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Assessment of Flood Losses with Household Responses: Agent-Based Simulation in an Urban Catchment Area

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Abstract

Densely populated coastal urban areas are often exposed to multiple hazards, in particular floods and storms. Flood defenses and other engineering measures contribute to the mitigation of flood hazards, but a holistic approach to flood risk management should consider other interventions from the human side, including warning information, adaptive behavior, people/property evacuation, and the multilateral relief in local communities. There are few simulation approaches to consider these factors, and these typically focus on collective human actions. This paper presents an agent-based model that simulates flood response preferences and actions taken within individual households to reduce flood losses. The model implements a human response framework in which agents assess different flood scenarios according to warning information and decide whether and how much they invest in response measures to reduce potential inundation damages. A case study has been carried out in the Ng Tung River basin, an urbanized watershed in northern Hong Kong. Adopting a digital elevation model (DEM) as the modeling environment and a building map of household locations in the case area, the model considers the characteristics of households and the flood response behavior of their occupants. We found that property value, warning information, and storm conditions all influence household losses, with downstream and high density areas being particularly vulnerable. Results further indicate (i) that a flood warning system, which provides timely, accurate, and broad coverage rainstorm warning, can reduce flood losses by 30–40%; and (ii) to reduce losses, it is more effective and cheaper to invest early in response measures than late actions. This dynamic agent-based modeling approach is an innovative attempt to quantify and model the role of human responses in flood loss assessments. The model is demonstrated being useful for analyzing household scale flood losses and responses and it has the potential to contribute to flood emergency planning resource allocation in pluvial flood incidents.

Keywords Flood risk and damage · Flood loss assessment · Adaptation and response · Urban area · Agent-based modeling · Pearl River Delta · Hong Kong

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1 Introduction

Globally, exposure to and potential damage from both river and coastal flooding are increasingly significant [1, 2]. As urban areas expand, more people and assets are exposed to flood risks [3]. Moreover, climate change is increasing the frequency of extreme weather events, and cities are among the most vulnerable regions to the impacts around the world [4–7]. Stakeholders in their bid to find solutions to cope with emerging floods need to better understand the process of a flood and its damages, and how to adapt or respond adequately to the disaster [8]. Therefore, growing concern has brought further urgency to implement flood loss assessment and promote flood adaptation for effective flood management [9]. In the following, we develop an integrated model approach that combines a physical model of rainfall scenarios and water flows in a geographical landscape with a multi-agent-based model of disaster response based on flood impacts and costs in a populated region of China.

1.1 Flood Loss Assessment and Adaptation

The purpose of a flood loss assessment is to evaluate the (potential) economic losses from a flood event to inform flood risk management [10]. The methodologies used in flood loss assessment are typically classified into three groups: integrated hydrological models, indicator systems, and post-flood surveys. Integrated hydrological models are driven by physical equations, while stage-damage relationships can be used to assess impacts [10]. Indicator systems usually combine a number of factors that influence the consequence of flooding, such as the depth of inundation, flow velocity, and duration of inundation, which are useful for comparing the flood risks or losses of several areas on a consistent basis [11], but has limited or no representation of the flood mechanism. Post-flood surveys can be implemented for loss evaluation and the results may be further used to verify mechanism models [12].

There is not a standard or recognized method for flood loss estimation. Merz et al. [13] reviewed this issue and indicated that economic evaluations of flood damages/losses are purpose-related and therefore context-dependent. There are, however, major issues that constrain the accuracy in flood loss assessment, resulting from limited available data, knowledge on damage mechanisms, and human response measures [13]. Thus, approaches typically simplify representation of the flooding process. Furthermore, they rarely consider human efforts during the flood to reduce any losses.

Flood adaptation is defined as the adjustment of a natural or human system to reduce vulnerability and enhance the response capacity to flood threats [14]. To date, flood adaptation has been analyzed and quantified in many ways, which has led to increased precision in cost-benefit analysis and more rational approaches to decision-making [15]. Effective adaptation requires understanding of the nature and magnitude of flood impacts. However, in our view, much attention has recently been given to the flood consequence assessment, whereas the process of proactive and reactive human responses is reduced to a couple of parameters or scenarios within a comprehensive analysis. Moreover, flood impacts are not spatially homogeneous; they are sensitive to rainstorm conditions, failure of flood protection infrastructure, warning times, evacuation strategies, and individual activities [16]. This uncertainty poses significant challenges to the implementation of a successful flood management plan.

1.2 Considering Human Responses in Flood Loss Assessment

People play a key role in mitigating flood impacts before, during, and after a flood. The US National Research Council summarized the various roles of human actions in countering flood disaster losses, including the local, state, and federal government, individuals, and also private sectors [17]. In fact, flood-related property damages and loss of human life could be reduced through decision-making, strategic planning, public awareness and communication, emergency responses, and mutual reliefs [18, 19]. In addition, an affected community could recover faster and more efficiently if it is well organized [20]. In order to cope with the projected increase in flood effects, adaptation strategies need to consider the potential of human responses (soft measures) and flood defense infrastructure (hard measures) [21].

The costs of human responses have been generally included in flood loss assessment. Dutta et al. [10] estimated flood losses in three groups—urban, rural, and infrastructure—and considered both damages and costs (emergency and cleanup). Merz et al. [13] also classified the types of flood damages (tangible/intangible, direct/indirect), while stating that flood loss should include the costs of emergency services. A report of the World Meteorological Organization [22] illustrated the categorizations of flood losses which cover various damages, costs, service/yield reductions, injury, deterioration, stresses, etc. Though existing approaches for flood loss assessment have already considered variables that describe human actions, the relationship between human responses, warning, and flood damage is in these methods often described in a black box manner and based on empirical survey data [23]. On the one hand, various flood response measures and costs were often presented in synthesized packages using a few static variables and physical-mathematical approaches that greatly simplify the response measures [10, 25]. However, this approach did not represent the implementing process of the response measures, the heterogeneity among actors, nor the complexity of non-linear human behavior. Also due to its black box properties, the modeling process is difficult to be validated and verified [24]. On the other hand, empirical statistical data or survey data were used to estimate savings of human response measures. For this purpose, data about household flood preparedness and damages are often collected and analyzed [23, 26, 27]. The method actually offered a post-flood revisit to the role of response measures by various households [28]. But still, it neglected the implementation process of the response measures and looked only at the consequences.

Only a few studies have investigated the interactive process between flood threats and human behavior in more effective response measures to mitigate flood risk [13, 15], but not using flood loss estimates. The process of involving human activities is inherently complicated and requires real-time flood information and a wide range of flood mitigation activities, including structural and non-structural measures such as flood warning [29]. However, limited attention has been paid to the adaptive process of humans, and how this process can be measured and modeled. Although this knowledge gap has been widely acknowledged [30], the role of human responses has up to now not been quantified and modeled in flood loss assessments. Thus, to integrate human response and mitigation efforts into flood loss assessment, a dynamic simulation approach is needed to couple both human and natural dimensions.

1.3 Agent-Based Modeling in Flood Studies

In recent flood disasters, society and decision-makers are increasingly requiring instant flood information from the natural side and participatory flood control from the human side, as well as the integration of the two [31, 32]. O'Connell and O'Donnell [33] have outlined the potential of agent-based model (ABM) in flood risk management for a coupled modeling of human and natural systems. In ABM, agents are self-contained computer programs that interact with its environment and with one another and can be designed and implemented to describe the rule-based behaviors and modes of interaction of observed social entities [34–36]. Regarding the field of flood studies, ABM has the advantage to simulate the response behaviors of agents (individuals, households, communities) facing flood threats in real time.

In fact, agent-based models have recently increasingly been adopted in flood research from various perspectives. Georgé et al. [37] and Scerri et al. [38] developed self-adaptive ABM systems of devices and robotics (boats), which supported real-time flood forecasting and offered quick situation awareness and relief supplies. ABM combined with a virtual geographic environment (VGE) has demonstrated the capacity to identify businesses affected by flooding in the UK [39], though the introduced model did not involve response activities of the businesses and thus did not make full use of the advantages of ABM. While these models took objects as agents, Dawson et al. [15] introduced human action into an ABM of flood incident management and used it to optimize flood evacuation. Consideration of human behavior was not a new concept to many existing ABMs. However, the study first captured the dynamics of both the natural and human systems over the duration of a flood event and ensured the flood evacuation scenarios to be more realistic. The ABM also delivered insights into emergent features such as evacuation routes prone to congestion, which could not be extracted from the other methods of flood risk management.

Recently, more ABMs were seen in flood-related studies and mostly had human agents, which brought new insights on how ABM can help flood disaster management. For instance, Haer et al. used ABM to test the effects of flood risk communication through a social network [40]. Though the modeling results were not surprising that targeted communication can be more effective than common communication, it demonstrated the significance of human behavior in flood risk management. Similarly, the heterogeneity of human behavior was tested with ABM in floods of a hypothetical case area which also showed the necessity to identify individual activities in small-scale flood management [41]. In addition, the ABM application in human decision-making also revealed the role of human behavior in prospected flood risks [42] and the significance of flood insurance in a public-private partnership [43].

ABMs have shown its value to inform flood management regarding evacuation, communication, behavioral heterogeneity, risk perceptions, and flood insurance. However, we have found no documented ABMs to model flood loss estimation and instant individual response behaviors. This study addresses the identified research gap in flood loss assessment and individual responses in the context of emergency management of floods. We present an agent-based model to increase the understanding of this dynamic process by considering the effects of household flood prevention measures when facing various rainstorm scenarios and different levels of warning information. The simulated flood events are pluvial floods generated from a surface runoff model in an urbanized river catchment. The ABM was conducted within the NetLogo modeling environment [44] which offers a framework to incorporate and simulate driving forces that affect response strategies of households in case of different flood scenarios. The next section introduces the ABM framework and model components. In Section 3, we present model findings from a case study in the New Territories of Hong Kong before finally concluding with some key findings and making recommendations for further research and development.

2 Model Design and Concept

2.1 Framework of the Agent-Based Model

The purpose of the study is to use an ABM to simulate aspects of human decision-making during a flood event. The focus here is on the role of individual household loss reduction through flood response investment and damage control. The model framework is structured in three steps: model initiation, runs, and outputs. An overview of the ABM used in this paper is given in Fig. 1.

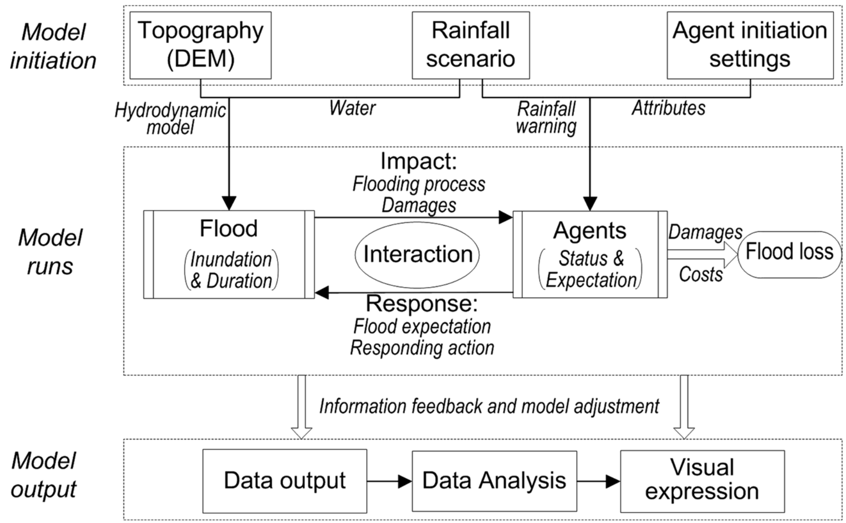


Fig. 1 Framework of the agent-based model for flood loss and response simulation

The model comprises three core components:

- Rainfall scenarios defined in terms of intensity and duration
- A hydrodynamic model driven by topography
- Agents, representing households in this model, who respond during a flood event according to a range of behavior rules.

In this framework, rainfall events and topography are the key inputs to the hydrodynamic model which generates flood scenarios. Agents with initiated attributes (see Table 1) take actions to respond to floods according to received rainfall warnings. Once the model is initialized, a rainfall event begins and agents start to assess their flood risk according to rain warning information. Depending on their initial knowledge as well as the information they receive on flooding, the agents

Table 1 Attributes of household agents in the presented flood ABM

Attribute	Definition and implication	Function
exposure	Household's location regarding flood impacts	To partly define location-specific flood vulnerability of a specific agent
response-rate	Fraction of a household's investment relative to its property values	Indicating the investment level
self-prediction	Expected rainfall and flood without receiving warnings	Distinguishing the different behaviors with and without warnings
adaptive-capacity	Adaptive capacity of the household	Limits the upper investment level
building-value	Value of the household's living building	Calculating flood loss
property	Value of non-building properties	Calculating flood loss
property-loss	Lost value of properties	Calculating flood loss
cost-c	Precautionary investment when receiving warning information	Calculating investment
cost-d	Response investments during flood	Calculating investment
warn-rainfall	Predicted rainfall according to warning	Predicting rainfall trend
inundation	Inundation depth of flood water	Actual depth of flood water
predict-inundation	Predicted potential inundation depth	Expected flood water depth which the investment was based on
duration	Duration of inundation	The period of being flooded
α_B	Building loss rate	Indicating the characteristics of buildings
α_P	Property loss rate	Indicating the characteristics of non-building properties
hhloss	Household's property loss in each step	Calculating the flood loss process
total-loss	Final total flood loss of a household	Calculating total flood losses

perform certain actions, including investment in their property, in response to the expected flood threat. More action by the agents leads to lower flood damages. The loop of agents' flood expectations, their response actions, and flood inundation impacts drives the model to run step by step, so that the flood and loss process can be analyzed. Finally, the model produces summary information that can be used to diagnose model behavior and inform flood management policy.

2.2 Components and Construction of the Agent-Based Model

2.2.1 Model Environment

The model environment includes topography, the river system, household locations, and roads within a river basin. A digital elevation model (DEM) of the study area was resampled to a lower resolution of 30×30 m to be imported to the NetLogo modeling platform, where each DEM cell is a "patch" (ground over which agents can move). Each cell has a slope, used to define the expected water flow, which is calculated as the difference between its elevation and the minimum elevation of its eight neighbor cells.

The elevation data are also used to generate the river basin and river system of the study area. A building area map was resampled to the same resolution as the elevation data and overlapped with the river basin layer in the NetLogo world.

2.2.2 Agent Attributes and Behaviors

The definition of an agent and its attributes and behaviors are central to an agent-based model. Households are agents in this model because they are the basic entities that suffer from and cope with floods. Their rule-based response decisions and interactions determine the feature and magnitude of flood loss. Household agents do not move in space but they do take measures to protect themselves from flooding and make predictions about future flood risk based on rainfall/rain warnings.

As shown in Table 1, each agent is characterized by several attributes, e.g., property, exposure, inundation, and flood losses, to represent its links to flooding events and losses. Agent properties are capitalized and composed of two parts, the construction property (residential building they live in) and the in-house property (contents they own and put at home). For every agent, a starting property value has been allocated, which is subject to loss during model runs. In the absence of a comprehensive metric for real household vulnerability (including its components: exposure, sensitivity, and adaptive capacity) to flooding, in the following, only exposure and adaptive capacity are considered for simplification. The exposure of a household is calculated according to its location (elevation) and the shortest distance to a river, while the adaptive capacity is based on the total properties, both using a min-max normalization method after Yang et al. [16]. Inundation-related attributes indicate the flood severity and duration. Agents will take response measures to prevent flooding according to the real-time inundation situation and predicted inundation. The measures taken by a household prevent potential flood damages. If a real-time inundation is higher than the level an agent ever experienced or predicted, it suffers flood damages from the effective inundation.

The household response behaviors from empirical studies [45, 46] are employed to construct the general rules for the agents' decision-making. In the present model, households perceive potential flood impacts according to warning information. They take response measures based on warning and their instant flood situation. Flood response measures are generally recognized as follows: "far-sighted precaution," "close-to-event measures based on forecasting and warning," "flood fighting actions," and "recovery actions after an event." The measures can be specific and different but they are all quantified as monetary investments (response cost) in the model. It was assumed that a higher-cost flood response measure has better effectiveness in flood control. Therefore, the model used response costs instead of specific measures, which facilitated the modeling process as the value of costs can be easily calculated. At the same time, the agent invests in flood control according to warnings. The more serious flood the warning indicated, the more the agent invests (in range of its capacity of cause), and the higher flood depth it can prevent, no matter which specific measure it took.

In addition, specific agent behaviors in this model are controlled by several global variables such as rainfall scenarios, lead time, and interval of rain warning. As the simulation progresses through time and the flood situation varies, values of some of these attributes change and thus inform the flood loss process of agents. An example of a typical agent's response loss decision-making process is briefly illustrated in Fig. 2: the agent has a chance to receive rain warning information and to invest in prevention accordingly; along with the raining and flooding process, the agent estimates flood trends instantly by considering updated flood situation and warning information; once an increasing risk is estimated, the agent will increase investments into flood fighting, unless the investment capacity is not reached; it is possible that the agent estimates flood trends inaccurately so that it may suffer some inundation damages.

The model in the present paper simulates a single flood event; thus, the agents do not have a learning experience regarding flood events but a certain level of initial knowledge so that they can take responses accordingly. The level of having knowledge was set based on two conditions: first, the agent was trained with a few specific rainfall warnings and associated flood intensity before the model officially runs (last part of Section 2.2.3). This pre-process was assumed to give the agent simple but direct experience on floods. Second, the agent increases knowledge when it receives advance warning. The

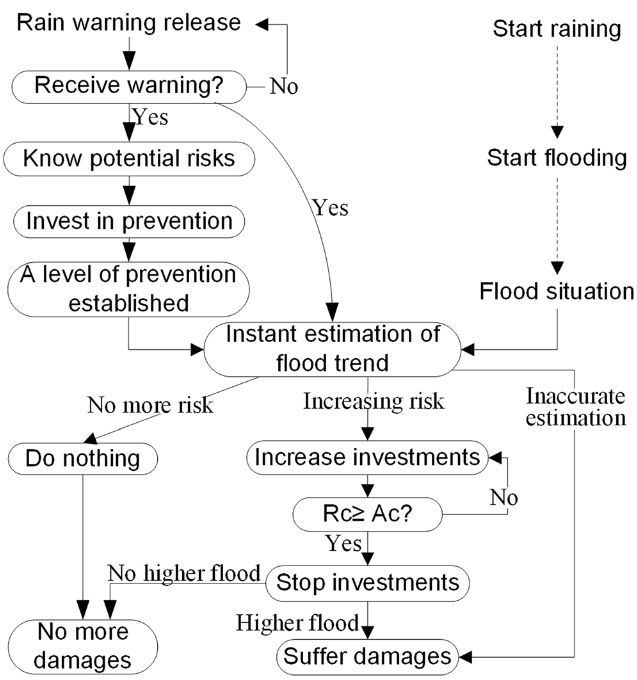


Fig. 2 Flow diagram of a typical agent's decision-making process in a flood event. Note: *Rc* refers to "rate of responding cost" and *Ac* refers to "adaptive capacity," both defined in Section 2.3.2

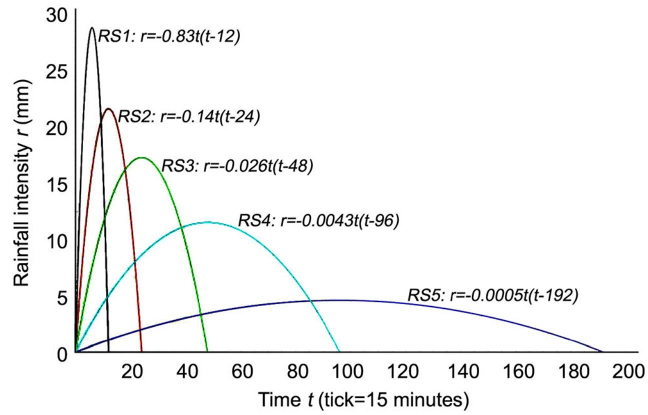


Fig. 3 Rainfall scenarios that have been pre-defined in the ABM model for the present case study

warning was assumed to bring rich and accurate flood information to the agent.

2.2.3 Scenarios of Rain/Flood Event

Rainfall Scenario A rainfall event is described by its intensity and duration [47]. Over small river catchments, it is acceptable to assume that the rainfall is spatially uniform [48]. Initially, the five rainfall scenarios shown in Fig. 3 have been pre-defined for the case study in the present paper, although further scenarios can be manually defined by the model user.

The Flood Inundation Process In general, a model of the flood inundation involves many processes such as topographic character, hydrological dynamic, flow route, surface roughness, hydraulic facility, and drainage system [49]. However, it is often hard to consider all of the processes in specific studies and it is acceptable to focus on those most crucial to the research aim [50].

In the present study, a simplified gravity-driven surface runoff model is used to simulate pluvial flooding over a digital elevation model (DEM). Since the study aims to investigate individual households' flood responses and their effectiveness, large-scale flood control measures like hydraulic facilities and sewer networks are not involved in the model. Thus, once a rainfall scenario is chosen, there is a corresponding flooding scenario because the land surface is initially set by the DEM and other factors are not considered. Flow is calculated using a computationally efficient surface water flow algorithm, which propagates flow at each time step, from higher elevation cells to lower ones (Fig. 4). With this surface runoff model, the slope factor and flow velocity are reflected indirectly in comparing the elevations of cells. Surface roughness n is assumed approximately related to elevation in the study area where high places (e.g., natural forests) have greater n and low places (e.g., constructed surface) have smaller n. Thus, the surface roughness is definite when the model environment was set at the very beginning. However, a range of the surface roughness values is artificially generated and tested in analyzing the variable sensitivities in Section 4.

This simplified surface runoff model principally indicated the physical drainage mechanism and enabled downscaling from complex social systems to individual households with limited computing requirements, which well supported the model goals to explore dynamic individual responses to flood scenarios, connecting the physical and the human world.

Water in a cell will flow to its eight neighbors according to the relative difference between water surface elevation (the sum of water depth and cell elevation) (Eqs. 1 and 2).

$$WD_{i+1} = \frac{1}{2}\left(E + WD_i + E_{\mathrm{TN}} + WD_{\mathrm{TN},i}\right) - E \tag{1}$$

or

$$WD_{i+1} = 0,\ \ WD_{\mathrm{TN},i+1} = WD_{\mathrm{TN},i} + WD_i \tag{2}$$

$$\text{when } E > \left(E_{\mathrm{TN}} + WD_{\mathrm{TN},i}\right) + WD_i$$

where

WD_{i+1} the water depth sof current cell
E the elevation of the current cell
E_{TN} the elevation of the target neighbor where water flows
WD_{TN} the water depth of the target neighbor

Due to infiltration, reservoir storage, and evaporation, not all precipitation becomes flood water which is considered as

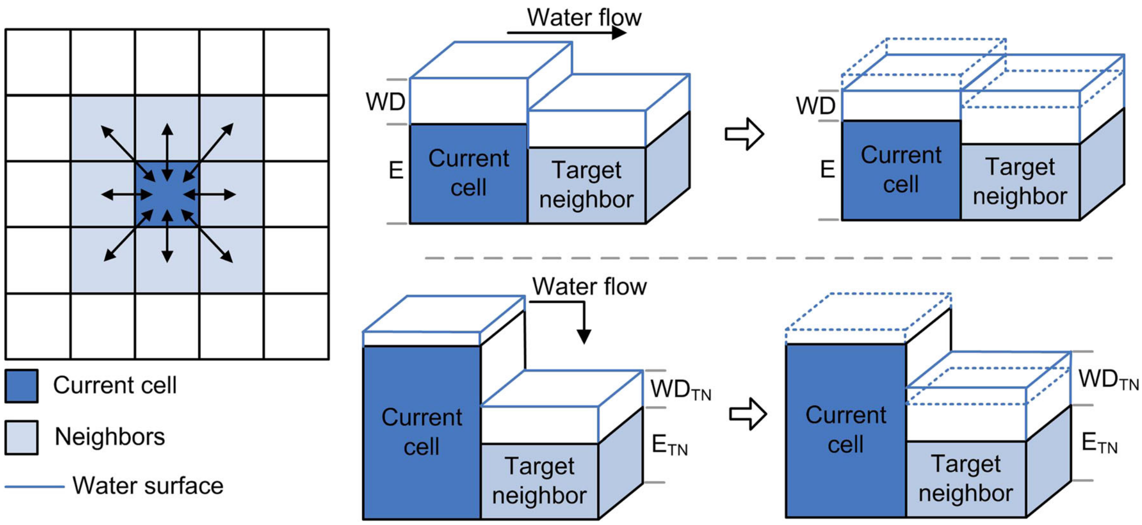


Fig. 4 Schematic representation of flow between neighboring raster cells (adapted from Dawson et al. [15])

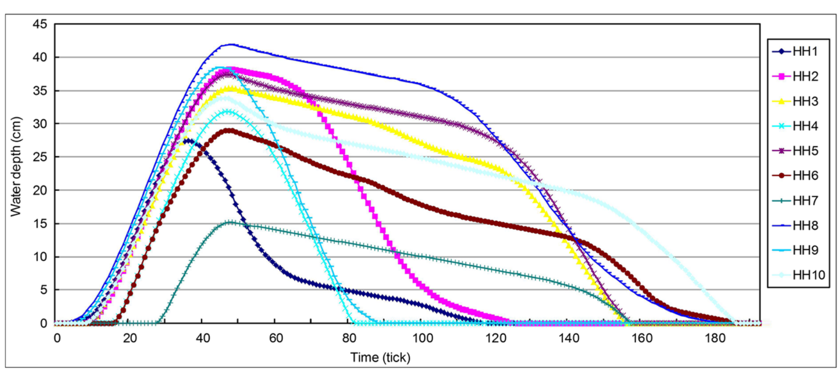
runoff loss. Following analysis by Ren and Guo [51], an interception and evaporation function reduces water depth in each cell by 0.4 mm/h. The depth of flood water in cells with households alters the impact on and the response of the agents.

Rain Warning and Households' Flood Expectations People's reaction to becoming informed about a potential flood event varies usually according to the warning information received [15, 52]. In this model, a household's flood knowledge is depending on the received warning information about the rainfall event as well as its instant flood situation. In addition, each of the rainfall scenarios and flood extents described above was preprocessed to provide a curve of inundation vs time for each cell within the domain. The recorded curve acts as a knowledge input which will be used for the agent's flood prediction. With the pre-procession and warning information, it is assumed that all agents have complete knowledge of the relationship between rainfall and flood extents (i.e., people know where the low-lying land is that likely be flooded).

During the model preprocessing, cell *i* recorded an inundation curve at the rainfall scenario 3. The agent *j* at the cell *i* will use this curve as its flood prediction in case it receives rain warning at the same rainfall scenario 3 during model running. This series of preprocessed modeling outputs yields rational inundation curves for all the cells in all the five rainfall scenarios. Figure 5 shows examples of the inundation curves for 10 selected cells with households under a moderate rainfall scenario.

To assess the effectiveness of warning, the model incorporates parameters for the lead time (LT) of warning and the warning interval (WI). LT represents the period from the time of warning release to the time of flood starting, and WI denotes the time period from one warning release to the next one. The two parameters LT and WI together indicate the time and frequency of rain warning release. A proportion of agents (80% in this study) receive the warning, but the actual agents that receive it are randomly selected in each simulation. Various types of warning can result in different flood predictions and responses. For this reason, the more specific the warning is, the more effective the remedial measure taken will be. In case there is no rain warning or the household does not receive any warning, the agent will respond to any nearby flooding that it observes.

Fig. 5 Depth-duration curves for 10 cells that contain households HH1–HH10 (shown in Fig. 7), during rainfall scenario 3



2.2.4 Flood Response Measures

Responses to flood events have the potential to reduce the impact of flooding and significantly reduce the damages [15]. Generally, flood responses are classified into four types according to flood phases [16]: (1) far-sighted precaution, (2) close-to-event measures based on forecasting and warning, (3) flood fighting actions, and (4) recovery actions after an event. Nevertheless, the model in the present paper does not deal with specific measures but considers only the costs and effectiveness of the measures. Different measures are represented by different investments required. Generally, a higher investment offers greater protection but this depends on the type of measure. Therefore, the model used response costs instead of specific measures, which facilitated the modeling process as the value of costs can be easily calculated.

All flood response measures require investment, which is capitalized and considered in the flood loss. Upon receiving a warning, an agent estimates the associated possible flood depth, and invests and establishes an according level of flood prevention. If the instant flood does not go over this prevention level, the flood is prevented and no damage occurs. If the instant flood goes over this prevention level, the agent suffers flood damage. The cost for far-sighted precaution measures is generally long-term investment for preventing all floods, which is usually not included in final loss estimates of a specific flood incident. However, such investment is considered in this study as damage and is calculated by the damage function. In addition, the resource an agent invests depends on the magnitude of potential flood impacts, the level of household exposure to flood impacts, and the adaptive capacity of a household as described in the following section.

2.3 Flood Loss Estimation

The total flood loss of a household (H_{loss}) in a flood event is composed of the loss from damages (L_{D}) and responding costs (R_{C}) (Eq. 3). This indicates that the total loss depends upon the rainfall scenario and flood response. Both the damage loss and responding cost are the function of flood water depth (Sections 2.3.1 and 2.3.2), which indicates the interactions that more responding costs would help preventing damage losses. The model was designed with adjustable precipitation scenarios and agents' response measures can vary, in order to compare the total loss caused in different situations.

$$H_{\text{loss}} = L_{\text{D}} + R_{\text{C}} \tag{3}$$

2.3.1 Damage and Loss by Inundation

Flood loss is usually estimated in terms of economic losses [13, 53]. To constrain the boundary of the analysis, this study only assesses the direct economic losses caused by inundation damage. In quantitative expression, the damage loss is the product of a loss rate and the pre-flood value of the property [10], as expressed in the Eq. 4:

$$L_{\text{D}} = \sum_{i=1}^{n} \alpha_i \cdot V_i \tag{4}$$

where L_{D} is the lost value by inundation damages, α_i is the damage loss rate for the ith property, and V_i is the pre-flood value of the ith property.

Quantifying α_i is a challenging task because it varies depending on the characteristics of the damaged property as well as the inundation depth and duration. Here we use rules of generalized depth-damage curves (Fig. 6) derived by Dutta et al. [10] and Moel and Aerts [54].

Since regions with similar flood and building characteristics could approximately represent each other [55], the model derived the specific mathematical equations of the depth-damage curves based on the study of Shi et al. [56]. Their flood depth-damage curves were drawn from post-flood surveys and interviews of 134 residences in 2008 in Shenzhen and Dongguan. Their data were resampled to derive simplified fitting equations (Eqs. 5 and 6) which calculate the loss, in terms of a proportion of overall potential losses, as a function of the mean inundation in a flood event.

$$\alpha_{\text{B}} = B_{\text{c1}} \cdot \ln(I_{\text{mean}} + 1) \tag{5}$$

$$\alpha_{\text{P}} = P_{\text{c1}} \cdot \ln(I_{\text{mean}} + 1) \tag{6}$$

where α_{B} is the building loss rate and α_{P} is the loss rate for in-house properties, I_{mean} is the mean inundation depth during the flood period, B_{c1} defines the type of residential buildings, while P_{c1} represents the contents of buildings (non-construction properties). These parameter values can be adjusted according to the nature of property in the case study domain.

2.3.2 Investments and Costs of Flood Responses

The level of flood risk determines the types and costs of flood risk management measures that could be taken. Typically,

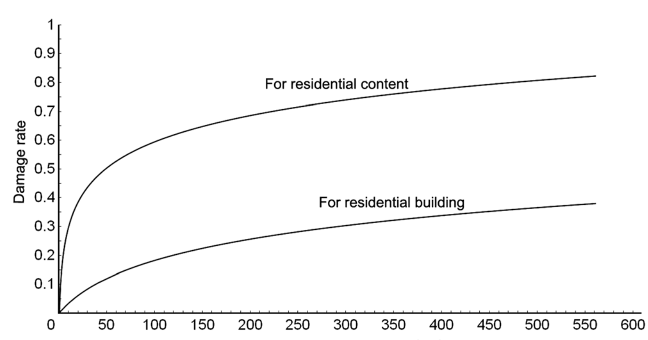


Fig. 6 Sketch of depth-damage curves for urban damage estimation

more expensive measures will provide greater flood risk reduction benefits. Households invest in prevention measures according to warning information. Once the flood exceeds these levels, it is inundated. Once the household receives a precise and timely warning, it may be able to take further action to reduce losses if it has the capacity and sufficient time is available. The amount a household invests in flood management measures should be related to the potential inundation depth. Agents are motivated to invest to protect their properties from being damaged by flooding, but only to a level they can afford. This threshold is referred to as the household's adaptive capacity. A household can increase investment in flood protection up to the level of its Ac, but not beyond it.

The cost of implementing response measures (Eq. 7) is related to the overall property of the household, its exposure level, and the maximum inundation depth (both instant and predicted):

$$Rc = \begin{cases} a \cdot P \cdot Ex \cdot I, & \text{when } Rc \le Ac \\ Ac, & \text{when } Rc > Ac \end{cases} \tag{7}$$

where

Rc rate of household property invested in responding cost
P property of the agent
I maximum inundation depth, both instant and predicted
Ex exposure
Ac adaptive capacity

Ex and Ac were calculated for each agent when initiating the catchment topography and agent attributes (Section 2.2.2). The parameter a in the equation is a constant to harmonize the scales of factor values. Since P, Ex, and Ac are fixed when the model is initiated, Rc subsequently depends only on the inundation depth I.

3 Case Study: Ng Tung River Basin

3.1 Ng Tung River Basin in Hong Kong

A case study was carried out in the Ng Tung River (NTR) basin in Hong Kong (Fig. 7). NTR is a branch river of the Shenzhen River that serves as the boundary between Hong Kong and Shenzhen. It originates from Safflower Ridge in the New Territories of Hong Kong and the mainstream is about 15 km long. The NTR forms a flood plain in the midstream and downstream areas, where the regional downtowns of Fanling and Sheung Shui are located. The total population in this area is about 280,000 in 2013, of which around 80% live in Sheung Shui and Fanling [57].

Due to seasonal rainstorms and the steep topography in the basin, areas along the river frequently suffer from floods. As illustrated by the Drainage Services Department (DSD) of Hong Kong in March 2013, 6 of the 13 flooding blackspots of Hong Kong were located in the NTR basin. Over the years, there have been repeated cases of localized rainstorms occurring in the NTR basin and its surrounding areas, which gave rise to significant flooding there. For example, on 22 July 1994, over 300 mm of rainfall was recorded in the northwestern part of the New Territories. Three hundred hectares of

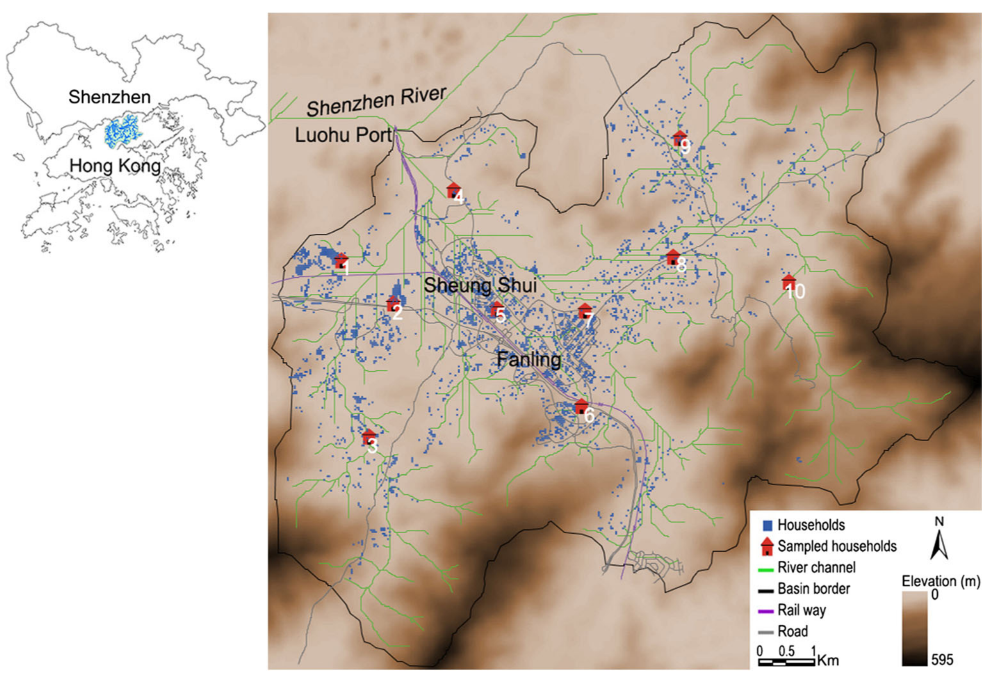


Fig. 7 Map of the Ng Tung River basin, showing its location, topography, watershed border, river network, building areas, and the selected 10 households

farmland and 150 ha of fish ponds were inundated. Firemen had to use dinghies to rescue villagers whose houses were surrounded by flood water [58].

Due to the frequent water logging in this area, a "Special Announcement on Flooding in the northern New Territories" is issued by the Hong Kong Observatory whenever heavy rain affects the area and flooding is expected to occur or is occurring in the low-lying plains [58]. The announcement is broadcast by radio and television to the public and is updated at appropriate intervals until heavy rain ceases. It is intended to prompt the public to take precautionary measures against flooding and to alert local people who are likely to suffer losses from flooding. The announcement also alerts the relevant government departments and organizations to take appropriate actions, such as opening of temporary shelters, search and rescue operations, closure of individual schools, and relief work. Like all weather warnings, the special announcement represents an assessment of the weather based on the latest information available at the time. In case of ineffective alarms, there will also be occasions when heavy rain leading to flooding develops suddenly and affects the area before an announcement can be issued. So rainstorm/rain warnings and active flood preventions are extremely important for local residents to reduce their flood risk, which has made the area being selected as the case in this study.

3.2 Data Preparation

The basic data for the NTR basin comes from a digital elevation model with spatial resolution of 30 m and altitude resolution of 1 m. The DEM was resampled and imported into the NetLogo world with 412 × 364 cells. The river network adopted in this model is also extracted from the DEM, using the hydrology module in ArcGIS. It is thus slightly different from the real channels that have been significantly regulated. Since the exact residence distribution data was unavailable for this study, a map of built-up areas in the case study region is adopted to approximately represent household locations. The building map generates 3294 households in the location of the urbanized areas with the same resolution of the elevation data. A 2-week field investigation in November 2013 was carried out in the study area and Google Street View was used thereafter to help further confirm some of the local situations.

In this model, elevation of the NTR basin ranges from 0 to 595 m, and elevation of households from 2 to 212 m. The distance of a household to the nearest river was calculated when the model was initialized, which uses a range of 0–570 m. Exposure is calculated based on the elevation and the distance to the river, ranging between 0 and 1 using the min-max normalization method. The extreme values 0 and 1 are not reached because it is unlikely that one household has the minimum/maximum value in both elevation and distance to river.

In the absence of detailed census data, the model initially set building values (building property, P_b) and fixture and fitting values (non-building property, P_n) of all households by randomly assigning a uniform distribution. Though the range of the random building values (P_b) is based on the real prices of residence apartments in the case area in 2013, which ranges from 1 to 10 million HK$ (http://www.hkproperty.com/, retrieved on May 4, 2014). The fixture and fitting value (P_n) was set between 1 and 10 million HK$ as well, which reflects a general capital range of households' assets in the case area of Hong Kong [59]. A household's building value and fixture and fitting values were set separately and while it is often the case that more expensive properties have pricier fittings, this is not always the case and the relationship is complex. The adaptive capacity of a household is the normalized value of its total properties in relation to the properties of all the 3294 households. The calculated value of Ac indicates the relative level of a specific household in the whole community of households regarding their properties. For the same reason, the extreme values 0 and 1 were not reached.

Table 2 Characteristics and attributes of the 10 highlighted households in the NTR basin

Label	Location (coordinates x, y)	Elevation (m)	Exposure	Adaptive capacity	Building (HK$)	Fixture and fitting (HK$)	Total property (HK$)
HH1	42, 227	7	0.767	0.243	3,136,155	3,245,481	6,381,636
HH2	72, 203	7	0.580	0.095	2,600,253	1,106,181	3,706,434
HH3	58, 129	12	0.595	0.463	1,383,948	8,961,083	10,345,031
HH4	107, 266	13	0.460	0.623	7,521,377	5,696,612	13,217,989
HH5	132, 200	9	0.542	0.462	6,999,475	3,313,360	10,312,835
HH6	181, 146	23	0.686	0.334	1,493,278	6,523,497	8,016,775
HH7	183, 199	30	0.625	0.464	4,974,238	5,377,416	10,351,654
HH8	234, 229	4	0.725	0.223	4,445,075	1,576,518	6,021,593
HH9	238, 295	6	0.691	0.286	2,856,933	4,284,147	7,141,080
HH10	301, 215	17	0.523	0.609	6,417,497	6,545,851	12,963,348

To explore model behavior in detail, 10 households are randomly selected and labeled with their ID numbers (Table 2).

Five rainfall scenarios were pre-processed. The Hong Kong Observatory (HKO) releases rain warnings in three levels: yellow warning with hourly rainfall over 30 mm, red warning with hourly rainfall over 50 mm, and black warning with hourly rainfall over 70 mm [60]. Given that a flood-triggered rainstorm is usually stronger than normal and the highest hourly rainfall in Hong Kong was recorded as 145 mm on June 7, 2008 [61], the model assumes five rainfall scenarios with the maximum rainfalls ranging from 20 to 120 mm/h (Fig. 2).

- Rainfall scenario 1 (RS1) rains for 3 h, with peak rainfall 120 mm/h, with intensity, r, through time, t, defined according to $r = -0.83\ t(t-12)$, $\{t \in \mathbb{R} \mid 0 \le t \le 180\}$.
- Rainfall scenario 2 (RS2) rains for 6 h, with peak rainfall 80 mm/h, with intensity function $r = -0.14\ t(t-24)$, $\{t \in \mathbb{R} \mid 0 \le t \le 360\}$.
- Rainfall scenario 3 (RS3) rains for 12 h, with peak rainfall 60 mm/h, with intensity function $r = -0.026\ t(t-48)$, $\{t \in \mathbb{R} \mid 0 \le t \le 720\}$.
- Rainfall scenario 4 (RS4) rains for 24 h, with peak rainfall 40 mm/h, with intensity function $r = -0.0043\ t(t-96)$, $\{t \in \mathbb{R} \mid 0 \le t \le 1440\}$.
- Rainfall scenario 5 (RS5) rains for 48 h, with peak rainfall 20 mm/h, with intensity function $r = -0.0005\ t(t-192)$, $\{t \in \mathbb{R} \mid 0 \le t \le 2880\}$.

In the flood damage section, all residence buildings have the same protection to flood damage. Therefore, the parameter in the loss rate function (Eq. 5) is set as $B_{c1} = 0.06$. Variant fixture and fittings of each household are packed as one property with the loss rate parameter (Eq. 6) $P_{c1} = 0.1$. In the flood response section (Eq. 7), parameter a has the value of $1/(5 \times 10^9)$, which is adjusted to the goal of making the Rc curve fitting with those in existing publications [e.g., 10, 62].

Before it actually starts raining, the model executes a precaution function if the rain warning option is checked on. Eighty percent of all households in the NTR basin receive the warning information and take precautionary measures that require investments. In case precautionary measures have been taken, the adaptive capacity of households will be fully applied and thus their exposure will be reduced.

3.3 Results

3.3.1 Flood Loss Pattern Across the NTR Basin

The model was running under five different rainfall scenarios and seven groups of warning scenarios to provide information on the flood loss patterns of the NTR basin (Fig. 8). The patterns are the model interfaces exported at the time the rain stops. The overall inundation pattern of the study area is a collective picture of individual household's inundation situations. Generally, individual households could better avoid inundation under the condition of receiving more precise warning information; therefore, the study area as a whole has less severe inundation patterns and vice versa. Spatially, the middle and downstream areas, which are highly populated, suffer more inundation than other areas, regardless of any warning information received or responding measures taken.

Under no warning and no flood response (as shown in the first row of Fig. 8), RS3 and RS4 cause the highest inundation levels for the households due to their relatively long raining period and larger rainfall volume, although the peak rainfall is moderate. It indicates that the extreme rainfall does not necessarily mean a more severe flood inundation. The duration of the rainfall does play an important role. Moreover, differences are found between the locations indicating that local elevation and distance to river channels have effects on the flood inundation process.

Under different warning information, the inundation patterns are different. Households start preventing potential inundation once they receive warning information. The measures they take, e.g., placing sandbags, will reduce the inundation depth in particular under moderate rainfall scenarios, which allows for more time to respond. Comparing the warning information, long lead time (LT) and short warning interval (WI), e.g., LT24-WI02, lead to the highest reduction of inundation levels while LT02-WI24 seems to have only a little effect on the inundation level. Although under LT02-WI24 warning information is sent, the responding time until the flood event is short. Generally, the large responding time under LT24-WI02 provides much time for the households to take responding measures which are applied dynamically.

The simulation also shows an interesting shift of the most serious inundation among the rainfall scenarios: The most serious inundation happens in RS4 in case of no warning released; it changes to RS3 within the warning LT04-WI12 and then to RS2 (LT06-WI08) and RS1 (LT04-WI12 and LT02-WI24) along with an increasing LT and decreasing WI. Overall, the results of the inundation patterns indicate that accurate warning information helps reduce the effective inundation that damages household properties, and benefits greatly from the flood preventing efforts in moderate and long duration raining event. Moreover, developing a more accurate and timely warning system will also help improving human response efficiency in short extreme raining event, as implied by the combined scenario of RS1 and LT02-WI24.

In addition, the inundation patterns further indicate potential impacts on human safety and economic losses under different scenarios. For instance, the middle stream area of the river basin is always the mostly submerged area in all the modeled scenarios. Even with most accurate warning and moderate rainfall, the area has relatively higher fraction of households who suffer from inundation.

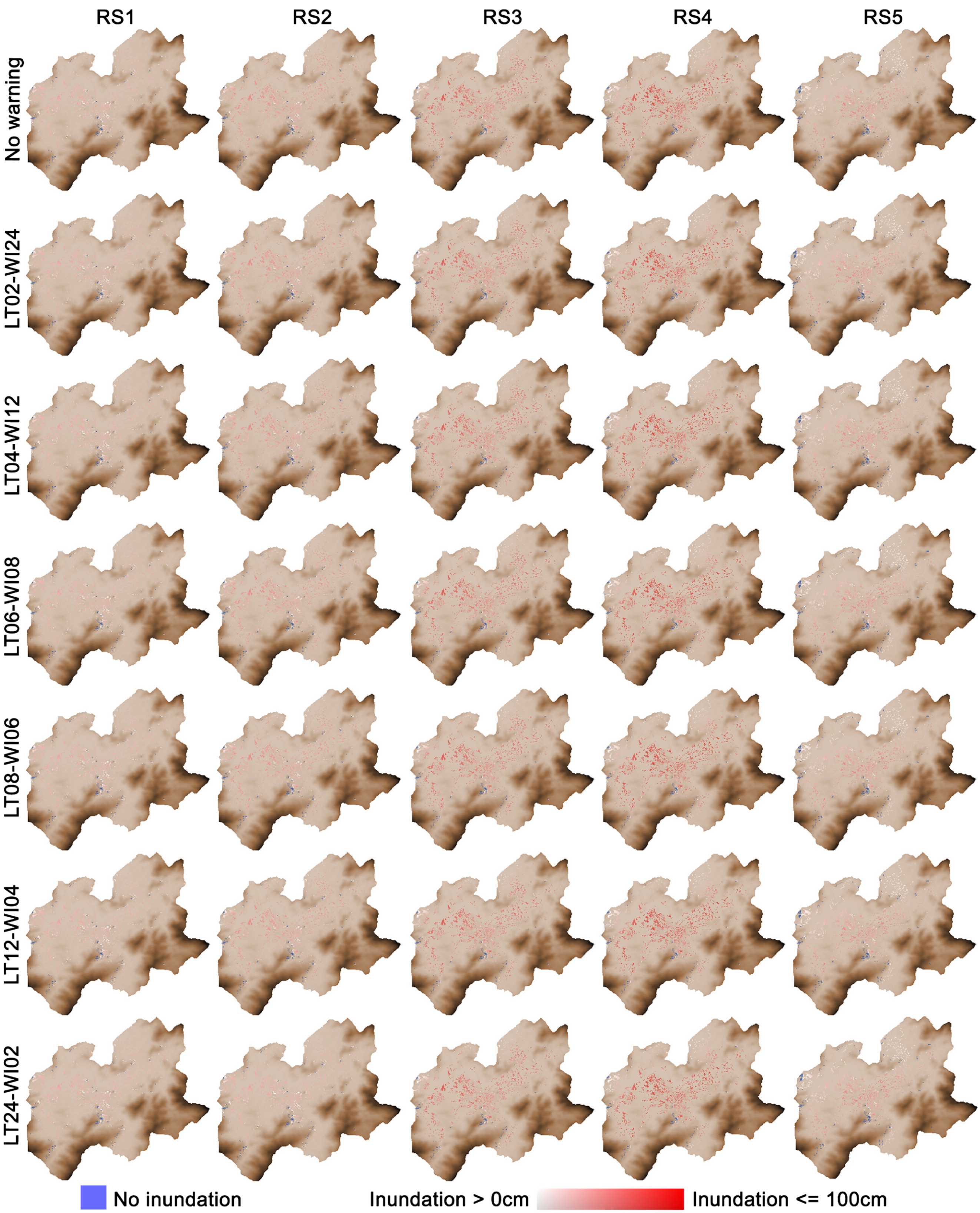


Fig. 8 Inundation patterns for the whole NTR basin with different rainfall scenarios and warning information

3.3.2 Flood Loss Among Households

As illustrated in Fig. 9, HH1, HH2, HH8, and HH9 suffer most damage among the sample households, as a result of their relatively lower investment in response measures. The lower response rates of the four households are mainly due to their lower property values. Due to their more limited economic resources, they have low adaptive capacity, which in turn limits their capacity to invest in flood protection. This indicates that the lack of economic resources significantly contributes to the absolutely larger extent of flood damages. This demonstrates that disadvantaged communities continue to be more affected by flood impacts. Conversely, the model shows that those households with greater financial resource are better able to reduce their flood losses. Households at relatively higher locations, such as HH3, HH4, HH6, and HH7, even respond so effectively that they do not suffer damages at all because their investments are sufficient to prevent the minor flood.

3.3.3 Flood Loss Under Different Rain Warnings

Rain warning is the main factor determining the household's flood response. The model has run several times under RS3 with different warning lead times and warning intervals, including an option of no warning at all. In the situations of no warning, households suffer flood damages without taking any response measures and the damages increase along with the growing of the flood water level until the flood recedes. The findings in Fig. 10 show that without warning, the flood loss of households is more likely to reach the highest damage level, whereas any warning reduces overall losses.

Further results show that, generally, warnings with shorter lead time contribute to higher flood damage whereas longer lead time helps reduce damages, and that a longer warning interval leads to higher damages (Fig. 10). The investigations focusing on the combined effect of lead time and warning interval suggest that a longer lead time and shorter interval can obviously alleviate the overall loss rate. However, this significant impact is not applied to the case of HH2, largely due to its features of poverty and very low adaptive capacity. Therefore, we argue that the effectiveness of warning systems on alleviating flood loss is strongly correlated with the household's economic situation. Rain warning does not help much if the adaptive capacity of a household is too low.

Analyzing the specific values in Fig. 10 further indicates that a flood warning system with timely and accurate rain warning, e.g., from LT02-WI24 to LT24-WI02, can reduce flood losses by 30–44%, if the household is assured to be able to receive the warning information and invest in prevention correspondingly.

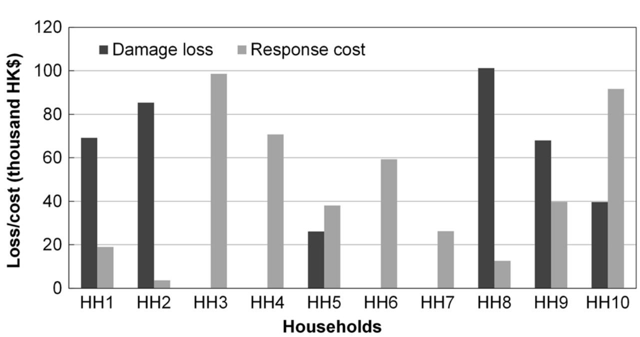


Fig. 9 Flood damage losses and response costs of the sample households in RS3 with rain warning of 12 h lead time and 3 h warning interval

3.3.4 Flood Loss Under Different Rainfall Scenarios

Following the discussion on warning information and response strategies above, the effects of rainfall scenarios were also tested in the model. As shown in Fig. 11, rainfall scenarios with high hourly rainfall (RS1 and RS2) generally cause more serious flood losses to all of the households, as they cause floods very soon and leave less time for responding. The moderate scenarios (RS3 and RS4) cause relatively moderate losses for all. While in a long period rainfall scenario with low peak rainfall, damages do not occur for some households as they can arrange some response measures. For instance, in Fig. 11, most households invest in response measures in RS5 and they do not suffer damages, except the poor HH2 due to its limited responding capacity. This finding suggests that it is necessary to pay high attention to extreme rainfall events when flood management decisions are made, but moreover, those with limited responding capacity need to be supported even in a moderate flood.

In addition, the comparison of the flood damages and flood response costs reveals that damages can be totally avoided with small investments in responding measures, e.g., HH7 has little flood loss (responding costs) but no damages except in RS1. This means that an effective response strategy will play a more significant role in flood control.

4 Uncertainty and Variable Sensitivity of the Model

Uncertainty analysis is receiving increasing attention by the flood modeling community and has become an indispensable part of model simulation for flood risk and loss assessment [50]. Sensitivity of variables and data input is also considered as a source of uncertainty and could influence model performance in flood studies [63, 64]. To address uncertainty and sensitivity issues systematically, it is essential not only to assess the probabilities and consequences of failure from the perspective of individual variables but also to consider the wider system performance. Therefore, in the following, we are going to analyze 10 sources of uncertainty and quantify

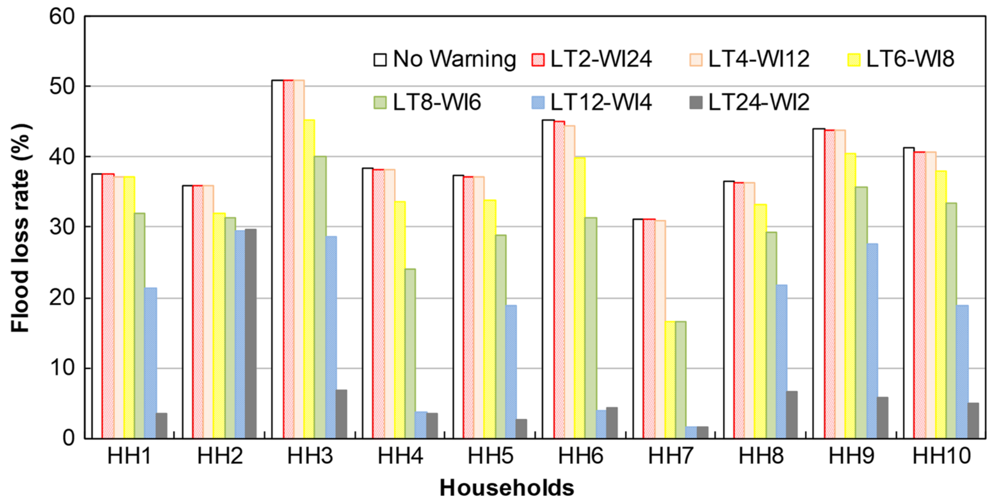


Fig. 10 The difference of flood loss rate, for the sample households in RS3 with different warning information (LT: lead time; WI: warning interval, both have unit in hour)

the sensitivity of six key variables in the presented ABM for flood loss assessment (Table 3).

The rain scenarios are obviously the first significant component in the model that influences flood situations and associated flood losses. It is the key factor in the present study to quantify the effects of various rain scenarios on flood losses at household level. Since the modeling results have shown the differences of the impacts of five rain scenarios in Section 3.3.4, it is unnecessary to further test the sensitivity of and the uncertainty from rain scenarios. This also applies to warning scenarios. The model results identified the effects of various warning lead times (LT) and warning intervals (WI) on flood losses in Section 3.3.3, which indicated the significance of warning scenarios to the model uncertainty.

Exposure is an attribute of the households that absolutely influences the model performance in flood loss assessment [1]. It depends on their location, which is unchangeable once the model is initiated (Table 1; Section 3.2). However, it would be meaningless to test the sensitivity of exposure in the case study model because the change of households' exposures basically means a change of the case area thus the produced results would not be comparable.

As in many flood inundation models, the evaluation and calculation of hydrological elements contribute to uncertainties [25, 49, 50]. The flood process in the model relies on the surface runoff model and associated variables. The simplified surface runoff model adopted in this study applies the gravity-driven drainage mechanism based on a DEM. It reflects the slope and velocity aspects of surface water flow but makes regular assumptions on other hydrological elements like roughness, infiltration, and evaporation (runoff loss). These elements could cause decrease/increase in the velocity and amount of flows and thus introduce uncertainties to the model [65].

The functions of depth-damage curves are usually criticized for its uncertainty related to the collected data and to the simplified functional structure. It is often suggested to use actual damage data rather than advanced model structures because the advantages may be largely absorbed by uncertainties [66]. The present model derived the depth-damage curves from empirical survey data attained from the neighboring area with similar social environment conditions, which are of high reliability. Other uncertainties associated with the curves are the two parameters that indicate the damage rate of buildings (B_{c1}) and the loss rate of

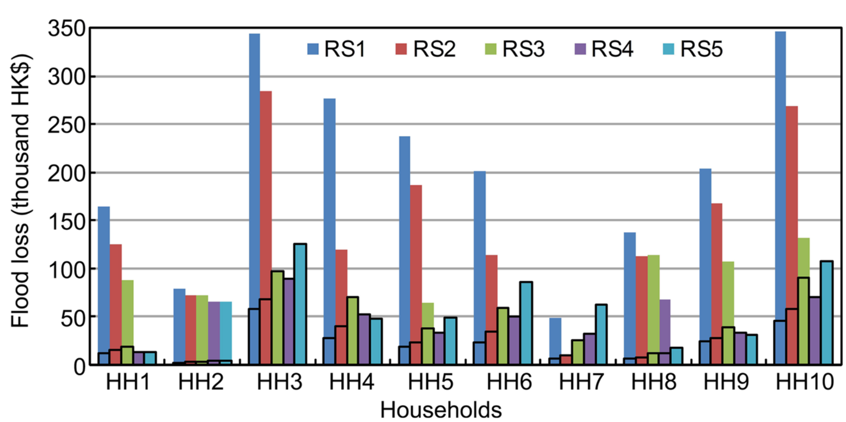


Fig. 11 The flood losses of the sample households for different rainfall scenarios and the same warning information (lead time 12 h and interval 3 h), with black boxes indicating the response costs

Table 3 Sources of uncertainty and analyzed sensitivity variables in the ABM of flood loss assessment

Variables	Value range	Distribution	Physical meanings
Rainfall scenario*	RS1–RS5	Definite	Initially set in the model (Section 2.2.3)
Warning lead time (LT)*	0–24 h	Uniform	The period from the time of warning release to the time of flood starting
Warning interval (WI)*	0–24 h	Uniform	The time period from one warning release to the next, indicating the frequency of warnings
Exposure (*Ex*)#	0–1	Definite	The *Ex* value of a household reflects its location that is unchangeable once the model is initiated (Table 1; Section 3.2)
Surface roughness (n)	0.01–0.15	Related to DEM	High places (e.g., natural forests) have greater n and low places (e.g., constructed surface) have smaller n
Runoff loss rate (*Rl*)	0.2–0.6 mm/h	Normal	The reduction of runoff depth due to the impacts of infiltration and evaporation
Damage rate of buildings (B_{c1})	0.01–0.1	Normal	It reflects the type of the residential building and thus defines the damage/depreciation rate of the building in a certain flood depth
Loss rate of non-construction property (P_{c1})	0.05–0.15	Normal	It reflects the properties in the building (fixture and fittings) and thus defines the loss rate of the non-construction properties in a certain flood depth
Response behavior (R_b)	60–100%	Normal	The probability of a household receiving warnings and taking response activities
Household property (P_h)	2–20 million HK$	Normal	The sum value of a household's building and non-building properties

*The variables are not involved in the sensitivity quantification, as they are the targeted components of the model itself

The variable never changes in the case modeling and thus is meaningless for sensitivity quantification

non-building properties (P_{c1}). Sensitivities of the two parameters are quantified below.

Another challenge faced in this study is the uncertainty of individual behavior and, in particular, of flood response activities. To address this challenge, the statistical value of warning coverage and responding rate was used [60] and set at 80% in the model. In fact, the warning coverage normally reaches 98% in Hong Kong but the responding rate could be much lower as it depends highly on individual behavior decisions and risk perceptions. In the sensitivity analysis, a range of 60–100% with normal distribution is tested.

The value of households' properties is essential in estimating flood damage and loss and is one of the sources of the uncertainty of the estimations [53]. The actual data on household properties is unfortunately not available in this study. Alternatively, the model used the data range (1–10 million HK$) derived from the local real estate market and assigned the data based on normal distribution. These data are credible at the macroscale but could cause uncertainties at household level. To test the uncertainty and sensitivity in this regard, the variable of household property (P_h) of the sampled 10 households is quantified in their value ranges (Table 3).

Sensitivities of the six variables are calculated using the one-at-a-time technique (OAT) that analyzes the effect of one variable on the model function at a time, keeping the other variables fixed [67]. For each variable, Microsoft Excel 2016 was used to generate 100 random values in its value range according to the data distribution. Each of the 100 random values was taken as a variable input into the model; therefore, 100 simulations were conducted to test the sensitivity of the variable (600 simulations in total for the six variables). A "Repeat" function button was added to the model so that it could repeat simulations and change only the value of a selected variable. All the testing simulations were run at the moderate rain scenario RS3 and warning scenario LT06-WI08. Figure 12 shows the specific results of the sensitivity analysis regarding the flood losses of both the sampled 10 households and the overall households in the study.

It is basically comparable that sensitivities of the six variables performed similar for the 10 sampled households and the overall households. The variable of household property (P_h) has the largest value range in the sensitivity analysis, indicating its significant role in controlling the model uncertainty. The essential reason might be that household property not only suffers directly from flood damages but also determines the household's adaptive capacity that links to response costs. We therefore argue that a precise database, e.g., household surveys and property statistics, would be very much helpful to streamline the model calculations and reduce uncertainties in this regard. The variables R_b and P_{c1} also introduce quite large uncertainty to the modeled flood losses, due to the fact that they are the main factors which reflect human activities in a flood event. However, the damage rate of buildings (B_{c1}) is less sensitive to the model performance because it is relatively harder to be protected in a short informed flood event. Different human decisions could greatly influence the effects of these variables, e.g., decisions on investments to the evacuation of valuable properties often derive from warning information and have effects only on non-building properties. The analysis of

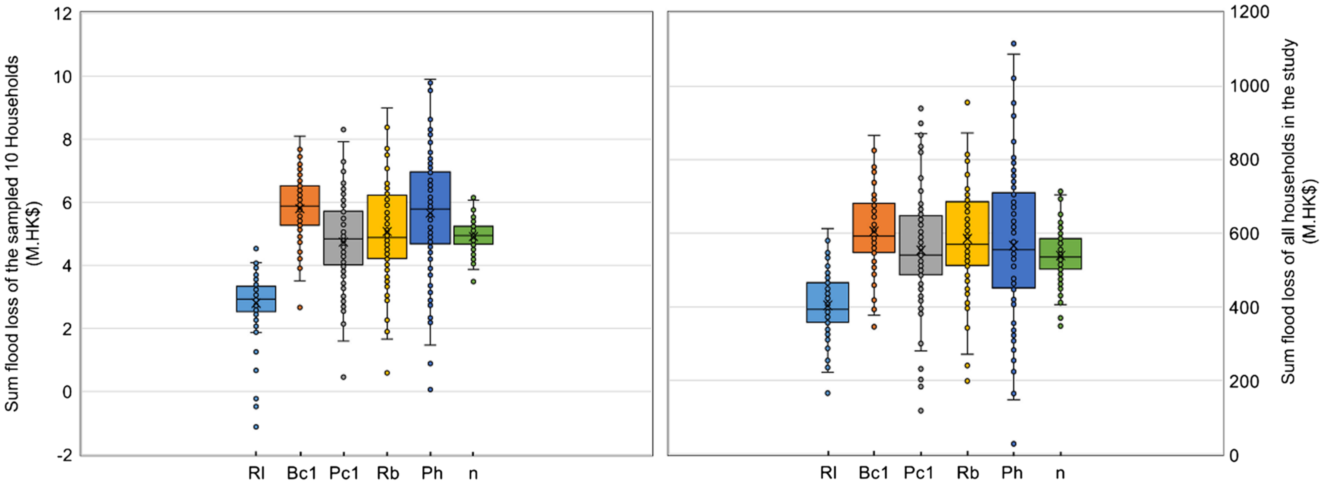


Fig. 12 Box-whisker plots of the six key variables for the sensitivity analysis. A range of the 100 simulated flood losses is plotted for each of the variables. The left panel indicates the sensitivity of the six variables to the sum flood losses of the sampled 10 households, while the right panel shows the sensitivity of the six variables to the sum flood losses of all the 3294 households

sensitivities from the human variables is consistent with former research findings that quantitative information on many of the "softer" elements is sparse (e.g., organizational, behavioral, health, and decision issues) [15], and that epistemic uncertainties are therefore difficult to treat formally by probabilistic methods [28].

The variable of runoff loss (*Rl*) contributes more to limit flood losses comparing with the other five variables. This is not surprising as the runoff loss function introduces infiltration and evaporation to the flood inundation model. An increase of the *Rl* variable deducts parts of the runoff from becoming floods. It is visible in the left panel of Fig. 12 that several dots have values less than zero, which is due to the extreme high *Rl*s tested (runoff loss is even higher than the runoff amount). It is worthy to notify that the surface roughness factor (*n*) demonstrates relatively concentrated patterns in Fig. 12 that indicate least sensitivity to flood losses. This derives to the surface runoff model in which the surface roughness factor was set as a global variable and regularly related to the DEM. An increase of the surface roughness (*n*) would influence little on the final flood losses, but would delay the flood or reduce the flood peak that was already reflected in rain scenarios. In one word, the physical factors runoff loss and surface roughness are less sensitive in the present model comparing with the variables at the human aspect.

5 Discussion and conclusion

5.1 Improving Flood Response Strategies

Based on a number of model simulations in the NTR basin in northern Hong Kong, this study has examined the effects of households' flood prevention measures when facing various rainstorm scenarios and warning information. The results show that exposed property amounts, rain warning information, and rainstorm conditions all contribute to households' flood losses.

When facing a rain-triggered flood, poor households with low adaptive capacity to flood threats have the potential to suffer more flood losses than the rich ones. And the individual adaptive capacity is very important to the actual responses. It implies a case that poor households may receive warnings and be willing to respond but may not able to or have no resource to respond. This suggests stronger flood prevention and mitigation especially for the poor, for instance lifting up the ground of residence buildings, connecting to timely weather forecasts, checking the conditions of the surrounding drainage facilities frequently, etc.

Findings from this study reveal that, in general, warning lead time affects flood loss significantly, while the effects are not great if the warning interval is short. Short warning interval means a high frequency of warning, which gives the households more opportunities to receive warning and take actions in a long raining duration. Receiving warnings with a short time interval can partly compensate the shortcomings of long warning lead time. Further results indicate that the damages go higher when the warning interval is longer, and a longer lead time with shorter interval can lower the loss rate greatly. Therefore, to improve the warning system with more frequent information release should be a priority in flood control planning and management. The findings are consistent with several studies that provided clear evidences on the substantial benefit of flood warning systems [29, 68].

The model results suggest that extreme rainfall scenarios generally cause more serious flood damages to all households, as they cause floods very soon and leave less time for responding. Although moderate rainfall scenarios with low peak rainfall may cause deeper flood water depth in a long raining period, the damages can be effectively and timely avoided because rain warnings were released, which ensures successful execution of certain response measures.

5.2 Policy Implications

The results of this study have several potential policy implications. First, simulation results show that rain warning plays a significant role in coping with a coming flood event. Changes in warning information, including lead time and warning interval, significantly contribute to the changes in total flood loss. It is therefore extremely important to keep improving the rain warning system with more accurate prediction, longer lead time, and more frequent information release. To achieve this, further research on the mechanisms of rain-triggered floods and appropriate channels for the release of warning information are highly recommended.

The exploratory analysis has found in particular that random response actions with no warning guidance do not help to reduce total flood losses, which suggests that some individuals who are not covered by warning systems are unable to effectively cope with flood impacts. Due to the lack of capacity of prevention and resilience, their adaptation to flood incidents relies on past experiences of dealing with similar risks. Thus, much adaptation is autonomous and facilitated by the social capital and resources of households. However, individual experiences are very limited and unorganized. This makes it complicated and difficult to operate a successful flood management. The current system of treating flooding as a public problem does not stress the increased individual role in responding to flooding risks and damages. The resulting mismatch in policy potentially exacerbates regional vulnerability in face of rising flood losses. Further analysis indicates that supportive government policies related to flood resistance can play a positive role in helping people to implement flood fighting measures. Improving individual capacity is a way to help them adopt appropriate measures during floods, and the government should pay particular attention to the marginal communities and people within the community who have a low level of access to public information. Enhancing adaptive capacity in this context requires a new vision on the populations and communities of the region as an integrated system, supported by institutions that facilitate cross-scale and intersectoral planning. Governmental institutions thus need to invest in simulating how floods affect various city sectors and what the role of individual effort is in response.

Furthermore, the results of this study also have implications for adaptation plans for floods under climate change in other regions and countries. Direct provision of early disaster warning and prevention information to local communities, particularly to marginalized people, is still not common in many urbanizing regions. Given the rapid development of communication technology, the widespread individual use of cell phones, and the cost-effectiveness of text messages to individuals, transparency disaster information and prevention services should be explored in more detail.

5.3 Value of the Model Approach and Outlook

This modeling study makes a shift from a simplistic flood loss assessment to simulating the effects of the interaction of rainfall, flood inundation, and human responses using an agent-based model. The ABM delivers insights into human response behavior for flood loss assessment and demonstrates the dynamic real-time process of flood damage and loss, which could not be extracted from the other methods reported in Sections 1.1 and 1.2.

It has to be pointed out that this study does not only aim to simulate real flood events and household behaviors, but more importantly to examine the effects of various flood response options according to rainstorm/rain warnings. It is an experimental model based on the natural environment in the case area. The data on water flows and household behaviors do not fully reflect the real world but are rather simplistic representations. The model reveals some interesting phenomena in the flooding process and responding strategies, though limitations exist in the following aspects, among others: (1) human engineering constructions for flood control were not considered; (2) flood response behavior was set simply based on warning information; (3) only one agent type (household) was simulated which does not reflect efforts from community, enterprises, and government departments; (4) only one flood event was simulated where flood experience has no chance to play a role. Any of these can be specified in future model developments and applications.

While it is desirable to have a model that represents the reality to a large degree, currently, there is insufficient information on the behaviors and responses of individuals and organizations during flood events to parameterize the agent behavior rules. In the present case study, the model borrows the general findings from some empirical studies to support exploring the process of flood loss along with various household responses and compares the effectiveness of different flood response measures. With these limitations, the model at its current stage is appropriate for modeling rainfall caused surface floods as the warning system is based on rain scenarios. Fluvial floods, coastal surge floods, dam failure floods, and others may be modeled in this model only when there are reliable warning systems for them. Especially, with very large flood depths (e.g., over 4 m), there is much less that can be done on the household level to prevent flood damages. In such cases, enterprise and government agents may be introduced to manage large-scale flood prevention measures.

Altogether, a lack of reliable behavior data in the specified case area and limited knowledge on quantitative human behavior jointly limit the reflection of the model to real-world situations and determine it as a pilot simulation. It therefore represents a first step towards the development of an integrative operational tool for guiding the design of more adequate flood response strategies and management plans. Combining simple individual components into a model framework that is easy to use, each of them can be expanded to model more complex dynamic interactions of flood impacts and responses. It represents a unique tool for scientists and scholars looking for a practical framework to explore the complex flood control system by focusing on the bottom-up individual actions and self-organization mechanisms of a real-world application. For full dynamic simulations of the process of flood responses, the model will be extended with realistic environment conditions and a more advanced flood response behavior module.

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