Subway travel risk evaluation during flood events based on smart card data

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ABSTRACT
The intensity and frequency of extreme weather is increasing in major metropolitan areas around the world, which results in unprecedented urban floods. However, subway systems lack consideration of flood risk, and few studies have assessed risk during flood events from the view of subway travel. In this study, subway travel risk was evaluated by flood hazard, subway travel exposure and population vulnerability under three groups of rainfall scenarios. The degree of spatial exposure was calculated based on smart card data and a census, and the vulnerability of the population was assessed based on human stability in floodwaters. The results in the study area indicate that subway travel risk grows with an increase in the rainfall return period, and the highest subway travel risk occurs in the morning peak period. The return periods of rainfall, time-to-peak, and duration have an impact on the spatiotemporal trajectory of subway travel risk. Furthermore, the traditional census tends to underestimate subway transportation exposure due to subway travel. Subway travel risk increases significantly under the extreme rainfall scenario and requires further research. This study provides risk maps for making travel decisions before departures and support for subway operators to develop risk warnings.

1. Introduction

The intensity and frequency of extreme weather is increasing with climate change, and major metropolitan areas around the world are at increased flood risk (Hettiarachchi et al. 2018). Flash floods resulting from torrential downpours can quickly turn deadly in a densely packed modern city. In a densely populated modern city, pluvial flooding caused by torrential downpours can be fatal. However, many
cities may be unaware of the flood hazards that their subway systems face (Forero-Ortiz and Martinez-Gomariz 2020).

In 2016, China suffered from extreme rainfall events that caused much flooding of underground infrastructures, and the Changpan Station of Metro Line 6 in Guangzhou was inundated on 10 May, resulting in eight deaths (Lyu et al. 2016). On 20 July 2021, a flash flood in Zhengzhou, a ten-million-person city on the Yellow River in China, caused a kilometre-long part of the subway line tunnel to flood. Many tragedies occurred on subway line 5 during this record-breaking rainstorm, which trapped more than 900 passengers and killed 14 (Disaster Investigation Group 2022). According to a survey produced by the Regional Plan Association, flooding of subway sites will become more frequent, with more than 20% of these sites being at risk from storms (NYC Subway Seen Likely to Flood as Storms Rise on Climate Change 2021). Eighty-five sites on the London underground are at high and rising risk of flooding, according to a report (Carrington 2016) that states it is ‘only a matter of time’ before serious flooding occurs.

Subways, the most common type of urban railway system, are becoming increasingly essential in transportation networks (Nan et al. 2019). Because of the environmental friendliness, efficiency, and comfort of subways, they have become primary means of transportation in many metropolitan regions (Zhang et al. 2016). The overland flow induced by rainfall creates road and traffic congestion, although the travel demand of urban residents is largely unaffected by the weather. As a key piece of subsurface engineering, subways play vital roles in alleviating urban traffic congestion. Subways are the best means of travel for residents to avoid congestion in flooding events; however, residents face greater flood risk when using the subway. We found that authorities in charge of transportation systems and urban planners around the world lack consideration of flood risk in their subway travel systems.

Recent studies have focussed on subway flood risk evaluation at the system and station scales. For example, flood risk reduction interventions for the New York City subway system were studied by Vermeij (2016). A study of flood risk in Guangzhou (a mega city in China) metro systems was presented using interval analytic hierarchy process (I-AHP) methods (Lyu et al. 2018). Wang et al. (2021) proposed a regional risk level method to depict the risk of flooding in the Beijing subway system. In addition, a waterlogging risk index (WRI) was established to study subway station exits to compare flood risks among different subway lines in the central urban area of Shanghai (Quan et al. 2011). A fuzzy synthetic evaluation model was developed by (Yu et al. 2019) for flood risks in the construction and operation periods of subway stations. A hydrodynamic modelling process was carried out on the Metro Line in Barcelona, and the results present a risk analysis focussed on the 26 stations of Metro Line 3 (Forero-Ortiz et al. 2020). In addition, questionnaire data were collected by Abad and Fillone (2019) among transit users who perceived risks to travellers using public metro services during a flood event. Most of the existing studies on subway flood risk have been carried out by constructing a comprehensive index system through a risk assessment approach from regional to local scales (Lyu et al. 2019), and these studies explore the flood risk of subway lines or individual stations. However, few studies have conducted risk evaluations during flood events from the
view of subway travel, and few have proposed corresponding risk reduction countermeasures.

In this study, flood events under different rainfall scenarios were simulated by the SCS-CN model with a flat-water method. The potential range of subway travel exposure of the population was estimated using traditional census data combined with subway smart card data. The risk during each 30-minute interval was evaluated for the coupled rainfall scenario and subway travel. The main objective of the modelling framework is to investigate spatiotemporal changes in subway travel risk during flooding events. Subway travel risk assessment during flood events is very important for providing a warning to citizens and for subway system managers to take measures to mitigate flood risk.

2. Materials and methods

2.1. Materials

2.1.1. Study area

Shenzhen is located south of Guangdong Province and is on the east bank of the Pearl River estuary (Figure 1). The average daily passenger flow of the Shenzhen subway was 3,982,100 in 2020. Among the residents who travel in Shenzhen, as many as 51.6% of them use the subway. The resident population density is 21,100 per square kilometer in the study area, ranking first among the ten districts in Shenzhen city and 3.14 times the average. The area has well-developed rail transportation, with 9 subway lines and 53 stations. It has the largest integrated subway hub in the city, and Futian Subway Station is the largest underground high-speed rail station in Asia and the fastest in the world. The city is always influenced by floods due to rainstorms and typhoons. In 2020, the strongest monsoon precipitation in the past decade was recorded. There were 28 local heavy rainfall events (44 days), including 14 days of local heavy rainfall and very heavy rainfall, resulting in serious flooding (Shenzhen
Climate Bulletin 2020). The study area experiences a higher risk during subway travel during flooding events than other cities due to the increased frequency of extreme rainfall.

### 2.1.2. Data source

The data used in the paper and their details are shown in Table 1. The resolution of the grid was set to 10 m for the study. A digital elevation model (DEM) at a detailed scale of 12.5*12.5 m was used, and the DEM data were resampled to 10 m using majority and nearest neighbour techniques (Tan et al. 2015). The 10-m resolution land cover data in 2017 were mapped and transferred from a 30-m resolution sample set collected in 2015 (Gong et al. 2019). Perception data of different return periods were provided by the Shenzhen Storm Design Manual (from the Meteorological Bureau of Shenzhen Municipality). Python 3.7 was used to obtain subway smart card data from the API platform at https://opendata.sz.gov.cn. Smart card dataset for subways, which includes 53 subway stations, was collected on 1 September 2018. This study used the subdistrict population statistics of 2018 in the study area, which were obtained from the statistical yearbook of the District Bureau of Statistics website (Shenzhen Futian Statistics Yearbook 2018). An urban land use category map was reported by Gong et al. (2020) for all of China using 10-m satellite images, OpenStreetMap, night-time lights, point of interests (POI) and Tencent social big data for 2018 as input features. The remote sensing image data used were provided by Google Earth, whose spatial resolution is 10 m.

| Dataset                     | Description     | Source                                      |
|-----------------------------|-----------------|---------------------------------------------|
| DEM                         | 12.5 m × 12.5 m | https://search.asf.alaska.edu/             |
| Land cover map              | 10 m × 10 m     | http://data.ess.tsinghua.edu.cn            |
| Rainstorm intensity equation| Year 2015       | http://weather.sz.gov.cn                   |
| Subway smart card           | 1 Sep 2018      | https://opendata.sz.gov.cn                 |
| Population statistics       | Year 2018       | http://www.szft.gov.cn/bmxx/qtjj/         |
| Urban land use categories   | Shapefile       | http://data.ess.tsinghua.edu.cn            |
| Remote sensing image        | 10 m            | https://earth.google.com/web/              |

2.2. Subway travel risk during flood events

In the scientific community, it is widely agreed that risk is the product of a hazard and its consequences (Koks et al. 2015). In places where there are no people or values that can be affected by a natural phenomenon, there is no risk. Hence, three components determine the subway travel risk during flood events, which can be defined as hazard * exposure * vulnerability (Kron 2005). Hazard and flood events include their probability of occurrence. Exposures occur to subway-travelling persons in hazard-prone areas. Population exposure is a key component in determining the risk due to subway travel (Cutter and Finch 2008). It is necessary to recognize the variation in the location and size of the exposed travel population during different return periods in flood events. Due to vulnerability and lack of resistance to damaging floods, people’s safety can be compromised when they are exposed to floodwaters that exceed their ability to remain standing (Chen et al. 2019). Therefore, considering the subway
travel risk connotation, the Subway Travel Risk Index (STRI) could be defined as follows:

$$STRI = \frac{FP}{C2}$$

where FP is the flood probability, STEI is the subway travel expose index, and PVI is the population vulnerability index. The estimated quantile of the risk index is used to characterize the level of risk (Wang et al. 2021), and the range is presented in Table 2.

### 2.3. Flood simulation and modelling

#### 2.3.1. Scenario design

The designed rainfall can easily show different rainfall characteristics, such as return period, storm duration and time-to-peak ratio, by changing parameters; therefore, the designed rainfall was used instead of the real rainfall events. The storm rainfall events were designed using the Chicago storm rainfall profile (Equation (2)), which is described by the rainfall intensity–duration–frequency equation of Shenzhen. The Chicago design storm was applicable to our study because it is recommended by the Shenzhen Storm Design Manual, which was formulated by the Meteorological Bureau of the Shenzhen Municipality.

$$i = \frac{8.701(1 + 0.594\log P)}{(t + 11.13)^{0.555}}$$

$$R = \int idt$$

where $i$ is the rainfall intensity (mm/min), $P$ is the return period (y), $t$ is the rainfall duration (min) and $R$ is the total rainfall depth (mm). Detailed information on the storm scenario in different return periods is presented in Table 3.

Since the subway smart card data is from 5:30 to 11:30, we coupled the subway travel scenario with the rainfall scenario to reflect the risk of subway travel under different scenarios. Figure 2a shows the population flow of subway travel, and the following three groups of scenarios were considered in the study (Figure 2).

In Group (1), the storm events have different return periods (20, 50, 100, and 500 years), and the corresponding total rainfall amounts range from 208.58 to 306.29 mm. They all have the same rainfall duration (6 h) and location of peak rainfall intensity ($r = 0.5$). In Group (2), the storm events have different time-to-peak ratios $r$
(0.1, 0.5, and 0.9), and they have the same r return periods (500 years) and rainfall durations (6 h). In Group (3), the storm events have different rainfall durations (3 h, 4 h, and 6 h). They have the same return periods (500 years) and locations of peak intensity (r = 0.5). The goals of groups 1, 2, and 3 are to study how the subway travel risk changes during flooding occurrences by combining travel and storm scenarios.

### 2.3.2. Rainfall-runoff simulation

The USDA-developed Soil Conservation Service Curve Number (SCS-CN) technique is commonly used as an empirical hydrological model that is widely applied for predicting direct runoff or infiltration for a particular rainfall event (Soulis and Valiantzas 2012). This model has been widely employed in recent years for runoff estimation at various spatial scales (Du et al. 2015; Hu et al. 2020). A direct relationship was developed between hydrological model parameters and remote sensing data based on rainfall and runoff, considering underlying surface features, and the influence of land use was shown. Several studies also suggest that the model can be used to evaluate runoff risk in densely populated locations where actual hydrological data are difficult to collect (Li et al. 2018; Yao et al. 2018).

We calculated runoff depth for various flood return durations, calculated inundation volume, and performed flood simulations in Python (Van Rossum 1995) using a

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Table 3. Details of the storm scenario in different return periods.

| Time (year) | Max rainfall density (mm/min) | Total rainfall depth (mm) | Flood probability (FP) |
|-------------|-------------------------------|---------------------------|------------------------|
| 20          | 4.05                          | 208.58                    | 0.05                   |
| 50          | 4.59                          | 236.40                    | 0.02                   |
| 100         | 4.99                          | 257.44                    | 0.01                   |
| 500         | 5.95                          | 306.29                    | 0.002                  |

Figure 2. Design storms for scenario analysis.

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DEM in conjunction with a rainfall intensity equation and the SCS-CN model. Finally, the flooding simulation results are visualized in a GIS.

\[ P = I_a + F + Q \]  
\[ \frac{Q}{P - I_a} = \frac{F}{S} \]  
\[ Q = \begin{cases} 
\frac{(P - I_a)^2}{P - I_a + S}, & P > I_a \\
0, & P \leq I_a 
\end{cases} \]  
\[ I_a = \lambda S \]  
\[ S = \frac{25400}{CN} - 254 \]

where \( P \) = total rainfall depth (mm); \( I_a \) = initial abstraction of the rainfall (mm); \( F \) = cumulative infiltration excluding \( I_a \) (mm); \( Q \) = runoff depth (mm); \( S \) = potential maximum retention or infiltration (mm); \( \lambda \) = initial abstraction coefficient (\( \lambda = 0.2 \), (Baltsas et al., 2007)); \( CN \) = curve number, which ranges from 0 to 100. It is an important parameter that represents the potential runoff depth of land use and cover (Lian et al. 2020). Moreover, the USDA has established four hydrologic soil groups (A, B, C, and D) to represent varied soil infiltration capacities (Yao et al. 2015). The antecedent soil moisture condition (AMC II) was primarily used in this study to estimate runoff, and the CN value is presented in the Supplementary material.

\[ V = Q \cdot S - C \]

where \( V \) = total flood inundation volume (m\(^3\)), \( S \) = land area (km\(^2\)), and \( C \) is the urban drainage capacity. The capacity of the urban sewer system was assessed. Detailed information is provided in the Supplementary material.

### 2.3.3. Urban flood simulation

Flood simulations improve the understanding of urban flood change and enhances attempts to reduce flood risk (Da Silva et al. 2020). Although hydraulic models provide accurate flood inundation modelling, they require higher computation time and data requirements (Apel et al. 2009). Furthermore, some of these models have not had open-source availability, and they have relatively high costs (Nkwunonwo et al. 2020). Therefore, based on the total flood inundation volume of the catchment area, the inundation area and depth are simulated by the flat-water model (Chen et al. 2009). In this study, storm water flooding is seen as passive inundation; the specific process of confluence is ignored, and only the gravitational features of water flow are used to fill each depression from high to low based on the topographic characteristics of runoff. The fundamental principle is that the total flood inundation volume equals
the total water volume, and the calculation procedure is shown in Equation (9) (Diaz-Nieto et al. 2012).

\[
W = \int \int_A \left[ E_W(x,y) - E_g(x,y) \right] d\delta
\]  

(10)

where \( W \) is the total amount of water that inundates; \( A \) is the inundated area; \( E_W(x,y) \) is the water surface elevation, \( E_g(x,y) \) is the ground elevation; and \( d\delta \) is the inundated area unit. The water surface height was initially set to the catchment elevation average. Then, \( W \) is compared to \( V \) as calculated by the SCS-CN model. If the difference is large, the water surface height is reset using the dichotomous method until the difference is less than the allowable error. Finally, the inundation elevation is equal to the water surface height. The technical process of the flood simulation is given as follows in Figure 3.

2.4. Subway travel exposure index

2.4.1. Urban population distribution

The general spatial distribution of the population is limited by the boundary (census regions), showing the same population density in an administrative area (Martin and Bracken 1993). However, the spatial distribution of flood hazards does not conform to administrative boundaries. To better evaluate subway travel risks during flooding disasters, administrative boundaries must be broken down, and the actual population distribution in urban areas must be simulated. The study area’s population statistics and land use classification data were used for multivariate population distribution statistical regression modelling to produce population estimates on land use classification scales. This study uses industrial land, public management and service land, transportation land, population scarce zones, commercial land, water surfaces, and residential land to spatialize the urban population. Because the water surface is vacant, the area of the remaining six land use types is employed as the independent variable, and the number of subdistrict populations is used as the dependent variable.
Multiple regression, which is a frequent model for estimating static population density (Langford 2006), is used to match the relationship between the independent and dependent variables, and its general form is:

$$POP_i = \sum_{v=1}^{n} \beta_v x_{iv}$$  \hspace{1cm} (11)

where $POP_i$ is the demographic value of the $i$th street, $\beta_v$ is the category $v$ land use of the population coefficient, and $x_{iv}$ is the area of the $v$th category of land use within the $i$th street. Thus, with the exception of the water surface, all coefficients must be positive, and the approach is adjusted by removing twice the lowest negative value from each regression coefficient value (Yuan et al. 1997).

$$\beta'_v = \beta_v - 2\beta_{\text{min}}$$  \hspace{1cm} (12)

$\beta'_v$ is the population density after eliminating negative values; $\beta_{\text{min}}$ is the lowest negative value in the regression coefficient. To match the actual population estimates, the coefficients $\beta$ are again corrected after eliminating the negative values. $p_i$ is the population estimate of the $i$th street.

$$\beta_{iv} = \left( \frac{p_i}{POP_i} \right) \times \beta'_v$$  \hspace{1cm} (13)

In this study, 10 m was chosen as the grid resolution; after grid population estimation, the population number of each grid was obtained. It was marked as $Grid_{\text{pop}}$.

### 2.4.2. Subway travel population spatialization

After eliminating the data rows with missing values, the subway smart card data for the morning of 1 September 2018 comprise 209,715 records and 53 stations. It has 13 fields, including time, type (inbound/outbound), station, etc. At 10-minute intervals, the population flow of each station is counted, and the spatial position is detected by the POI. The inverse distance weighted (IDW) approach (Prasetyowati and Sibaroni 2018) was used to spatialize subway population flow. When taking the subway, most people go to the nearest station. According to some studies of urban travel (Zhang and Yao 2015; Sun et al. 2016), the walking time before taking the subway is approximately 8–12 minutes. As a result, the buffer zone of the subway station is the area that can be reached by walking for 10 minutes (average walking speed 1.37 m/s, interpolation radius 820 m), and the spatial distribution of the population travelling by subway is simulated, where $Grid_{\text{pop},ST}$ is the estimated population of subway travellers for each grid.

### 2.4.3. Subway travel exposure index

The Subway Travel Exposure Index (STEI) is calculated by the ratio of subway travel population to static residential population on each grid. This index is used to present the exposure due to subway travel on each grid.
2.5. Population vulnerability index

Understanding population vulnerability to flooding is important for providing a scientific basis for risk assessment and mitigation. Because the population vulnerability to floods is more difficult to assess, past research has focused more on indicator analyses (Sarmah et al. 2020). In this study, population vulnerability index (PVI) is quantified by combining the gait speed with human stability in floodwaters. A flat gait speed of 20–60 year old adults could be obtained from previous research (Lee et al. 2019). Chen et al. (2019) improved human stability criterion curves in a study. The average adult gait speed was added to the human stability formula, and we calculated that when the pace is 1.37 m/s and the water depth is 0.87 m, the person will be unstable in floodwaters. Walking is slightly affected when the inundation depth is less than 0.2 m, and there is also a risk of instability. We also set the vulnerability to 0.1 for a 0.2 m inundation depth. Thus, we create a curve of population vulnerability vs. inundation depth, assuming that human vulnerability increases linearly as inundation depth increases (Kron 2002). Therefore, the segmentation function of the PVI is defined as Equation (15), and D is the inundation depth.

\[
PVI = \begin{cases} 
0.526D, & D \leq 0.2 \\
1.471D - 0.279, & 0.2 < D < 0.87 \\
1, & 0.87 \leq D 
\end{cases} \quad (15)
\]

\[
STEI = \frac{\text{Grid}_{pop}ST}{\text{Grid}_{pop}} \quad (14)
\]
3. Results

3.1. Flood simulation results

The inundation status in the study area was represented by the inundated area and inundation ratio (percentage of inundated area to total area). Overall, with flood return times ranging from 20 to 500 years, the inundation ratio (Table 4), inundated area (Figure 4), and flood depth gradually increased. The lowest inundated area was 2.38 km², which accounted for 3.5 percent of the total regional area in the 20-year flood return period, while the largest covered 8.03 km² and accounted for 11.7 percent of the total area in the 500-year flood return period. Inundated areas exhibited a rising tendency in five levels of depth with flood return times ranging from 20 to 500 years. During urban flood events, Futian district suffered from an apparent change in inundated areas from 2.38, 5.28, and 6.65 km² to 8.03 km² and continuously increased in inundation ratio from 3.5, 7.7, and 9.7 percent to 11.7 percent.
The region of flood depths greater than 1 metre varied from 0.88 to 2.71 km², with flood return periods ranging from 20 to 500 years.

Inundated areas were spatially concentrated in the south-central areas and low-lying areas in Futian district. The northern part of the Futian District is mountainous, while the southern part is located along the river. The elevation dropped from north
to south, with the south occupying the dominant inundated area. The normal spatial and regional variances in inundated areas and ratios were evident in the whole district. Furthermore, the area of inundation at different flood depths was beneficial and useful in understanding the severely inundated area, and it reflected the contribution of elevation to inundation.

### 3.2. Exposure of subway travel population

Figure 5 depicts the subway-travelling population exposure from 6:00 to 11:30 AM based on the STEI. Even in this urbanized area, the STEI figure for 8:00 to 10:00 AM more properly depicts the higher core concentrations and lack of subway travel areas. There is considerable variation in the population, and the disparities in exposure during the half
day are especially noticeable among travellers. During the half day, there are regional and temporal fluctuations in populations potentially exposed to flood hazards.

The STEI is higher in the southern and northern residential areas of the case study area than in the central area between 6:00 and 8:30 a.m., which marks the beginning of the commute. The results suggest that the population was exposed to subways travelling throughout time, with the largest exposure at 8:30 AM. After 8:30, the STEI starts to decline in the whole area, and the exposure index in the central commercial region begins to be higher than that in the residential region. After 9:30 a.m., the exposure drops as the urban commuting activity comes to an end.

### 3.3. Spatiotemporal variation in subway travel risk

#### 3.3.1. Subway travel risk of different return periods

Subway travel risk with variable return periods results in a time variant grid file that records travel risk at a chosen time interval for each location in the case study area.

Figure 7. STRI of three time-to-peak ratios at 10:00 AM, scenario 2a: \( r = 0.1 \), base scenario: \( r = 0.5 \), and scenario 2 b: \( r = 0.9 \).
Figure 6 shows the estimated subway travel risk during flooding events (represented by a red-colored ramp) created by the design rainfall event. The results of the minimum and maximum subway travel risk are determined by the year of the return period. The risk of subway travel for three flood return dates was compared because the STRI at 9:30 AM was the highest during the 6-hour designed storm. In the case of the STRI, the range of values is shown with a quantile reclassification that has five zones for better representation. Light red (range of 0 to 20 percent) represents the lowest travel risk. The parcels shown in red have a medium risk (40 to 60 percent) compared to previous ranges. The map is shown in deep red in a class representing the highest risk. The classification helps in comprehending the spatial variability in the STRI. During the 20-year return period, several of the southern roads are at high risk, affecting people traveling near the subway station. It displays the spatial distribution of medium risks obstructing travelled roads as well as a very high risk of residential parcels throughout the 50-year and 100-year return periods. More land parcels, including residential, commercial, and industrial parcels, are at risk in the 500-year return period, and the travel risk area is larger than that in the 100-year return period.

3.3.2. Subway travel risk of three designed rainfall time-to-peak ratios

This section describes the results of the STRI based on $r$. $r$ created a significant difference in the initial time of inundation, with scenario 2a starting at 7:00 a.m. and the base scenario at 8:29 a.m., while the beginning of flooding was delayed to 9:46 a.m. with $r = 0.9$. To compare the spatial differences, the STRI map at 10:00 AM was chosen. Figure 7 represents the results of $r = 0.1$, $r = 0.5$, and $r = 0.9$ (STRI-2a, STRI-base, and STRI-2b). At 10:00 a.m., the majority of the land parcels in the centre of the case study area show considerable risk at $r = 0.1$ and $r = 0.5$. Analysing the maps indicates that the STRI between the base scenario and 2b has changed since the peak of the design rainfall. The inundated region of 2b is smaller and the subway travel
risk is lower when $r = 0.9$. Normally, the population density of residential land parcels decreases, while other areas increase as a result of commuting. As a result, the high-risk regions for subway travel start moving from the south residential areas to the central commercial areas, and the map shows the risk in most central metropolitan areas. With the propagation of overland flow, more central areas become hazardous and restricted.

3.3.3. Subway travel risk of different rainfall durations
The spatial distribution of the STRI at 9:30 AM in Group III storm events with different rainfall durations is shown in Figure 8. The results indicate that some of the case study area experiences a travel risk during flood events. Residential parcels on the south side have a lower risk than those in the centre of the case study area during this period. As a consequence of obstruction on the road from the STRI, at 3 b (during the 4-hour design storm), their risk of travel increased considerably, resulting in a high hazard. The situation on the south side and central part of the study area worsens even further during the 3-hour and 4-hour designed storms as the inundation flood volume increases. Most of the study area on the north and west sides is comparatively reliable, while some exceptions are found in these land parcels, namely, those that have experienced higher levels of exposure show significant subway travel risk.

4. Discussion
4.1. Analysis of subway travel risk
Overall, our research establishes a subway travel risk calculation model during flooding events. The STEI and PVI are two major factors that determine the risk in this study. The STEI is calculated by the ratio of the estimated subway travel population to the static residents on each grid. Population exposure to urban floods was assessed in a previous study (Zhu et al. 2020) by the relationship between the population and the building. Mohanty and Simonovic (2021) understand the dynamics of population flood exposure with population datasets alongside census data. Previous studies have concentrated on population spatialization, whereas the STEI proposed in this study presents the flood exposure risk of subway travel to each location. The average STEI is considerably high at 8:30 compared to 06:00 and 11:30, which shows the concentration period of departure. When expected, as more individuals take the subway to depart from the residential area, travel exposure within this area typically increases. Because of subway travel, this spatiotemporal variance differs strongly from the static estimate of population exposure obtained by the traditional census, which tends to underestimate subway transportation exposure.

The human vulnerability index (HVI) was proposed in a previous study and was constructed using population density, lack of knowledge and other indicators (Khan and Salman 2012). In addition, human vulnerability curves for flash floods were fitted through the statistical relationship between mortality and flash flood characteristics to rapidly estimate the loss of life (Liu et al. 2022). The limitations in subjectivity as well as statistical data in previous population vulnerability studies are compensated to
some extent by assessing the population vulnerability to floods through the human stability formula combined average gait speed.

4.2. Analysis of subway travel risk under extreme rainfall scenarios

From the results of the STRI, it is shown that the return periods of rainfall, time-to-peak, and duration have an impact on the spatiotemporal trajectory of subway travel risk, and it will generate useful warning information that can help residents avoid risk. In several designed rainfall scenarios, our results indicate that the area of subway travel risk grows with the increase in the rainfall return period, and the highest value of subway travel risk occurs in the morning peak period. With the frequency of extreme rainfall due to climate change (Du et al. 2014; Zhang et al. 2020; Zhongming et al. 2021), we have to discuss the risk of subway travel under extreme rainfall scenarios. Two extreme rainfall scenarios are set, namely, ‘8·29 Shenzhen Rainstorm’ (29
August 2018, maximum 24-hour sliding rainfall of 414.1 mm, breaking the extreme value record since 1952) and ‘7-20 Zhengzhou Heavy Rainstorm’ (20 July 2021, maximum 24-hour sliding rainfall of 552.5 mm, breaking the extreme value record since 1951). The extreme rainfall and subway travel scenarios are coupled, and the STRI maps are presented in Figure 9.

Overall, compared with the base scenario, the total risk area of the 8-29 and 7-20 scenarios increased by 56.7% and 86.8%, respectively (shown in Figure 10). The very low-risk zones of 8-29 and 7-20 are reduced by 33.6% and 29.1%, respectively, demonstrating that the regional overall subway travel risk is rising due to the growth in the total area at risk. For the 8-29 Shenzhen scenario, the low- and medium-risk areas for subway travel increased by 3.135 and 1.424 km², respectively. The areas of high and very high risk for subway travel grew dramatically in the 7-20 Zhengzhou scenario, by 0.328 and 0.1 km², respectively. Subway travel risk increases significantly under the extreme rainfall scenario. Travel decisions by urban residents during flood events will be affected according to the results of risk assessments. The STRI maps can be used by citizens to choose the best travel methods before departures. Subway travel under extreme rainfall is worth more attention because risk is likely to spread through the subway line in the underground space, thereby causing greater losses of life.

Figure 10. Flooded area of the STRI in three scenarios.

4.3. Limitations and future direction

Although this study performed subway travel risk under the scenarios of different flood return periods, there are also limitations in the flood simulations based on the flat-water model (Chen et al. 2009). First, the flat-water model in flood simulation instead of hydrodynamic model: this means that this method may overestimate total volume of surface runoff as well as inundation conditions. Second, the unit rainfall was homogenous in the scenario design, and the spatial variation of rainfall was not considered in this study. Third, the drainage capacity was estimated by the situation of the sewer system. Here, the underground sewer system’s conveyance was assumed to be equal to its designed conveyance. However, the interaction between surface flow and the underground sewer system was not considered, which means that the extent of surface flooding might be overestimated in surcharge situations. In addition, flood
water may enter the subway tunnels and impact the entire subway system under extreme scenarios, which was not considered in this paper, but it is an important consideration in our future work.

On the other hand, a subway travel risk model was established in this study to capture risk variation considering the STEI and PVI. An important future direction is to assess the STEI during travel using widespread social sensing data. Moreover, the effect of flood flow velocity is simplified by the average gait speed of adults combined with human stability curves in this study. The PVI of children, elderly persons and other disadvantaged groups need to be further explored in the future.

5. Conclusion

In this study, urban flood modelling based on SCS-CN and the flat-water model by Python was performed to analyse subway travel risk during flooding events while taking travel exposure and population vulnerability into account. The risk was mapped based on the travel population estimation model in scenarios of different flood return periods.

We discovered that flooded areas had a rising tendency at five depth levels, with flood return times ranging from 20 to 500 years. The population was exposed to subways traveling throughout time, with the largest exposure occurring at 8:30 AM. Traditional censuses tend to underestimate subway travel exposure. Return periods of rainfall, time-to-peak, and duration all have an effect on the spatiotemporal trajectory of subway travel risk, which increases dramatically in extreme rainfall scenarios.

To reduce subway travel risk during flooding events, we suggested that each commuter should check the risk maps before departure and subway operators improve the risk mitigation plans for the timely release of early warning information. The effect of climate change and multisource travel data should be considered for fine flood risk assessment in future work.

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Authors’ contributions

Sun Dianchen contributed to conceptualization, methodology, software, formal analysis, investigation, data curation, writing-original draft preparation, visualization. Wang Huimin contributed to conceptualization, resources, writing-review and editing, supervision, project administration, funding acquisition. Lall Upmanu contributed to writing-review and editing, supervision. Huang Jing contributed to validation, investigation, writing-review and editing, funding acquisition. Liu Gaofeng contributed to funding acquisition.

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Data availability statement

The data used to support this study are openly available and the sources are included within the paper.

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