Development of an integrated socio-hydrological modeling framework for assessing the impacts of shelter location arrangement and human behaviors on flood evacuation processes

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Abstract

In many flood-prone areas, it is essential for emergency responders to use advanced computer models to assess flood risk and develop informed flood evacuation plans. However, previous studies have limited understanding of how evacuation performance is affected by the arrangement of evacuation shelters regarding their number and geographical distribution and human behaviors regarding the heterogeneity of household evacuation preparation times and route searching strategies. In this study, we develop an integrated socio-hydrological modeling framework that couples (1) a hydrodynamic model for flood simulation, (2) an agent-based model for evacuation management policies and human behaviors, and (3) a transportation model for simulating household evacuation processes in a road network. We apply the model to the Xiong'an New Area and examine household evacuation outcomes for various shelter location plans and human behavior scenarios. The results show that household evacuation processes are significantly affected by the number and geographical distribution of evacuation shelters. Surprisingly, we find that establishing more shelters may not improve evacuation results if the shelters are not strategically located. We also find that low heterogeneity in evacuation preparation times can result in heavy traffic congestion and long evacuation clearance times. If each household selects their own shortest route without considering the effects of other evacuees' route choices, traffic congestion will likely occur, thereby reducing system-level evacuation performance. These results demonstrate the unique functionality of our model to support flood risk assessment and to advance our understanding of how multiple management and behavioral factors jointly affect evacuation performance.

Keywords:

Socio-hydrology; Flood management; Agent-based model; Emergency evacuation; Shelter allocation

1. Introduction

Flooding is one of the most devastating natural disasters and can lead to significant numbers of fatalities, social and economic disruptions, property and infrastructure damage, and environmental degradation around the world (Smith and Matthews, 2015; McClymont et al., 2020; Brunner et al., 2020; Tanoue et al., 2016; Kreibich et al., 2014; Wang et al., 2019). The global flood database shows that the global flood inundation land area is approximately 2.23 million km^2, with 255~290 million people being directly affected by floods (Tellman et al., 2021). Flood-related economic damage increased globally from $94 billion in the 1980s to more than $1 trillion U.S. dollars in the 2010s (Hino and Nance, 2021). Furthermore, the severity, duration and frequency of damaging floods are expected to continue to increase in the future due to changes in climate, land use and infrastructure (Jongman et al., 2012; Moulds et al., 2021; Wedawatta and Ingirige, 2012; Tellman et al., 2021). In many areas facing flood threats, it is essential for emergency responders and decision-makers to use advanced computer models to assess the flood risk and to establish effective disaster-mitigation plans (Simonovic and Ahmad, 2005).

Before an extreme flood occurs, evacuation is a critical emergency preparedness measure and a common practice because it is impractical and/or economically costly to construct the necessary infrastructure to resist floods (Wang et al., 2016; Liu and Lim, 2016; Islam et al., 2020; Kreibich et al., 2015). However, studies have shown that emergency evacuation is a complex and dynamic process that can be affected by factors from a wide range of interdisciplinary domains (Zhuo and Han, 2020; Hasan et al., 2011; Huang et al., 2012; Chen et al., 2021; Sung et al., 2018). These factors include but are not limited to (1) the accuracy, lead time and sources of flood early warnings and the broadcasting channels through which flood information is disseminated to the affected population (Shi et al., 2020; Verkade and Werner, 2011; Alonso Vicario et al., 2020; Palen et al., 2010; Nester et al., 2012; Goodarzi et al., 2019), (2) the infrastructure and engineering facilities needed for emergency evacuation, which are influenced by the accessibility of transportation networks, road capacity and locations of evacuation zones (Mostafizi et al., 2017; Chen and Zhan, 2008; Saadi et al., 2018; Mostafizi et al., 2019; Koch et al., 2020; Oh et al., 2021; Liu and Lim, 2016), and (3) demographical attributes and household behavioral characteristics, such as residents' beliefs and risk perception, previous knowledge, social networks, and past experience with flood events (Hofflinger et al., 2019; Huang et al., 2017; Lindell et al., 2020; Wang and Jia, 2021; Shahabi and Wilson, 2014; Du et al., 2017). These studies highlight the need to develop comprehensive socio-hydrological modeling tools that can adequately incorporate various factors and processes to support flood management plans in the context of coupled flood-human systems.

Among the many emergency management policies and plans that can be implemented, appropriate shelter location arrangement is essential for massive evacuation operations. City planners and policy makers need to identify safe areas outside of flood inundation regions as feasible shelter locations for households who live in at-risk areas. Some studies have explored the criteria for shelter location arrangement and evacuation planning (Alçada-Almeida et al., 2009; Nappi and Souza, 2015; Bayram et al., 2015; Li et al., 2012; Alam et al., 2021). For instance, Bayram et al. (2015) developed an optimization model to allocate evacuation sites and assign each evacuee to the nearest shelter, with the objective of minimizing the total evacuation time. However, in this study, each evacuee's travel time was estimated based on a simple traffic volume-travel time function, which was not able to fully represent evacuees' complex interactions in a road network. Liu and Lim (2016) applied spatial analysis methods to assign shelters to households, considering the spatial relationships between households and shelter sites. A limitation of this study is that evacuee's travel time was obtained from a simplified traffic model, and the road network was not well represented in the network analysis. In a recent study, Alam et al. (2021) used a massive traffic simulation model and a multiple criteria evaluation method to identify candidate evacuation shelters and considered environmental conditions, structural attributes, emergency services and transportation factors. However, this study focused on obtaining a suitability score for each candidate shelter site with various weighting factors, yet failed to examine to what extent evacuation performance could be affected by the number of shelters and their geographical distribution in the community. Nevertheless, current studies have left a research gap that warrants research efforts to use physically-based flood simulation models to identify safe areas as feasible shelter locations and more importantly, to use transportation models to address such a question: How evacuation performance is affected by the number and geographical distribution of evacuation shelter locations? This is the major research question we seek to explore in this study.

The second research question to be explored in this study is associated with the role played by human behaviors in evacuation processes, which is an important research direction in disaster management (Aerts et al., 2018; Simonovic and Ahmad, 2005; Urata and Pel, 2018). After receiving flood evacuation warnings, households will make decisions based on flood risk information, spend some time completing a set of preparation tasks, and then evacuate from their homes to safe areas. Among these decisions and behaviors, households' evacuation preparation times (i.e., from the time when they receive flood evacuation orders to the time when they start to evacuate via a road network) play an important role in evacuation performance. Many empirical studies have examined the geographic, demographic and behavioral factors that affect households' preparation times (Lindell et al., 2005, 2020; Huang et al., 2012, 2017; Chen et al., 2021). They found that household evacuation preparation times can vary significantly from one household to another, exhibiting a certain degree of behavioral heterogeneity in a community (Lindell et al., 2005, 2020; Rahman et al., 2021). As a result, we hypothesize that the heterogeneity in households' evacuation preparation times affects the traffic flows in the corresponding road network and consequently influences the final evacuation outcomes. However, few studies have explicitly examined how traffic conditions and evacuation performance are affected by different degrees of heterogeneity in evacuation preparation times (Wang et al., 2016). This is the second question we aim to explore in this study.

Furthermore, in this study, we also seek to assess how evacuation processes are affected by households' evacuation route searching strategies, a process that involves emergency responders and policy makers. Previous studies have typically applied the shortest distance path searching method to simulate how evacuees find evacuation routes from their original locations to evacuation destinations (He et al., 2021; Bernardini et al., 2017; Du et al., 2016; Li et al., 2022). However, each evacuee's search for the shortest evacuation path may not ensure system-level evacuation outcomes. In this study, we focus on comparing the evacuation scenario in which each household chooses the shortest path for evacuation with the scenario in which system-level global optimal routes are assigned to the evacuees. Such comparative analyses are expected to provide policy implications in terms of evacuees' route selections to improve evacuation performance during natural disasters.

Motivated by the above research questions and knowledge gaps, we develop an integrated socio-hydrological modeling framework in this study that couples (1) a physically-based hydrodynamic model (MIKE 21) for flood inundation simulation, (2) an agent-based model (ABM) for simulating flood management plans and human behaviors, and (3) a large-scale traffic simulation model (MATSim) for simulating households' evacuation processes in a road network. Specifically, the hydrological component of the socio-hydrological modeling framework is represented by the MIKE 21 model, which simulates flood inundation processes across space and over time in a flood-prone area for a given storm event. The simulation results of the MIKE 21 model can provide flood risk information and will be used by policy makers to make flood management plans. The social component of the modeling framework is represented by ABM and MATSim, which simulate policy makers' flood management plans, households' responses to flood management plans, and households' collective evacuation activities in the road network. By coupling the three models, our modeling framework is capable of simulating a wide range of components and processes in a coherent manner to support flood evacuation management.

We apply the modeling framework to the Xiong'an New Area, a large residential area with a high risk of flooding in northern China. Using a 100-year flood hazard as an example, a set of scenario analyses are conducted to explore how residents' evacuation processes are jointly affected by management policies (i.e., the number and geographical distribution of evacuation shelter locations) and human behaviors (i.e., the heterogeneity in households' evacuation preparation times and route searching strategies). This study aims to provide both modeling and policy implications for researchers and emergency responders to develop advanced socio-hydrological modeling tools for flood risk assessment and to improve the overall understanding of how flood evacuation performance is jointly affected by various management and behavioral factors.

The remainder of this paper is organized as follows. Section 2 presents the modeling framework. Section 3 introduces the case study site, model construction and scenario design. Section 4 presents the modeling results. Section 5 discusses the insights, limitations, and future research directions of this study, followed by the conclusions in Section 6.

2. Methodology

This section introduces the integrated modeling framework of this study. As illustrated in Figure 1, the modeling framework consists of three models: (1) an ABM for simulating household decision-making and emergency responders' flood management policies, (2) a transportation model for simulating residents' evacuation activities in a road network, and (3) a hydrodynamic model for simulating flood inundation processes. A detailed introduction to the three models and their coupling methods are described in turn as follows.

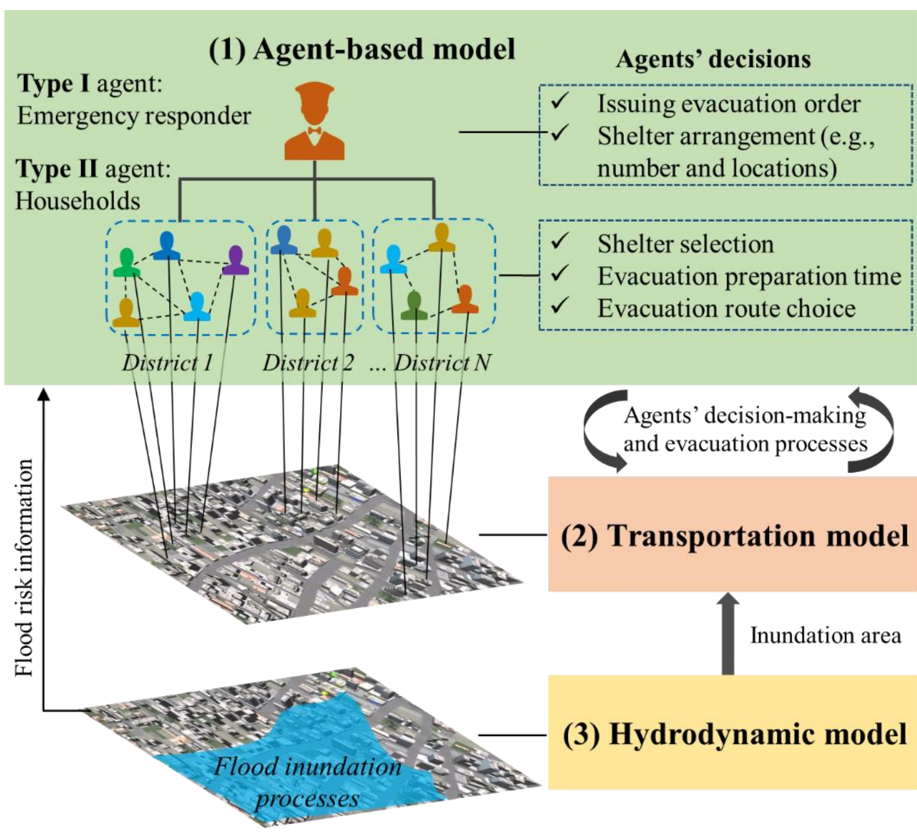

Figure 1. Illustration of the integrated modeling framework that couples an ABM for simulating household decision-making and emergency responders' flood management

policies, a transportation model for simulating residents' evacuation processes in a road network and a hydrodynamic model for simulating flood inundation processes

2.1. The ABM for human decision-making during flood events

In this study, an ABM is developed to simulate the government's disaster management plans and residents' flood evacuation behaviors. Therefore, two types of agents are considered in the ABM: (1) an emergency responder (Type I agent) and (2) the set of households (Type II agents), which are described in turn below.

An emergency responder agent is a government institution that makes flood management plans. As shown in Figure 1, in this study, we specifically consider two flood management decisions: (1) issuing a flood evacuation order to the residents who live in flood-prone areas and (2) shelter arrangement (i.e., deciding the number and location of evacuation zones that should be used to protect evacuees from flood hazards). Note that other management practices (e.g., sandbagging and levee construction) are also important flood management measures that are not explicitly discussed in this study.

In this study, each household is represented by an autonomous decision unit (i.e., an agent), considering that all the family members in a household typically evacuate in a shared transportation mode after communicating with each other to arrive at a final evacuation decision (Du et al., 2016). After receiving evacuation orders, an agent will spend some time completing a set of evacuation preparation tasks and then evacuate from its household location to a chosen evacuation destination. The following three decisions and/or behaviors are explicitly considered during this process.

The first decision is selecting an evacuation shelter if multiple optional shelters are available. During evacuation processes, the agents seek to evacuate to safe areas as soon as possible, aiming to minimize their traveling times. However, during an emergency situation, it is unclear and/or quite challenging for the agents to assess which shelter can ensure the shortest traveling time due to, for example, uncertainties of real-time traffic conditions and traffic load (e.g., the number of evacuating agents on the road). Here we follow the classic approach in evacuation simulation and assume that an agent focuses on choosing the shortest route from its original location to the safe area, thereby choosing the geographically nearest shelter in the system to as its evacuation destination. Based on the above reasons, in this study, we assume that an agent will choose the evacuation shelter that is located the shortest geographical distance from its residential location.

The second decision is associated with evacuation preparation activities (e.g., gather family members, pack bags, board up windows, and shut off utilities). These activities are aggregated and represented by a behavioral parameter called evacuation preparation time. This parameter measures how long it takes an agent to prepare for evacuation and is indicated by the interval between the time when an agent receives an evacuation order and the time when they start to evacuate via a road network. Previous studies have shown that households' evacuation preparation times are influenced by both psychological and logistical preparation tasks, which may vary among agents, with noticeable behavioral heterogeneity even at the community scale (Lindell et al., 2020, 2005; Wang et al., 2016). In this study, the heterogeneity in agents' evacuation preparation times is represented by the variation (i.e., standard deviation) in the evacuation preparation times of all households, and we explicitly examine the role of human behavioral heterogeneity in community evacuation outcomes.

The third decision is related to agents' route selection strategies during evacuation processes. In a complex road network, an agent may have multiple route choices from its original location to a destination. In this study, we assume that all of the agents have good knowledge of the road network in their community. Thus, two route search methods are incorporated into the model: (1) the shortest distance route search method (Mode 1) and (2) the system optimization-based route search method (Mode 2). In the shortest distance route search method, each agent seeks to reduce its evacuation time without considering the effects of other agents' evacuation route selections. The agents focus on finding the shortest route from their current location to the selected evacuation destination in the road network (Gallo and Pallottino, 1988; Fu et al., 2006; Li et al., 2022). Therefore, an agent's choice of evacuation route in Mode 1 will not be affected by its departure time, because it will always choose the shortest route regardless of the time at which it starts to evacuate. The optimization-based route search method (Mode 2) adopts a heuristic iterative method to optimize all of the agents' collective evacuation routes so that system-level evacuation efficiency is achieved (Zhu et al., 2018; He et al., 2021). In contrast with Mode 1, an agent's evacuation route in Mode 2 is affected by real-time traffic condition and other agents' evacuation status. Therefore, an agent's evacuation route in Mode 2 might be different if it starts evacuation at a different time.

It is worth noting that the agents will typically focus on reducing their own traveling times, and do not necessarily consider system-level evacuation efficiency. Among the above two route search modes, Mode 1 represents the case in which every agent in the system focuses on achieving individual-level evacuation efficiency (i.e., chooses the shortest route for evacuation), while Mode 2 represents the case that represents system-level evacuation efficiency (i.e., all the agents' route choices are optimized at the system level). In this regard, Mode 1 is the baseline evacuation scenario and Mode 2 is the benchmark scenario. The results of Mode 2 can be used to assess the extent to which the evacuation outcome of Model 1 can be improved by changing agents' route choices. Policy makers can compare the results of the two modes to improve evacuation performance by, for example, providing recommended evacuation routes for the agents who may encounter and/or cause severe traffic congestion during their evacuation processes. Based on the above three decisions and behaviors, all the agents' movements and interactions in the road network are incorporated into a transportation model, which is described in the following section.

2.2. Transportation model for large-scale evacuation simulation

As mentioned in Section 2.1, after an agent decides to evacuate, it will move from its household location to a chosen evacuation destination through the traffic network. During evacuation processes, an agent interacts with other agents and with the environment to adjust their movement in the road network over time. There are a number of modeling platforms and software packages used to model agents' evacuation processes. These include the Network Explorer for Traffic Analysis (NEXTA), the Transportation Analysis and Simulation System (TRANSIMS), the Planung Transport Verkehr (PTV) VISSIM, the City Traffic Simulator (CTS), and the Multi-Agent Transport Simulation model (MATSim) (Mahmud and Town, 2016; Lee et al., 2014; Murray-Tuite and Wolshon, 2013).

This study applies MATSim to simulate agents' evacuation processes. MATSim is a widely used open-source software for large-scale transportation simulation. The model can provide detailed information about each agent's movements in a road network (Horni, 2016; Lämmel et al., 2010; Zhuge et al., 2021). As shown in Figure 2, MATSim requires a variety of data as model inputs. The *plan* data include the initial locations, evacuation destinations, and departure times of all agents, and these data can be retrieved from agents' attributes and evacuation decisions in the ABM. The *network* data describe the attributes of the road network, such as the geographical structure of the road network, the number of lanes of each road, and road segment lengths and speed limits. These data are available from local or regional government institutions (e.g., the Department of Transportation) or from online data retrieval platforms such as OpenStreetMap or Google Maps (Farkas et al., 2014). Finally, the *config* input includes a model execution engine that defines a set of global model environments. Three modules, namely, an execution module, a scoring module, and a replanning module, are incorporated into MATSim for transportation simulation. This model has been widely used by researchers and practitioners to support evacuation planning and simulation for various types of natural disasters, such as earthquakes (Koch et al., 2020), hurricanes (Zhu et al., 2018), tsunamis (Muhammad et al., 2021), and floods (Saadi et al., 2018). For more details about MATSim and its applications in transportation simulation, see the studies of Lämmel et al. (2009) and Horni (2016).

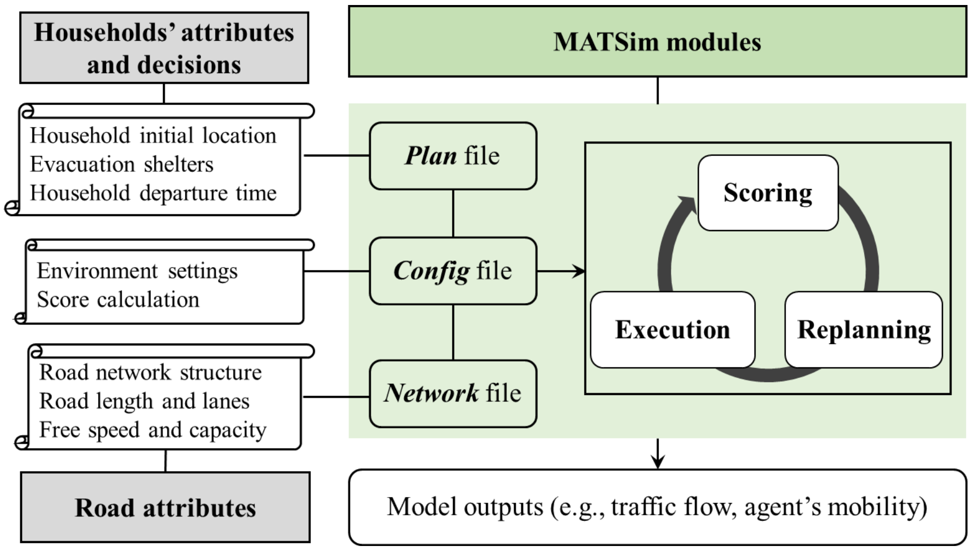

Figure 2. Inputs, modules and processes of the MATSim model

2.3. The hydrodynamic model for flood inundation simulation

Information on flood inundation processes (e.g., flood extent and water level) is essential for governments and the public to make flood management and evacuation decisions. Hydrodynamic models are important tools for simulating the timing and duration of flood dynamics by solving a set of mathematical equations that describe fluid motion (Guo et al., 2021). There are many hydrodynamic models available for flood dynamics simulation. These include but are not limited to HEC-RAS, MIKE11, MIKE 21, JFLOW, TRENT, TUFLOW and DELFT3D (Teng et al., 2017).

Following our prior work (Wu et al., 2021), in this study we use the classic hydrodynamic model MIKE 21 to simulate flood inundation processes in a floodplain. MIKE 21 numerically solves the two-dimensional shallow water equations to obtain water levels and flows across space and over time in various watershed environments, such as rivers, lakes, estuaries, bays and coastal areas. MIKE 21 has been widely used to simulate flood inundation processes in many floodplains across the world and is considered one of the most effective modeling tools for flood risk mapping, flood forecasting and scenario analysis (Nigussie and Altunkaynak, 2019; Papaioannou et al., 2016). Interested readers may refer to our prior work (Wu et al., 2021) for detailed introductions to the construction, calibration and validation of the MIKE 21 model in the specific study area.

2.4. Model integration and flowchart of the modeling framework

In the prior sections (Sections 2.1-2.3), the structures and functionalities of the three models were introduced; this section introduces how they are coupled in an integrated modeling framework. Previous studies have shown that computer models can be coupled in either a loose or a tight manner (Harvey et al., 2019; Bhatt et al., 2014; Murray-Rust et al., 2014; Du et al., 2020; Li et al., 2021). The former refers to models that are linked together by input/output data interfaces. That is, the output of one model is used as the input of another model. In contrast, for the latter, a model uses a common data pool and workload to exchange data among multiple model components, and as a result, components affect each other during modelling processes.

In this study, both the loose and tight coupling methods are employed to combine the three models. Specifically, MIKE 21 is coupled with the ABM and MATSim in a loose manner, while ABM and MATSim are coupled in a tight manner. The model coupling process and flowchart of the integrated model are illustrated in Figure 3. First, MIKE 21 simulates flood inundation processes for a specific flood event (e.g., a 100-year flood). The modeling results of MIKE 21 are then used to assess the inundated area and affected households in the flood zone, which are used as input data for the ABM and MATSim. Next, based on the modeling results of MIKE 21, two types of agents in the ABM are generated. The household agents who are located in the flood zone will receive flood warnings from an emergency responder agent and make evacuation decisions. Finally, all the agents' movements and evacuation activities are simulated by MATSim. By integrating the three models, the proposed modeling framework is capable of simulating flood inundation processes, flood management practices, and household decision-making and evacuation processes in a coherent manner. In the next sections, we will use a real-world case study to demonstrate how the modeling framework can be used by researchers and practitioners for flood risk assessment and evacuation management.

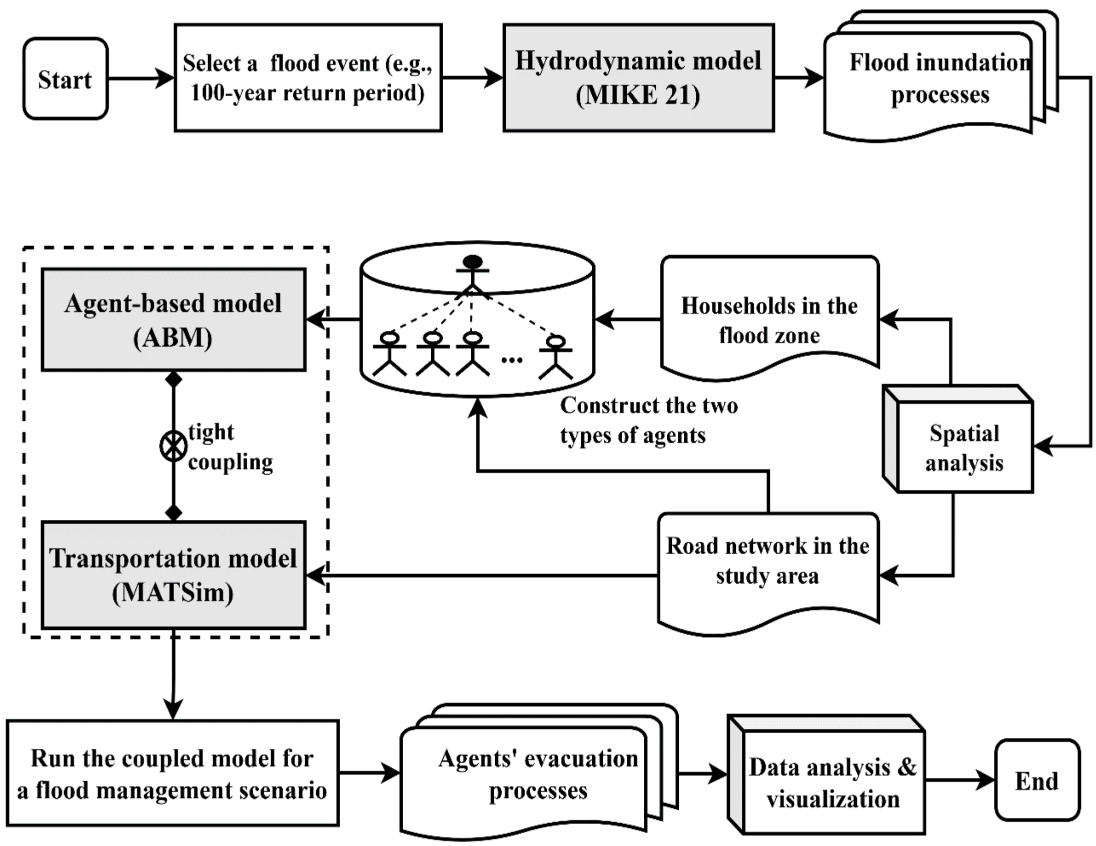

Figure 3. Flowchart of the integrated modeling framework

2.5. Measurement of flood evacuation performance

Agents' evacuation processes reflect their evacuation status and movements across space and over time in a road network. In this study, we use multiple parameters and indicators to represent agents' evacuation processes and evaluate their evacuation performance. For a residential area with *n* household agents, we first use a categorical variable, $S_{j,t} \in \{1,2,3\}$, to describe agent *j*'s evacuation status at time step *t*. $S_{j,t} = 1$ denotes that agent *j* has not started its evacuation process at time *t*. $S_{j,t} = 2$ denotes that agent *j* has already started evacuation but has not arrived at its evacuation destination at time *t*. $S_{j,t} = 3$ denotes that agent *j* has arrived at its evacuation destination at time *t*, which represents a successful evacuation case. Let τ_0 denote the time when the flood evacuation order is issued to the public, and let τ_j and τ_j^* denote agent *j*'s departure time (i.e., the time when the agent starts its evacuation in the road network after the evacuation preparation time) and arrival time (i.e., the time when agent *j* arrives at its evacuation destination), respectively. The agent's evacuation time ϕ_j is defined as the time period from its departure time τ_j to its arrival time τ_j^* (i.e., $\phi_j = \tau_j^* - \tau_j$).

By summarizing all the agents' evacuation statuses over time, the effectiveness of flood evacuation processes in a region can be reflected by a matrix with two indicators at the system level: (1) agents' average evacuation time Φ and (2) the system-level evacuation clearance time Γ. The agents' average evacuation time Φ is the average value of all the agents' evacuation times, which is calculated by $\Phi = \frac{1}{n}\sum_{j=1}^{n}\phi_j$. In comparison, the system-level evacuation clearance time Γ for a region is the duration from the time when the flood evacuation warning is issued in a residential area to the time when the last agent arrives at its evacuation destination (i.e., $\Gamma = \max(\{\tau_j^* \mid j = 1,2,3,...,n\}) - \tau_0$).

3. Case study and scenario design

3.1. Study site

The Xiong'an New Area (XNA) is used as a case study to illustrate the functionality of the proposed modeling framework in flood simulation and evacuation management. The XNA is located in the Baiyangdian River Basin, which includes the largest freshwater wetland in North China. This region covers three counties (Xiongxian, Rongcheng, and Anxin), encompassing a total area of 1768 km^2 (Figure 4). The region has a population of 1.1 million, and the GDP is 21.5 billion RMB (Sun and Yang, 2019).

The XNA has a typical continental monsoon climate, with annual average precipitation totaling approximately 570 mm. The region is influenced by various natural disasters and environmental problems, such as water pollution, heat waves, and groundwater overexploitation. In particular, the XNA has a high risk of flooding due to frequent extreme rainstorm events (Jiang et al., 2018; Su et al., 2021). Historical climate records show that a total of 139 flood events have occurred in the XNA over the past 300 years (Wang et al., 2020). For example, the heavy storm from 19 July to 21 July in 2016 affected a total population of approximately 517,000, leading to severe destruction and economic losses. Studies have found that compared with historical flood conditions, both the frequency and intensity of extreme flood events in the region are expected to increase under future climate change (Zhu et al., 2017; Wang et al., 2020). The flood problems in the XNA and many other flood-prone areas worldwide call for developing advanced computer models and decision support systems for robust flood risk assessment and informed management practices during extreme flood events.

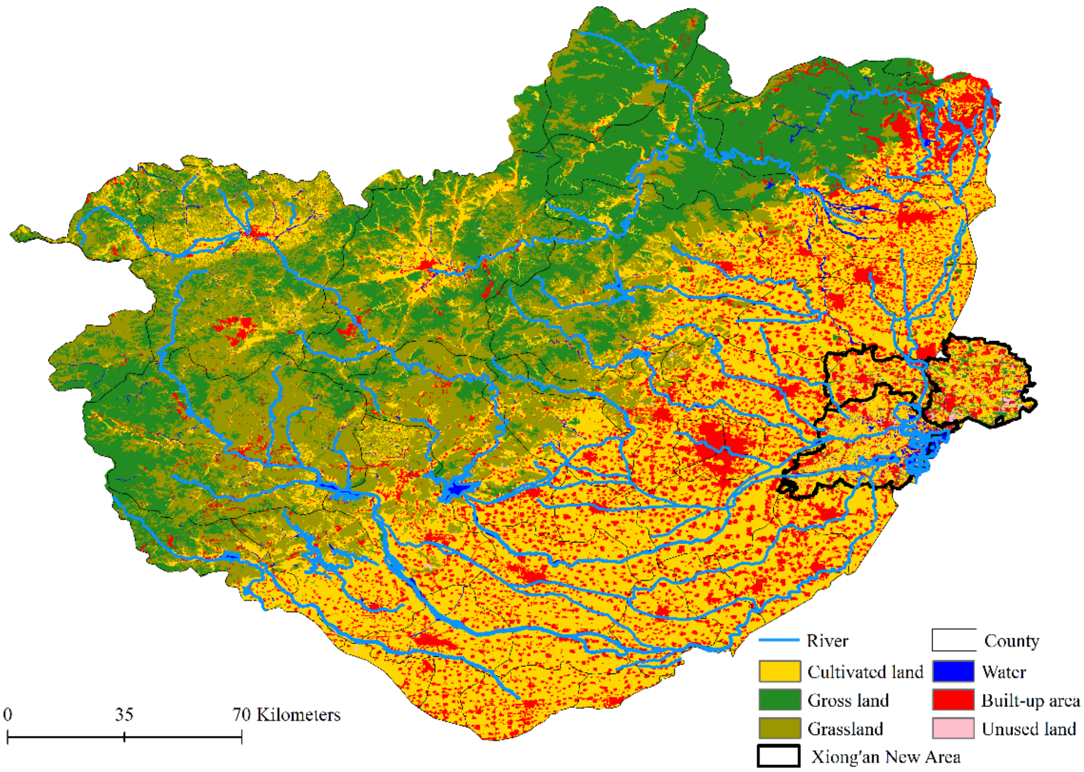

Figure 4. Map of the Baiyangdian River Basin and the Xiong’an New Area (marked with solid black lines)

3.2. Data collection and model construction

Based on the modeling framework, data from various sources were collected and compiled to construct the model, including meteorological, land use, hydrological, transportation and census data. Among them, land topology was retrieved from a 7-meter resolution DEM from the State Bureau of Surveying and Mapping. Meteorological data (e.g., daily precipitation, temperature, solar radiation and wind speed) from 98 stations in the study area were collected from the China Meteorological Administration. Population and household distribution were based on 30-meter resolution census data from the census bureau of the local government. Road network data were retrieved from Open Street Map, an open source global map data repository. Table 1 presents the data used in this study and their sources.

Table 1. List of data used in the integrated model

Data type	Data source	Period	Resolution	Format
Land elevation	State Bureau of Surveying and Mapping	2019	7 m	TIF
Land use	Data Center of the Chinese Academy of Sciences	2015	30 m	TIF
River network	Data Center of the Chinese Academy of Sciences	2015	-	SHP
Streamflow	Hydrological Yearbook in China	1980-2010	Daily	EXCEL
Weather conditions	China Meteorological Administration	1980-2010	Daily	EXCEL
Soil type	Data Center of Science in Cold and Arid Regions	2009	1 km	TIF
Population	Census Bureau of the local government	2020	30 m	EXCEL
Household distribution	Census Bureau of the local government	2020	30 m	TIF
Road network	Open Street Map	2022	-	XML

Figure 5 illustrates how the data are merged and integrated into the modeling framework. As introduced in Section 2, the modelling process starts by running the MIKE 21 model, with meteorological, DEM, land use, soil type and river network data as the model inputs. For a given storm event, the MIKE 21 model generates flood processes, which can be used to predict the inundated area and the affected population. These data are then used to construct the ABM and the MATSim model to simulate agents' flood management and evacuation behaviors.

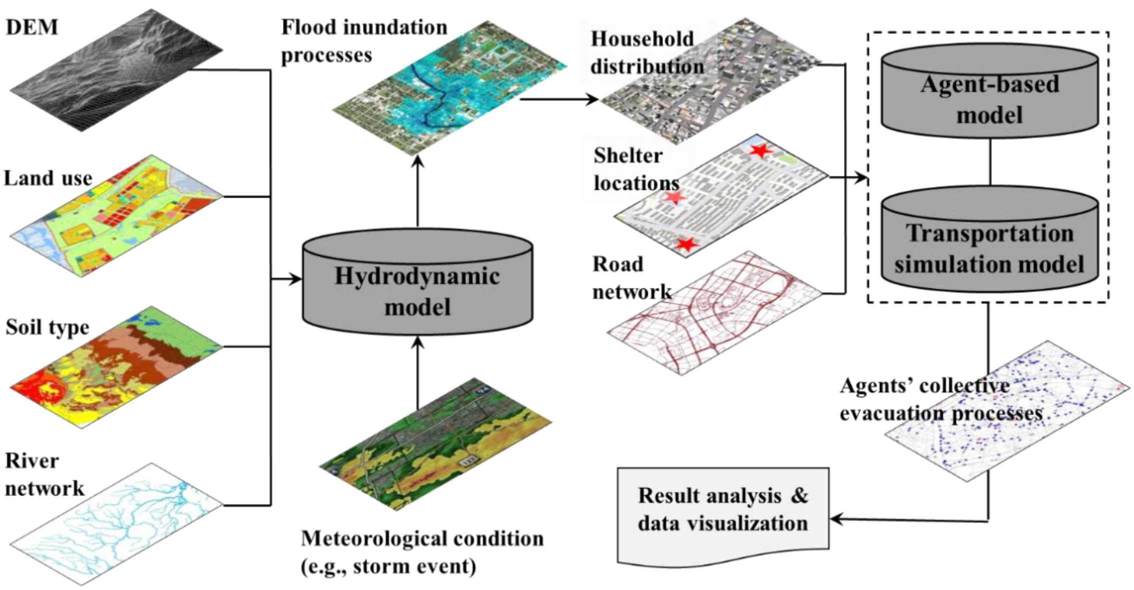

Figure 5. Data sources and flowchart of the integrated modeling framework

3.3. Flood simulation and scenario design

As mentioned above, the case study site has a high risk of flooding due to frequent extreme rainstorm events. Following the precautionary principle in natural disaster management (Etkin et al., 2012), we use the 100-year flood event as an example to evaluate the impacts of extreme flooding on the study area, and then examine the impacts of various management policies and human behaviors on household evacuation processes.

We run the hydrodynamic model to simulate flood inundation processes for the flood with 100-year return period. The modeling results show that the inundated area is 66.5% of the land area (Figure 6). The affected population is 508,986 (45.8% of the total population). These modeling results are consistent with the results that were reported in our prior work, and are empirically similar to the flood hazard experienced in this region in July 2016. For detailed introductions regarding the construction, calibration and validation of the hydrodynamic model, see Wu et al. (2021). With such a high flood risk, it is essential for emergency responders to understand how flood evacuation performance is affected by various human behavioral factors and evacuation management plans.

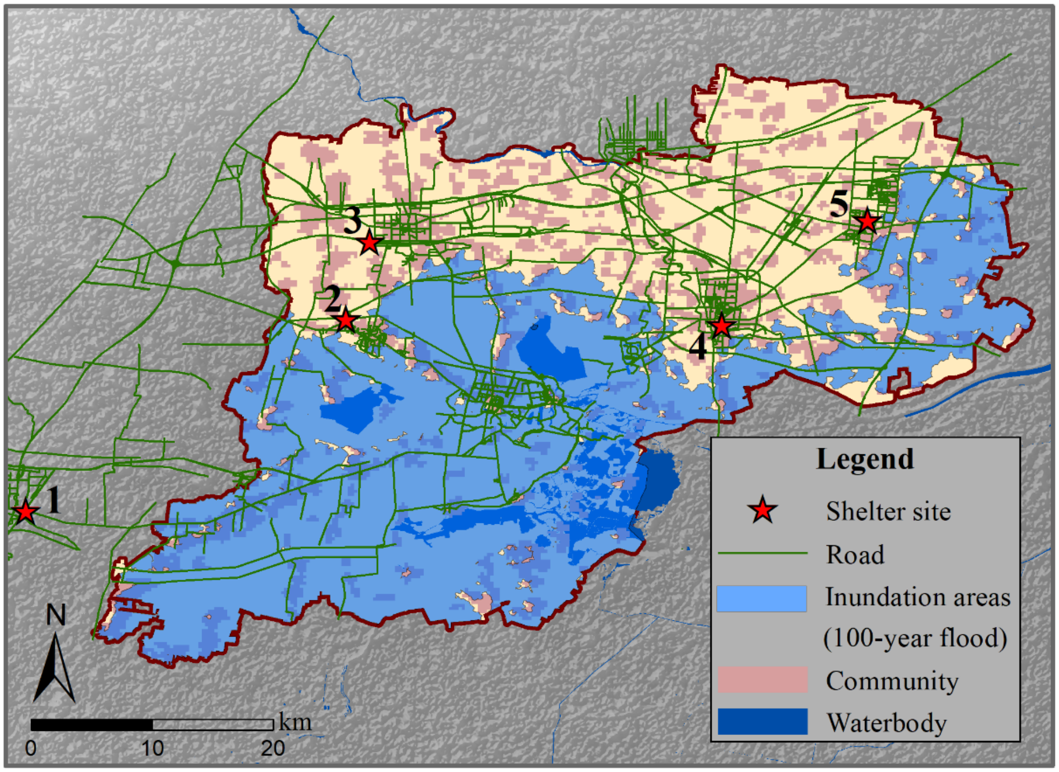

Figure 6. Flood inundation areas for a 100-year flood in the study area

A scenario-based analysis is conducted to examine the roles played by the following factors in flood evacuation simulations: (1) evacuation shelter establishment (i.e., the number and geographical distribution of shelter locations), (2) heterogeneity in households' evacuation preparation times, and (3) evacuees' route search strategies. Three experiments are designed to assess the joint impacts of the above three factors (Table 2), which are introduced in turn below.

The first experiment focuses on assessing the impact of the number and geographical distribution of evacuation shelters on agents' evacuation processes. Note that in the XNA, five optional sites for evacuation shelters are identified based on the flood inundation area for the 100-year flood (illustrated by the red stars in Figure 6). Considering all the possible combinations of these shelters, a total of 31 simulations are performed in this experiment (5 simulations for single-shelter scenarios and 26 simulations for multiple-shelter scenarios). Experiment 2 assesses the impacts of agents' behavioral heterogeneity (i.e., variations in households' evacuation preparation times) on traffic flow and evacuation outcomes. Note that in the first and second experiments, agents apply the shortest-distance route search method (Mode 1) to evacuate from their household locations to evacuation destinations. Experiment 3 simulates evacuation processes in which agents apply the system-level optimization method (Mode 2) for route selection. The simulation results of experiment 3 are compared with those of the first and second experiments to explore the effects of agents' route search strategies on evacuation outcomes.

Table 2. Scenario design for simulating household evacuation processes

Experiment	Shelter arrangement	Heterogeneity in agents' evacuation preparation times	Evacuation route search strategy
1	All the combinations of the five optional shelters #1, #2, #3, #4, and #5	1.5[a]	Mode 1 (Shortest distance)
2	{#1, #2, #3, #4, #5}[b]	0.2~3.0[a]	Mode 1 (Shortest distance)
3	Five one-shelter scenarios and {#1, #2, #3, #4, #5}	0.2~3.0[a]	Mode 2 (System optimization)

Note:

[a] Residents' behavioral heterogeneity is measured by the variation (i.e., standard deviation) in their evacuation preparation times. In the study area, the average evacuation preparation time of residents is set to 4 hours based on our communication with the local flood management authorities.

[b] The set {#1, #2, #3, #4, #5} denotes that all five shelters are selected for this scenario.

4. Modeling results

4.1. An example of household evacuation processes

In this study, the results of household evacuation simulations are extracted and analyzed with the data visualization tool *Senozon Via* (Milevich et al., 2016). Figure 7a presents a snapshot of residents' evacuation schemes for the case in which all five evacuation shelters are used in the study area (note that each household is illustrated by a green dot in Figure 7a). Figure 7b depicts the change in the ratio of the three groups of the population during the evacuation processes. The percentage of the population in the S=1 group (i.e., the agents that have not started evacuating) displays a consistent decreasing trend, as more agents start their evacuation processes over time. Consequently, the S=3 group (i.e., the agents that have arrived in a safe zone) exhibits a consistent increasing trend. The S=2 group (i.e., the agents that have started evacuating but have not arrived at a safe zone, representing the residents who are moving in the road network) increases at the beginning of the evacuation period, reaching a peak of 43.1% after approximately 6.5 hours, and then decreases until the end of the evacuation period. The entire evacuation process takes approximately 15.5 hours (i.e., the evacuation clearance time). In the following sections, the factors that influence the evacuation process will be assessed under different conditions.

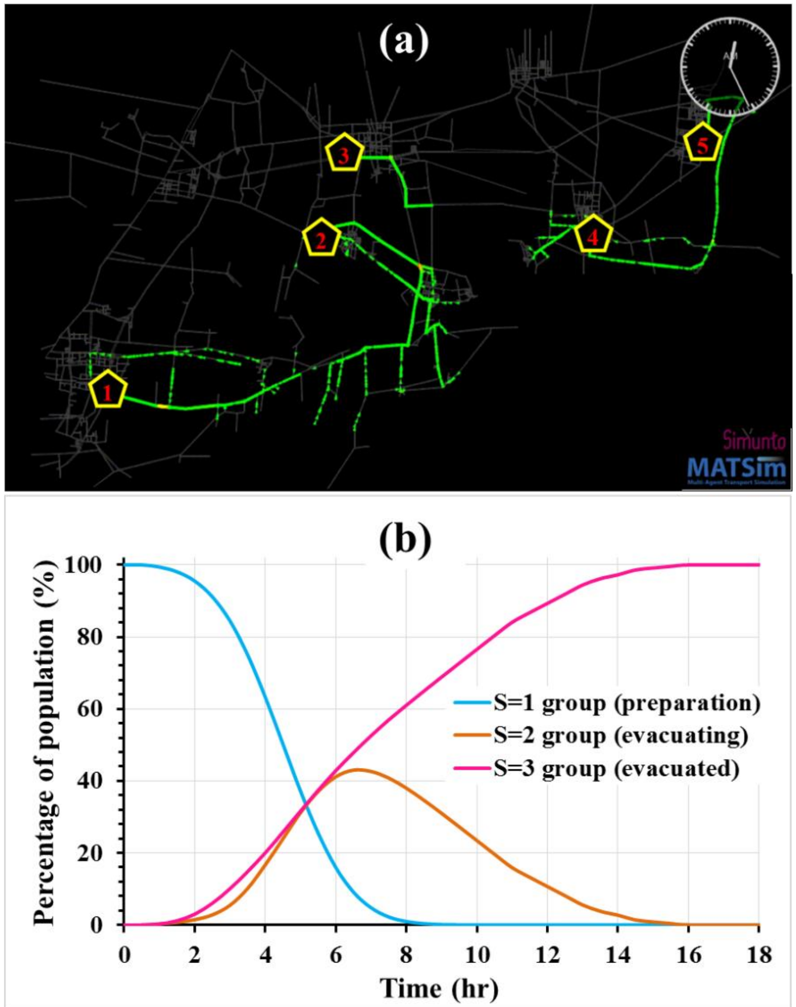

Figure 7. (a) A snapshot of residents' evacuation schemes when all five evacuation shelters are established in the study area; (b) The percentages of the population in the three groups of agents. Note that the S=1 group includes agents who have not started evacuating, S=2 includes agents who have started evacuating but have not arrived at an evacuation destination, and S=3 includes agents who have successfully arrived at their destinations.

4.2. Impacts of shelter location arrangement on evacuation processes

We first conduct experiment 1 to examine agents' evacuation processes for the five scenarios in which only one evacuation shelter is established. Figure 8 shows that the geographical location of an evacuation shelter has a fundamentally important influence on residents' flood evacuation performance. Residents' average evacuation time is the shortest for shelter site #1 (20.1 hours), followed by sites #2 (23.7 hours), #5 (33.3 hours), #3 (35.7 hours) and #4 (46.8 hours). The boxplot of all the agents' evacuation times also shows that the variation in agents' evacuation time is the largest for shelter site #4 (32.4 hours) and the smallest for shelter site #1 (15.4 hours). In terms of the system-level evacuation outcomes, shelter sites #1 and #2 are associated with the shortest evacuation clearance time (~ 56 hours), and shelter site #4 is associated with the longest evacuation clearance time (~108.9 hours) (the embedded figure in Figure 8). In this regard, among the five optional shelter locations, sites #1 and #2 are the best locations for shelter establishment, and site #4 is the worst, with the longest evacuation time.

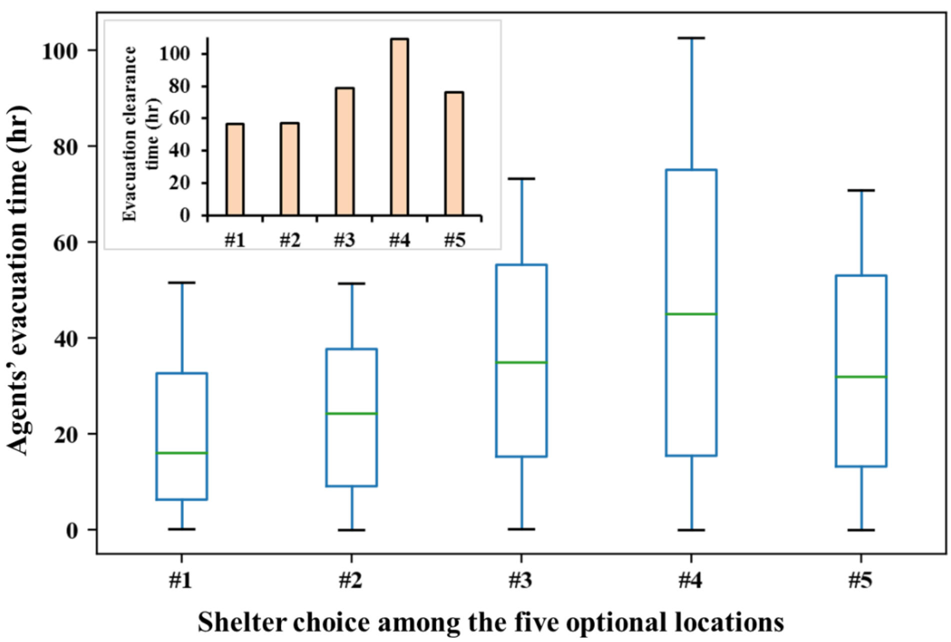

Figure 8. Boxplot of agents' evacuation times (the main figure) and the system-level evacuation clearance times for the five one-shelter scenarios

Next, we compare the average evacuation time of agents for simulations in which all 31 combinations of the five optional evacuation shelter locations are considered. As shown in Figure 9, when there are a small number of evacuation shelters, establishing more shelters in the system can notably reduce agents' evacuation times, and this effect is more noticeable for the worst shelter allocation scenario (illustrated by the blue line) than for the best shelter allocation scenario (illustrated by the red line). For example, as the number of shelters increases from two to three, the average evacuation time is reduced from 44.7 hours (shelter set {#4, #5}) to 29.7 hours (shelter set {#3, #4, #5}) for the worst shelter allocation scenario (a total reduction of 15 hours). In contrast, the reduction in evacuation time is only 5 hours for the best shelter allocation scenario (from 13.1 hours for set {#2, #3} to 8.1 hours for set {#1, #2, #3}). These results can yield policy implications in terms of the number and geographical locations of evacuation shelters needed to meet a particular flood management goal. For example, if the management goal is to evacuate all the residents to a single safe zone, shelter #1 would be the best choice, among the five optional locations, in terms of minimizing the evacuation clearance time. However, for the case of establishing two shelters in the region, shelter set {#2, #3} is a better choice as compared with the other shelter site combinations.

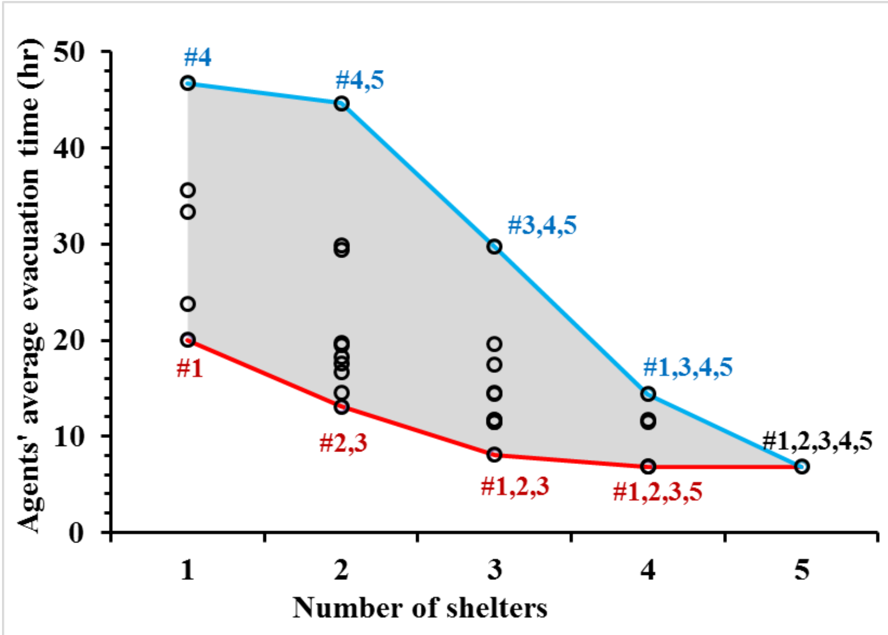

Figure 9. The average evacuation time of residents under the scenarios that consider all the possible combinations of the five optional evacuation shelters

Notably, the modeling results show that agents' evacuation time decreases if shelters are located closer to denser residential areas. This is because a shelter located closer to denser areas can reduce agents' travel distances. Furthermore, the modeling results show that the reduction in residents' evacuation times, due to the increase in the number of evacuation shelters, is significantly affected by the existing number of evacuation shelters and, in particular, their geographical distribution in the region. After a certain number of evacuation shelters are established (larger than three in this case), including more shelters in the system has a marginal effect on reducing evacuation times. Taking the best shelter allocation scenario as an example (the red line in Figure 9), when there are only two evacuation shelters ({#2, #3}), adding one more evacuation shelter (#1) in the system can reduce the evacuation time by 5 hours (from 13.1 hours for set {#2, #3} to 8.1 hours for set {#1, #2, #3}). In contrast, the reduction in evacuation time is only 1.3 hours when shelter #5 is added to the shelter set {#1, #2, #3}. In particular, the average evacuation time is 6.8 hours for shelter sets {#1, #2, #3, #5} and {#1, #2, #3, #4, #5}, which indicates that adding one more shelter in the system did not reduce the average evacuation time. This phenomenon is supported by the Braess paradox phenomena in the field of transportation research (Braess et al., 2005; Pas and Principio, 1997; Murchland, 1970), which suggests that including a new link in a traffic network could possibly result in heavier traffic congestion and longer travel times. This phenomenon and its policy implications will be further discussed in Section 5.

4.3. Impacts of residents' behavioral heterogeneity on evacuation processes

Previous studies have shown that the evacuation preparation time of households plays an important role in their emergency evacuation outcomes during natural disasters (Lindell et al., 2005, 2020). However, the heterogeneity in human behaviors has not been explicitly examined in flood evacuation processes. In this section, we conduct experiment 2 to assess the impacts of human behavior heterogeneity (measured by the variance in agents' evacuation preparation times) on evacuation processes. Figure 10 shows that human behavioral heterogeneity has a nonlinear effect on agents' evacuation outcomes. Increasing the heterogeneity in households' evacuation preparation times will result in reductions in the average evacuation time and the system-level evacuation clearance time, and this effect is more significant when the variation in the evacuation preparation time is small (< 1.5 hours). In particular, when the variation in preparation time is large (> 2 hours), the change in the heterogeneity of preparation times will not notably affect the average evacuation time or the system-level evacuation clearance time. These results are consistent with the modeling results obtained from our prior work, which examined the role of heterogeneity in residents' tolerance to flood risk during evacuation processes (Du et al., 2016).

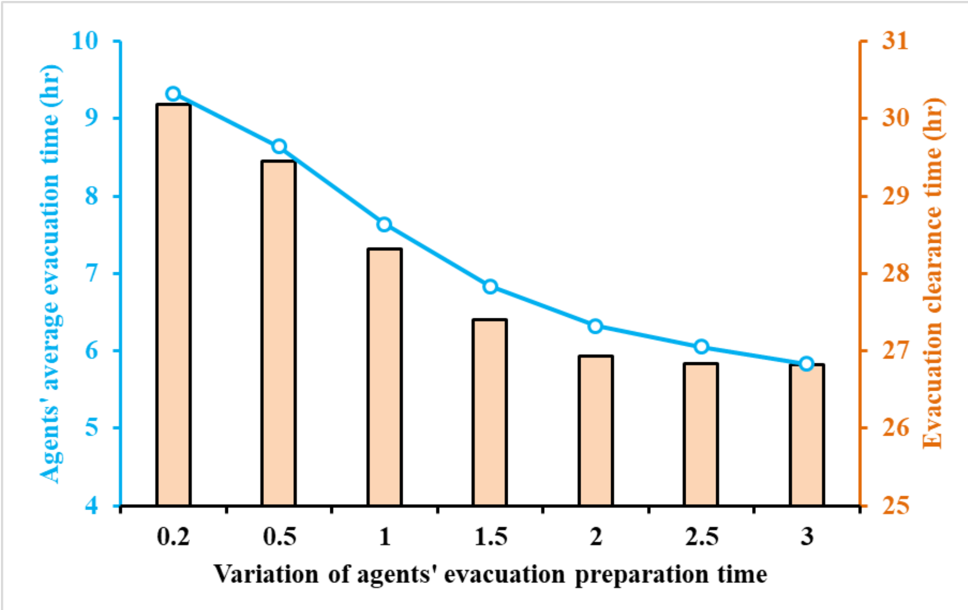

Figure 10. The impacts of human behavioral heterogeneity (i.e., the variation in agents' evacuation preparation times) on their average evacuation time (the left Y-axis) and the system-level evacuation clearance time (the right Y-axis)

Next, we assess the impacts of human behavioral heterogeneity on the traffic flow conditions in the road network. Figure 11 plots the percentage of the three groups of the population during evacuation processes, and the S=2 group (illustrated by the two brown lines) includes the agents who are evacuating in the road network. The modeling results show that the peak traffic time (i.e., the time when the number of agents in the road network reaches a maximum during the evacuation period) is delayed as the level of agent behavioral heterogeneity increases. In addition, the percentage of agents in the road network at the peak traffic time is significantly lower in the high behavioral heterogeneity scenario than in other scenarios. For example, the traffic peak time can be delayed from

6.0 hours to 8.5 hours as the variation in the evacuation preparation times increases from 1.0 hours to 3.0 hours. At the time of the traffic peak, the percentage of agents in the road network is reduced from 67.9% (the low-heterogeneity scenario) to 46.6% (the high-heterogeneity scenario), and the system-level evacuation clearance time is reduced from 28.5 hours (the low-heterogeneity scenario) to 27 hours (the high-heterogeneity scenario). Figure 12 compares the peak traffic time and the percentage of evacuating agents at the peak time under various levels of heterogeneity in agents' evacuation preparation times. The modeling results show that as agents' behavioral heterogeneity increases, flood evacuation outcomes can be improved (i.e., the traffic congestion problem is alleviated, the peak traffic time is delayed, and the evacuation clearance time is reduced).

These modeling results highlight the importance for policy makers to pay explicit attention to households' behavioral heterogeneity during flood evacuation processes. For example, the modeling results show that the variation in agents' departure times can significantly affect traffic load in the road network and evacuation clearance time. Traffic congestion condition can be alleviated if the variation of agents' departure times is larger. Thus, to improve evacuation efficiency, emergency responders may need to divide all the households in the community into a number of groups and guide them to evacuate in batches, rather than let them start evacuation in a chaotic manner without appropriate coordination.

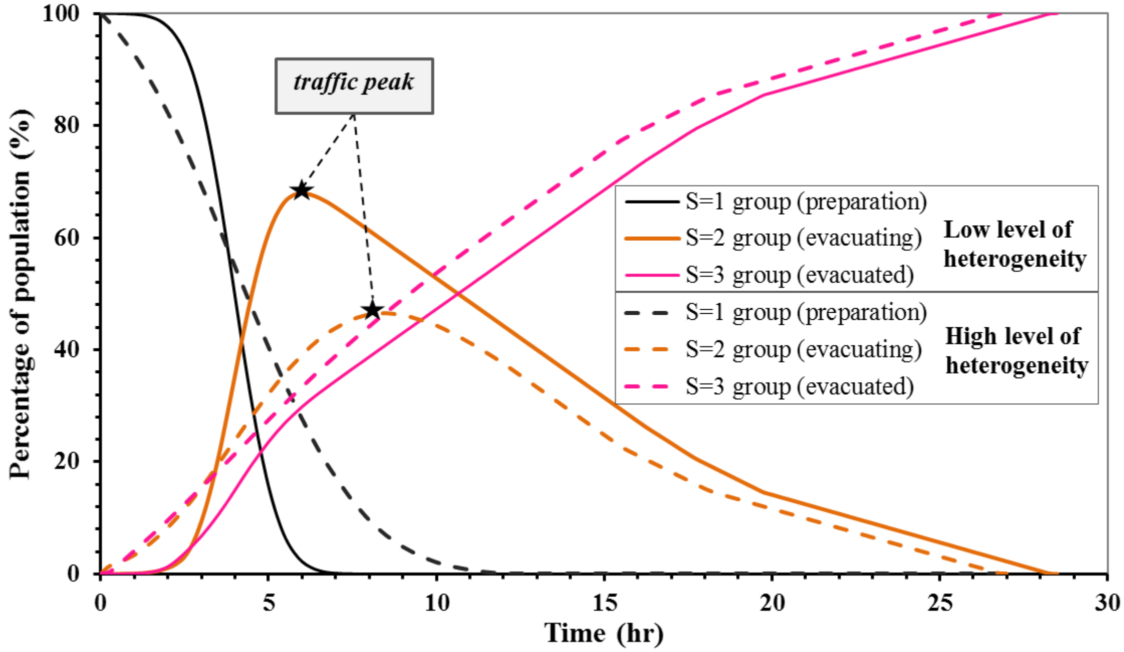

Figure 11. Comparison of the evacuation processes for low (solid lines) and high (dotted lines) levels of human behavioral heterogeneity. Note that agents' behavioral heterogeneity is measured by the standard deviation of their evacuation preparation time, and the low and high levels of heterogeneity are 1.0 hours and 3.0 hours, respectively.

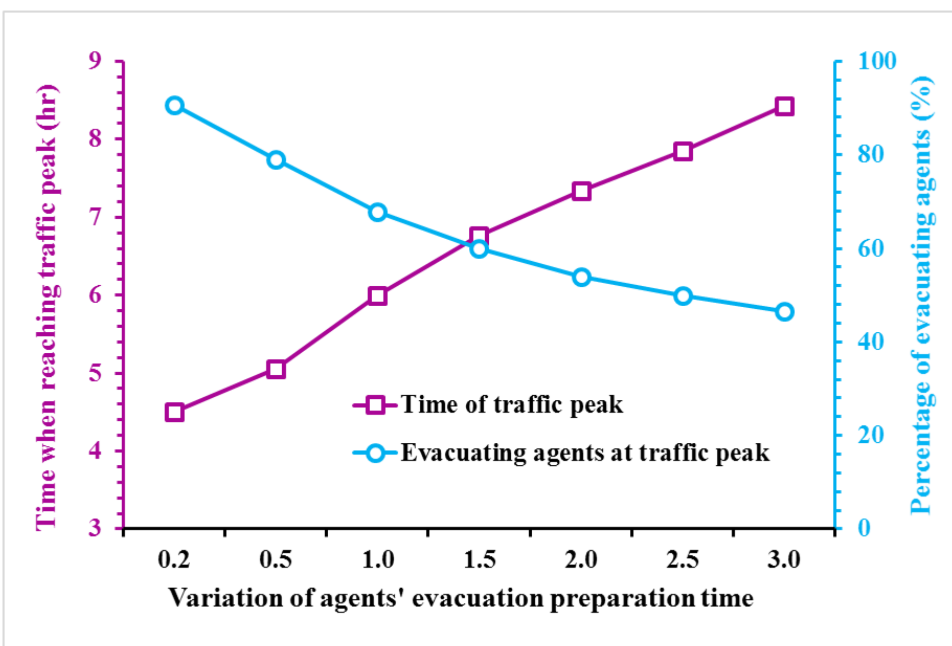

Figure 12. Peak traffic time (the left Y-axis) and the percentage of evacuating agents (i.e., S=2 group) at the peak traffic time (the right Y-axis) for various levels of human behavioral heterogeneity.

4.4. Impacts of households' evacuation route choices on evacuation processes

In the above sections, the modeling results for scenarios in which the agents apply the shortest-distance route search method to travel from their original locations to destinations (Mode 1) during evacuation processes were presented. In this section, we conduct experiment 3, in which agents' evacuation routes are obtained based on a system-level optimization approach (Mode 2). Then, we compare the three experiments to explore the joint impacts of the route search method and behavioral heterogeneity of residents on evacuation processes.

Figure 13 compares agents' average evacuation times for the two travel modes. Two implications are obtained from the modeling results. First, the results show that the average evacuation time is consistently smaller for Mode 2 than for Mode 1. This result agrees with the common belief in transportation research. That is, if each agent selects their shortest evacuation route without considering the effects of other agents' route choices, traffic congestion will likely occur in the road network. In contrast, if agents' evacuation route choices are optimized from the system level, traffic flow conditions can be improved, leading to a noticeable reduction in traffic congestion and shorter evacuation times.

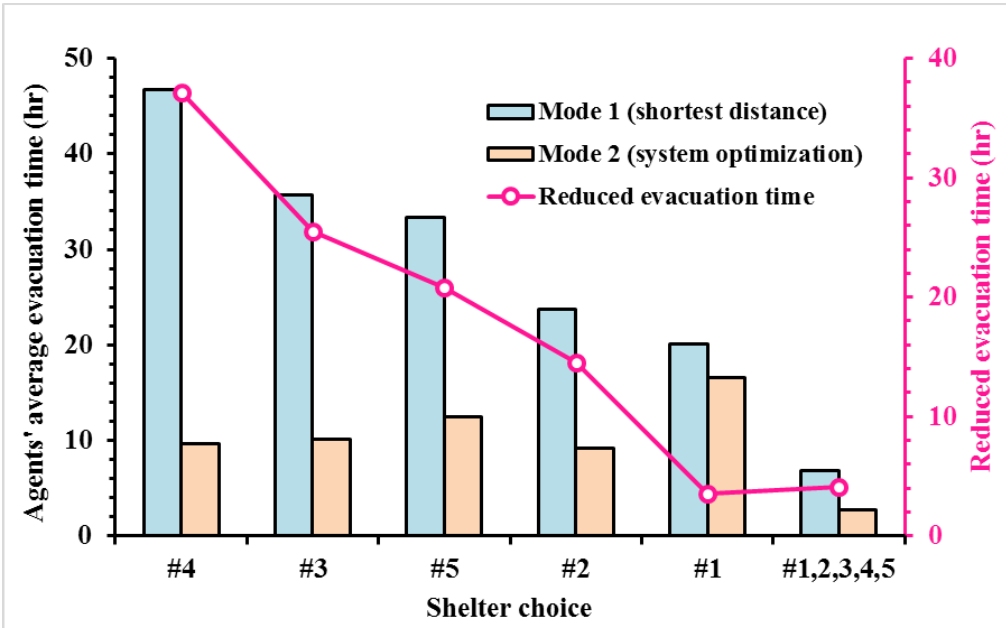

Figure 13. Comparison of the average evacuation time of agents for the two evacuation route search strategies

Second, one can observe that the variation in evacuation time across different shelter establishment scenarios is significantly higher for Mode 1 than for Mode 2. For example, among the five one-shelter scenarios, the agents' average evacuation time ranges from 46.7 hours to 20.1 hours (a difference of 26.6 hours) for Mode 1. In contrast, this value ranges from 16.5 hours to 9.2 hours (a difference of 7.3 hours) for Mode 2. This result implies that shelter establishment plays a more important role when residents only seek to minimize their individual evacuation times. In comparison, if agents' evacuation routes are optimized from the system level, shelter establishment will become a less significant factor affecting evacuation performance.

Figure 14 presents the percentages of the three groups of agents during the evacuation process to explicitly examine the impacts of different route search strategies. Compared with the shortest-distance search strategy (Mode 1), the system-level optimization route search strategy (Mode 2) can reduce the evacuation clearance time by 12 hours (from 27.5 hours for Mode 1 to 15.5 hours for Mode 2). In addition, the percentage of agents in the road network at the peak traffic time is reduced from 60.4% for Mode 1 to 43.1% for Mode 2, indicative of a significant improvement in traffic congestion during the evacuation period. However, the peak traffic time is similar in the two scenarios, suggesting that changing agents' route search strategies does not considerably affect the peak time of traffic flows.

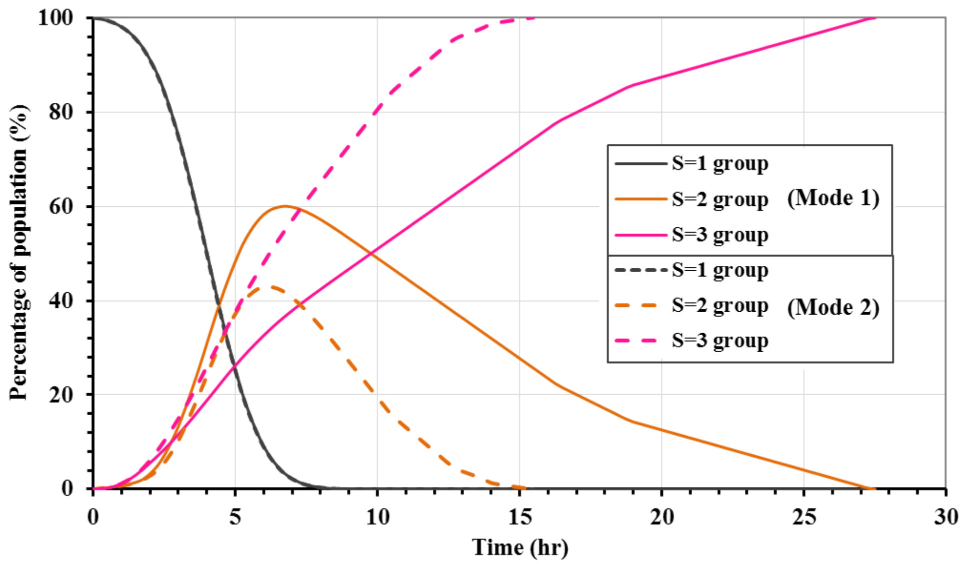

Figure 14. Comparison of residents' evacuation processes for the two route search strategies (note that all five evacuation shelters are selected for the two scenarios, and the variation in residents' evacuation preparation times is 1.5 hours)

The above analyses focused on assessing the impacts of a single factor (agents' behavioral heterogeneity or evacuation route search strategies). Figure 15 examines how the two factors jointly affect evacuation processes. Notably, in general, the average evacuation time of agents and the system-level evacuation clearance time are small when the variation in the evacuation preparation time is low and/or when agents use Mode 2 to determine their evacuation routes. Interestingly, when the variation in agents' evacuation preparation times is low (<1.0 hour), the difference between Mode 1 and Mode 2 is not significant in terms of the peak traffic time or the percentage of evacuating agents at the peak traffic time. This result indicates that changing agents' route search strategies will not considerably affect the peak traffic time or the maximum traffic flow if all the agents start their evacuation activities within a short time window. In contrast, as the variation in the evacuation preparation time of agents increases, the evacuation route search strategy used can significantly affect the peak traffic time and the maximum traffic flow (Figures 15c-15d). However, the variation in agents' evacuation preparation times does not notably affect the changes in the average evacuation time or system-level evacuation clearance time between the two route search strategies.

The comparisons of the two route search methods, as have been presented in the above sections, show that households' route choices play an important role in their evacuation processes. Evacuation clearance time and traffic congestion will be significantly alleviated and become more robust against the change in shelter location arrangement if evacuation routes are optimized. In this regard, policy makers may improve flood management by providing clear guidance to all the households in terms where (i.e., shelter choice), when (i.e., departure time) and in particular, through which route (i.e., route selection) to evacuate. On the other hand, households need to follow the evacuation guidance and take the recommended routes to improve evacuation efficiency.

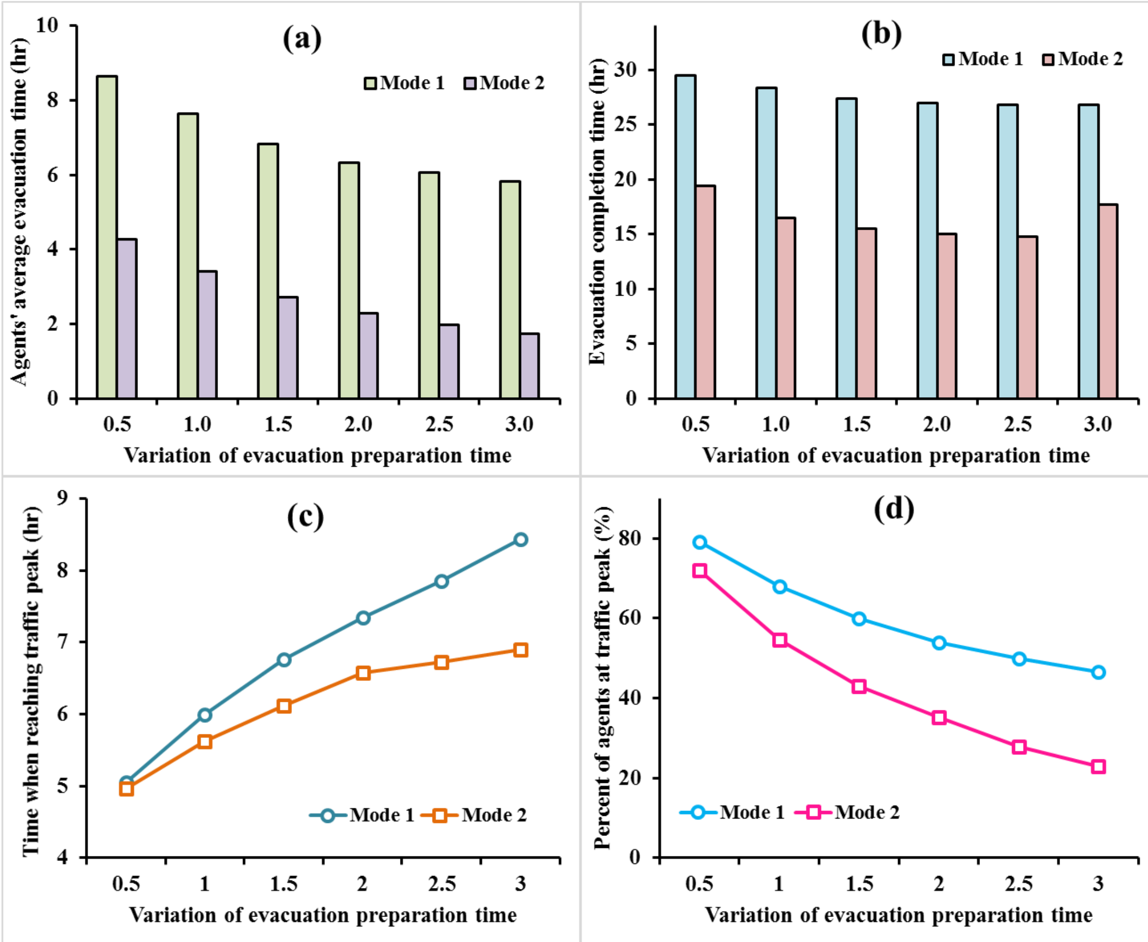

Figure 15. The joint impacts of evacuation route search strategies and the variations in agents' evacuation preparation times on (a) the average evacuation time, (b) the system-level evacuation clearance time, (c) the time when the traffic peak is reached during evacuation processes, and (d) the percentage of evacuating agents at the peak traffic time

5. Discussion

5.1. Implications for flood risk assessment and evacuation management

In this study, we employ an interdisciplinary socio-hydrological approach that incorporates a physically-based hydrodynamic model, an agent-based human behavior model, and a large-scale transportation model into an integrated modeling framework. The proposed modeling framework is motivated by previous socio-hydrological studies that called for incorporating various factors in the context of coupled human-flood systems to support flood management. These factors may be associated with a wide range of interdisciplinary domains, such as hydrogeological conditions, flood inundation process, information dissemination platforms, risk perception and awareness, social preparedness, public policy, and urban infrastructure development (Barendrecht et al., 2019; Di Baldassarre et al., 2013; Yu et al., 2022; Pande and Sivapalan, 2017; Troy et al., 2015; Fuchs et al., 2017; Viglione et al., 2014). We apply the model to the XNA in China to assess the inundated areas of an extreme flood event and to examine household evacuation outcomes under various management policies and human behaviors. Several modeling and policy implications can be obtained based on the model construction and simulation results.

First, the simulation results of this study show that the flood risk and flood damage to an area are affected not only by the hydrological characteristics of flood events but also by infrastructural, socioeconomic and human behavioral factors. In particular, the results show that household evacuation outcomes are significantly affected by shelter location arrangement, route selection strategies, and evacuation preparation times. Therefore, it is essential for researchers and policy makers to incorporate various social, hydrological and human behavioral factors into an integrated framework to obtain more robust estimations of flood risk and to design informed policies to support holistic flood management.

Second, the modeling results show that the number of evacuation shelters and, in particular, their geographical distributions have important effects on flood evacuation processes. For example, by comparing the evacuation outcomes obtained for the five optional shelter sites in the case study area, we find that the average evacuation time of residents varies from

20.1 hours (shelter site #1) to 46.8 hours (shelter site #4) (Figure 8). In this regard, if there are limited available resources and only one evacuation site can be established in the area, shelter #1 would be a better site than shelter #4 if the management goal is to minimize the average evacuation time of residents. Another implication associated with shelter choice is that establishing more shelters in the area does not necessarily lead to improvements in a community's evacuation processes if there is already a sufficient number of evacuation shelters or if the shelters are not well distributed in the region. For example, in the case in which there are three shelters (e.g., {#1, #2, #3}), including more shelters in the system (e.g., #4, #5, or both) will not effectively reduce the average evacuation time of households (Figure 8). This finding, although somewhat contrary to what one would intuitively expect, is in line with the classic Braess paradox in the field of transportation research; notably, adding a new link in a traffic network may not improve the operation of the traffic system (Frank, 1981; Murchland, 1970). Some studies have shown that the occurrence of Braess paradox phenomena may be affected by the road network configuration, travel demand, and travelers' route search behaviors (Pas and Principio, 1997; Braess et al., 2005). Therefore, regarding emergency management policies such as where to establish new shelters, policy-makers need to assess the relationships among these factors to determine the number and geographic distribution of shelters in the system.

Third, flood evacuation is a complex process in which residents' evacuation activities can be affected by various social, economic, environmental and infrastructural factors. Thus, in a particular flood-prone area, residents' decisions and evacuation behaviors could be highly heterogeneous, varying from family to family, from community to community, and from time to time (Paul, 2012; Huang et al., 2017). This study shows that human behavioral heterogeneity can significantly affect flood evacuation outcomes in a given region. For example, the modeling results show that variations in residents' evacuation preparation times could result in noticeable differences in traffic congestion conditions and the time required for evacuees to complete their evacuation processes (Figures 10-12). Therefore, in flood management practice, emergency responders need to explicitly consider the heterogeneity in residents' behaviors and determine how to promote behavioral changes by providing the needed resources to vulnerable groups who are not able to take effective flood mitigation actions to improve the overall disaster management performance of the community (Nakanishi et al., 2019; Hino and Nance, 2021).

5.2. Limitations and future research directions

Our modeling framework and the simulations in this study have a number of limitations that warrant future research to make improvements and extend the current approach. First, similar to other studies on emergency evacuation simulation (Wood et al., 2020; Zhu et al., 2018; Koch et al., 2020; Saadi et al., 2018), this study focuses on car-based traffic simulation without considering other transportation modes (e.g., motorcycles). In real-world evacuation cases, residents may use various types of transportation modes to evacuate, including by automobile, motorcycle, bus, or foot (Melnikov et al., 2016). Residents may also change their travel modes during evacuation processes, for example, due to a change in the available transportation facilities. Recent studies have attempted to improve emergency evacuation simulations by considering more factors in evacuation simulation, such as multiple transportation facilities, changes in traffic network accessibility, variations in travel demand, pedestrian/vehicle interactions and speed adjustments (Dias et al., 2021; Takabatake et al., 2020; Wang and Jia, 2021; Sun et al., 2020; Chen et al., 2022). Future study could also improve the transportation model to consider more complex agent-agent and agent-environment interactions during evacuation processes. For instance, besides the two route search methods that have been analyzed in this study, future work may consider another type of route search method, in which agents have fully access to the real-time information on traffic conditions and may decide to change their evacuation routes over time (referred to as mode 3). The three travel modes can be systematically compared to achieve a better understanding of how agents' route searching strategies may affect their evacuation results. This extension will enhance the functionality of the transportation model MATSim and improve the simulation of agent behaviors during community evacuation processes.

Second, regarding the analyses of shelter establishment, we primarily focus on the number and geographical distribution of evacuation shelters without considering other important shelter characteristics, such as shelter capacity. However, it is sometimes necessary to consider the constraint of shelter capacity in evacuation management, especially in large-scale evacuation scenarios. Recently, studies have analyzed the impacts of shelter capacities and their geographic distribution on evacuation outcomes (Alam et al., 2021; Khalilpourazari and Pasandideh, 2021; Oh et al., 2021; Liu and Lim, 2016). Future studies should consider more shelter properties to improve the current modeling framework.

Third, in this study, the hydrodynamic model is coupled with the ABM and the transportation model in a one-way coupling manner. That is, the hydrodynamic model generates flood inundation results as the input for the ABM and the transportation model, but the modeling results of the ABM and the transportation model do not affect the hydrodynamic modeling process. Such a one-way model coupling method is suitable for simulating residents' evacuation activities before a flood occurs, but it is not suitable for cases in which evacuation processes and flood inundation processes have an overlapping time period. In particular, the model is not capable of simulating how human behaviors affect river channel and flood inundation processes (Chen et al., 2016; Witkowski, 2021). This is another limitation that needs to be addressed in future work.

Finally, it is worth noting that this study is still subject to many simplifications and assumptions due to data incompleteness and the specific research scope of the current work. Future study could incorporate more psychological and social factors to describe agents' decisions during evacuation processes. For example, future study can conduct surveys and questionnaires to quantify households' evacuation preparation times after receiving flood evacuation orders (Lindell et al., 2020). Also, future studies could consider other factors that may affect human flood risk perception and risk awareness, such as social memories, social interactions and observations of neighbors' actions (Du et al., 2017; Girons Lopez et al., 2017). These extensions and improvements can make the model capable of simulating more realistic decision-making processes and more complex human-flood interactions to support emergency management during floods.

6. Conclusions

A fundamental aspect of societal security is natural disaster management. Computational models are needed to assess the flood risk in flood-prone areas and to design holistic management policies for flood warning and damage mitigation. In this study, we propose an integrated socio-hydrological modeling framework that couples a hydrodynamic model for simulating flood inundation processes, an ABM for simulating the flood management practices of emergency responders and human behaviors, and a large-scale transportation model for simulating household evacuation processes in a road network. Using a case study of the XNA in China, we demonstrate the effectiveness of the modeling framework for assessing flood inundation processes for a 100-year flood event and examining households' evacuation outcomes considering various evacuation management policies and human behaviors. A number of scenario analyses are performed to explore the impacts of shelter location arrangement, evacuation preparation times and route search strategies on evacuation performance.

Through a set of scenario analyses, the modeling results show that for a 100-year flood event, approximately 66.5% of the land area will be flooded, affecting 0.5 million people. Household evacuation processes can be significantly affected by the number and geographical distribution of evacuation shelters. For the five optional sites of evacuation shelters, the average evacuation time of residents ranges from 20.1 hours to 46.8 hours, depending on where the evacuation shelters are located. Counterintuitively, yet in line with the Braess paradox in the transportation field, we find that including more shelters in the system may not improve evacuation performance in a region if the number of shelters or shelter distribution is already optimal or near optimal. In addition, the simulation results show that residents' flood evacuation outcomes are significantly affected by human decision-making processes, such as the selection of evacuation route search strategies. Compared with the system-level route optimization method, the shortest-distance route search method is associated with a longer evacuation travel time because evacuees seeking to minimize their own travel time may experience traffic congestion. We also find that a low level of heterogeneity in agents' evacuation preparation times can result in heavy traffic congestion and long evacuation clearance times. These modeling results indicate that the flood risk of, and the ultimate damage to, an area is affected not only by the magnitude of the flood itself but also by flood management practices and household behavioral factors. This study is therefore in line with some previous studies that highlighted the significance of using socio-hydrological methods for hydrological science and watershed management (Di Baldassarre et al., 2013; Sivapalan et al., 2012; Abebe et al., 2019).

This study still has a number of limitations that need to be addressed. Recommended future work includes incorporating more types of transportation facilities and route selection methods in the transportation simulation model, considering more psychological and behavioral factors in human decision making, and improving the model coupling method by employing a two-way coupling approach to simulate the impacts of human behaviors on flood inundation processes. We envision that these extensions will improve the functionality of the proposed modeling framework, and the simulation results with these improvements can provide more useful modeling and policy implications to support flood risk assessment and emergency evacuation management.

Code availability

The code used in this study is available upon request from the corresponding author.

Data availability

The data used in this study can be freely accessed from the data repository in Github (https://github.com/54549877777/FloodManagementProject).

Author contributions

ED and CZ designed this study. HJ, ED, NG and FW developed the model and wrote the code. HJ, ED and YT performed the experiments. ED analyzed the results and wrote the original draft. CZ, FW and YT edited the paper.

Competing interest

The contact author declares that none of the co-authors has any competing interests.

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