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Review papers

An overview of flood evacuation planning: Models, methods, and future directions

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ABSTRACT

Floods are one of the most destructive disasters and require a range of structural and non-structural measures to reduce their impacts. Evacuation is an effective non-structural measure to increase the resilience of flood-affected areas. This study aims to provide a systematic overview of evacuation planning for urban flood scenarios in terms of theories, methods, models, and techniques for both pedestrians and vehicles. The review addresses key components such as flood simulation modelling, flood hazard assessment methods, shelter identification, evacuation route development, and evacuee movement modelling. Among these, we highlight the comparison and analysis of flood hazard assessment methods, shelter optimisation and route optimisation. Additionally, a systematic analysis and comparison of evacuation shelters, evacuation route algorithms, and evacuee movement models are presented. Metaheuristic algorithms have been shown to perform well for evacuation routes. Finally, the insights into four recent directions for enhancing evacuation plans include consideration of pedestrian and vehicle movement speeds, evacuee psychology, multimodal emergency evacuation, and the effect of overhead power lines on rescue operations.

1. Introduction

In recent years, climate change has led to higher and more significant extreme natural disasters, including floods, draughts and hurricanes (IPCC, 2023; UNDRR, 2022). Among these disasters, floods have a high frequency, affect a large number of people, cause large economic losses, and have a high death toll (WEF, 2021, 2020, 2019), as also summarised in Figs. 1 and 2. We processed the database collected by the University of Leuven, Belgium, there were 175 floods worldwide, with direct economic losses of $44,767 billion, affecting 577,066,696 people, and 7,910 deaths in 2022 (EM-DAT/CRED). Pakistan floods in 2022 affected 33 million people, killed 1,739, and caused $15 billion in economic damage in 2022 (CRED., 2022). Serbia's mega-floods led to the evacuation of more than 39,000 people in 2014 (Radosavljevic et al., 2017). Indonesia suffered flooding, affecting about 1 million people in 2021 (ADRC, 2021, 2020).

Measures taken to mitigate flooding can be categorized into two types: structural and non-structural measures (Zhou et al., 2017). Structural measures include dams, levees, flood control reservoirs, bank protection, and so on (Kryžanowski et al., 2014). Structural measures take a long time to build, are very costly to design, construct, and maintain, cannot be easily altered after construction, expected to have a negative impact on the environment (D'Ayala et al., 2020). Non-structural measures include flood forecasting and warning (Borowska-Stefańska et al., 2023; Bernardini and Ferreira, 2021), increasing the resilience of flood-prone areas, implementation of Natural Flood Management (NFM), including low-impact development (LID) and Sustainable Drainage Systems (SuDS) and reducing risk through evacuation, and so on (Wang et al., 2024a; Suresh et al., 2023). For instance, implemented of "sponge city" programmes, including green infrastructure (GI), best management practices (BMPs), and low-impact development (LID), has achieved remarkable results without the construction of significant infrastructures (Ding et al., 2022). Non-structural measures do not generally cause significant damage to the environment and

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are more in line with the concept of sustainable development (Suresh et al., 2023; Wang et al., 2021b).

Flood hazard assessment and evacuation planning are effective flood damage mitigation measures (Yang et al., 2022b). Evacuation's most prominent factors are evacuation experiences, evacuation instructions, and hazard assessment (Jiang et al., 2022). Urban flood and flash flood hazard assessment can be conducted with flood information such as water depth and velocity, combined with the topography of the inundated area, to classify the level of hazard (He et al., 2021; Li et al., 2021), In addition, the compounding effects of strong winds and tidal currents can affect the flood hazard and needs to be taken into account particularly in coastal flood-prone areas (Leijnse et al., 2021).Different hazard level thresholds have to be determined based on the receptors, e.g. pedestrian, vehicle, or infrastructure (Musolino et al., 2020a; Pregnolato et al., 2017; Martinez-Gomariz et al., 2016). Flood information such as depth and velocity of water can be obtained from hydrodynamic models such as Delft3D, HEC-RAS, MIKE11, SOBEK, DIVAST, Tuflow, Jflow, Flood Modeller and SFINCS are widely used in flood simulation (Baky et al., 2019; Farooq et al., 2019; Hunter et al., 2008). These models are developed with different accuracy and computational efficiency. Furthermore, considering the compound impact of flooding from different sources, including fluvial, pluvial, tidal, wind- and wave-driven flooding, can be important (Leijnse et al., 2021). Selecting correct models is crucial as unsuitable models can lead to incorrect velocities which have a significant impact on flood hazard (Arrighi et al., 2019; Ahmadian et al., 2018; Kvočka et al., 2017), as well as having a reasonable trade-off between accurate physical representation and computational efficiency for the intended flood problems.

Flooding particularly can be very destructive in dense urban areas (Yang et al., 2022b). Hazard mapping is the fundamental of identifying safe shelters, safe routes, and saving for trapped populations, and in turn is crucial for flood evacuation (He et al., 2021). Evacuation planning can be initiated after the flood hazard mapping. Significant aspects of evacuation are the identification of safe evacuation shelters, routes to evacuation shelters, and the evacuation of people (Esposito Amideo et al., 2019). An effective evacuation plan can be key to minimizing injuries and fatalities.

Flood evacuee movement models are used to observe the evacuee,

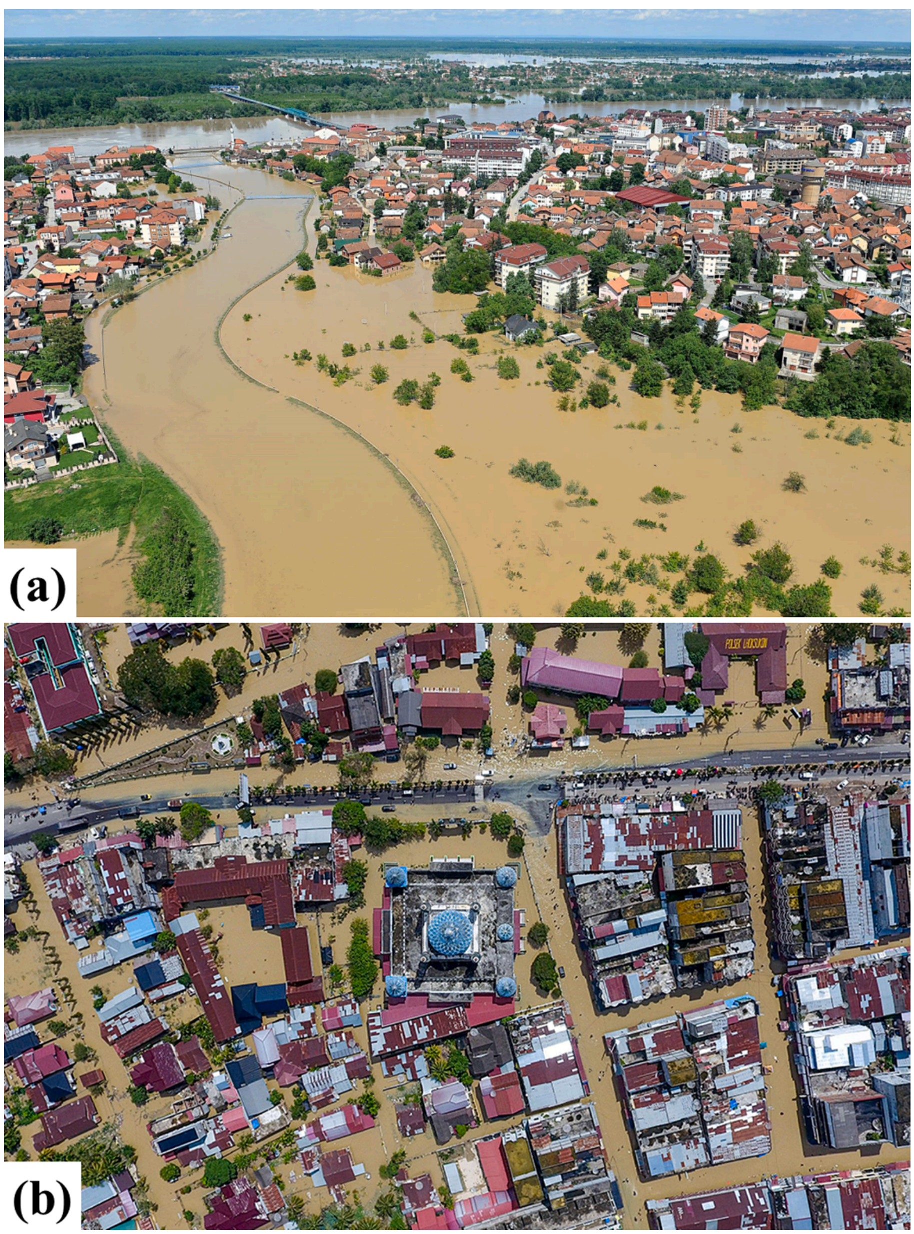

Fig. 1. Frequent occurrence of global flood disasters. (a) Floods in Serbia in 2014 (The guardian, 2014). (b) Floods in Indonesia in 2022 (The paper, 2022).

categorized into macro-evacuation models and micro-evacuation models (Kaur and Kaur, 2022). Macro-evacuation models treat evacuee movement as a homogeneous flow, abstracting the system as a whole and considering the movement of evacuees as a group. Micro evacuation models incorporate specific characteristics of evacuees (e.g., age, gender, ability, body structure, and speed of movement) (Musolino et al., 2022; Xia et al., 2011; Yusoff et al., 2008). Gwynne et al. (1999) classified evacuation models into three categories: optimisation, simulation, and risk assessment, and summarised 22 evacuation models. Zheng et al. (2009) summarised seven optimised evacuee movement models. Moreover, Niyomubyeyi et al. (2020) believes that evacuation planning is a multi-objective optimisation problem for which metaheuristics are appropriate solutions, and classical metaheuristic algorithms such as Simulated Annealing (SA) (Yusoff et al., 2008), Artificial Bee Colony (ABC) (Karaboga, 2005), Standard Particle Swarm Optimisation algorithm (SPSO) (Shami et al., 2022), and Genetic Algorithms (GA) (Holland, 1975), as well as their multi-objective versions, have been used in the field of evacuation route planning. Yin (2023) stated that a successful flood evacuation would recommend evacuation times, evacuation routes, and evacuation shelters, indicating areas around the city that are more vulnerable to flooding. Sadri et al. (2017) pointed out that the transmission of crowd information affects evacuee decisions. Therefore, evacuation shelters, evacuation routes, and evacuee movement models should be emphasized in flood evacuation.

This study will summarise the outline of the evacuation planning process through reviewing three research cases, with flood hazard mapping being a cornerstone for developing an evacuation plan. We analyse the three main aspects of evacuation: methods for determining safe evacuation shelters, algorithms for planning evacuation routes, and models for evacuee movement. Finally, three future research directions are proposed.

2. Research cases

The evacuation planning process involves components such as obtaining flood information, identifying flood hazards, selecting evacuation shelters, planning evacuation routes, and observing evacuees (Esposito Amideo et al., 2019). To demonstrate components of evacuation planning in this study, three case studies that represent typical flood evacuation processes are briefly reviewed and then summarised in this section. It should be noted that since evacuation planning is an interdisciplinary research area, these studies were provided to ensure all readers are familiar with the steps being discussed in the next step. The first case is Musolino et al. (2020b) who conducted an evacuation route study for the Boscastle (UK) area. On August 16, 2004, the picturesque village of Boscastle was hit by an unexpected extreme flash flood which left the village inhabitants and visitors devastated during the event. An evacuation route study was carried out for the area. In house widely used numerical model, namely DIVAST TVD, was used for obtaining the flood information. After that, two methods were used for mapping the flood hazard, the empirically based method and the mechanics-based and experimental calibrated method. The result of the hazard mapping proved that the method based on mechanics and experimental calibrated methods is more in line with the actual situation of the human body and more sensitive to hazard classification. The methodology and conclusions have been employed by many scholars in the subsequent flood hazard mapping (Dong et al., 2022; Li et al., 2021).

The second case is focused on an evacuation route study conducted by He et al. (2021) for a suburban area in Yangzhou, China. The area with a total area of 13.83 km^2 and about 19,000 inhabitants living. On foot human evacuation speed in flood was set to 1.0 m/s. MIKE 21 was used to model the flood in the area, obtaining the flood information, to construct a flood hazard mapping, and develop a Dynamic Route Optimisation (CADRO) algorithm to determine dynamic Flood Evacuation Routes (FER) in an evacuee movement model, which was compared with

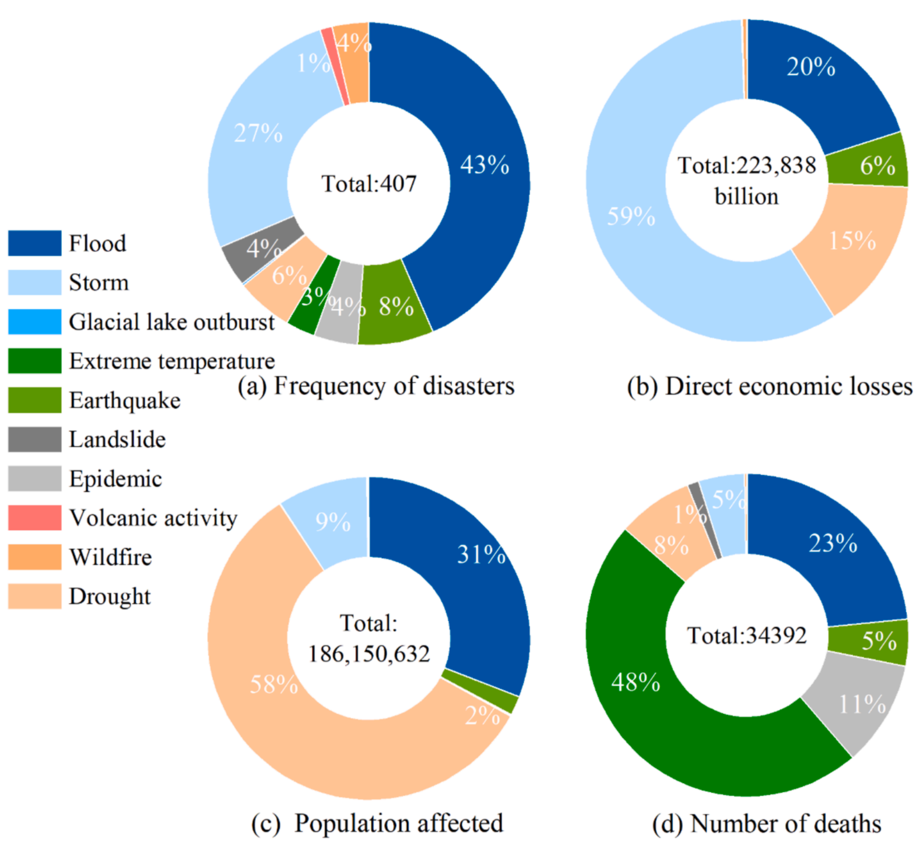

Fig. 2. Breakdown of frequency and losses per disaster type worldwide in 2022.

the evacuation route generated using A* (Hart et al., 1968), and the results showed that the route of the (CADRO) algorithm was more realistic than the route of the A* algorithm, and could evacuate more people. In this approach, the initial locations of evacuees are randomly set based on the number of inhabitants. The evacuees start moving to shelter locations once the flood starts. As the flood develops, more areas become flooded and less routes are available for evacuation. The remaining evacuees are squeezed towards a few available routes, and some of the evacuees may be destabilised during their evacuation. CADRO was tested to generate routes that evacuate more evacuees to the shelter locations compared to the A* algorithm.

The third case study selected was conducted by Lee et al. (2020) who were planning to identify an evacuation shelter in Seoul, Korea (Seocho-gu and Gangnam-gu). Their study was mainly divided into three stages. First, SWMM and FLO2D were used to obtain flood information: the flood inundation area, inundation depth, and flow velocity. Next, selecting candidate shelters by using a hierarchical model based on accessibility, flood safety, service accessibility, and facility capacity. Finally, evaluation of candidate and existing evacuation shelters. The study showed that candidate evacuation shelters planned using the hierarchical model were preferable in terms of safety and serviceability, and it objectively defines the hierarchy of shelters, which helps to quantify and improve the city's flood protection.

Through reviewing a large number of studies and as demonstrated by the three typical research cases, flood evacuation can be divided into two stages as outlined below:

Stage 1: Flood hazard mapping

- Obtaining flood information through flood models, namely hydrodynamic or hydrological models.
- Hazard mapping based on predefined criteria using flood information from a pedestrian or vehicle perspective.

Stage 2: Flood evacuation planning

- Selecting evacuation shelter.
- Identifying evacuation routes.
- Assessing evacuee movements.

This framework for flood hazard mapping and evacuation planning is concise, clear, scientific, and has strong practical properties that can be well used in the field of flood research. Therefore, based on this framework, Fig. 3. was developed. This figure also serves as a structure for subsequent contents.

3. Flood hazard mapping

3.1. Flood model

Flood hazard assessment and mapping is a crucial tool for evacuation planning (Yang et al., 2022b). In the process of mapping, it is divided into two broad steps (Qi et al., 2021; Xia et al., 2011):

- Obtaining flood information (from hydrologic models and hydrodynamic models).
- Assessing hazard based on the receptors, namely people, vehicles, or infrastructure.

3.1.1. Obtaining flood information from hydrologic models and hydrodynamic models

The flood model is a useful method for obtaining detailed flood information (Bulti & Abebe, 2020; Wade et al., 2006). Modelling historical floods and analysing patterns of change (Zhu et al., 2023a), contribute to improving the resilience of the city against future flooding. Flood models are divided into hydrological and hydrodynamic models (Bodoque et al., 2023; Qi et al., 2021).

Hydrological models are a vital component of water resources and environmental management (Brunner et al., 2021; Devia et al., 2015), mainly including precipitation, surface runoff, infiltration, and evaporation that are affected by the underlying city surface. Hydrological modelling is systematic in its consideration of multiple segments of flood formation which is fitting for the simulation of small to medium scales areas (Guo et al., 2020). Meanwhile, with the development of remote sensing and drone technologies, flood simulation by hydrological models has also been popularized (Karamuz et al., 2020; Knoben et al., 2019; Mioc et al., 2008).

Hydrodynamic models have advantages over hydrological models in terms of hydraulic properties (Qi et al., 2021). Urban flood processes are more influenced by topography, and hydrodynamic models can consider microtopography such as urban drainage systems, river systems, and streets (Yazdani et al., 2022). At the same time, these models can be directly linked to hydrological and river models to provide flood hazard information, flood forecasting, and scenario analysis(Anees et al., 2016). Thus, hydrodynamic models are widely used in the mapping of flood hazard.

The hydrodynamic models commonly used are categorized as one-dimensional (1D) models (Ma et al., 2022), two-dimensional (2D) models (Farooq et al., 2019; Connell et al., 2001), coupled one- and two-dimensional (1 ∼ 2D) models (Liu et al., 2014; Chen et al., 2007; Tayefi et al., 2007; Chang et al., 2005), and three-dimensional (3D) models (Dong et al., 2022; Azhar & Sanyal, 2019; Baky et al., 2019; Anees et al., 2016). These models have been studied by many researchers from different perspectives, including simulation dimensions, numerical methods, advantages, limitations, and application scenarios (Guo et al., 2021; Nkwunonwo et al., 2020; Teng et al., 2017). Therefore, the specific details will not be discussed in this study.

3.1.2. Hazard mapping

The level of hazard is different based on the receptors, e.g. adults, children, or vehicles. For example, adults can withstand deeper water and higher flow velocities than elderlies and children (Lee et al., 2019) or that instability can be linked to individuals Body Mass Index (BMI) (Kvočka et al., 2018; Xia et al., 2011). Vehicles are susceptible to stalling in deep water areas with water depth thresholds lower than people (Dong et al., 2022).

Flood evacuation is generally carried out by walking or driving and therefore hazard mapping for people and vehicles is a fundamental part of evacuation planning (Shirvani et al., 2021a; Xia et al., 2011). The flood hazard should be assessed from two hazard perspectives: hazard to people and vehicles.

- Assessing hazard to people

It is considered to be dangerous for people to walk in flood water, due to the hazard of instability, collision of debris, or blinding effect of flood water on potential obstacles on the road (Musolino et al., 2020a). However, walking is considered an inevitable way to evacuate, especially for those who do not have access to a vehicle (Renne, 2018) or where safe locations are not accessible with vehicles. Human instability in flood water is generally caused by sliding or toppling as shown in Fig. 4 which is commonly determined using experimental studies, mechanics analysis, image and video analysis of the critical conditions. Foster and Cox (1973) was an early pioneer in initiating human instability experiments, concluding that relatively low flow depths ($h < 0.3$ m) may be unsafe at high velocities (i.e., greater than about 1.5 m/s). Many researchers have followed him since then and conducted experiments using children, adults elderlies and different terrain slopes, shoe material, etc. as to obtain more evidence for reference (Martinez-Gomariz et al., 2016; Cox et al., 2010b; Jonkman and Penning-Rowsell, 2008; Yee, 2003; Karvonen et al., 2000). Abt et al. (1989) developed a generalized equation for instability criteria which depends on velocity

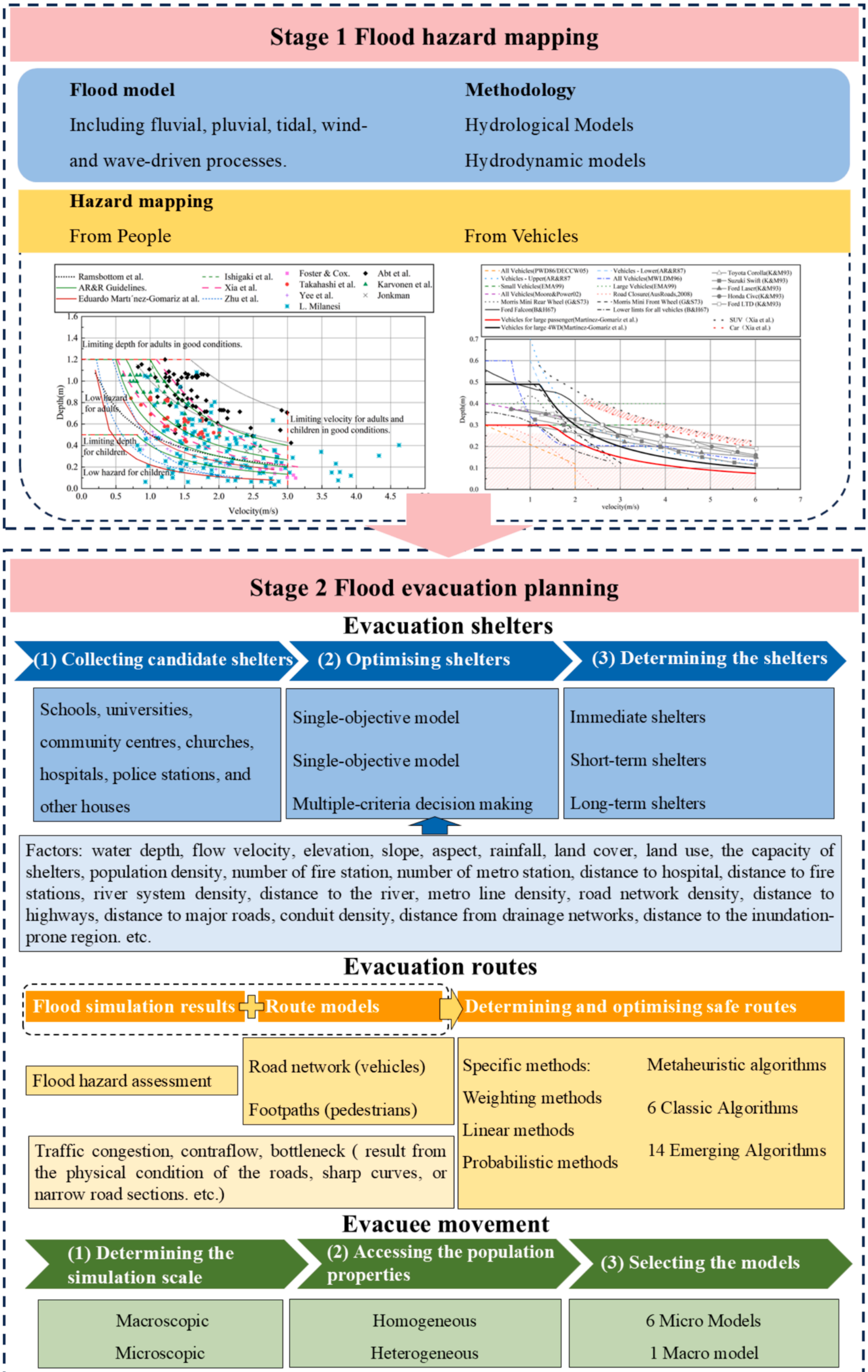

Fig. 3. The Flowchart of Flood Risk Assessment and Evacuation.

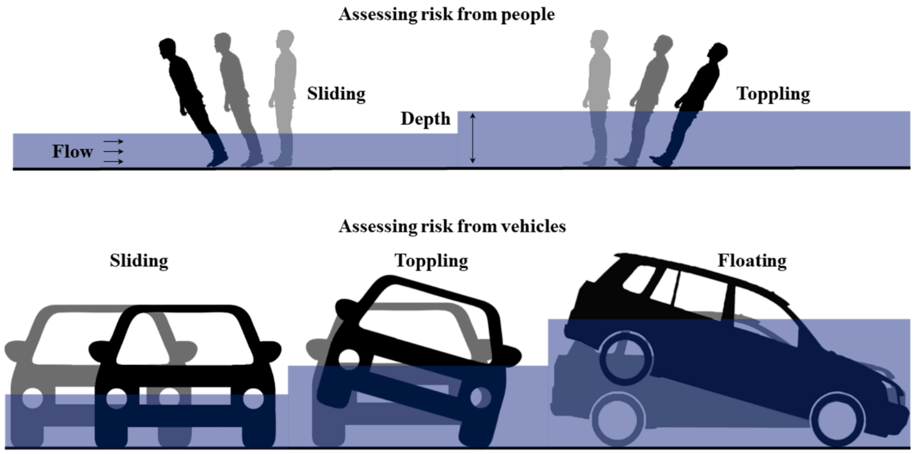

Fig. 4. Flood Hazard Assessment form people and vehicles.

and depth. Debris in water were considered in the instability formula proposed by Ramsbottom et al. (2004). Xia et al. (2014) constructed a formula for mechanical instability based on experimental data. Chen et al. (2019) corrected the body parameters in Xia's formula to a more generic BMI which makes the formula applicable globally. Zhu et al. (2023b) incorporated the effect of turbulence intensity in Xia's formula. In addition, as technology advances, video and images of evacuee instability recorded during the real floods can also be used as a complement to the experimental studies to obtain critical water depth and velocity (Quagliarini et al., 2023; Alizadeh et al., 2022; Milanesi et al., 2016). However, actual flood videos and images are rarely recorded because of the power cut and the flood destructiveness. Summary of the key studies conducted on human instability in floods are summarised in Table 1 and the results are summarised in Fig. 5.

The results of 13 studies summarised in Table 1 are aggregated in Fig. 5. It can be seen that adults and children can barely withstand velocity of more than 3 m/s at any depth and the maximum water depth that they can stand is 1.2 m. The red curve at the bottom was proposed by Martinez-Gomariz et al. (2016), it is the most conservative, and exceeding it means that the person starting to be at risk. The uppermost curve was proposed by Ramsbottom et al. (2004), it covers all experimental data, and water depths and velocity above this line must be considered unsafe. Musolino et al. (2020a) studied various approaches to human stability in floods and highlighted the revised Mechanics Based Methods (rMBM) which represents the MBM method such as Xia's formula (Xia et al., 2011), in which the slope of the ground is considered, could be the most accurate representation of human instability.

The data obtained from the flood model, combined with the human instability determination criteria described above, allows for a pedestrian instability flood hazard assessment.

- **Assessing hazard to vehicles**

Vehicles can be an effective part of evacuation, especially for flood hazard evacuation of large areas. The critical conditions for vehicles are: floating, sliding, and toppling (Martínez-Gomariz et al., 2018) which are also illustrated in Fig. 4. The instability thresholds are different for different vehicles (Suwanno et al., 2023). Wang et al. (2021a) showed hazard severity thresholds of adult < child < SUV < small cars. Bonham and Hattersley (1967) tested the car at 46 different combinations of depth and velocity, and the results of the experiment can be used to determine a range of automotive stability limits. Gordon and Stone (1973) considered three modes of motion resistance, and stability was found to be slightly higher for front wheel lock conditions than for rear wheel lock conditions. Keller and Mitsch (1993) conducted a purely theoretical study of automobile and human stability, assessing stability perpendicular to the vehicle by comparing the vertical reaction forces (FV) on each axle. Cox et al. (2010a) summarised various guidelines and other determination criteria. Xia et al. (2010) derived a formula for determining vehicle instability based on the theory of equilibrium mechanics of slip dynamics and applied it to vehicle hazard assessment in the flooded area of Zhengzhou, China. Martínez-Gomariz et al. (2017) conducted experiments using three different scales, totalling 12 vehicle models, and delineated thresholds, which are more comprehensive and adaptable to modern models. Major studies identified in the literature are summarised in Table 2.

The results of different vehicle instability studies are summarised in Fig. 6. A similar trend but different criteria for different vehicles can be seen. As a result, some regulatory authorities use a conservative value to communicate the possibility of vehicle instability to the public. For instance, the Emergency Management in Australia advises public to avoid driving through more than 30 cm to reduce the risk of vehicle instability (Suwanno et al., 2023; Cox et al., 2010a). Martínez-Gomariz et al. (2017) proposed a line for large passenger carrier vehicles which is more conservative than other curves. Xia et al. (2010) proposed the highest threshold in the figure, and therefore once the flood conditions exceed the threshold suggested by Xia et al (2010), it indicates that instability could occur to a high level of certainty.

By comparing Fig. 5. and Fig. 6., we can make the following conclusions. Primarily, the ultimate destabilising water depth for a person is greater than that of a vehicle. The ultimate water depth of the vehicle is 0.6 m, and the ultimate water depth of the person is 1.2 m. This indicates that walking can be used for evacuation when the water depth is high. Secondly, the ultimate destabilising velocity of a vehicle is greater than that of a person. The ultimate flow velocity of a person is 3 m/s and the ultimate flow velocity of a vehicle is 6 m/s, so in the case of low water depth and high flow velocity, vehicle evacuation is more feasible. Finally, there is a cross-over area between the two figures. When the water depth is lower than 0.6 m and the flow velocity is lower than 3 m/s, the two figures will overlap, which indicates that evacuation can be carried out either on foot or by vehicle. Evans et al. (2024) recently proposed the flood hazard level based on a combination of the results of the Martinez-Gomariz's equations by considering the overlap area. In addition, although flood risk is assessed from different perspectives, they all demonstrate that it is more common to use the mechanic-based method of assessment.

Coastal flooding is a compound process that involves the effects of water depth, flow velocity and the effects of wind, using the SFINCS model can well simulate the compound flood process in coastal area (Leijnse et al., 2021). It is important that the effects of wind are included in experiments and mechanistic analyses on humans or vehicles. Wang and Marsooli (2021) incorporated the effect of wind into the human instability formula based on a mechanics method and corrected the formula with simplified experiments, which was finally used for New

Table 1
Summary of findings on human flood instability.

Researcher	Method	Parameters considered		Brief summary
		Depth	Velocity	
Foster and Cox (1973)	Experiment	√	√	Experimental flume: 6 m × 0.6 m × 0.75 mResearch subjects: 6 male children, (aged:9 ~ 13 height:1.27 ~ 1.45 m, weight:25 ~ 37 kg). Experimental content: Children were tested for standing, walking, turning, and sitting in the flume facing upstream and downstream respectively. Results: Relatively low flow depths (h < 0.3 m) may be unsafe at high velocities (i.e., greater than about 1.5 m/s).
Abt et al. (1989)	Experiences	√	√	Experimental flume: 61 m × 2.44 m × 1.22 m. Research subjects: (males and females, 1.52 to 1.83 m tall, 41 to 91 kg in weight, and 62 to 172 kg in height). Results: an equation for water depth and velocity.
Karvonen et al. (2000)	Experiment	√	√	Experimental field: 130 m × 11 m × 5.5 m. Experimental subjects:2 subjects were professional rescuers. Results: expressions defining the limits of human stability under good, normal, and poor conditions were derived.
Yee (2003)	Experiment	√	√	The test procedure was similar to that previously reported by Foster and Cox (1973). Experimental subjects: 4 young children (2 males and 2 females, age: 6 ~ 8, height: 1.09 ~ 1.25, weight: 19 ~ 25). Results: critical D.V values of 0.51——0.55 m^2/s showed very similar unstable behavior.
Ramsbottom et al. (2004)	Experiment	√	√	Various empirical equations were tested using experimental data from Abt et al. (1989) and Karvonen et al. (2000). Results: The strongest correlation was observed for H*M = K(D*V) + C.
Ishigaki et al. (2006)	Experiment	√	√	Experimental conditions: water depths of 0.1——0.4 m and velocities of 0.5——1.125 m/s. Experimental subjects: 16 females and 33 males were tested for evacuation time. Results: an evacuation criterion of V^2*D = 1.2 was derived.
Wade et al. (2006)	Experiences	√	√	Adjust the formula H.M = K(D*V) + C to modify the velocity factor from + 1.5 to + 0.5 and the debris factor (DF) from 0 ~ 2 to 0 ~ 1.
Jonkman and Penning-Rowsell (2008)	Experiment	√	√	Experimental subject: a professional stuntman (height:1.7 m, weight: 68 kg). Experimental content: Standing and walking at right angles to and into the flow of water Results: The flow leading to failure ranged from 2.4 to 2.6 m/s (D*V = 0.84 and 0.91).
Cox et al. (2010b)	Experiences	√	√	For children with height and mass product (H*M) between 25 ~ 50, the risk is lower for D*V flow values < 0.4 m/s. For adults (H*M > 50), with a maximum depth limit of 1.2 m at shallow depths and a maximum flow velocity of 3.0 m/s, the risk is lower for D*V values < 0.6 m/s.
Xia et al. (2014)	Experiment	√	√	Analysed the forces on the human body and derived slipping and toppling formulas.
Milanesi et al. (2016)	Experiment	√	√	A method for deducing water depth and velocity from video frames is presented and unstable data for children, youths, and adults are obtained.
Martinez-Gomariz et al. (2016)	Experiment	√	√	Summarizing the results of the Russo (2009) experiment with those obtained in this iteration of the experiment, a lower bound function (v*y) = 0.22 m^2/s was defined, and the most conventional stability criterion (v*y) = 0.5 m^2/s.
Chen et al. (2019)	Experiment	√	√	Re-correcting Xia's formula for European characteristics.
Lee et al. (2019)	Experiment	√	√	Experimental site: Swimming pool. Subjects: 32 subjects (20 males and 12 females) acted as proxies for older adults, wearing an elderly simulator that produced movements associated with older adults. Results: Regression equations were derived for the evacuation speed of older adults in different water depths.
Zhu et al. (2023b)	Experiment	√	√	Upgrading Xia's toppling formula makes it more conservative, with k taking the value of 0.45.
Alizadeh et al. (2022)	Picture	√	√	A methodology is presented that employs a combination of user-provided photographs of

(continued on next page)

Table 1 (*continued*)

Researcher	Method	Parameters considered		Brief summary
		Depth	Velocity	
Quagliarini et al. (2023)	Videotape	√	√	flooded streets to reliably estimate flood depths. Analysed 139 videotapes of recent real-life flood evacuations in outdoor built environments involving approximately 1,000 people around the world. The most common flood conditions and thresholds triggering each behavior involved waters between the ankles and the waist.

York, USA. Wind has both stabilising and destabilising effects, which can enhance stability or weaken it. Studies have indicated that the destabilising effects of wind are greater, therefore it is important to consider factor winds in flood hazard and vulnerability assessments for coastal-flood-prone areas (Li et al., 2022; Sebastian et al., 2021).

3.2. Flood evacuation

Flood evacuation is a purposeful, organized, and planned action to save more people (Pel et al., 2011; Alsnih & Stopher, 2004). The public's concerns during a flood include inundated areas, safe locations, dangerous routes, trapped people, and supplies during a flood (Esposito Amideo et al., 2019). It is consequently proposed that the paramount study topics of flood evacuation are (Yang et al., 2022a; Haghani, 2020; Liu et al., 2019b; Jozefowiez et al., 2008):

- Evacuation shelters
- Evacuation routes
- Evacuee movement

3.2.1. Evacuation shelters

Evacuation scenarios occur in flood disasters where people in the affected disaster area need to be transported to a safe place (e.g., a gymnasium or sports arena) (Goerigk et al., 2014). These safe places are referred to as shelters in here as used in several studies (Edirisinghe et al., 2021; Lim et al., 2021; Rahman et al., 2021). Shelter sites are expected to protect people from disasters and provide food, medical care, and accommodation for evacuees (Bayram, 2016; Mesa-Arango et al., 2013). Shelter identification and evacuation of vulnerable populations are key aspects of disaster response (Esposito Amideo et al., 2019). London Resilience Team (2022) classified evacuation sites into three categories: Direct Movement to an Emergency Rest Centre (DMERC), Emergency Evacuation Centre (EEC), and Emergency Rest Centre (ERC). which determining factors are the capacity of the shelter, the time of using the shelter, the distance of the shelter, etc. In general, the area around the inundated region is the most susceptible area where the immediate shelters can be simply sought by considering factors such as distance and risk level. Focusing on the area more likely to be affected by the flood, referred to here as a high-risk area for simplicity, and expanding to the area with lesser likelihood of flooding, it is possible to find short-term or even long-term large-scale shelters by considering service accessibility, medical equipment, and other conditions. The concept of different types of evacuation shelters is shown in Fig. 7.

There are three steps to planning for shelter: collecting candidate shelters, optimising shelters, and determining the shelters, Stage 2 evacuation shelters flowchart as shown in Fig. 3. Candidate shelters are schools, universities, community centres, churches, hospitals, police stations, and other houses, they can be optimised by a single-objective model, a multi-objective model, or multiple-criteria decision making (Bera et al., 2023; Ma et al., 2019). Single-objective models consider one aspect of the evacuation point such as distance, size, accessibility, etc. with a single objective function and all parameters are deterministic and constant over time. The approaches taken are p-median, p-center, and covering methods (Hakimi, 1964). A multi-objective model is one that contains at least two objectives, such as the selection of shelters taking into account the site capacity, accessibility, and medical facilities (Alam et al., 2021). The multiple-criteria decision making is an orderly division of immediate, short-term, and long-term flood preparedness emergency

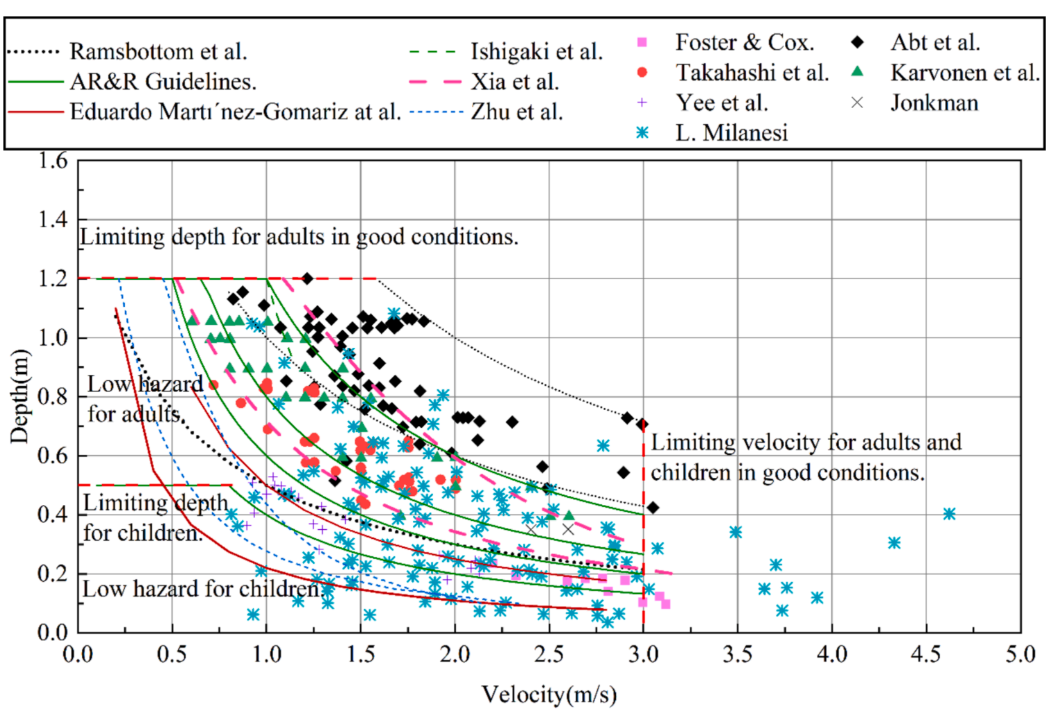

Fig. 5. Results of human instability in floods.

Table 2
Summary of findings on vehicle flood instability.

Researcher	Method	Parameters considered		Brief summary
		Depth	Velocity	
Bonham and Hattersley (1967)	Experiment	√	√	Experimental object: Ford Falcon model Experimental scale: 1:25 geometric length scale. Experiment: Tests were conducted at 46 different combinations of depths and velocities ranging from 0.11 to 0.57 m and velocities ranging from 0.48 to 3.09 m/s (all at prototype scales) Results: The experimental data could be used to determine the float and friction stability limits for a range of cars available at the time. These automobiles were categorized into seven categories, including small, medium, and large automobiles, rear-engine automobiles, and sports cars.
Gordon and Stone (1973)	Experiment	√	√	Experimental scale: 1:16 Experimental content: Three modes of resistance to motion were considered. These included Including:1. front wheels locked.2. rear wheels locked.3. both locked. The total horizontal reaction force and vertical reaction force of the front and rear wheels were measured under fine threaded vertical and lateral restraints Results: Stability was found to be slightly higher for the front wheel locking condition than the rear wheel locking condition.
Keller and Mitsch (1993)	Theory	√	√	Subjects: a Suzuki Rainier, a Ford Laser, a Toyota Corolla and a larger Ford Limited. Experimental content: This study assessed the stability of the vehicle perpendicular to the vehicle by comparing the vertical reaction force (FV) on each axle. Results: instability occurs when the vertical reaction force is less than or equal to zero (the vehicle floats) or when the horizontal force is equal to the vertical restoring force (assumed to be a function of the coefficient of friction and the vertical reaction force)
Cox et al. (2010a)	Guidelines	√	√	Guideline/ Recommendation: Department PublicWorks, NSW (PWD86/DECCW05), Australian Rainfall and Runoff (1987), Melbourne Water Land Development Manual: Floodway Safety Criteria(1996), Emergency Management Manual (EMA1999), Moore and Power(2002), Aus Roads Guide to Road Design – Part 5: Drainage Design(2008)
Xia et al. (2010)	Experiment	√	√	All potential energies acting on the flooded vehicle were considered, and a general formula for the initial velocity of the flooded vehicle was deduced based on the theory of sliding equilibrium mechanics. Results: the flooded vehicle is most likely to move when the depth of water is just close to the height of the vehicle.
Martínez-Gomariz et al. (2017)	Experiment	√	√	Experimental subjects: 12 models Experimental scale: three different model scales (1:14, 1:18 and 1:24) and the effects of friction and buoyancy were analysed Results: a new methodology was developed to obtain the stability threshold of any real vehicle exposed to flooding.

shelters based on accessibility, flood safety, service accessibility, and facility capacity, it is more appropriate for making large-scale global analyses (Lee et al., 2020). Lyu et al. (2020) obtained the inundated area of the City of Shenzhen based on three criteria: hazard, exposure, and vulnerability. Edirisinghe et al. (2021) considered elevation, accessibility, land use, availability of buildings, presence of water features, rainfall, and population density when making evacuation shelter arrangements, totalling seven criteria. Based on the flood hazard assessment, the modified particle swarm optimisation algorithm (MPSO), local search particle swarm optimisation algorithm (LMPSO), genetic algorithm (GA), ant colony optimisation algorithm (ACO), and simulated annealing algorithm (SA) can be used to find the optimal shelters (Samany et al., 2021; Campos et al., 2012). GIS and remote sensing are widely used as effective tools for shelter site planning (Edirisinghe et al., 2021; Rahman et al., 2021).

In the application of these models for shelter identification, the single-objective model focuses on only one aspect of the shelter and is not considered comprehensive enough. Multi-objective models consider multiple aspects, but the results are generally sub-optimal. For example, it is highly unlikely that shelters will satisfy the maximum capacity and the shortest distance to travel. Multiple-criteria decision making subdivides the problem and solves it with lots of criteria, while the criteria weights are subjective as determined by the expert's experience. Different models were selected depending on the scale of the area inundated and the number of objectives.

3.2.2. Evacuation routes

Evacuation routes are possible paths points the evacuation zone to shelters or safety zones. Identifying the routes with the shortest distance and lowest risk which are dynamically updated has been the focus of several studies (Alizadeh et al., 2022; Musolino et al., 2022; Thapa et al., 2022; Shirvani et al., 2021a). The concept of evacuation routes is demonstrated in Fig. 8. Identifying the safest evacuation route or identifying the shortest route between the inundated area and shelter or identifying the shortest route with an acceptable level of risk, e.g. Route A, B, or C as shown in Fig. 8, can be very challenging. This is due to the complexity of road structure in large urban areas and the range of other

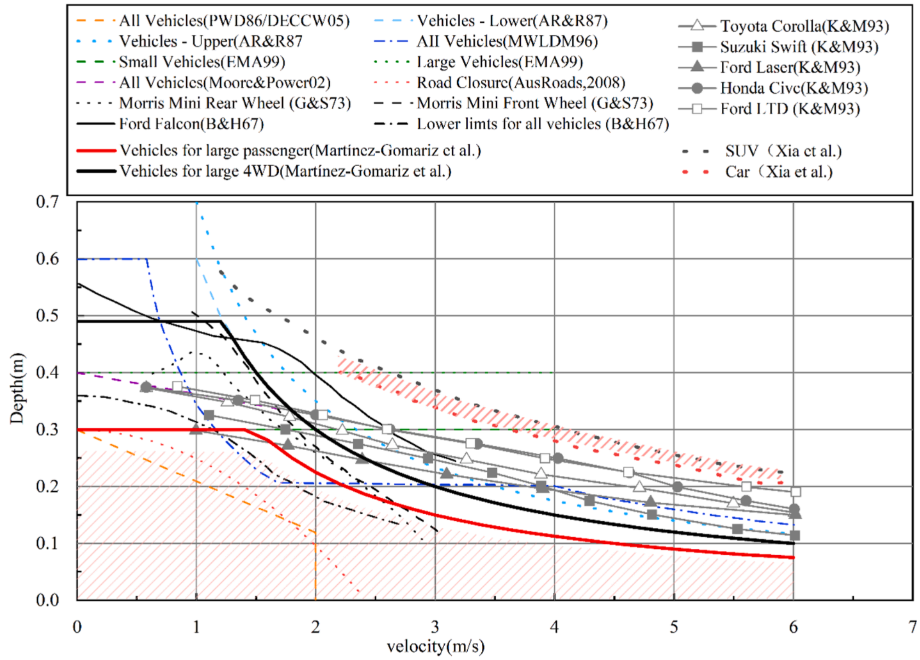

Fig. 6. Results of vehicle instability in floods.

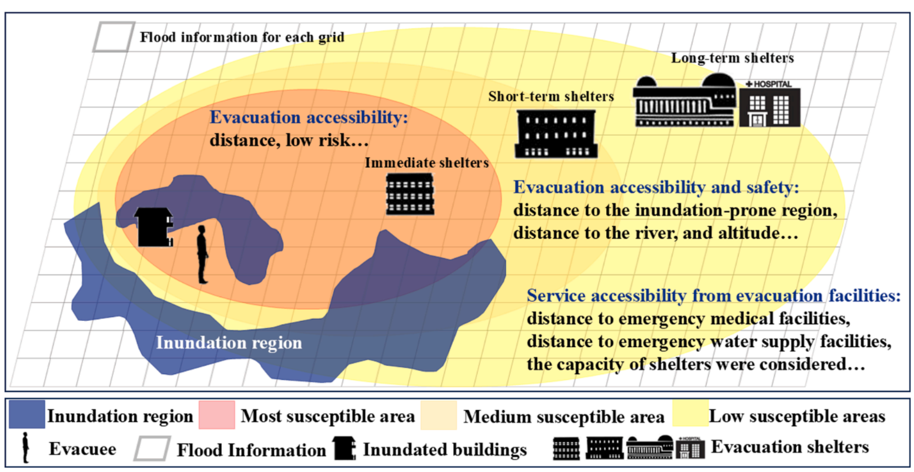

Fig. 7. Evacuation shelters for different objectives.

parameters potentially affecting the route, such as the level of risk.

Evacuation route planning is carried out by combining flood simulation results and road models. The road model can be as large as the road network for vehicles and as small as the pedestrian footpaths as included in the Stage 2 evacuation routes flowchart in Fig. 3. There are two main methods for determining and optimising evacuation routes: specific methods and metaheuristic algorithms. Specific methods include weighting methods and direct identification methods. Ogawa et al. (2023) used the weighting method to determine evacuation routes based on flood changes during a period to increase the number of evacuees being saved in Osaka, Japan. Dong et al. (2020) employed Bayesian combination of existing road network and flood data to determine the failed evacuation road sections. Thapa et al. (2022) conducted field surveys via drone and mapped the disaster to directly identify emergency evacuation routes from road networks for pedestrians. Shirvani et al. (2021a) used an agent-based model to investigate dynamic human interactions with flood water during evacuation. Evans et al. (2024) provided a hazard assessment that integrates people and vehicles and can be used to determine the flood risk level of a route. Musolino et al. (2022) also developed flood evacuation routes based on the revised MBM and considered retrofitting existing infrastructures to remove bottlenecks to safe evacuation where there was no alternative route. However, specific methods can become more time-consuming as the scope of the study becomes larger. Additionally, there are subjectivity in these models. For example, in weighting methods, weightings are assigned to different aspects to reflect expert judgements towards the importance of these aspects, yet these weightings have not been tested with reality. Optimising routes mainly addresses route capacity, traffic congestion, reverse flow and bottlenecks (Borowska-Stefańska et al., 2023; Haghani, 2020). Metaheuristic algorithms are widely applied in this optimisation process, they are randomly generated based on flood data and evolutionary principles, consistent with the phenomenon of population evacuation, and are more objective (Li et al., 2024; Niyomubyeyi et al., 2020; Yusoff et al., 2008).

As for metaheuristic methods, Di Caprio et al. (2022) proposed that they can provide optimal or near-optimal route solutions in small and large networks within a reasonable computational time. Metaheuristic algorithms are categorized into two groups: those based on biological,

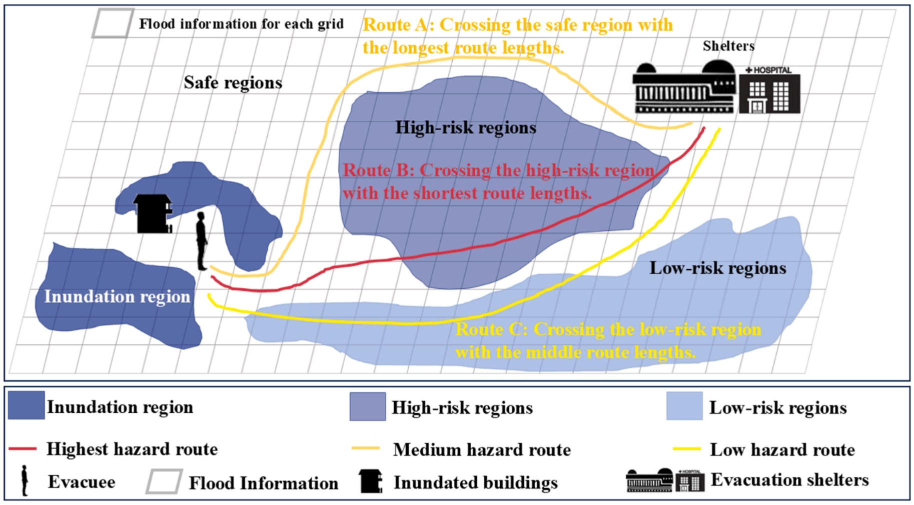

Fig. 8. Evacuation routes from considering risk level and route length.

physical, chemical heuristics and group intelligence, such as annealing algorithms, ant colony optimisation algorithms, genetic algorithms, and particle swarm optimisation algorithms, and other metaheuristic algorithms, such as Dijkstra's and A* algorithms. These algorithms have been widely used to solve flood problems (Zhang et al., 2021a; Abdel-Basset et al., 2018). The summary of the metaheuristic algorithms used in evacuation planning is shown in Table 3. Different metaheuristic algorithms used to identify the best evacuation route can be classified into two categories as follows:

- **The classical metaheuristic algorithms**

In the field of evacuation routes, the classical algorithms which include: A* algorithm, Dijkstra's algorithm, CCRP algorithm, Genetic algorithm, Ant colony optimisation algorithm, and Particle swarm optimisation algorithm, have been widely used by many scholars and are being continuously improved (Li et al., 2023; Xu et al., 2022; Liu et al., 2021; Abusalama et al., 2020; Dokeroglu et al., 2019).

Dijkstra's algorithm is an algorithm for finding the shortest route between two points. It is based on expanding outward in layers centred on the starting point until the end point is found (Li et al., 2023; Zhang et al., 2021b; Dijkstra, 1959). The A* algorithm is based on Dijkstra's algorithm with an added evaluation function. The purpose of the evaluation function is to compute the cost of a new node to ensure that the new node will have the lowest cost in the next direction of travel, and finally, the route connecting all the points is guaranteed to have the lowest cost (Hart et al., 1968). The A* algorithm combines the iterative checking of the Dijkstra algorithm with the directionality of the best-first algorithm for good performance and accuracy (Faroqi et al., 2022). Liu et al. (2021) used A* algorithms to help intelligently driven vehicles choose the best route in the traffic network with constraints such as limited heights, widths, weights, accidents, and traffic jams during emergencies. They also incorporated a priori knowledge judgments combined with the A* algorithm for search optimisation to propose an optimal route planning algorithm for traffic jams, accidents, and temporary restrictions. Given a transportation network, an evacuation start point, an evacuation endpoint, and the number of evacuees, Evacuation route planning (ERP) can compute the route that minimizes evacuation time and cost (Cova & Johnson, 2003). To extend the algorithm to a larger scale, the Capacity Constrained Route Planner algorithm (CCRP) was developed (Shekhar et al., 2012; Qingsong et al., 2005). The algorithm adds pseudo-source nodes to improve scaling performance (Choe et al., 2023; Abusalama et al., 2020; Kim et al., 2007).

Genetic algorithms are based on the theory of biological evolution in nature (Holland, 1975). The best solution is developed through crossover, mutation, and selection where the crossover is an exchange of different parts of the route, and a uniform crossover is more probably to achieve the best (Nur et al., 2023). In addition, multi-criteria genetic algorithms and multi-objective genetic algorithms have been generated to realize multi-objectives for evacuation distance, evacuation time, and evacuation route (Ikeda & Inoue, 2016). Genetic algorithms can also be combined with fuzzy algorithms to improve simulation performance (Pourrahmani et al., 2015). Genetic algorithms are widely used in transportation planning, flood disasters, fire, and other emergency evacuation (Li et al., 2019a).

Ant colony optimisation algorithm (ACO) derived from the feeding behaviour of ants (Dorigo & Blum, 2005). Ants search for food around the nest and release pheromones along the route. Depending on the distance to the food, the pheromones that the ants leave behind on their way to and from the nest change. The pheromone can be used to find the shortest route from the food to the nest. In the ACO algorithm, the strength of the algorithm can be judged by the number of ants M, pheromone strength Q, information heuristic factor α, expectation heuristic factor β, and pheromone volatilization factor ρ (Di Caprio et al., 2022).The traditional ant colony algorithm is easy to fall into the local optimum and has poor convergence. On this basis, it can be improved by the clustering algorithm, fuzzy algorithm, introduction of A* algorithm, or introduction of optimal and worst solutions to shorten the convergence time and improve the convergence effect (Dai et al., 2019; Luo et al., 2019). Ant colony algorithms are more commonly used in emergency evacuation routes (Xu et al., 2022).

The particle swarm optimisation algorithm (PSO) is a population-based stochastic algorithm, which simulates the social behaviour of birds and fish to solve optimisation problems (Kennedy & Eberhart, 1995). It is worth mentioning that PSO just has three key control parameters: inertia weight w, cognitive component c_1, and social component c_2. These parameters have a great influence on the performance of particle swarm, and the best performance can only be obtained by setting these parameters appropriately (Eberhart & Kennedy, 1995). The particle swarm optimisation algorithm can be improved by modifying the control parameters and by combining the particle swarm algorithm with metaheuristic algorithms such as genetic algorithms and differential evolutionary algorithms (Shami et al., 2022).Based on particle swarm optimisation algorithms, discrete particle swarm optimisation algorithm (DPSO), modified particle swarm optimisation algorithm (MPSO), and local search particle swarm optimisation algorithm (LMPSO) have been proposed (Samany et al., 2021).

Based on the flood simulation results, the safe roads are selected and the retrieval and implementation algorithms are performed on these road networks. The roads are simplified as lines and at the road

Table 3
Summary of metaheuristic algorithms for flood research.

Researcher	Algorithm names	Application
Dijkstra (1959)	Dijkstra algorithm	Flood evacuation routes (Li et al., 2023; Zhang et al., 2021b; Dijkstra, 1959)
Hart et al. (1968)	A* algorithm	Flood evacuation routes (Faroqi et al., 2022; Liu et al., 2019a)
Qingsong et al. (2005)	CCRP algorithm	Reasonable allocation of route capacity (Choe et al., 2023)
Holland (1975)	Genetic algorithm (GA)	Route planning (Di Caprio et al., 2022)
Kennedy and Eberhart (1995)	Particle swarm optimisation algorithm (PSO)	Route Optimisation (Shami et al., 2022)
Geem et al. (2001)	Harmony search (HS)	Optimise the layout of urban pipeline network (Kwon et al., 2019)
Passino (2002)	Bacterial foraging optimisation (BFO)	Real time flood disaster monitoring (Wilson & Radhamani, 2021)
Karaboga (2005)	Artificial bee colony optimisation (ABC)	Accurate prediction of flood-prone flood areas (Plataridis & Mallios, 2023)
Dorigo and Blum (2005)	Ant colony optimisation algorithm (ACO)	Route planning (Dai et al., 2019; Luo et al., 2019)
Simon (2008)	Biogeography-based optimisation (BBO)	Flood susceptibility maps (Plataridis & Mallios, 2023)
Yang and Deb (2009)	Cuckoo search algorithm (CSA)	Flood forecasts (Chaowanawatee & Heednacram, 2012)
Rashedi et al. (2009)	Gravitational search algorithm (GSA)	Model parameter optimisation (Akbari et al., 2019)
Yang, (2010a)	Firefly algorithm (FA)	Process optimisation, robotics and civil engineering (Fister et al., 2013)
Yang (2010b)	Bat algorithm (BA)	Flood susceptibility maps (Rahmati et al., 2020)
Gandomi and Alavi (2012)	Krill herd (KH)	Optimisation issues, positional assignment (Sitoy & Gamot, 2019)
Rao et al. (2011)	Teaching-learning-based optimisation (TLBO)	Estimation of flood discharges for different return periods (Anılan et al., 2017)
Cuevas et al. (2013)	Social spider optimisation (SSO)	Computer vision, image processing, and energy (Luque-Chang et al., 2018)
Cheng and Prayogo (2014)	Symbiotic organisms search (SOS)	Task and resource scheduling, construction and civil engineering (Gharehchopogh et al., 2019)
Mirjalili et al. (2014)	Grey wolf algorithm (GWO)	Spatial prediction of urban flood-inundation (Darabi et al., 2021)
Mirjalili and Lewis (2016)	Whale optimisation algorithm (WOA)	Evaluation model of regional flood disaster resilience (Liu et al., 2020)
Xue and Shen (2020)	Sparrow Search Algorithm (SSA)	Engineering Optimisation (Gharehchopogh et al., 2023; Zhang & Ding, 2021)

intersections are simplified as nodes (Yang et al., 2022a; Liu et al., 2021; Dong et al., 2020). Among these classical algorithms, Dijkstra's algorithm and A* algorithm are centred on the starting point to find the path to the end point, traversing a large number of nodes with a large workload (Faroqi et al., 2022; Zhang et al., 2021b).On the other hand, GA, PSO, and ACO are able to search for optimal solutions globally, but they tend to fall into local optima and poor convergence when solving dynamic evacuation problems (Zhang et al., 2021b; Luo et al., 2019). Nevertheless, these classical algorithms are used in many industries because they require fewer parameters, have a flexible structure, and can be easily modified and combined with other algorithms to improve their performance (Shami et al., 2022; Dai et al., 2019; Pourrahmani et al., 2015).

- **The other recent metaheuristic algorithms**

In addition, 15 other metaheuristic algorithms have been introduced since 2000: Harmony search (HS) (Geem et al., 2001), Bacterial foraging optimisation (BFO) (Passino, 2002), Artificial bee colony optimisation (ABC) (Karaboga, 2005), Biogeography-based optimisation (BBO) (Simon, 2008), Cuckoo search algorithm (CSA) (Yang & Deb, 2009), Gravitational search algorithm (GSA) (Rashedi et al., 2009), Firefly algorithm (FA) (Yang, 2010a), Bat algorithm(BA) (Yang, 2010b), Krill herd (KH) (Gandomi & Alavi, 2012), Teaching-learning-based optimisation (TLBO) (Rao et al., 2011), Social spider optimisation (SSO) (Cuevas et al., 2013), Symbiotic organisms search (SOS) (Cheng & Prayogo, 2014), Grey wolf algorithm (GWO) (Mirjalili et al., 2014), Whale optimisation algorithm (WOA) (Mirjalili & Lewis, 2016), Sparrow Search Algorithm(SSA) (Xue & Shen, 2020).

These algorithms are applied to optimise the layout of urban pipeline networks (Kwon et al., 2019)、real-time flood disaster monitoring (Wilson & Radhamani, 2021), flood susceptibility maps (Plataridis & Mallios, 2023) flood forecasts (Chaowanawatee & Heednacram, 2012), and route planning (Dai et al., 2019; Luo et al., 2019). Among the newer algorithms, SSA (Sparrow Search Algorithm) is also a metaheuristic developed based on bird behaviour (Xue & Shen, 2020). It divides the population into producers and scroungers, and currently outperforms the Wolf Optimizer (GWO), Gravitational Search Algorithm (GSA), and Particle Swarm Optimisation algorithm (PSO) in terms of accuracy, convergence speed, stability, and robustness (Gharehchopogh et al., 2023; Zhang & Ding, 2021). Currently, SSA has not been applied to evacuation routes and its performance has not been evaluated.

Among the route algorithms mentioned above, the most suitable classical algorithms are the Dijkstra algorithm, A* algorithm, CCRP algorithm, GA, ACO and PSO, and the emerging algorithm that has been proved to be better is SSA. There are two main differences between them: the first is whether or not they are biologically characterized. It is obvious that GA, ACO, PSO, and SSA are developed based on biological principles. Flood evacuation, which is a process of evacuee movement, has commonality with the communication of biological entities in these algorithms in the selection of routes and transmission of social information (Xu et al., 2022). The second is the relevance to route optimisation. The formation of evacuation routes is based on step-by-step iterative selection or top-down global iterative selection. Dijkstra algorithm, A* algorithm, CCRP algorithm, ACO belong to step-by-step iterative selection. GA, PSO and SSA belong to the top-down global iterative selection, which is less computationally intensive.

3.2.3. *Evacuee movement*

Efficient and organised movement of evacuees can help improve the evacuation process and reduce mortality rates during large-scale flood events (Tripathy et al., 2021; Bernardini et al., 2017b). London Resilience Team (2022) identified three types of evacuation: Self-Evacuation, Assisted Evacuation, and Supported Evacuation. Self-Evacuation: individuals can use of transport or walk to a safe place. Assisted Evacuation: individuals can move but need the public authorities or community to provide information on safe places, routes, and even transportation. Supported Evacuation: individuals cannot move and require more help from the public authorities or community. When evacuees are moving, more people will choose routes that are shorter and less hazardous. This unplanning evacuation can cause crowd jams which will lead to herd effect and panic (Chen et al., 2020; Helbing & Johansson, 2013), as is illustrated in Fig. 9. Therefore, the evacuee movement model was established to better investigate the evacuee movement patterns. There are two types of evacuee movement models: classified as macro and micromodels (Yang et al., 2021; Li et al., 2019b). It is necessary to determine the simulation scale and access the population properties before selecting the models, Stage 2 evacuation movement flowchart as shown in Fig. 3.

Macroscopic models, although having high computational efficiency, cannot reflect the interactions and heterogeneity among individuals and are only suitable for modelling large-scale populations. Microscopic models are relatively less computationally efficient, but the motion description is more accurate and natural (Zheng et al., 2009). Macro models are mainly fluid dynamics models (Twarogowska et al.,

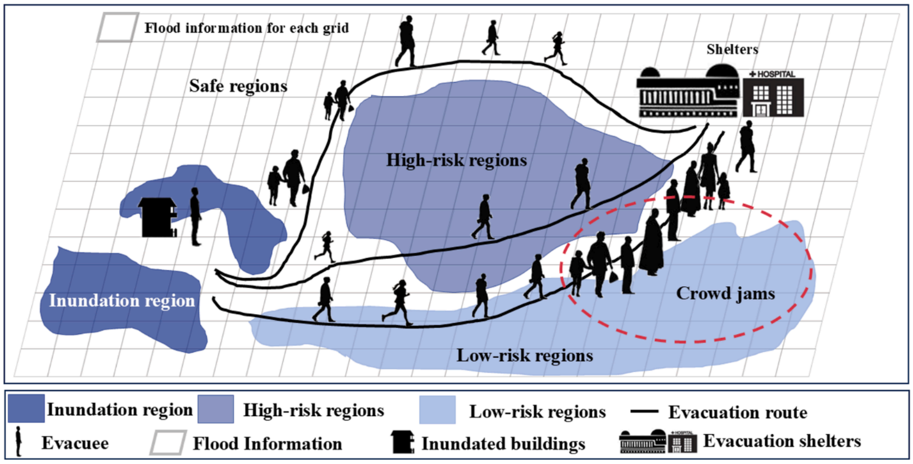

Fig. 9. Evacuee movement for simulation of reality.

2014). The motion of a traveling evacuee is similar to that of a gas or a liquid, has fluid-like properties, and is often used as a macroscopic model for evacuee movement. The use of partial differential equations of fluid dynamics to study the typical characteristics of evacuee flow allows more general conclusions to be drawn.

There are 6 types of microscopic models: cellular automata models, lattice gas models, social force models, agent-based models, game models, and animal experimentation-based approaches (Bernardini et al., 2017a; Vermuyten et al., 2016). Different models discretize differently for group characteristics, size, time, and space. Different microscopic evacuation modelling for crowds is summarised in Table 4.

The cellular automata model, proposed by von Neumann, is a discrete dynamical system consisting of a grid of regular cells, where each cell changes according to the value of its domain cell at the previous time step and is updated synchronously according to a set of local rules (Li et al., 2019b). The cellular automata (CA) model has become one of the most widely used evacuation models due to its advantages such as high efficiency, scalability, and simplicity of implementation. The method has been used in real cases by obtaining flood information for flood hazard assessment through hydrodynamic modelling, and then evacuation simulation of the crowd, which can observe the people trapped situation (He et al., 2021; Li et al., 2021). Lattice gas models are a special case of cellular automata models (Muramatsu et al., 1999; Wolfram, 1984; Fredkin & Toffoli, 1982). In the lattice gas model, each pedestrian is considered as an active particle on the lattice, which can well simulate pedestrian evacuation dynamics and simulation is more accurate, but the more people there are, the less scalable it is (Wąs et al., 2016; Helbing et al., 2003). The social force model suggests that pedestrians have a desired speed when traveling to a destination and are subject to attractive and repulsive forces from obstacles. The social force model is a good representation of individual pedestrians and their interactions in a crowd and can be used in conjunction with flood modelling to effectively plan evacuation routes (Bernardini et al., 2017b; Helbing & Johansson, 2013).

Table 4
Microscopic evacuation modelling for crowds.

Model Name	Proposer	Group Description	Scale	Time and Space
Cellular automata model	Von Neumann	Both	Micro	Discrete
Lattice gas model	Fredkin, Toffoli, Wolfram	Homogeneous	Micro	Discrete
Social Force Model	Helbi and Molnar	Homogeneous	Micro	continuous
Agent-based model	Bonabeau	Heterogeneous	Micro	Both
Game theory model	John nash	Homogeneous	Micro	Discrete
Animal experimentation-based methods	Saloma	Homogeneous	Micro	

Based on the Agent-based model, the social structure is constructed “from top to bottom” through the virtual simulation of individuals, and the operating rules for the interaction between agents are created for the pedestrian simulation accordingly. The various agent parameters considered during evacuation are age, gender, income, awareness, education level, and risk perception (Bernardini et al., 2017a; Liu et al., 2008). Shirvani et al. (2021b) combined agent modelling with flood scenarios to study the evacuation movements of pedestrians, but did not take into account the uncertainty of psychological characteristics. It is important to highlight that the more heterogeneity considered, the higher the cost. The Game theory model is a simulation of individuals generating competitive behaviours in an emergency which can examine the rational interactive behaviour of evacuees, which is currently less used because it is not possible to quantify and focus on only one aspect of competition during the flood evacuation (Lo et al., 2006).

Animals have also been used to study evacuee movement and some features of the collective behaviour of animals during panic escapes are very similar to those of humans (Saloma et al., 2003). Therefore, animal experiments can be utilized to simulate the human evacuation process (Altshuler et al., 2005). Haghani (2020) reviewed 18 experiments using animals to study evacuation. However, the experimental results did not show diversity, and animal experiments are becoming less. Among the above-mentioned evacuee movement as a microscopic model, the cellular automata model is widely used due to its advantages such as high efficiency, accuracy, and fast computation speed. This is followed by social force models and agent-based models, which are used to explore evacuee behaviour details, such as herd and follower effects. Evacuee movement models apply to general disasters and are less often specifically combined with floods.

4. Future directions and limitations

The prominent focus of flood evacuation planning is people, but people have psychological activities and can choose their way, which leads to a diversity of evacuation options. At the same time, critical thresholds of instability are often considered when developing evacuation shelters and evacuation routes, but during evacuation, the speed of movement of people or vehicles changes dynamically with the evolution of the flood. Therefore, we propose the following four future research directions to be helpful in flood evacuation planning:

1) Movement speed of pedestrians and vehicles

Evacuation time depends on the speed of evacuation, including the speed of pedestrian movement and the speed of vehicle movement (Vermuyten et al., 2016). In addition, the choice of route is determined not only on the flood hazard but also on the ability to move pedestrians or vehicles (Chen et al., 2022). The main factor impacting the vehicle speed is the water depth, the deeper the water the slower the vehicle speed (Suwanno et al., 2023; Yazdani et al., 2022). He et al. (2023) summarised that the maximum speed at which a vehicle can be safely driven under floodwater. The speed of pedestrian movement is affected by water depth and flow velocity. Studies on pedestrian speeds show that as water depth increases, pedestrian speeds decrease, especially for elderlies or vulnerable people (Quagliarini et al., 2023; Dias et al., 2021; Lee et al., 2019). Shirvani and Kesserwani (2021) used an agent-model to simulate the evacuation of crowds and estimated the speed of pedestrian movement based on water depth and flow velocity. He et al. (2021) set the speed of pedestrian movement to be 1 m/s in the cellular automata model. Vermuyten et al. (2016) pointed out that setting the speed of a pedestrian in a cellular automaton is generally a constant, and the agent model is set according to the individual properties, but this makes the computation more expensive and the computation time longer and has limitations for large-scale evacuation. Therefore, the movement speed characteristics of pedestrians or vehicles are one of the areas where future evacuation models need to focus.

2) Evacuee psychology

There are four psychological stages that humans go through when making an evacuation decision, concern, hazard recognition, reception, and evacuation decision (Borowska-Stefańska et al., 2023; Simonovic & Ahmad, 2005). Evacuees develop multiple psychologies through different stages, such as denial, inactivity, calmness, stunned, uncontrolled, dependency and emotional expression. Pel et al. (2011) indicated these psychologies create a herd effect, familiarity principle, etc. which affects the evacuation decision. Helbing and Johansson (2013) proved that the herd effect was irrational and could increase the number of fatalities and lead to poor overall outcomes. Bernardini et al. (2017) applied the attraction formula to represent fear in the social forces model. Kaur and Kaur (2022) suggested that micro-models could take psychological factors into account, but there were limitations to using them for large-scale evacuations. Chen et al. (2020) stated that the familiarity principle causes people to choose familiar evacuation routes or evacuation shelters. Evacuees often rely on past experiences, known as “experience dependence,” to choose routes and shelters. While correct decisions can improve evacuation efficiency, mistakes may have serious consequences, especially during rare but extreme events and areas. Overconfidence in flood forecasts and early warnings can also slow evacuation. Future research should explore how such planning affects decision-making to prevent errors caused by underestimation. Additionally, human psychology changes dynamically over time, and how to take these uncertainties into account is a challenge for evacuation planning (Haghani, 2020; Ma et al., 2019).

3) Multimodal emergency evacuation

People can get to shelters in one or more ways, for example, by car, by bus, or on foot (Goerigk et al., 2014). Renne (2018) highlighted four main reasons for multimodal emergency evacuation and summarised large-scale, multimodal evacuation plans in the US and the UK for dealing with carless and vulnerable populations. Shiwakoti et al. (2013) identified three modes as the focus of multimodal evacuation: auto, pedestrian, and transit. Evans et al. (2024) suggested combining both people and vehicle to create a flood hazard map, which can be used to develop a multimodal evacuation plan. Currently, very limited multimodal evacuation researches are carried out for flood hazards, and it is valuable to see how they can be linked to minimise fatalities.

4) Effect of overhead power lines on rescue operations

As flood events progress and water levels continue to rise, the available space between the water surface and overhead power lines decreases, increasing the risk of electric shock during evacuation, reducing rescue efficiency, and raising mortality rates. This issue is particularly pronounced in areas with low-hanging or aging overhead power lines, where evacuation and rescue operations become extremely challenging or even isolated. Wang et al. (2024b) proposed an integrated emergency response framework by considering the layout information of overhead power lines. The results suggest that early evacuation is one of the effective methods to avoid isolation. This reemphasise the need for on foot evacuation to safe shelters where the risk from overhanging lines is limited and do not affect air evacuation. Research on conducting rescue operations in isolated areas, such as regions with dense overhead power lines or areas with poor infrastructure, is limited but highly valuable.

5) Limitations

This study provides a systematic review of flood evacuation planning. The evacuation planning process is multifaceted and interdisciplinary, involving numerical simulation, mechanistic methods, theoretical analysis, psychological simulations, and geography. We reviewed and summarised 211 papers and documents to provide a comprehensive overview on the state-of-the-art evacuation planning for urban flooding, especially on flood hazard assessment and algorithms for the optimisation of evacuation shelters and evacuation routes. Therefore, the selected paper and literature reviewed are highly relevant to these aspects.

Nevertheless, Flood risk and evacuation involve issues beyond flood modelling, flood hazard assessment and evacuation shelter and route optimisation. For example, the impact of flooding would depend on the countries or regions being flooded, the vulnerability of their populations, and the varying levels of infrastructure and medical resource availability. While it is essential to select appropriate methods and refine them accordingly within this framework, these challenges were not specifically considered in this study.

5. Conclusion

Flooding is one of the most damaging natural disasters which is expected to be exacerbated in the future due to climate change, population growth, and intensive urbanisation. While reducing the occurrence of floods and their intensity is still an important part of flood hazard management, understanding that flood cannot be stopped completely and creating resilience to flooding is also crucial in our preparedness to flooding. Evacuation is one approach to creating resilience which has attracted more attention in recent years. This study included a comprehensive review of the existing literature on evacuation planning and provided a broad overview of the research content encompassing the topic. Through this review, two stages were identified in all evacuation models: assessment of flood hazard to pedestrians and vehicles and evacuation planning. Flood hazard assessment consists of a two-step process (i) flood modelling, to derive flood depth and velocity, and (ii) an assessment of the instability of the subjects, i.e. humans or vehicles, to establish the hazard level given the flood depth and velocity. Evacuation planning includes finding evacuation shelters, planning evacuation routes, and the simulation of evacuees. The key conclusions are summarised as follows:

1) The revised Mechanic’s based method developed by Xia et al. (2014) provided a flexible and comprehensive assessment of hazard to humans (Musolino et al., 2022), and the methodology introduced by Martínez-Gomariz et al. (2018) was found to be the most comprehensive method for vehicles instability assessment.
2) There are three commonly used methods for selecting evacuation shelters: the single-objective model, the multi-objective model, and hierarchical model. Several factors need to be considered: elevation, accessibility, land use, availability of buildings, presence of water features, rainfall, and population density.
3) Evacuation routes can be planned using metaheuristic algorithms. The classic algorithms are the Ant Colony Optimisation algorithm (ACO), Particle Swarm Optimisation algorithm (PSO), and Genetic Algorithm (GA), Besides, the emerging algorithm Sparrow Search

Algorithm (SSA) is shown to be better than them except in the case of evacuation routes planning, which needs to be tested in the future.
4) In the study of evacuation crowds, the cellular automata model is currently the most widely used, but the social force model and the agent-based model simulate more accurately.

This review also highlights four areas that require further studies to significantly enhance evacuation planning. These includes: movement speed of pedestrians and vehicles, evacuee psychology, multimodal emergency evacuation, and the effect of overhead power lines on rescue operations.

CRediT authorship contribution statement

Chuannan Li: Writing – original draft, Visualization, Software, Methodology, Conceptualization. **Changbo Jiang:** Writing – review & editing, Supervision. **Jie Chen:** Writing – review & editing, Supervision. **Man Yue Lam:** Writing – review & editing. **Junqiang Xia:** Writing – review & editing. **Reza Ahmadian:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

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.

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Data availability

Data will be made available on request.

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