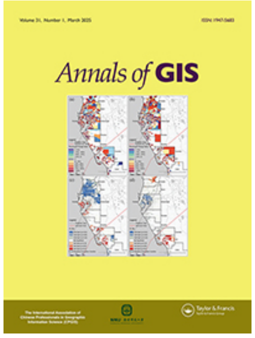

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Urban flood risk assessment and evacuation planning: a bi-level optimization model for sustainable high-density coastal areas

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ABSTRACT

Flooding caused by extreme climate change is becoming increasingly severe, especially in high-density coastal areas worldwide. Although many studies have conducted risk assessments of urban floods, most have not formed a comprehensive evacuation plan considering population distribution and flood disaster risk. To further enhance urban flood planning and emergency management for coastal areas, this study uses Victoria Harbor in Hong Kong, a typical flood-prone region, as a research area. The study first conducts a flood exposure risk assessment and classifies different regions according to flood risk levels. Then, by combining evacuation ability with the changing flood disaster and road evacuation flows, a novel bi-level optimization model is proposed to allocate zones for the citizens day and night. With the upper level using a genetic algorithm to minimize the total system evacuation time and the lower level applying a user equilibrium model for evacuee allocation, this model forms an evacuation that considers the distribution of population hotspots and the impact of flood risks on the road network. The findings of the study show that functional urban areas with high pedestrian flow, tourist spots, commercial centres, and schools are exposed to higher flood risk. Besides, the evacuation simulation of the bi-level optimization model proposed in this study matches the zoning results of actual urban activities and can effectively achieve the goal of evacuating 480,000 people within 12–18 minutes. This study innovatively proposes an effective evacuation plan that can reference the government's emergency evacuation planning work.

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Urban flooding; InVEST model; Bi-level programming; disaster evacuation strategies; hazard management

1. Introduction

Urban flooding poses a significant threat to coastal areas worldwide, particularly in densely populated regions where the risk of flood disasters is compounded by high-density infrastructure and settlement (Alderman, Turner, and Tong 2012; Felsenstein and Lichter 2014). Increased urbanization further exacerbates the impact of flooding. This is particularly prevalent in areas of high population density, where population, economic activity, and housing tend to be concentrated in less desirable flood-prone areas (Campion and Venzke 2013; Mondino et al. 2020). As extreme weather events become more frequent and severe due to climate change (Thapa, Watanabe, and Regmi 2022), effective flood risk assessment and evacuation planning in these areas becomes paramount (Ahmad, Shao, and Javed 2023; Ajjur and Al-Ghamdi 2022; Esparza et al. 2024). Therefore, exploring more effective ways to assess the flood risk and evacuate the population is still an urgent and important research issue.

Traditional studies related to flooding assessment and evacuation mainly focus on qualitatively identifying areas of refuge in the extreme event of flooding (Thapa, Watanabe, and Regmi 2022). Most of them determine the evacuation zoning by following these steps: hydrological analyses, flood disaster risk mapping (Ahmad, Shao, and Javed 2023), evacuation needs estimation (Han et al. 2023), evacuation zoning and route planning (Thapa, Watanabe, and Regmi 2022). These studies start with evacuation planning under flooding, and the research perspectives are also mostly in terms of single micro-influences such as hazard warning systems, infrastructure resilience, structural vulnerability, and flood modelling and mapping (Alabbad et al. 2024; Ye et al. 2024). For example, Thapa, Watanabe, and Regmi (2022) created detailed hazard maps using drone photogrammetry and the results of field surveys by the River Analysis System of the Centre for Hydrological Engineering and later determined appropriate evacuation routes for the population based on the disaster risk. Lee et al. (2020) designed and tested a flood-risk-considered evacuation route design methodology to plan evacuation routes based on the occurrence and

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change of evacuation possibilities in pedestrian hazardous areas.

While these traditional studies have focused on assessing urban flood risks and improving evacuation planning, many lack comprehensive evacuation zoning and planning methodologies that integrate population distribution dynamics and flood risk considerations (Chen et al. 2012; Han et al. 2023). Notedly, recent studies proposed that it is important to consider more aspects when modelling the evacuating routes and zones (Chen et al. 2012). Particularly, Han et al. (2023) combined time-varying flood hazards and estimated congestion levels to improve evacuation planning. Bernardini et al. (2019) modelled the dynamic process of crowd movement towards a safe area for the safe evacuation of citizens based on historical flood risk data. This research also further emphasizes the need to anticipate the time-varying characteristics of the population while considering the actual evacuation capacity of the roads. The spatial distribution and evacuation efficiency of citizens are different during the day and night, but this comparative analysis is still understudied.

In response to this challenge, this study presents a novel bi-level optimization model for sustainable high-density coastal areas, focusing on Victoria Harbor in Hong Kong – a prototypical flood-sensitive region (Qiang et al. 2021; Shen et al. 2023). The model begins with a thorough flood exposure risk assessment, delineating areas based on varying levels of flood risk. Subsequently, it combines considerations of evacuation capacity with evolving flood disaster scenarios and road network dynamics in daytime or night-time to develop a comprehensive evacuation zoning and planning model. At the core of this model is a bi-level framework that addresses both strategic and tactical aspects of evacuation planning. The upper level employs a genetic algorithm (GA) to optimize the allocation of evacuation zones, minimizing overall system evacuation time. Meanwhile, the lower level utilizes a user equilibrium (UE) method to allocate evacuees efficiently, considering factors such as traffic flow and road network resilience.

In this study, the overarching goal is to enhance the resilience and sustainability of coastal communities in the face of increasing urban flooding and climate change threats. The main aim is to present an effective flood risk assessment and planning framework that incorporates a bi-level optimization model. This model is designed to accurately measure flood risk and optimize evacuation strategies specifically for high-density coastal areas. Through this research, we seek to contribute to the advancement of urban flood management practices and provide actionable insights for emergency planning authorities and organizational management departments.

In the following sections, we detail the methodology employed in conducting flood risk assessments, elucidate the formulation and implementation of the bi-level optimization model, and discuss the implications for urban flood management and emergency preparedness. The results section offers practical assessment and planning strategies to accurately measure flood risk and optimize evacuation in high-density coastal areas. The discussions of this research contribute to advancing urban flood management practices and provide valuable insights for emergency evacuation planning authorities and organizational management departments.

2. Methodology

2.1. Research area and scenario

This study takes the famous tourism spot, Victoria Harbor in Hong Kong, as the research area, as shown in Figure 1. Victoria Harbor is located around 31.40527° E, 121.48941° N, between Hong Kong Island and the Kowloon Peninsula in Hong Kong, China. It is one of the world's three great natural harbours, leading the economic and tourism development of Hong Kong.

According to the Hong Kong Observatory (HKO)'s observations in Victoria Harbor, the annual rate of increase in rainfall over the period 1884–2023 is 2.3 millimetres per annum, and the mean sea level in Hong Kong has been rising at a rate of 31 mm per decade during 1954–2019 (Qiang et al. 2021; Shen et al. 2023). Frequent extreme weather events superimposed with rising sea levels pose an increasing risk of flooding in low-lying coastal areas, especially in densely populated Hong Kong (Dang et al. 2018; Gu and Liu 2024; Wu and Lin 2012). Therefore, Victoria Harbor is an excellent place to conduct this study and test the proposed bi-level optimization model.

The flooding scenario under study was set at the moment of the heaviest extreme rainfall to simulate the most extreme flooding risk and evacuation of crowds. According to the HKO, 158.1 mm of rainfall was recorded in one hour between 11:00 and 12:00 midnight on 7 September 2023, the highest recorded since 1884 when records were kept. This severe and extreme rainfall has caused severe flooding on roads in Hong Kong, greatly affecting the safety of residents travelling there. Therefore, we use this extreme rainfall record as the research scenario.

Figure 1. Geographical location, road information, and planning units of the research area.

2.2. Data preparation

The data used in this study can be divided mainly into the one used for input into the InVEST model for calculating flood risk (section 3.1) and the other used to simulate evacuation routes for input into the bi-level optimization model (section 3.2).

The data used to calculate the flood risk include the area of interest (AOI), land-use/land-cover data (LULC), and Global Hydrologic Soil Groups (HSG) (Lu et al. 2007). The AOI and the corresponding planning unit are obtained from the Hong Kong Government Open Data Platform (DATA.GOV.HK). We also download LULC data with a resolution of 30 m from annual land cover datasets (Yang and Huang 2021), divided into nine categories: Cropland, Forest, Shrub, Grassland, Water, Snow/Ice, Barren, Impervious, and Wetland. Meanwhile, HSG is downloaded from ORNL-DAAC and cropped to the study area with a resolution of 250 m. Types A, B, C, and D of the HSG data correspond to low, medium-low, medium-high, and high runoff potentials, respectively (Ross et al. 2018). Since the basic unit of the study is the planning unit and the HSGs in the study area are essentially the same, the impact accuracy of the acquired remote sensing data meets the needs of the study.

For the data used to model the evacuation paths, this study obtained the intersection points and centerlines from the road network product on the DATA.GOV.HK platform. These data are cropped by the AOI of the area in ArcGIS Pro, and each intersection is connected to the head and tail of the centerline using the Spatial Join tool to obtain the origin intersection (O) and destination intersection (D) of each road section. From this, we get 3,744 road sections, corresponding to a total of

2,602 intersections. Subsequently, based on the connectivity between road segments and the actual length, the connectivity of each intersection is obtained, and the $2{,}602 \times 2{,}602$ adjacency matrix and distance matrix between each pair of intersections (ODs) are further constructed.

Meanwhile, we also assigned the following parameters to each road section to better simulate the actual road conditions, including the road length, design speed (60 km/h), occupancy (1000 pcu/h), free-flow travel time, lane number, one-way land, or not. Last but not least, the study selects 15 evacuation exits as alternatives based on the connectivity of the peripheral roads to the surrounding urban roads. The bi-level optimization model in Section 3.2 will select the most effective six evacuation exits to evacuate the crowd in the shortest time.

2.3. Urban flood risk assessment

This study uses the Urban Flood Risk Mitigation module of the InVEST 3.14.1 model to calculate runoff and flood volumes for a certain rainfall depth, which has been practiced and validated in several urban flood-related studies.

The InVEST model is an Integrated Valuation of Ecosystem Services and a trade-off model. It is a modelling system developed jointly by Stanford University, The Nature Conservancy (TNC), and the World Wide Fund for Nature (WWF) to provide decision-makers with a scientific basis for weighing the benefits and impacts of human activities by simulating changes in the quantity and value of ecosystem services under different land cover scenarios for the assessment of ecosystem service functions (Capital Project, Mandle, and Batista 2020). The InVEST model can quantify and express the ecosystem service function in spatial form, effectively identifying urban spatial flooding hazard points. The study is based on the following steps and calculation methods to obtain the corresponding flooding volume of each fishing net through the InVEST model.

Firstly, we input the fishing nets as the study area, the maximum ever precipitation of 158.1 mm as the rain flow depth, and the land use data were imported into the HSG after inputting them and based on the number of curves used by the United States Department of Agriculture (USDA) for estimating the rainfall-runoff, as follows (Gopal 2016):

$$Q_{p,i} = \begin{cases} \frac{\left(P-\lambda S_{maz_i}\right)^2}{P+(1-\lambda)S_{max_i i}} & \text{if } P > S_{max_i i} \\ 0 & \text{otherwise} \end{cases} \quad (2-1)$$

$$S_{max_i i} = \frac{25400}{CN_i} - 254 \quad (2-2)$$

$$R_i = 1 - \frac{Q_{p,i}}{P} \quad (2-3)$$

$$R_{m3_i} = R_i \cdot P \cdot pixel.area \cdot 10^{-3} \quad (2-4)$$

$$Q_{m3_i} = Q_{p,i} \cdot pixel.area \cdot 10^{-3} \quad (2-5)$$

Where, $Q_{p,i}$ represents the runoff for each 500×500 pixel i defined by a land use type and soil characteristics in mm with the Curve Number method. P is the design rainfall depth which equals 158.1 mm. $S_{max_i i}$ is the potential retention in mm, and λS_{maz_i} is the rainfall depth needed to initiate runoff ($\lambda = 2$ for simplification). S_{max} is a function of the curve number, calculated by CN, the empirical parameter that depends on land use and soil characteristics (NRCS-USDA 2004). Based on these settings, the runoff retention per pixel R_i, the runoff retention volume per pixel R_{m3_i} and the runoff volume (also referred to as flood volume) per pixel Q_{m3_i} can be measured.

Based on the flood volume results from the InVEST model, this study can use the natural breakpoint method to classify the flood risk of different areas within the study area into five classes, from low to high. The Natural Breaks (Jenks) method is a commonly used hierarchical classification method that uses clustering to maximize the similarity within each group and the dissimilarity between external groups while also considering that the range and number of elements between each group are as similar as possible. As a result, this study assessed the flood risk of each subarea in Victoria Harbor when faced with extreme precipitation, which will further guide the road network and evacuation planning for the next section 2.4.

2.4. Bi-level optimization model

After urban flood disasters occur, evacuation planning often needs to simultaneously fulfil multiple objectives, such as minimizing the evacuation time for all evacuees and selecting the most suitable routes. In practical evacuation planning, achieving multiple objectives often involves decision-makers at multiple levels (Li, Qiang, and Cervone 2024). To address the decentralized decision-making problems and achieve multiple objectives, this study establishes a bi-level optimization model. The technical route is shown in Figure 2.

The bi-level optimization model targets system optimization problems and typically consists of two hierarchical levels, each with its objective functions and constraints. The upper level (or leader model) possesses certain control and

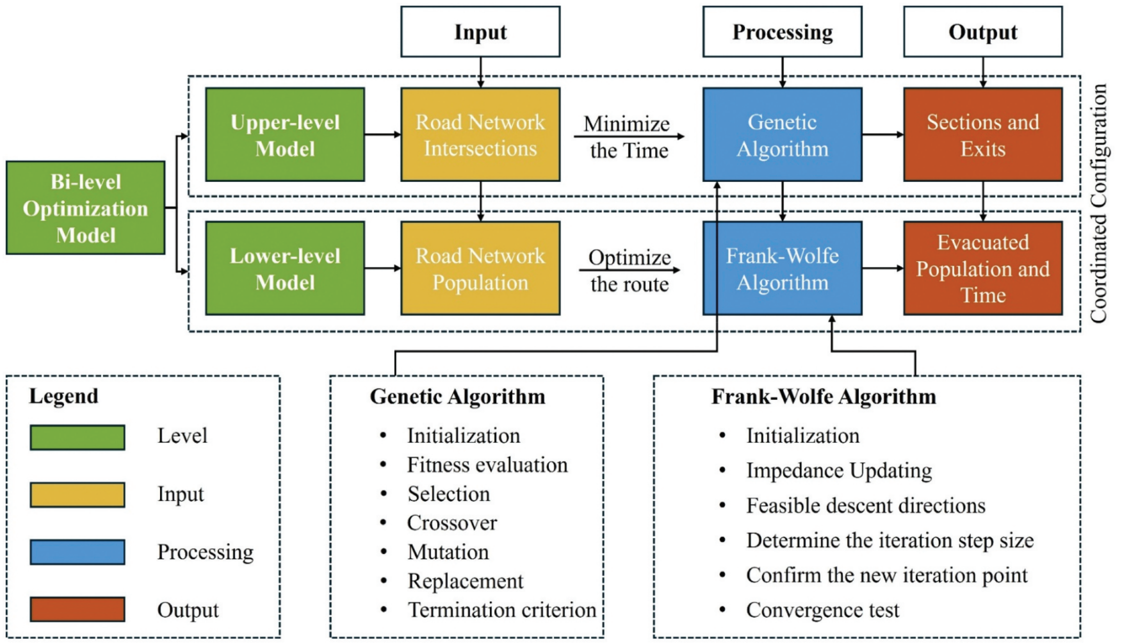

Figure 2. The framework of the bi-level optimization model in the study.

guidance rights, holding a more significant and global position, and formulates overall development strategies to guide the decisions of the lower level (or follower model). Decision-makers at the lower level make decisions within their authority based on the development strategies and ideas formulated by the upper-level decision-makers, and their decisions must comply with the overall strategy set by higher-level decision-makers. Meanwhile, when making decisions, upper-level decision-makers must also consider the reactions of the followers. A general bi-level optimization model can look like the one proposed by Bracken and McGill (1973):

Upper Level (Leader Model):

$$\min_{x} F(x, y) \quad (2-6)$$

$$\text{s.t.} G(x, y) \le 0 \quad (2-7)$$

Lower Level (Follower Model):

$$\min_{y} f(x, y) \quad (2-8)$$

$$\text{s.t.} g(x, y) \le 0 \quad (2-9)$$

In the upper level, F is the objective function, x is the controlled variable, and the constraints on variable x are denoted by G. In the lower level, f is the objective function, y is the controlled variable, and the constraints on variable y are denoted by g. $y = y(x)$ represents the response function, which serves as a common constraint linking the upper-level and lower-level models. The value of variable$x$ constrains y in the lower level, while the value of y in the lower level influences the upper level in return. The response function affects the decisions of both the upper and lower levels, thus achieving a balance of feasible solutions under dual constraints.

In this study, the objective of the upper-level model is to minimize the total evacuation time of the system by identifying the optimal evacuation points, while the objective of the lower-level model is to determine the optimal evacuation routes for each evacuee. Once the upper-level model identifies the optimal solution, the lower-level model is activated. Through this iterative process between the two levels, the model can identify a combination of evacuation points and corresponding personnel allocation schemes that minimize the total evacuation time.

2.4.1. Upper-level model

The optimization of evacuation point locations is crucial for improving the efficiency of flood evacuation. Depending on the allocation of locations, evacuation points significantly impact the total evacuation time of individuals (Bayram, Tansel, and Yaman 2015; Xie et al. 2014). GA, as a heuristic optimization method, is widely used in the field of evacuation planning, demonstrating excellent performance in the selection of evacuation points (Mollah et al. 2018; Xie et al. 2018; Zhong et al. 2020). Therefore, the upper-level model employs the GA to determine the optimal evacuation points, aiming to minimize the total evacuation time of the system.

GA was proposed by John Holland in 1975 (Holland 1992), drawing inspiration from natural adaptation and following the principle of natural selection, 'survival of the fittest'. Through continuous iterative evolution, excellent genes accumulate persistently, leading to the emergence of even better individuals. Similar to the process of biological evolution, favourable traits are continuously inherited, while unfavourable traits gradually disappear. In this way, GA gradually finds the global optimal solution through generations of genetic operations within the population.

2.4.1.1. Model building.

$$minT(y) = \sum_{a(i,j)\in A} x_{ij}(y) \times t_{ij}\left(x_{ij}(y)\right) \qquad (2-10)$$

The objective function of the upper-level model is defined as Equation 3-10. In this equation, $T(y)$ represents the total evacuation time, given an evacuation network $G(N, A)$, where the sets of nodes and directed links are denoted by $N(n \in N)$ and $A(a \in A)$ respectively. $a(i,j)$ represents the link a connecting nodes i and j. $x_{ij}(y)$ denotes the evacuation personnel from node i to node j. $t_{ij}\left(x_{ij}\right)$ represents the evacuation time from node i to node j, which is determined by the flow capacity of link $a(i,j)$ in the network.

2.4.1.2. Constraints. The upper-level model is subject to the following constraints:

(a) Construction of the travel time cost impedance matrix: This matrix defines the travel time between each pair of locations and is used to calculate the shortest paths. The construction of the travel time cost impedance matrix ensures that the calculated evacuation time is based on the actual road network and traffic conditions under flood disasters.
(b) Shortest path constraint: A function is set to compute the shortest path for each pair of origin and destination points, ensuring that people always choose the fastest route for evacuation.
(c) Population evacuation constraint: For each location, if the population is greater than 0, the evacuation time from that location to its corresponding evacuation point is calculated; otherwise, the evacuation time is 0.
(d) Evacuation point constraint: Each location is assigned to an evacuation point based on its distance to each evacuation point, ensuring that each location has a clear evacuation destination.

2.4.1.3. Model solving. The specific steps of the GA are as follows:

STEP 1. Initialization: Randomly generate the initial population.

STEP 2. Fitness evaluation: For each individual in the population, its fitness is validated.

STEP 3. Selection: Select pairs of individuals from the population to be parents based on their fitness scores.

STEP 4. Crossover: For each pair of parents, create an individual child by randomly choosing from one of the two parents.

STEP 5. Mutation: Mutation is the process in which one or a few features from the genotype/features within the chromosome are altered. An adaptive strategy is adopted here to dynamically adjust the probabilities of crossover and mutation based on the fitness of the population, which helps the algorithm explore the search space more effectively and find the optimal solution.

STEP 6. Replacement: Replace the least fit individuals in the population with the child individuals.

STEP 7. Termination criterion. After reaching the maximum number of iterations, the algorithm terminates and outputs the computed results.

2.4.2. Lower-level model

Given the evacuation strategy determined by the upper-level model, further research is conducted to construct the lower-level model. The objective of the lower-level model is to determine the optimal evacuation route for each evacuee. Based on Wardrop's first principle, a fundamental assumption in the evacuation network is that evacuees will choose a path they perceive to be the shortest under the current circumstances (Wardrop and Whitehead 1952): Each non-cooperative user seeks to minimize the cost of transportation. The traffic flows that satisfy this principle are usually called UE flows since each user chooses the best route. Specifically, a user-optimized equilibrium is reached when no user may lower his transportation cost through unilateral action. The UE traffic assignment model is formulated as the lower-level model to model the behaviour of evacuees.

2.4.2.1. Model building. According to the assumption constructed by Beckmann that there is a fixed demand between OD pairs, the objective function of the lower-level model is formulated as below equation 2-11, subject to equations 2-12, 2-13, 2-14. (Beckmann, McGuire, and Winsten 1956):

$$minZ(x) = \sum_{a\in A} \int_0^{x_a} t_a(x)dx \qquad (2-11)$$

$$\text{s.t.} \sum\nolimits_{k} f_k^w = q^w, \forall k \in P^w, w \in W \quad (2-12)$$

$$f_k^w \geq 0, \forall k \in P^w, \forall w \in W \quad (2-13)$$

$$x_a = \sum_{w} \sum_{k \in P^w} f_k^w \sigma_{ak}^w, \forall a \in A \quad (2-14)$$

2.4.2.2. Constraints. The lower-level model is subject to the following constraints:

(a) All pedestrian evacuation demands are met: $\sum_{k} f_k^w = q^w, \quad k \in P^w, w \in W$;
(b) Non-negative constraint on the number of evacuees: $f_k^w \geq 0, \quad k \in P^w, \quad w \in W$;
(c) The number of evacuees for the specified link is equal to the sum of the number of evacuees for all paths passing through it: $x_a = \sum_{w} \sum_{k \in P^w} f_k^w \sigma_{ak}^w, \quad a \in A$.

In this equation, W is the set of all OD pairs, $t_a(x)$ is the evacuation time function for link a, f_k^w is the number of evacuees on path k between OD pair w, q^w is the number of evacuees waiting to be evacuated between OD pair w, P^w is the set of all paths between OD pair w, x_a is the number of evacuees on link a, and σ_{ak}^w is a binary parameter, it takes a value of 1 if link a is on path k between OD pair w, otherwise it takes 0.

When the traffic volume increases, the evacuation speed decreases. This study quantifies the evacuation time caused by congestion using the classical BPR (Bureau of Public Roads) function (United States 1964):

$$t_a(x_a) = t_a^0 \left[1 + \alpha \frac{x_a}{\gamma c_a}^{\beta} \right] \quad (2-15)$$

In Equation 3-13, $t_a(x_a)$ is congestion resultant evacuation time on link a under the number of evacuees x_a, t_a^0 denotes free-flow travel time on link a, γ denotes the road capacity discount factor based on the flood risk levels, The discount factor is taken from 1 to 5 as 1, 0.75, 0.5, 0.25, 0 depending on the flood risk levels. c_a denotes capacity of the link a, α, β are constants, set as 0.15 and 4.

2.4.2.3. Model solving. The upper-level model provides the proportion of evacuees that each evacuation point should accommodate, with these allocation proportions stored in chromosomes as inputs for the lower-level model. The lower-level problem utilizes the incoming allocation proportions to calculate the evacuation flow for each OD pair, which is then used to evaluate the fitness of the upper-level chromosomes. The lower-level model is implemented using the Frank-Wolfe algorithm (Frank and Wolfe 1956). Applying the Frank-Wolfe algorithm to solve the lower-level UE model. The specific steps are as follows:

STEP 1. Initialization: Perform a 0–1 traffic assignment to obtain the allocated traffic flow on the shortest paths.

STEP 2. Update the link impedance: Based on the BPR function.

STEP 3. Construct feasible descent directions: Based on the updated impedance, perform another 0–1 traffic flow assignment to obtain an additional set of traffic flows.

STEP 4. Determine the iteration step size: Employ a binary search method for the solution.

STEP 5. Confirm the new iteration point.

STEP 6. Convergence test.

Through the use of a bi-level optimization model, this study is able to address complex evacuation planning problems in a more detailed manner. The application of the bi-level optimization model not only ensures the global minimization of total evacuation time but also achieves individual minimization of evacuation personnel travel time.

3. Results

3.1. Flood risk assessment results

Figure 3a shows the flood volume calculated based on the InVEST model in the study area, divided into five disaster risk levels from low to high using the Natural breaks (Jenks) method. Combined with the real community map in 2023 from ArcGIS Pro shown in Figure 3b, it can be observed that the highest level of risk occurs in the middle of Victoria Harbor, corresponding to the urban functions of Elizabeth Hospital and Kings Park Playground, as well as the northwest (corresponding to Mong Kok Shopping District). Considering the urban topography, it can be seen that the high-risk areas are also related to the distribution of mountains.

The regions with the fourth risk level are mainly around the areas affected by the highest risk: firstly, there are four planning units distributed in the south, with famous attractions such as Kowloon Park, Yau Ma Tei Shopping District, Tsim Sha Tsui Shopping District, a University, and several high-end hotels situated from west to east; secondly, there are five units in the east, with the University dormitories and high-density old residential areas; and one unit in the north is distributed with several important hospitals, such as Kowloon Hospital. The third risk level further surrounds the high-risk areas, covering almost the entire eastern part of

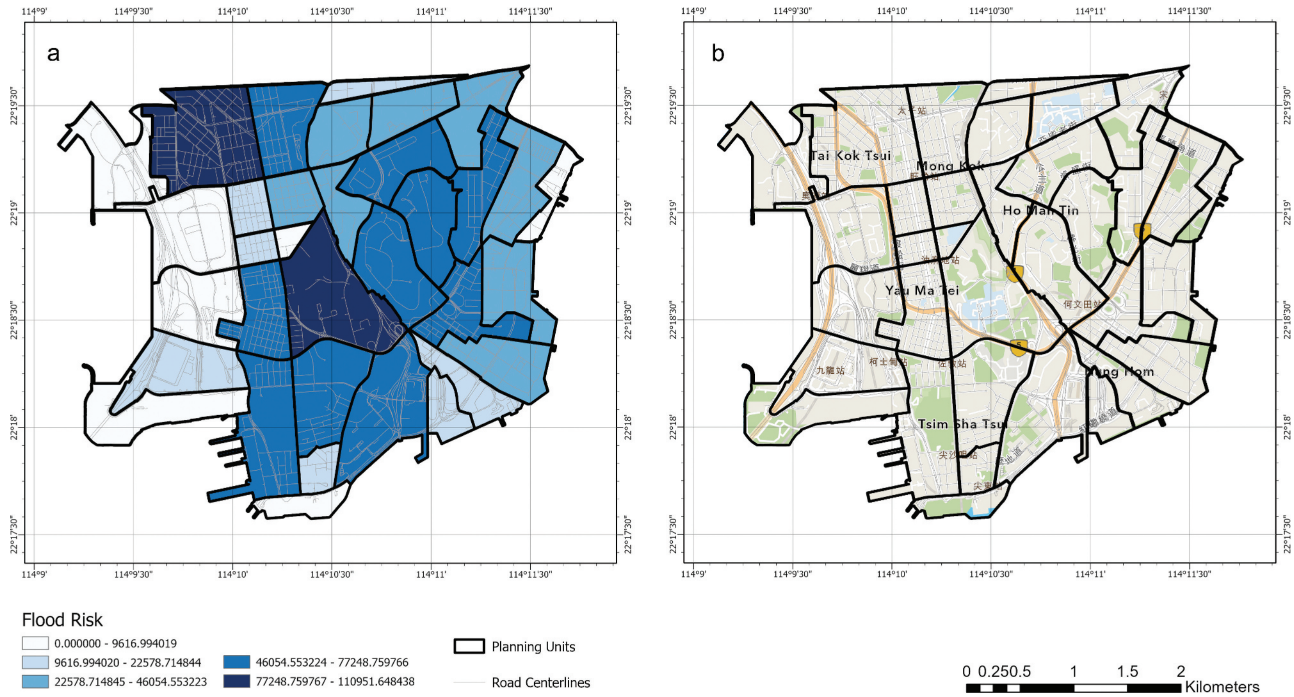

Figure 3. Five flood risk levels of the planning units based on the natural breakpoint approach.

Victoria Harbor, where more urban high-density communities are located. Only a few units, such as the Kowloon Cultural District and the Avenue of Stars along the coast, show a low flood risk status. However, these areas still face the risk of seawater inundation during prolonged extreme rainfall, thus still facing significant disaster risks that cannot be ignored.

Overall, Victoria Harbor is home to various tourist attractions and important urban functional areas. In contrast, areas with higher pedestrian traffic (such as Mong Kok, Avenue of Stars, and playgrounds) face more severe flood risks. Therefore, conducting flood risk assessments and improving evacuation efficiency in these areas are particularly important.

3.2. Flood evacuation planning results

The site of this study, Victoria Harbor, is a significant tourist area. According to the population flow, the total population to be evacuated during the day is 480,000, and the remaining total population to be evacuated after the departure of tourists at night is 240,000. Additionally, the spatial distribution of the population varies. We assume that the population is more dispersed during the day, while it is more concentrated in residential buildings at night.

Figure 4 illustrates the results of the daytime evacuation sections and six exits obtained using the bi-level optimization model. It can be observed that the evacuation sections roughly divide Victoria Harbor into six blocks according to the road network, namely, east, south, west, and north, and take into account the impact of flood risk: areas with higher risks are jointly covered by 2–3 sections, while areas with lower risks are covered by one section. Essentially, each block corresponds to an evacuation exit, which tends to be located on the edge of units with the highest risk levels in each area, thereby facilitating the rapid evacuation of the population more effectively. Exits 1–4 connect the northern part of Victoria Harbor to the main roads of other areas in Hong Kong, while exits 5 and 6 can rely on Hong Kong's developed dock and shipping systems for evacuation.

Figure 5 displays the results of the night-time evacuation sections and six exits based on the model. Comparing with the daytime results, it can be observed that the overall evacuation zones are roughly similar, except that in the northern part, section 4 now accommodates a larger portion of the population evacuation originally attributed to section 5 during the day. This could be due to the fact that the Mong Kok and Prince Edward areas corresponding to section 5 are not only bustling commercial areas but also densely populated with residential buildings and apartment hotels, resulting in significantly higher population density at night compared to the areas corresponding to section 4. Regarding the evacuation exits, exits 1–3 are close to

Figure 4. Evacuation sections and six exits based on the daytime bi-level optimization model.

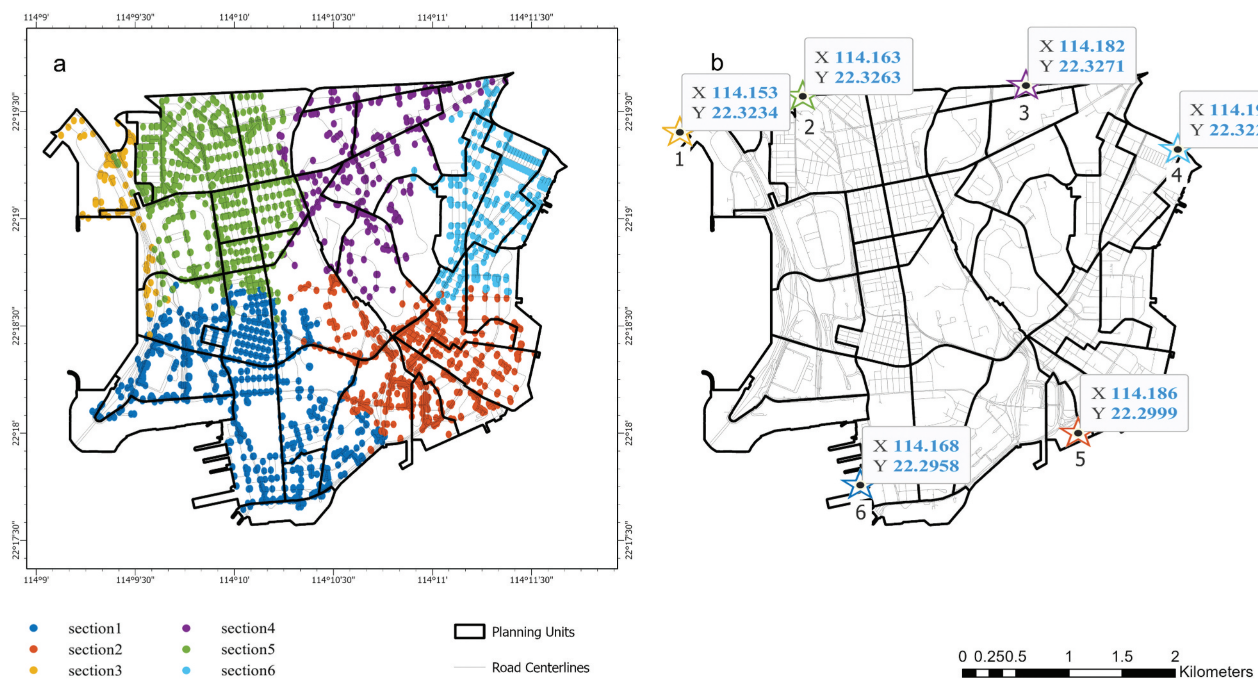

Figure 5. Evacuation sections and six exits based on the nighttime bi-level optimization model.

their daytime positions but with slight differences. This adjustment is due to the aforementioned modifications in the coverage of zones. However, the zones corresponding to exits 4–6 remain unchanged, hence their positions are consistent with the daytime exits.

Table 1 further illustrates the evacuation population and the estimated maximum time required for complete evacuation for each evacuation exit during the day and night. The results indicate that the majority of evacuations can be completed within 12–18 minutes. The average evacuation time for all exits during the day is approximately 14.6 minutes, while at night, it is around 14.5 minutes. It can be observed that although the total evacuation population is lower at night, considering factors such as sleep

Table 1. Based on the bi-level optimization model, the evacuee population and maximum travel time for each exit in daytime and nighttime.

Model	Measurement	Exit 1	Exit 2	Exit 3	Exit 4	Exit 5	Exit 6
Daytime	Population (people)	65320	154226	28153	53667	141720	36914
	Travel Time (mins)	13.1308	15.1100	14.1791	14.2514	18.1000	12.7541
Nighttime	Population (people)	32467	81168	15865	23982	61061	25457
	Travel Time (mins)	15.9951	12.1409	12.1485	18.1000	15.6653	12.7541

and navigating downstairs, people's awareness and response to evacuation are not as rapid as during the day, resulting in roughly similar average times. Furthermore, regardless of day or night, exit 6 has the shortest evacuation time. This is because the corresponding zone has the lowest flood risk coverage, thus not significantly impacting the road speed and capacity. Conversely, exits 4 and 5 have relatively longer average times, attributed to the lower road network density and moderate flood risk coverage in their corresponding zones, resulting in comparatively slower overall road capacity than other areas.

4. Discussion

This study conducts a flood risk assessment for the Victoria Harbour area in Hong Kong and proposes an optimized bi-level model to implement evacuation simulations. The research provides an improved evaluation and planning framework for urban flood management. The findings offer valuable insights to emergency evacuation planning agencies and organizational management departments. This chapter will further explore the practical implications of our results for urban flood management and emergency preparedness.

This study first utilized the InVEST model to calculate flood volumes in the Victoria Harbour area and divided the research zone into five distinct disaster risk levels using the natural breaks method. The results indicated that the central area and surrounding tourist attractions, shopping districts, and schools are all at high risk of flooding. These high-risk areas are located in densely populated urban communities, particularly around schools, where identifying safe locations and evacuation routes is crucial (Karpouza et al. 2023).

Notably, the InVEST model used in this study provides a more rapid and efficient risk assessment approach, integrating geospatial synthesis methods, including GIS, remote sensing, and rainfall-runoff modelling, which aligns with previous studies (Gu and Liu 2024; Youssef et al. 2021). However, it did not focus on detailed hydrological and hydraulic factors of flood disasters (Bathrellos et al. 2016; Long and Gao 2023), as fine-scale flood simulations, although accurate, are time-consuming and not conducive to governmental decision-making in practical planning processes (Kadaverugu et al. 2022). This study aimed to achieve rapid regional flood zoning and understand the heterogeneity of flood risk levels between evacuation zones, which is significant for formulating swift flood prevention measures and evacuation plans.

Many flood disaster studies may focus more on the impact of terrain and hydrology on floods (Baratti et al. 2012; Sriwongsitanon and Taesombat 2011), whereas our study focuses on urban places, particularizing the impact of floods on cities. Even in relatively flat areas, if they are located in high-density population or commercial activity zones, their risk level can be several times higher than in uninhabited areas (Gu and Liu 2024; Tang et al. 2024). Considering Victoria Harbour is an important tourism area, the number of people needing evacuation during the day reaches 480,000; at night, it drops to 240,000. We assume that the daytime population distribution is more dispersed, whereas it concentrates in residential areas at night. The study's findings show that the six evacuation exits identified using an optimized bi-level model effectively consider differences in flood risk and utilize Hong Kong's advanced wharf and shipping systems as supplementary evacuation means. These six exits correspond to different directions around Victoria Harbour, capable of quickly and effectively evacuating people. This model takes into account road networks, flood risks, and population distribution, demonstrating performance and effects superior to those of relevant models in previous studies (Apivatanagul, Davidson, and Nozick 2012; Liu et al. 2024; Wang and Zhang 2018). In addition, the optimized bi-level model is highly applicable and is not only applicable to Hong Kong but also other cities for exploring evacuation issues.

Through the above discussion, we can see that the current research not only provides specific flood risk assessments for the Victoria Harbour area but also offers references for flood risk management in other similar cities.

Nevertheless, ongoing research remains necessary to improve and refine existing evacuation strategies and technologies continuously.

5. Conclusions

In this study, a flood risk analysis was carried out for Victoria Harbor, a famous tourist attraction in Hong Kong, and a bi-level optimization model was proposed and improved to simulate the evacuation of the population from the flooded area with evacuation sections and exits. The improvement of this model over the traditional model is that it takes into account the flood risk, road capacity, and the difference in the total number and distribution of population between day and night in each sub-area.

Our results indicate that Victoria Harbor continues to face an extremely high risk of flooding, and areas with higher pedestrian traffic face higher flood risks. Besides, the bi-level optimization model obtains zoning results in the evacuation simulation of Vitoria Harbor that are more compatible with actual urban functional activities and effectively achieve the evacuation of hundreds of thousands of people in 12–18 minutes. Taken together, this study contributes to further accurately identifying the flood risk and achieving more efficient crowd evacuation under multifactorial considerations in high-density areas, thereby enhancing urban resilience and safety to disaster risks and achieving sustainable development in high-density areas.

However, there are some limitations that can be improved in future studies. Firstly, the impact of seawater inundation could be considered superimposed on the assessment of flood risk in addition to rainfall, topography, and site conditions. However, due to the lack of available data for this modelling, it was not carried out in this study. In addition, when evacuating the population, it could be refined to take into account the proportion of the population in vulnerable groups, which may affect the exit and time of evacuation (Wu and Lin 2012). Thirdly, more consideration can be given to the evacuation response time and individual behavioural patterns (Li, Qiang, and Cervone 2024), which may vary depending on the type of disaster event. Finally, in the evacuation process, it may be beneficial to integrate various modes of transportation (such as motorcycles or cars) to plan evacuation behaviours, thus further enhancing the efficiency of the evacuation process.

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