from being the most likely scenario, this relatively lower impact case also means the regular travel demand is least impacted, and the proposed behavior model is still applicable. In addition, two analysis periods, “AM” and “OP” are considered, as the flooding events are expected to cause different levels of impact depending on the time of the interruptions.

Following the scenarios in Zhang et al., 2019, a base case with no station closure and five additional water level rise scenarios (1m-5m) are investigated. Stations with entrance elevation below the water level rise are assumed to be affected under each scenario, and no entrance, exit, or transfer is allowed. Travelers either choose to take another nearby station as described in the behavior model in Section 3.1, or they will need to cancel their trips if no nearby station within 1km is available. The numbers of affected stations under each scenario are given in Table 2. Specifically, as there is no station with an entrance elevation between 1-2m, the scenario with a water level rise of 1m and 2m will produce the same results.

Table 2
Numbers of affected metro stations under different water level rise scenarios.

Scenario/ water level rise	Base (0m)	1m	2m	3m	4m	5m
# affected stations	0	1	1	2	24	53

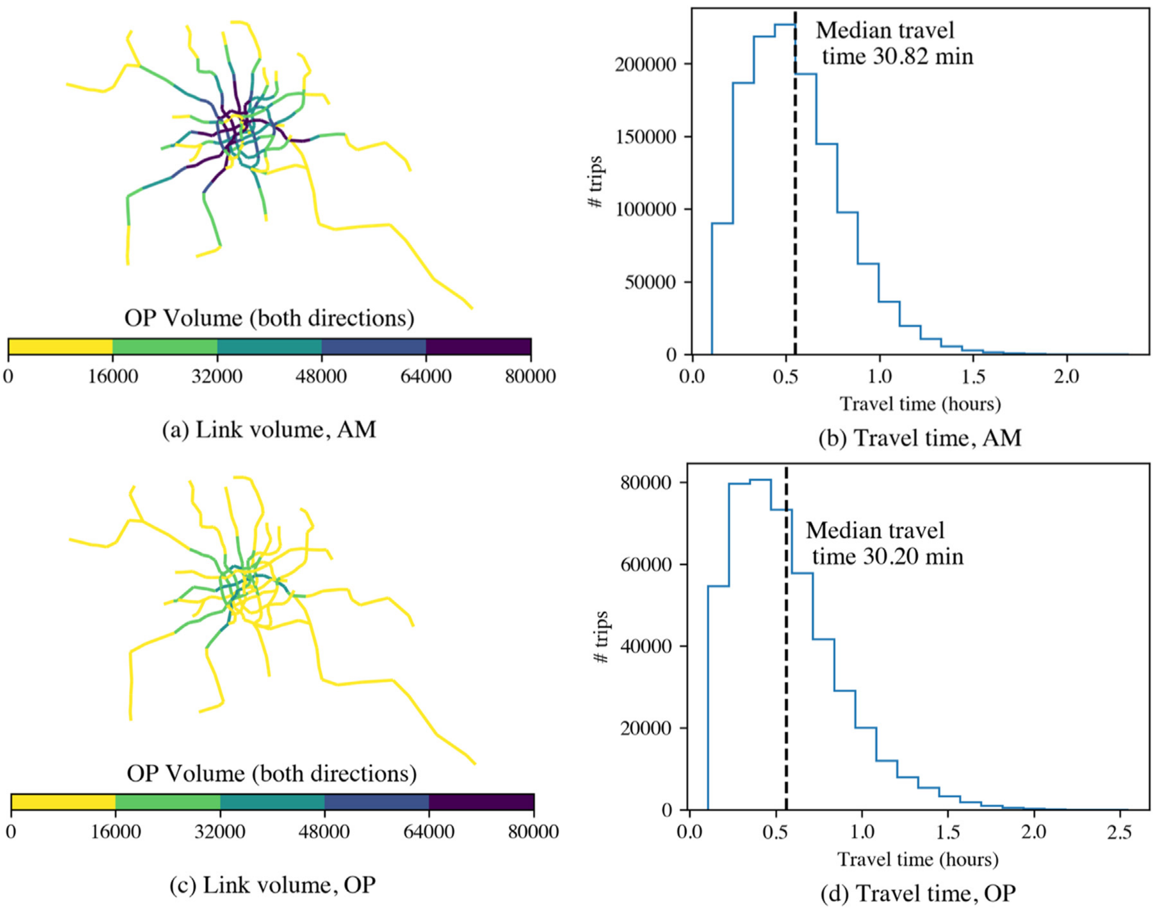


Fig. 6. Passenger volume by Metro sections and travel time distribution.

5. Results and discussion

5.1. Base scenario and validation

Simulated results for the two base scenarios (AM and OP period, no station closure) are plotted in Fig. 6, where Fig. 6(a) shows the numbers of trips per segment (between two stations) for the AM period. Trip volumes from the two directions are added together in Fig. 6(a) due to the difficulty of distinguishing two opposite directions of the same metro line in the plot. Based on the knowledge of the traffic patterns as shown in Fig. 5(a) and (b), more trips are going towards the city center during the AM period, thus a heavier contribution from the trips going into the city is expected. The estimated total trip distance for the AM period under the base scenario is 17.2 million kilometers (13.2 km per trip on average). Distributions of travel time under the AM base scenario are shown in Fig. 6(b). The median travel time is slightly over 30 min. Among all the AM trips, 28.8% have travel times over 40 min and 5.8% have travel times over 1 hour. A similar set of plots for the OP base scenario are shown in Fig. 6(c) and (d). Compared with the AM base scenario, the trip volume in the OP time period reduces significantly, marked by the lighter color of the trip volume map in Fig. 6(c). The total trip distance is 6.2 million kilometers, with an average trip distance of 13.1 km per trip. The median travel time is 30.2 min, which is similar to the AM period. However, there is a higher proportion of longer trips in the OP period, with 30.9% trips having travel times over 40 min and 9.6% over 1 hour.

The simulated travel times are validated against the smartcard tap-out data. For the AM period, the mean difference in travel time is 0.5 min. The standard deviation is 6 min. 50% of the trips are within +/- 3 min compared to the smartcard data, and 90% of trips are within -10 ∼ + 8 min. For the OP period, a larger validation variation is expected due to the long train service interval. The mean difference in travel time is 0.3 min with a standard deviation of 7.2 min. 50% of the trips are within +/- 3.5 min compared to the smartcard data, and 90% of trips are within -13 ∼ + 9 min. During the validation process, it was found that the service frequency has the biggest impact on the result. For busy lines such as Line 3, where the scheduled peak hour interval is 2.5 min, a simulation with the service interval of 4 min would mean a nearly 40% reduction in metro services. Setting larger train intervals in the simulation than in the real schedule leads to insufficient service capability and can potentially result in significant overcrowdedness on platforms and slowdowns of passenger travel times in the simulation. Due to the longer service interval in the OP period, a traveler could easily save or miss 5-15 min of waiting time if they catch or miss a train, thus bigger variations (in terms of standard deviation or interquartile interval) in the validation are expected for the OP period.

5.2. Large scale flooding

The analyses of the flood-induced station closure scenarios are presented in this section. For individual travelers, the impacts of station closures on their trips and travel times are classified following the tree structure introduced in Fig. 3. In the first layer, the trips under the station scenarios are either finished (fulfilled trips) or not finished (unfulfilled trips). Moreover, the unfulfilled trips can be further distinguished by their causes: trips are unfulfilled either because there are no alternative stations available within walking distance or because the loss of transfer stations leaves no other routes to reach the destination. On the other hand, for trips that are still able to be fulfilled under station closure scenarios, two outcomes are expected: the travelers either complete the

Table 3
Impacts on travelers under different water level rise scenarios and analysis time periods.

	AM (7:00-9:00)					OP (12:00-14:00)				
Water level	**0m**	**1m/2m**	**3m**	**4m**	**5m**	**0m**	**1m/2m**	**3m**	**4m**	**5m**
Total OD	1,296,934					468,649				
(a) Unfulfilled trips (absolute value and percentage)										
(a1) No alternative station	0	0	0	165,082	290,291	0	0	0	58,185	98,202
	-	-	-	12.7%	22.4%	-	-	-	12.4%	21.0%
(a2) Lack of transfer	0	0	0	0	22,946	0	0	0	0	7,812
	-	-	-	-	1.8%	-	-	-	-	1.7%
(b) Fulfilled trips (absolute value and percentage)										
(b1) Change OD	0	4,901	16,948	30,720	36,091	0	958	4,285	8,274	10,349
	-	0.4%	1.3%	2.4%	2.8%	-	0.2%	0.9%	1.8%	2.2%
(b2) Same OD	1,296,934	1,292,033	1,279,986	1,101,132	947,606	468,649	467,691	464,364	402,190	352,286
	100%	99.6%	98.7%	84.9%	73.1%	100%	99.8%	99.1%	85.8%	75.2%
(b2.1) Detour	0	0	0	213	11,771	0	0	0	74	3,255
	-	-	-	-	0.9%	-	-	-	-	0.7%
(b2.2) Queue	0	2,631	1,103	438	440	0	94	119	114	189
	-	0.2%	0.1%		-	-	-	-	-	-
(b2.3) Not impacted	1,296,934	1,289,402	1,278,883	1,100,481	935,395	468,649	467,597	464,245	402,002	348,842
	100%	99.4%	98.6%	84.9%	72.1%	100%	99.8%	99.1%	85.8%	74.4%

trips from the original entrance or exit station if both are not affected by the flooding (same OD), or they may need to switch to a nearby entrance or exit station with some additional time spent on walking (changed OD). Furthermore, in the former case, three sub-situations can be identified: even if their origin and destination stations stay the same, they may need to take longer routes due to the closures of transfer stations or spend longer time queuing on the platform due to the increase in demand migrated from nearby stations. The last portion of travelers are those minimally affected by station closures, and their travel times do increase significantly.

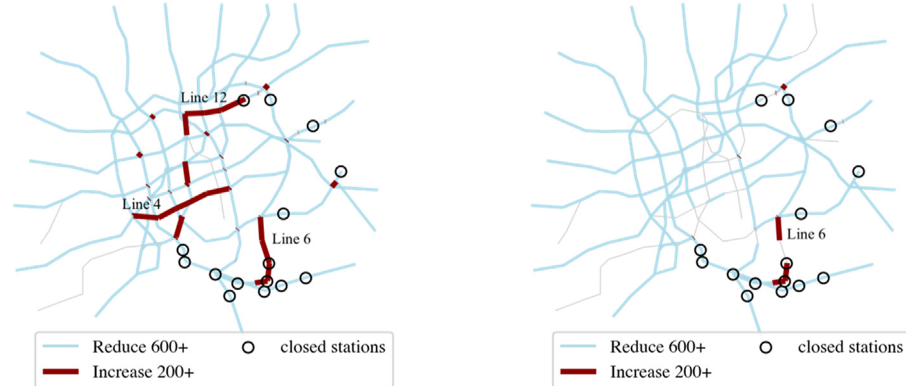
The percentages of travelers falling into each category in Fig. 3 under various water level rise and time period scenarios are given in Table 3. When the water level is below 3m, only 1 or 2 individual stations are affected. Both stations are located near the Huangpu River in the city center and have several stations nearby (Fig. 4). As a result, no trips fall into the unfulfilled or significantly delayed categories. Around 1% of the trips changed to a different origin or destination. Most trips did not change the origin or destination or experienced significant delays. The results indicate that impacts on travelers are almost negligible when the water level rises below 3m. Given the uncertainty of flooding locations in reality that is opposed to the uniform increase assumed in this study, different results may be expected if the affected stations are distributed differently spatially. For example, suppose the closed station is in a residential area without nearby stations within walking distance. In that case, many travelers will not be able to enter the metro in the morning peak hours unless alternative modes of transport (e.g., replacement buses) are available to cover the distance to other unaffected stations.

Under the 4m water level rise, 24 stations are closed for entrance, exit, or transfer. For the 1.3 million trips in the AM period, 165,082 (12.7%) are not able to take place because the original entrance or exit stations are closed, with no alternative stations within 1km walking distance. 30,720 (2.4%) trips change the entrance or exit (or both) to an alternative station within 1km walking distance. The entrances and exits are not affected for the remaining 1.1 million trips (84.9%). The percentage statistics are similar in the OP period, except for a slightly lower number of trips needing to change the origin and destination. This can be explained by comparing the locations of the affected stations and demand patterns in Figs. 4 and 5. Under the 4m water level rise scenario, most of the affected are in the suburban area, which coincides with the origins of trips in the AM period, but less so with the trip origins or destinations in the OP period.

The affected trips almost doubled when the water level rise is 5m, as 54 stations are closed. In the AM period, 290,291 (22.4%) trips are canceled, or 98,202 (21.0%) in the OP period, primarily due to the lack of nearby stations as an alternative. For trips that can still be fulfilled, there are 36,091 (2.8%) trips in the AM period, or 10,349 (2.2%) in the OP period that need to switch to a different origin or destination. Among the trips that are impacted, the lack of alternative stations is the main factor.

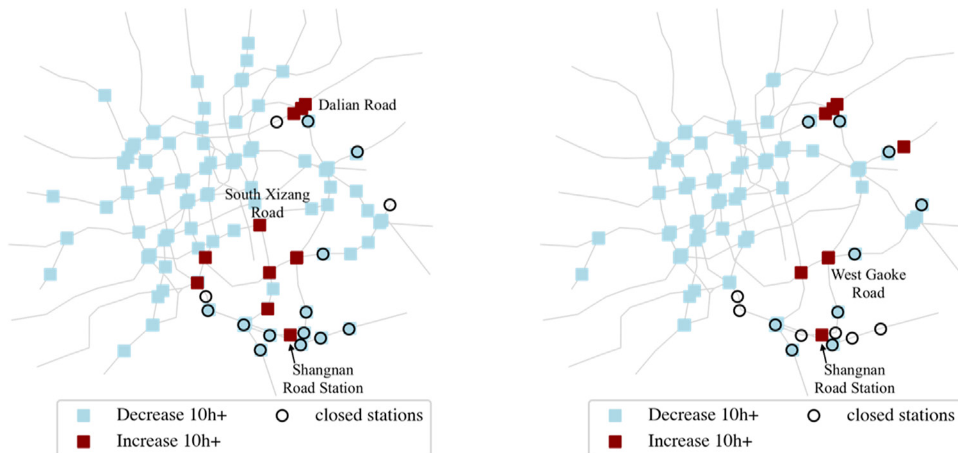
Results in Table 3 indicate an overall reduction in the number of trips by up to 25% under the 5m water level rise scenario. However, further exploration shows an increase in congestion on specific lines or increased crowdedness on certain platforms despite the overall reduction of travelers. These locations are shown in Fig. 7 and Fig. 8. Fig. 7 shows the passenger volumes by line segments (total passengers passing a link). The blue color indicates segments with reduced passenger volumes and the red color highlights line segments with increased passenger volumes. Due to the overall reduction in unfulfilled trips, most line segments serve reduced numbers of passengers under the 5m water level rise scenario both in the AM and the OP periods. The increased volume on the red segments is primarily associated with the changes of the entrance/exit stations (b1 in Table 3), or detours (b2.1 in Table 3): for example, by breaking down the passenger volume of the red segments in Fig. 7(a) by traveler status, it was found that the increase in passenger volume of Line 6 and Line 12 are predominantly due to the changes in the OD, while the increase in Line 4 is caused by detoured travelers with unchanged OD.

The overall reduction in traffic levels is also reflected on the platform level. Fig. 8 shows the changes in the cumulative platform waiting time, where blue indicates less total waiting time compared to the baseline, while red means increased platform waiting time. Typically, two types of platforms have increased waiting time under station closure scenarios: they are either the alternative stations that travelers choose to replace a closed station (e.g., Shangnan Lu Station in Fig. 8), or interchange stations along the segments of increased passenger volume shown in Fig. 7 (e.g., Dalian Road Station after the segments of increased volume on Line 12, and South Xizang Road Station after the segments of increased volume on Line 4). The platform with the longest increase in waiting time is the northbound platform of the Shangnan Lu Station. The crowdedness on this platform in the baseline and 5m water level rise scenarios are shown in Fig. 9. The increased crowdedness is evident, as shown by the orange line (station closure scenario). In addition, the plot also shows the arrival time of the trains marked by the gray vertical lines. The number of passengers waiting on the platform reduces when a train comes, as some passengers board the train. In the baseline scenario, most of the waited passengers can board the train each time, shown by the low values of the blue curve at each gray line. In the road closure scenario, however, the orange curve does not fall back to zero,



(a) Link volume change at 5m water level rise, AM (b) Link volume change at 5m water level rise, OP

Fig. 7. Link volume changes at 5m water level rise scenarios. (a) AM; (b) OP.



(a) Platform waiting time, AM (b) Platform waiting time, OP

Fig. 8. Platform waiting time changes at 5m water level rise scenarios. (a) AM; (b) OP.

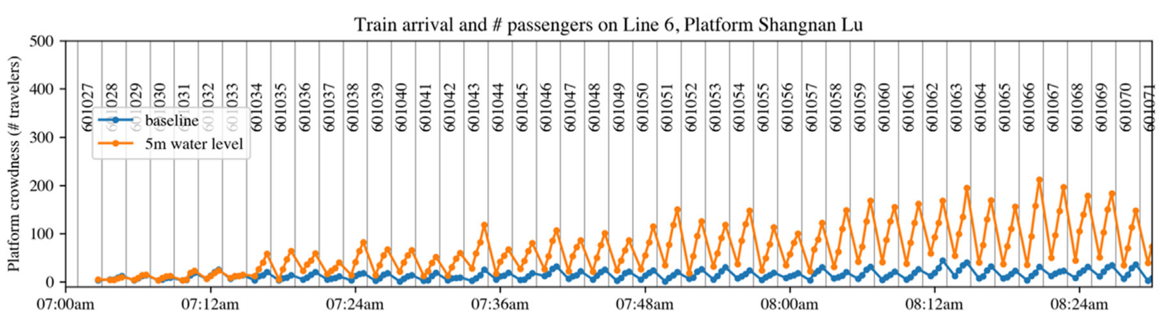


Fig. 9. Increase in platform crowdedness at Shangnan Lu station.

indicating some travelers cannot board the train and must wait for the next one.

6. Conclusions

With growing public awareness and concerns of the disruptions by metro service under heavy rainfall and flooding events reported in recent years, a more thorough understanding and detailed plan for such emergency situations is called for from the metro operators. On the other hand, knowledge of the system is becoming increasingly available with the standardization of key information such as the metro operation schedules, and travel demand smart card data. Based on these standard data products available to the metro operators, we propose a data-driven agent-based model (ABM) to study the outcomes of the system across components and scales under various flooding scenarios. Specifically, we demonstrate the flexibility of the proposed ABM to incorporate realistic behaviors and constraints, such as traveler origin and destination redistribution behaviors, route updates, service schedules, and train capacity constraints.

A case study is presented for the Shanghai Metro based on the 2015 network and travel demand, as well as the previously published station elevation data and flooding scenarios. The smart card data shows spatiotemporal patterns of travel demand, with more trips going from the suburban area to the city center during the morning peak ("AM") hours and fewer trips with no obvious direction of movements in the midday off-peak period ("OP"). The elevation data reveals that apart from two stations located in the city center near the Huangpu River that are subject to water level increase, most other stations under the threat of flood-induced closures are in the suburban areas, coinciding with the origins of the AM trips. The baseline simulation results are validated against the smart card tap-in, tap-out data. The validation shows a good match in the mean travel time, but larger variations of the simulation results compared to the smart card data when the train service intervals are large.

On the individual level, the impacts of flood-induced station closures can be categorized depending on the interruptions exerted on individual travelers, such as trip cancellation, change of origins/destinations, rerouting, delay, or low impact. It was found that all scenarios can be distinguished into two categories based on the locations of the closed stations: either with minimum impact if the closed stations are in the inner city with many alternative stations nearby (water level < 3m) or resulting in up to 25% of trip cancellations in the suburban areas with few stations within walking distance (water level is 4-5m). On the system level, from a spatial perspective, large amounts of trip cancelations under the most extreme water level rise scenario (5m) lead to an expected overall reduction in passenger volume on most lines and shorter waiting time on most platforms. However, at specific lines and platforms, the passenger loads increase locally, mainly due to the redistribution of the origin and destinations of some passengers.

Admittedly, the scenarios studied in this paper cover a common but less disruptive type of flooding emergency, where some stations are skipped, but the train service remains functional otherwise. The spatial and sub-system perspective of the data-driven ABM offers a more intuitive tool for asset managers in designing the emergency plans, such as providing replacement buses or increasing the personnel at the illustrated locations. In addition, the framework is also flexible to be used in other emergency scenarios, such as coupling with other civil infrastructures to facilitate the design of co-operational plans in reducing infrastructure vulnerability and improving urban resilience. The framework is also capable of quantifying uncertainties in the system if combined with forward propagation techniques such as Monte Carlo simulation. Future studies can also incorporate operational strategies and network designs for emergency responses and evaluate the system performances and impacts of the common or natural disasters.

Declaration of Competing Interests

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

CRediT authorship contribution statement

Bingyu Zhao: Conceptualization, Methodology, Resources, Software, Validation, Formal analysis, Investigation, Visualization, Writing – original draft, Writing – review & editing, Data curation. **Yili Tang:** Conceptualization, Methodology, Resources, Investigation, Writing – original draft, Writing – review & editing, Validation. **Chaofeng Wang:** Methodology, Writing – original draft, Writing – review & editing, Validation. **Shuyang Zhang:** Conceptualization, Validation, Writing – review & editing. **Kenichi Soga:** Supervision, Validation, Writing – review & editing.

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