Flood Emergency Mobility: Archetype-Based Modeling of Human Behavior

Erica Arango
Delft University of Technology, Faculty of Civil Engineering and Geosciences
e.a.arango@tudelft.nl

Maria Nogal
Delft University of Technology, Faculty of Civil Engineering and Geosciences
M.Nogal@tudelft.nl

ABSTRACT

Evacuation remains a critical challenge for emergency management, particularly in densely populated urban environments where human behavior strongly influences evacuation outcomes. Although substantial progress has been made in hazard modeling, early warning systems, and evacuation logistics, many models still rely on simplified assumptions of homogeneous compliance. Empirical evidence from past disasters shows that awareness of evacuation orders does not necessarily lead to timely or complete evacuation. This paper presents an archetype-based modeling framework to represent heterogeneous human behavior during flood emergencies, capturing coordinated, passive, and chaotic action patterns within an agent-based evacuation model. The framework is applied to a case study in Rotterdam, the Netherlands, considering three dike failure scenarios that generate flash flooding. By integrating behavioral archetypes with high-resolution geospatial data, flood dynamics, and urban infrastructure networks, the model can enable more realistic simulation of evacuation processes and emergent mobility patterns. The results highlight the significant influence of behavioral diversity and infrastructure exposure on evacuation efficiency, advancing human-centered approaches for crisis decision-making and urban governance.

Keywords

Flood emergencies, Evacuation behavior, Archetype-based modeling, Decision support systems, Crisis management

INTRODUCTION

Evacuation planning remains one of the most widely implemented mechanisms for reducing loss of life during emergencies. Effective evacuation planning requires prior knowledge of hazard characteristics, an understanding of population vulnerabilities, and detailed logistical and mobility considerations (Mort et al., 2018). Over recent years, substantial research efforts have focused on advancing technical and operational evacuation strategies, including early warning systems, evacuation route optimization, and prioritization schemes (Liang et al., 2023; De Albuquerque et al., 2024). These approaches have significantly improved the capacity of authorities to issue warnings and manage large-scale evacuations.

However, the effectiveness of evacuation strategies does not depend exclusively on institutional planning and decision-making. Citizens also play a decisive role in determining evacuation performance, yet their behavior is often oversimplified or insufficiently represented in evacuation models (Moradi et al., 2025; Wang et al., 2021). Many evacuation protocols implicitly assume that individuals will comply with official guidance, evacuating when and where they are instructed to do so. This assumption fails to reflect the complexity of real human behavior during crises. Empirical evidence consistently demonstrates that awareness of evacuation orders does not necessarily translate into compliance. For example, prior to Hurricane Sandy making landfall in New Jersey in October 2012, although 71% of residents in designated evacuation zones were aware of a mandatory evacuation order, more than 50% did not evacuate (Schuerman, 2013). Recent research shows that evacuation behavior is shaped by a range of personal, social, and contextual drivers that influence how individuals interpret warnings, assess risk, and decide whether to evacuate, delay evacuation, or evacuate incompletely (e.g., Sairam et al., 2025; Lanza et al., 2022; Li et al., 2022). These findings highlight the need for evacuation models that explicitly incorporate behavioral heterogeneity and decision-making under uncertainty.

Floods remain among the most frequent and disruptive natural hazards worldwide. In the last twenty years, floods have affected over 1.6 billion individuals and caused economic damages exceeding €600 billion. Projections indicate that both the occurrence and intensity of flood-related disasters are likely to rise in the coming decades, driven by climate change and increasing urban exposure. Recent events illustrate this growing risk: during the first two months of 2026 alone, flood events occurred in Portugal, France, the United Kingdom, and Spain, leading to the evacuation of more than 3,000 people (Fisayo-Bambi, 2026; European Space Agency, 2026).

Previous studies on disaster response highlight the importance of accounting for heterogeneous human behavior when analyzing system resilience. Nogal and Honfi (2019) show that, under certain conditions of traffic disruption, variability in drivers' behavior can enhance the resilience of transport systems, emphasizing the role of information availability and risk perception (Nogal and Honfi, 2019a). More recent research further demonstrates that evacuation dynamics and outcomes are strongly shaped by heterogeneity in mobility patterns, decision-making, and access to resources (e.g., Lanza et al., 2022, Sairam et al., 2025). In particular, large-scale mobility data analyses reveal significant disparities in evacuation behavior linked to socioeconomic factors such as income and race, affecting both evacuation timing and destination choice (Deng et al., 2020). Similarly, recent modeling and empirical studies show that incorporating behavioral diversity improves the realism and predictive capability of evacuation models, as it captures non-uniform responses to risk, infrastructure constraints, and information (Li et al., 2024; Zhang et al., 2025). Understanding how populations respond and move under such critical conditions has therefore become central to disaster response and crisis management. This is particularly important because populations exposed to flooding often exhibit resistance to evacuation, even in the presence of official warnings. These behavioral patterns have been repeatedly documented in major disasters, where non-compliance with evacuation orders has contributed to increased exposure and, in some cases, loss of life. This gap between warning issuance and human response represents a critical challenge for decision-support systems and emergency management practice.

To address this challenge, this study adopts an archetype-based modeling approach to represent heterogeneous human behavior during flood emergencies. Archetypes are used to capture distinct decision-making and response patterns, including those who are coordinated and follow official guidance, those who are passive and delay or avoid evacuation, and those who are chaotic and act autonomously and opportunistically. By modeling these behavioral archetypes within an agent-based evacuation model, the approach enables the simulation of differentiated responses to warnings, evolving hazard conditions, and infrastructure constraints. This supports the understanding of emergent evacuation dynamics that cannot be captured by homogeneous or compliance-based models.

The proposed approach is demonstrated through a case study in Rotterdam, the Netherlands, using three dike failure scenarios that result in flash flooding events. The integration of behavioral modeling with high-resolution geospatial data, digital representations of the urban environment, and dynamic flood hazard information illustrates how such models can support crisis decision-making. This work contributes to the development of more realistic, people-centered evacuation models that can inform the design of adaptive decision support systems and enhance situational awareness during flood emergencies. The rest of this paper is structured as follows. Section 2 introduces the archetype-based modeling and its behavioral foundations. Section 3 describes the Rotterdam case study and the flood scenarios considered. Section 4 presents the simulation results, and the framework potential of extension, followed by a discussion of implications for crisis management and decision support in the conclusions (Section 5).

MODELLING PEOPLE BEHAVIOR DURING CRISIS

Research in disaster sociology and crisis has shown that human behavior during emergencies is heterogeneous and context-dependent (Huang et al., 2025). Archetype-based approaches offer a way to reduce behavioral complexity while preserving diversity. Archetypes have been used in climate adaptation and disaster risk research to represent typologies with similar patterns and to support decision-making in complex socio-environmental contexts. For example, archetype analysis has been used to identify recurring patterns of municipal climate risk (Riach et al., 2023), guide adaptive pathways planning by categorizing contexts based on awareness and capacity (Di Fant et al., 2025), synthesize patterns across social-ecological systems to support evidence-based policy (Oberlack et al., 2019), and reveal distinct problem contexts and governance responses in water management (Gotgelf et al., 2020).

In emergency response, archetypes can capture differences in risk perception, information processing, mobility capacity, and response timing, whereas an agent-based model (ABM) makes possible to represent the heterogeneous dynamic, and non-linear nature of evacuation processes in urban environments by the archetypes. ABMs are widely used to simulate evacuation processes because they enable representation of individual-level decision-making and movement, and are particularly effective at capturing emergent phenomena arising from interactions between individuals, infrastructure, and hazards (Senanayake et al., 2024; Templeton et al., 2024; Wang et al., 2025). When combined with behavioral archetypes, ABMs provide a powerful framework for studying evacuation dynamics under realistic conditions.

Archetype-Based Modeling for Flood Emergency

Evacuation is modeled following the emergency archetype model proposed by Arango and Nogal (2026), as a dynamic behavioral process reflecting how citizens exposed to flood hazards respond to evolving conditions considering available infrastructure and official guidance. Consequently, the urban environment is considered as a network of buildings, roads, and shelters. The buildings are 3D residential units to which citizens are assigned based on population data and floor heights, while the road network supports pedestrian and vehicular movement. Shelters are characterized by elevation, accessibility, and capacity, the latter estimated from building floor area and number of floors using a standard per-person space assumption. Exit points are defined solely based on elevation and accessibility. Flood hazards are represented using time-varying water depth maps. At each time step, hazard exposure is calculated for each citizen based on its location and water depth, influencing movement feasibility.

Evacuation decisions are triggered by official warnings, with response times varying by archetype. Agents plan routes to the nearest shelter or exit the affected area and dynamically re-plan if conditions along their path become unsafe. Movement speed is adjusted according to age, differentiating between individuals aged 0 to 65 and those over 65, as well as accounting for congestion and water depth.

Behavioral Archetypes

Citizens are assigned to one of three behavioral archetypes summarized in Table 1. Each archetype is defined by distinct decision-making styles and evacuation actions. By explicitly distinguishing these profiles, the proposed model structure captures the non-linear and heterogeneous mobility dynamics frequently observed in real-world flood evacuations. These archetypes influence evacuation timing, route choice, movement speed, and hazard tolerance.

Table 1. Behavioral archetypes and associated evacuation decision styles

	Coordinated	**Passive**	**Chaotic**
			
Behavior archetype:	Who complies with official warnings and evacuate promptly using planned location.	Who remains unactive or delay evacuation until conditions become critical.	Who acts autonomously, sometimes evacuating early, improvising routes, or deviating from official guidance.
Evacuation strategy:	Efficient evacuation (e.g., horizontal/vertical based on local info).	No evacuation, or only as a last resort.	Selective evacuation.
When:	In a timely manner, following warnings or evacuation orders.	Delayed or not at all, typically after direct impact or loss of access forces movement.	Early or impulsively, often before official warnings or independently of evacuation orders.
Where:	Vertical evacuation or to officially designated shelters using recommended evacuation routes, with potential for orderly return once conditions stabilise.	If movement occurs, it is short-range and unplanned, often remaining within the immediate neighborhood or moving to nearby familiar locations.	To self-selected, destinations perceived as the safest (e.g., upper floors, relatives' homes), which may fall outside designated shelters or official evacuation routes.

The selection of these three behavioral archetypes is based on the literature, which consistently identifies three broad categories of human response in emergency situations. Prior studies distinguish between controlled or cooperative behavior, inhibited or delayed response, and impulsive or weakly regulated actions (Mawson, 2005; Kuligowski, 2011; Lanza et al., 2022). These categories reflect differences in personal drivers and decision-making capacity during emergencies. Building on this theoretical foundation, the proposed archetypes represent observable evacuation behaviors: individuals who follow official guidance, those who delay or avoid action, and those who act autonomously and may deviate from instructions.

In practice, modeling individual behavior is extremely complex, as it depends on many contextual and psychological factors that are not yet fully understood and remain difficult to measure. For instance, there is not a clear empirical connection between individual agency and risk perception (Wachinger et al., 2013). While individual agency can be operationalized and tracked through observed actions, risk perception is considerably more challenging to quantify. This motivates the definition of the archetypes based on their observable response rather than their underlying motivations. Socioeconomic and sociocultural attributes are then used for assigning individuals to behavioral archetypes, given the existing literature relating some of these attributes with the observed response in previous events (e.g., Endendijk et al., 2023, Yang et al., 2021). Socioeconomic attributes include age and income, which influence both exposure and behavioral response. Lower-income individuals often face resource constraints that delay or limit evacuation, while older adults experience reduced mobility and greater dependence on caregivers, increasing vulnerability during floods (Yang et al., 2021; Shan, 2023; ACC, 2025). Together, these factors capture two of the most critical mechanisms affecting the timing and capacity of protective movement.

Importantly, these socioeconomic characteristics are not considered in isolation but are shaped by broader sociocultural contexts that vary across countries, regions, and communities. Differences in social norms, cultural expectations, trust in authorities, and collective experience with hazards can lead to distinct behavioral responses, even among individuals with similar socioeconomic profiles. Therefore, the studies used to assign the archetype distribution based on the socioeconomic attributes must be restricted to the specific cultural context under investigation, in this case, the Netherlands.

By linking these attributes to archetype assignment, the model represents realistic diversity in responses across different social and cultural settings. The model operates in discrete time steps, enabling dynamic tracking of hazard evolution, decision-making, and individual response.

APPLICATION TO ROTTERDAM CONTEXT

The proposed flood evacuation model is applied to the urban context of Rotterdam, in the Netherlands, a densely populated and low-lying city characterized by a complex network of rivers, canals, and infrastructure. The city is exposed to coastal and river flooding, particularly due to the potential failure of flood defenses along key waterways, which makes Rotterdam a highly relevant case for studying evacuation behavior during flood emergencies. This study considers three distinct dike failure scenarios: Boerengatbrug, Parksluizen, and Maashaven (dike km 36.1), each representing a possible breach event that impact different urban districts and evacuation dynamics. Each scenario assumes a complete dike failure with an exceedance frequency of 1 in 1,000,000 years. All scenarios provide risk data to define water depths, velocity, arrival time and inundation extents, enabling the assessment of evacuation dynamics across diverse urban topographies. These hazard scenarios are available in the national flood risk datasets provided by the Dutch government (Rijkwaterstaat, 2024). This return period is adopted based on the availability of open-source data on dike failure probabilities in the Dutch context; however, the modeling framework is generic and can be readily applied to other return periods or hazard scenarios.

Figure 1 shows the three scenarios. Scenario 1 (Boerengatbrug) represents a breach event that primarily impacts the northern and central districts of Rotterdam, including the Stadsdriehoek, Rubroek, Kralingen-West, and Struisenburg neighborhoods. These areas are predominantly characterized by medium–high income levels, with the exception of Rubroek, which is classified as low–medium income. Scenario 2 (Parksluizen) affects the western port districts of Rotterdam, specifically Spangen, Nieuwe Westen, Middelland, Oude Westen, and Dijkzigt. Among these neighborhoods, Spangen and Nieuwe Westen are classified as low–medium income, while Middelland, Oude Westen, and Dijkzigt are categorized as medium–high income. This area is characterized by relatively limited shelter capacity. Scenario 3 (Maashaven, dike km 36.1) represents a potential breach along the southern port region of Rotterdam, with direct implications for densely populated districts along the riverfront. The affected neighborhoods include Zuidplein, Bloemhof, and Vreewijk, which are predominantly classified as low–medium income.

Population data are available at the postal-code level from the CBS PDOK (2024) and are uniformly distributed across buildings based on building volume and subsequently allocated per floor. Income data are obtained from the StatLine dataset (CBS, 2023) as average neighborhood-level income values. These are subsequently classified from low to high categories, following the energy poverty classification for Zuid-Holland (Batenburg et al., 2023), with each category uniformly assigned to all residents within the corresponding neighborhood.

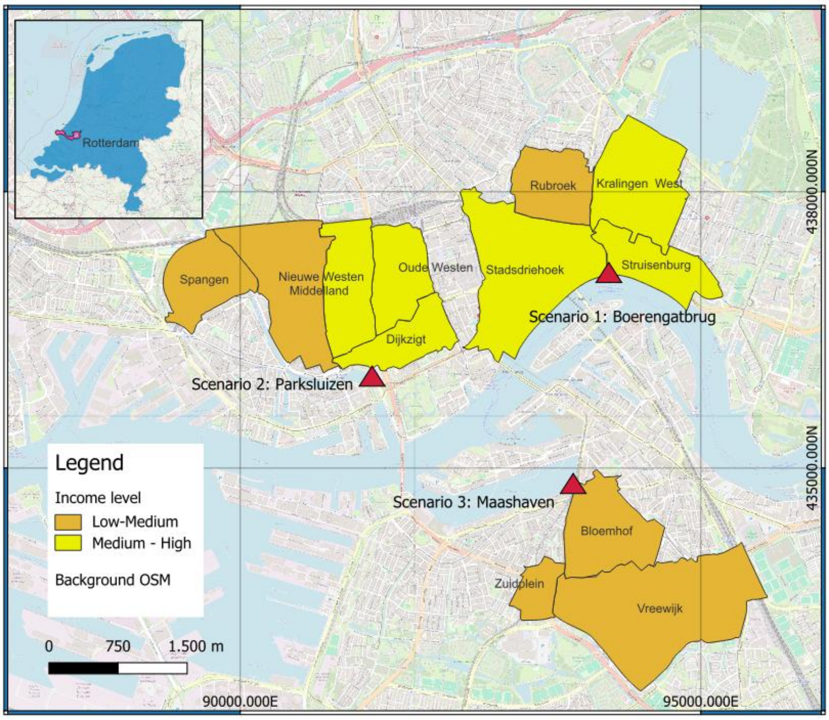


Figure 1. Rotterdam case study: dike failures at Boerengatbrug, Parksluizen, and Maashaven.

Road networks and shelter locations are extracted from OpenStreetMap, while building geometry and socioeconomic data are obtained from national open data platforms provided by Statistics Netherlands (CBS, 2023). Shelter capacity is defined volumetrically, assuming 4 m² per person, and decreases monotonically over time as building floors become flooded; once its capacity is lost, it cannot be recovered.

Agent archetype assignment is informed by observations from past flood events, including the 2021 Limburg floods, which revealed heterogeneous compliance levels and evacuation timing. The overall population is distributed across archetypes as 60% coordinated, 20% passive, and 20% chaotic. This distribution is partly grounded in empirical evidence of Endendijk et al. (2023), which analyses a household survey of 1,509 households affected by the Limburg floods. They report that 24.3% of respondents did not evacuate despite receiving an evacuation warning. This finding is consistent with previous evacuation modeling studies (e.g., Maaskant et al., 2009) which estimate that approximately 20% of the population may remain behind. This proportion is therefore used as a conservative estimate for the passive archetype. As no direct empirical evidence was found to quantify chaotic behavior, a value of 20% is assumed. The relative distribution between coordinated and chaotic agents is further explored through sensitivity analysis (Arango and Nogal, 2026).

Socioeconomic attributes (income and age) are available at postal-code level. The baseline 60/20/20 allocation is therefore implemented at the postal-code level. Within each postal code, agents are then randomly assigned to buildings (and floors) using a uniform distribution.

To reflect empirical evidence linking advanced age to delayed evacuation behaviour (Sairam et al., 2025), the postal-code share of residents aged ≥65 years is used as a weighting factor when allocating passive agents. For instance, a postal code having a 15% higher amount of ≥65-year-old people receives 15% more passive agents than a reference postal code, while preserving the overall population-level constraint that passive agents constitute 20% of all agents. Archetypes for non-elderly agents are assigned according to the baseline proportions. Income does not affect archetype assignment; instead, it influences within-archetype decisions, such as whether to shelter in place or leave the affected area.

In this sense, for coordinated and chaotic agents, the initial decision is whether to remain at home or evacuate, conditioned primarily by physical exposure, especially whether residents occupy ground floors at risk of flooding. When evacuation is required, destination choice, namely, shelter versus leaving the area, is influenced by income level, assuming that higher-income individuals are more likely to have the resources to evacuate outside the affected area, while lower-income residents are more likely to rely on public shelters. Coordinated individuals comply with guidance and make decisions consistent with both safety conditions and available resources; whereas chaotic individuals act autonomously, making less predictable decisions regarding timing and destination. Passive agents tend to delay action or remain at home even under unsafe conditions. Figure 2 summarizes how behavioral archetypes adapt their actions depending on physical exposure conditions (dry or wet floor) and socioeconomic proxy variables. The agent-based model is implemented in Python using the Mesa library.

The model operates dynamically over a 10-hour simulation period. The first two hours represent baseline conditions, prior to the emergency phase. An official warning is issued at Hour 2, representing a short-notice scenario. Flooding begins at Hour 4, thereby defining a two-hour reaction window for residents. Due to dike failure can lead to flash flooding, there is limited time to inform the population in advance. Therefore, an official warning is issued two hours before flood arrival, advising residents to remain at home if possible, i.e., residents on the ground floor need to evacuate. Water depth then increases progressively, with peak impact occurring around Hour 8, when most areas experience maximum flooding. Although the most severe hazard conditions occur within this period, the simulation continues until Hour 10 to better capture evacuation dynamics, including residual impacts and ongoing population movements after the peak event. The model also accounts for proximity to shelters and major evacuation routes, as well as dynamic behavioral adjustments in response to evolving flood conditions.

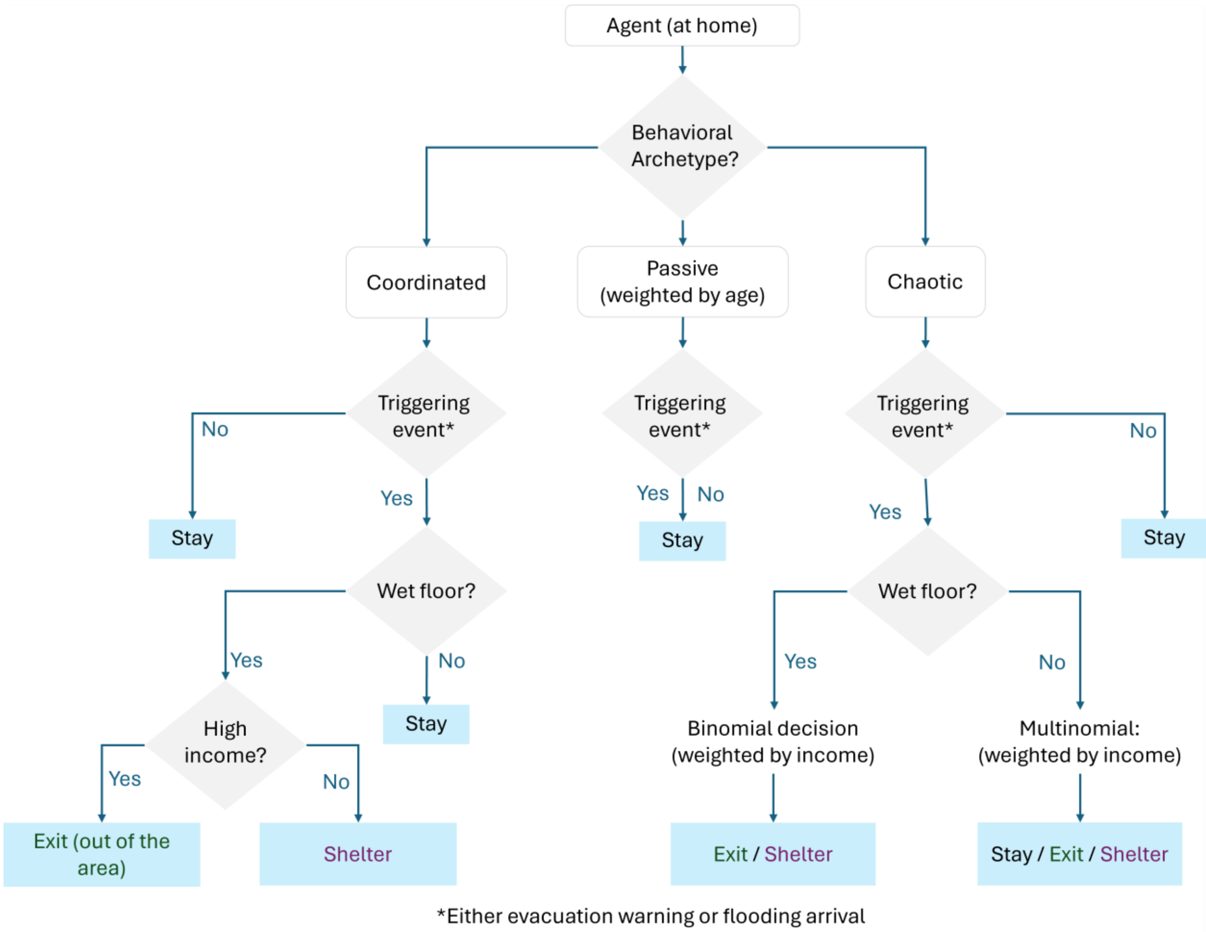
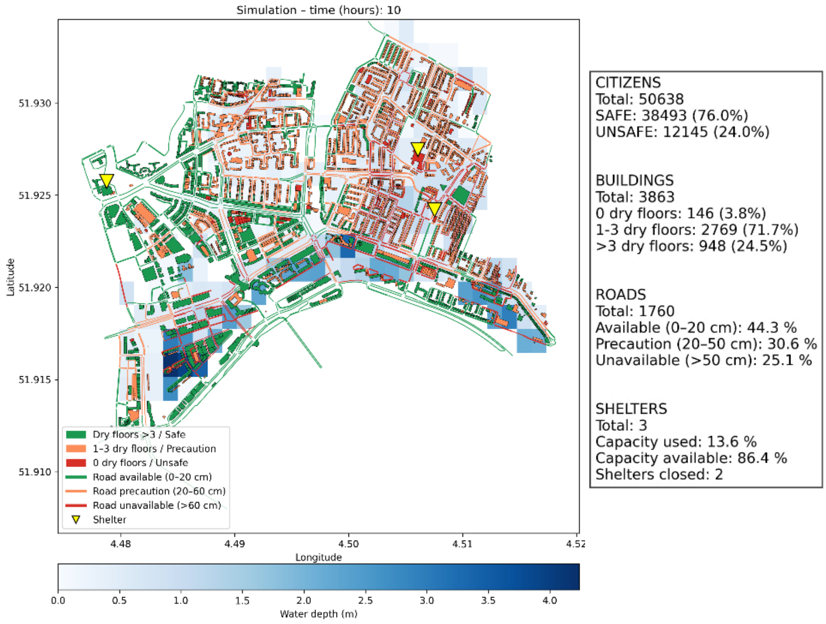


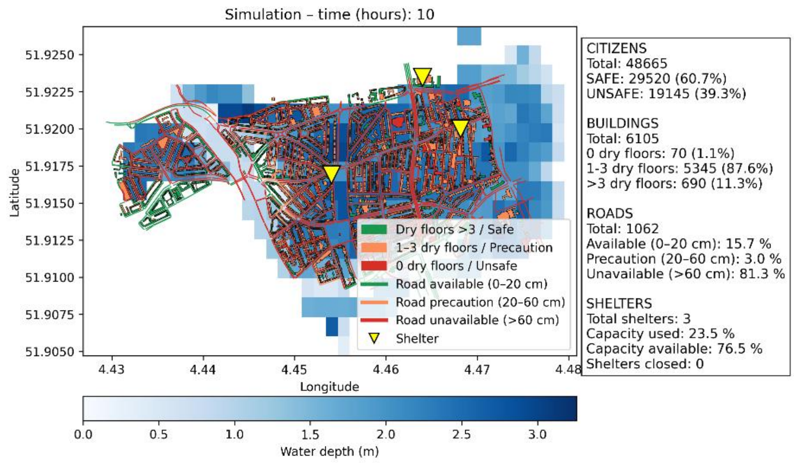
Figure 2. Archetype-based initial actions under different exposure conditions and socioeconomic characteristics

RESULTS

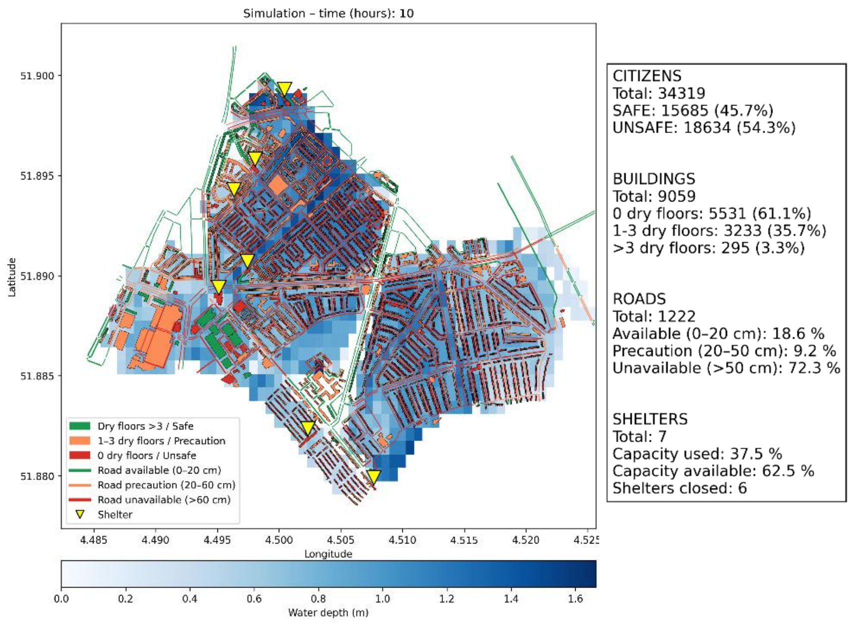
Simulation results show significant differences in evacuation outcomes across the three scenarios as shown in Figure 3 that shows the impact at hour 10, reflecting the maximum impact on the area.



a)



b)

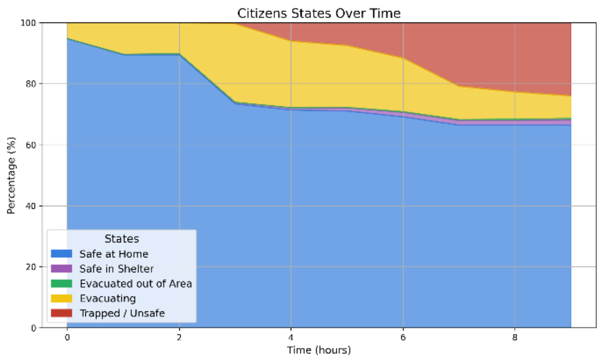


c)

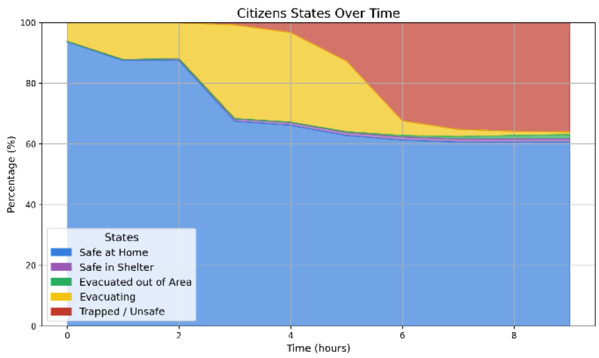
Figure 3. Flood impact assessment: dike failures Rotterdam a) Boerengatbrug, b) Parksluizen and c) Maashaven

Scenario 1 (Boerengatbrug) experiences the least overall impact, both in terms of infrastructure and social exposure. Flooding is primarily concentrated near the canal, and most buildings remain with more than 1 dry floor (96.2%), allowing for effective vertical evacuation. Additionally, only 25% of roads are seriously affected or not available, so horizontal evacuation is not that compromised. Scenario 2 (Parksluizen) represents the most critical flooding conditions, as its impact spans the entire area. The road network is severely affected, with 81.3% of roads either inoperable or unsafe, reducing the effectiveness of horizontal evacuation. Approximately 39% of the 48,665 citizens considered are exposed to unsafe flood conditions. However, this scenario includes the highest number of tall buildings, with 98.9% retaining at least one dry floor, which allows vertical evacuation to cover a significant portion of evacuation dynamics. Scenario 3 (Maashaven), in contrast, presents the greatest overall exposure. Although the maximum water depth reaches only 1.6 meters, flooding extends across the entire area, and most structures are one- or two-story homes, leaving 61.1% of buildings without any dry floors,which forces horizontal evacuation in most cases. Unlike the previous scenarios, where residents could stay at home and shelter capacity was not fully utilized, the predominantly low- to medium-income population in this scenario relies on shelters. Rapid floodwater ingress and compromised access lead to shelter closures, increasing citizen exposure, with 54% of the 34,319 residents considered being in unsafe conditions.

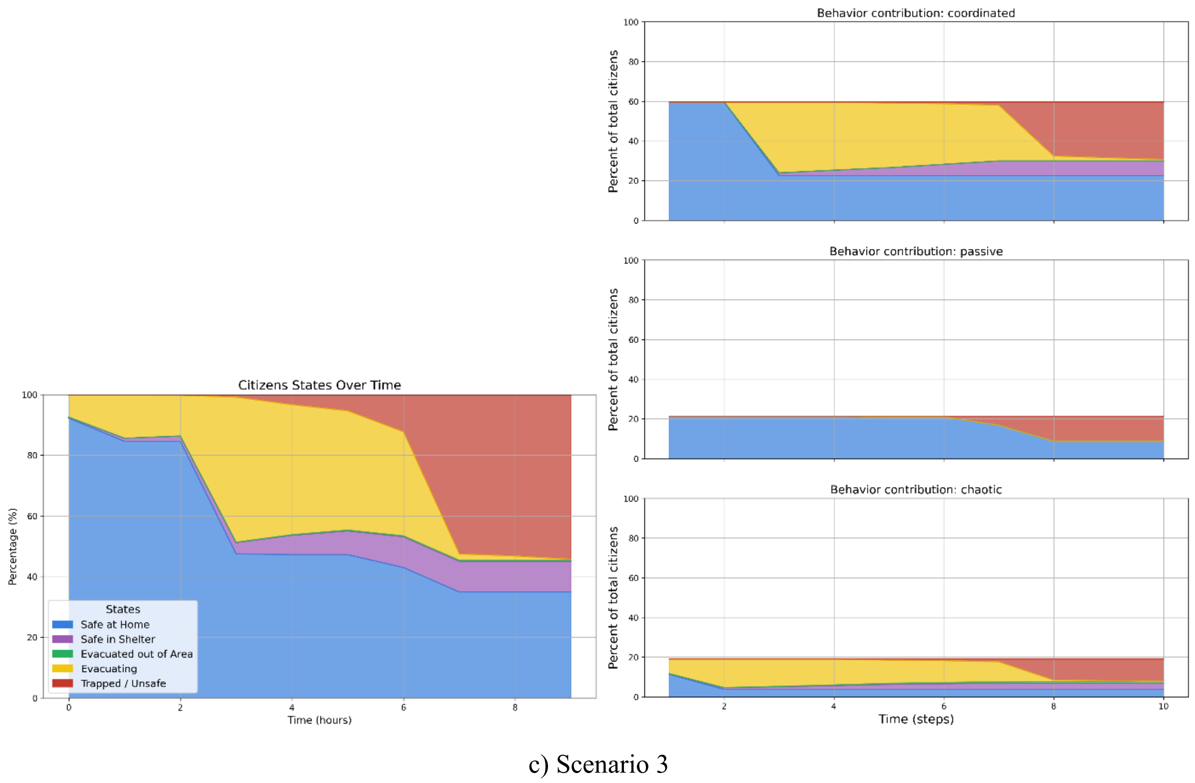
Figure 3 shows the evacuation dynamics over time. It can be observed that in Scenarios 1 and 2, vertical evacuation dominates, with many residents able to stay safe at home.



a) Scenario 1



b) Scenario 2



c) Scenario 3

Figure 4. Evacuation dynamics: dike failures Rotterdam a) Boerengatbrug, b) Parksluizen and c) Maashaven

In contrast, Scenario 3 requires extensive horizontal evacuation, and when flood impact peaks, many citizens become trapped on the roads, in addition to passive individuals who choose to remain at home despite the evacuation warning in each case.

The importance of distinguishing behavioral archetypes lies in the additional explanatory value they provide for interpreting these results. To illustrate this, Figure 3 (Scenario 3) further disaggregates emergency outcomes by archetype. Chaotic citizens, who considers the possibility of acting early and independently of official timing and initiating evacuation sooner than other groups. This behavior introduce some degree of flexibility into the system by reducing congestion at later stages.

In contrast, passive individuals tend to delay evacuation or remain at home regardless of warnings, which contributes to early instances of unsafe exposure once flooding begins (see at Hour 4, Figure 4). Under flash flood conditions, most trapping events occur after Hours 6–7, when water depth intensifies and residents who are still evacuating become trapped on increasingly unsafe roads. By separating these behavioral profiles, the model reveals how timing differences across groups directly shape congestion dynamics, exposure patterns, and overall evacuation performance.

CONCLUSIONS

This study illustrates an approach for representing heterogeneous human behavior in evacuation modeling. Conventional evacuation simulations that assume homogeneous compliance, systematically underestimate societal exposure, and fail to capture the complex interplay between individual decision-making and infrastructure performance. By contrast, the archetype-based agent modeling provides a tractable yet behaviorally rich approach to representing heterogeneity in evacuation responses.

This framework is applied to multiple dike failure scenarios in Rotterdam, illustrating how behavioral diversity and infrastructure exposure fundamentally shapes evacuation outcomes. The results show that population safety is determined by hazard intensity, the interaction between warning timing, behavioral responses, building characteristics, and the functionality of critical infrastructure such as roads, shelters, and vertical evacuation capacity. The framework also enables simultaneous assessment of social safety and infrastructure performance, revealing where evacuation bottlenecks emerge, when road networks become unsafe, and how shelter accessibility evolves under dynamic flood conditions. As the framework integrates physical and social domains, it can also support the evaluation of different types of adaptation measures aimed at increasing urban resilience, including grey and green infrastructure interventions as well as soft adaptation measures designed to influence human behavior and decision-making.

These outputs provide actionable insights beyond traditional evacuation metrics for emergency management. The model allows stakeholders to identify vulnerable behavioral groups, quantify compliance and non-compliance with evacuation guidance, and evaluate the effectiveness of vertical versus horizontal evacuation strategies under different flood scenarios. Such insights support more adaptive evacuation planning, targeted communication strategies, and improved allocation of emergency resources. In addition, the archetype agent-based modelling has capabilities to be integrated with digital twins and large-scale mobility data, make it possible to inform intelligent planning by anticipating population movement patterns rather than relying only on observed behavior during crises. This transition toward anticipatory mobility management represents a significant advance for crisis preparedness and response enabling authorities to test strategies, explore "what-if" scenarios, and enhance situational awareness during unfolding events.

Despite its contributions, this work has limitations. Archetypal proportions are derived from observations of past events but remain subject to uncertainty, and social influence mechanisms such as home coordination and evolving risk perception are represented in a simplified manner. Future research will focus on advancing the behavioral and data integration components of the framework. In particular, incorporating dynamic information exchange and enabling real-time coupling with early warning systems and digital twins will allow agents to adapt their decisions based on evolving conditions. In addition, integrating large-scale mobility datasets, such as those derived from GPS-enabled devices, mobile phones, social media, and census data, offers the potential to represent population movements and decision-making at high spatial and temporal resolution (Oliveira et al., 2025; Yabe et al., 2020). This would enable more scalable and transferable behavioral representations without relying solely on case-specific surveys. Furthermore, embedding the archetype-based modeling approach within digital twin environments can support the continuous assimilation of real-time observations, dynamically updating agent states, evacuation flows, and system-level indicators such as shelter occupancy and population safety. This integration would enhance anticipatory planning capabilities, allowing authorities to test strategies, explore "what-if" scenarios, and improve situational awareness during unfolding events. Ultimately, such developments would contribute to more realistic evacuation modeling, more effective emergency response, and the advancement of human-centered, data-driven crisis decision support systems. The proposed approach is not limited to flood risk but can be extended to other hazards such as wildfires and earthquakes.

ACKNOWLEDGMENTS

This work is financed by the Dutch Research Council (NWO) and the Department of Science & Technology, India (DST), through the Merian Fund under Grant No. 482.482.302.

REFERENCES

Mort, M., Walker, M., Williams, A. L., & Bingley, A. (2018). Displacement: Critical insights from flood-affected children. *Health & Place, 52*, 148–154. https://doi.org/10.1016/j.healthplace.2018.05.006

Liang, B., van der Wal, C. N., Xie, K., et al. (2023). Mapping the knowledge domain of soft computing applications for emergency evacuation studies: A scientometric analysis and critical review. *Safety Science, 158,* 105955. https://doi.org/10.1016/j.ssci.2022.105955

De Albuquerque, N. L. B., Da Silva, L. B. L., Alencar, M. H., & De Almeida, A. T. (2024). A multicriteria decision model to improve emergency preparedness: Locating–allocating urban shelters against floods. *International Journal of Disaster Risk Reduction, 111*, 104695. https://doi.org/10.1016/j.ijdrr.2024.104695

Moradi, H., et al. (2025). Improving evacuation policies through agent-based modeling and stakeholder engagement in hazard-prone areas. *International Journal of Disaster Risk Reduction, 119*, 105280. https://doi.org/10.1016/j.ijdrr.2025.105280

Wang, Y., Kyriakidis, M., & Dang, V. (2021). Incorporating human factors in emergency evacuation: An overview of behavioral factors and models. *International Journal of Disaster Risk Reduction, 60*, 102254. https://doi.org/10.1016/j.ijdrr.2021.102254

Schuerman, M. (2013). *Evacuation rate during Sandy dangerously low*. WNYC. http://www.wnyc.org/story/291228-highs-and-lows-citys-sandy-response/

Sairam, N., Sánchez, D. M., Dillenardt, L., & Thieken, A. (2025). Evacuating flash flood victims: Key drivers and psychological burden. *Journal of Flood Risk Management, 18*(2), e70065. https://doi.org/10.1111/jfr3.70065

Lanza, V., Dubos-Paillard, E., Charrier, R., et al. (2022). An analysis of the effects of territory properties on population behaviors and evacuation management during disasters using coupled dynamical systems. *Applied Network Science, 7*, 17. https://doi.org/10.1007/s41109-022-00450-6

Li, W., Wang, Q., Liu, Y., Small, M. L., & Gao, J. (2022). A spatiotemporal decay model of human mobility when facing large-scale crises. *Proceedings of the National Academy of Sciences, 119*(33), e2203042119. https://doi.org/10.1073/pnas.2203042119

Fisayo-Bambi, J. (2026). *France on record flood alert as storms slam Spain with deadly winds.* Euronews. https://www.euronews.com/2026/02/16/france-on-record-flood-alert-as-storms-slam-spain-with-deadly-winds

European Space Agency. (2026). *Intense rainfall brings floods across Iberian Peninsula*. https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-1/Intense_rainfall_brings_floods_across_Iberian_Peninsula

Huang, F., Tang, J., Zhao, P., Chen, Z., Li, J., & Lyu, W. (2025). Human mobility under disasters: A systematic review and framework for equitable and resilient mobility governance. *Nature Hazards, 2*(1), 99. https://doi.org/10.1038/s44304-025-00153-9

Nogal, M., & Honfi, D. (2019). Assessment of road traffic resilience assuming stochastic user behaviour. *Reliability Engineering & System Safety, 185*, 72–83. https://doi.org/10.1016/j.ress.2019.01.010

Nogal, M., & Honfi, D. (2019a). Resilience assessment of the traffic network Luxembourg–Metz: The power of information. In *Proceedings of the 29th European Safety and Reliability Conference (*ESREL 2019) (pp. 1389–1395). https://doi.org/10.3850/978-981-11-0708-0_1636-cd

Deng, H., Li, X., Wang, Q., & González, M. C. (2020). *High-resolution human mobility data reveal race and wealth disparities in disaster evacuation patterns*. arXiv. https://doi.org/10.48550/arXiv.2008.05989

Li, X., Zhang, Y., Wang, J., & Gao, S. (2024). Modeling heterogeneous human mobility responses during disasters using large-scale data. *Transportation Research Part C: Emerging Technologies, 158*, 104456. https://doi.org/10.1016/j.trc.2023.104456

Zhang, Y., Wang, J., & Li, X. (2025). Integrating behavioral heterogeneity into evacuation modeling: Implications for urban resilience. *Transportation Research Part D: Transport and Environment, 130*, 104123. https://doi.org/10.1016/j.trd.2024.104123

Riach, N., Glaser, R., Fila, D., Lorenz, S., & Fünfgeld, H. (2023). Climate risk archetypes: Identifying similarities and differences of municipal risks for the adaptation process. *Climate Risk Management, 41*, 100526. https://doi.org/10.1016/j.crm.2023.100526

Di Fant, V., Middelkoop, H., Dunn, F. E., & Haasnoot, M. (2025). Supporting adaptive pathways planning using archetypes for climate adaptation. *Regional Environmental Change, 25*, Article 31. https://doi.org/10.1007/s10113-024-02349-7

Oberlack, C., Sietz, D., Bürgi Bonanomi, E., et al. (2019). Archetype analysis in sustainability research: Meanings, motivations, and evidence-based policy making. *Ecology and Society, 24*(2), 26. http://dx.doi.org/10.5751/ES-10747-240226

Gotgelf, A., Roggero, M., & Eisenack, K. (2020). Archetypical opportunities for water governance adaptation to climate change. *Ecology and Society, 25*(4), 6. https://doi.org/10.5751/ES-11768-250406

Senanayake, G. P. D. P., Kieu, M., Zou, Y., & Dirks, K. (2024). Agent-based simulation for pedestrian evacuation: A systematic literature review. *International Journal of Disaster Risk Reduction, 111*, 104705. https://doi.org/10.1016/j.ijdrr.2024.104705

Templeton, A., Xie, H., Gwynne, S., Hunt, A., Thompson, P., & Köster, G. (2024). Agent-based models of social behaviour and communication in evacuations: A systematic review. *Safety Science*. https://doi.org/10.1016/j.ssci.2024.106520

Wang, Y., Ge, J., & Comber, A. (2025). Modelling emergent pedestrian evacuation behaviors from intelligent, game-playing agents. *Journal of Computational Social Science, 8*(2). https://doi.org/10.1007/s42001-025-00369-9

Arango, E., & Nogal, M. (2026). *Modeling heterogeneous human mobility patterns during emergencies using archetypes* (under review). Reliability Engineering & System Safety.

Wachinger, G., Renn, O., Begg, C., & Kuhlicke, C. (2013). The risk perception paradox—Implications for governance and communication of natural hazards. *Risk Analysis, 33*(6), 1049–1065. https://doi.org/10.1111/j.1539-6924.2012.01942.x

Mawson, A. R. (2005). Understanding mass panic and other collective responses to threat and disaster. *Psychiatry, 68*(2), 95–113. https://doi.org/10.1521/psyc.2005.68.2.95

Kuligowski, E. D. (2011). Predicting human behavior during fires. *Fire Technology, 49*(3), 101–120. https://doi.org/10.1007/s10694-011-0245-6

ACC - Asociación Cluster Catástrofes. (2025). *Barómetro de las catástrofes en España 2024.* Instituto de Ingeniería de España. https://www.consaludmental.org/publicaciones/Barometro-Catastrofes-2024.pdf

Shan, X., Scussolini, P., Wang, J., Li, M., Wen, J., & Wang, L. (2023). Deficiency of healthcare accessibility of elderly people exposed to future extreme coastal floods. *International Journal of Disaster Risk Science, 14*(5), 840–857. https://doi.org/10.1007/s13753-023-00513-x

Rijkswaterstaat. (2024). *LIWO maps: Combining flood scenarios.* https://basisinformatie-overstromingen.nl/#/combine/7

CBS. (2023). *Kerncijfers wijken en buurten 2023*. https://opendata.cbs.nl

CBS PDOK. (2024). *Population data by postal code*. https://www.pdok.nl/

Batenburg, A., Schuurman Hess, T., Croon, T., Wijlhuizen, E., & van Tilburg, X. (2023). *Energiearmoede in Zuid-Holland (TNO Report P11510).* TNO.

Endendijk, T., Botzen, W., de Moel, H., et al. (2023). Experience from the 2021 floods in the Netherlands. *Journal of Coastal and Riverine Flood Risk, 2*, 9. https://doi.org/10.59490/jcrfr.2023.0009

Maaskant, B., Kolen, B., Jongejan, R., Jonkman, B., & Kok, M. (2009). *Evacuatieschattingen Nederland (HKV Report No. PR1718.10).*

Yang, Y., Metcalf, S., & Mao, L. (2021). Modeling transit-assisted hurricane evacuation. *International Journal of Geographical Information Science, 35*, 2424–2441. https://doi.org/10.1080/13658816.2020.1828590

Yabe, T., Tsubouchi, K., Fujiwara, N., Sekimoto, Y., & Ukkusuri, S. (2020). Understanding population evacuation dynamics using mobile phone data. *Nature Communications, 11*, 407. https://doi.org/10.1038/s41598-023-48130-4

Oliveira, H. S. (2025). Optimizing crowd evacuation: Evaluation of strategies for safety and efficiency. *Journal of Reliable Intelligent Environments, 11*, 2. https://doi.org/10.1007/s40860-024-00241-z