

Flood evacuation models: A simplified probabilistic approach with application to a case study in Rome

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ABSTRACT

Flood events clearly induce significant impacts in urbanized regions. Over the last decades, advances in computational capacity, high-resolution digital elevation data, and open-access geospatial datasets have enabled the development of Evacuation Models (EM). However, many EMs are often not so suitable for operational use by civil protection authorities, due to their significant data requirements, high computational burden and complex parametrisation. In this context, this work aims to bridge this gap by proposing a screening-level, operational tool based on a simplified probabilistic methodology, that integrates pedestrian movement under uncertainty with a streamlined representation of flood arrival time, and then produces evacuation-time distributions and spatially explicit estimates of floodwater-pedestrian interaction probability. The approach is applied to a flood-prone urban area in Rome (Italy). Results highlight the role of network topology, route branching and behavioural variability in determining evacuation performance, revealing critical areas where existing Evacuation Plans (EPs) may require revision. Finally, we state the need for integrating simplified evacuation models into emergent decision-support frameworks, including Digital Twins for urban flood management.

1. Introduction

River Floods are among the most impacting natural hazards affecting urbanized areas [1–7]. Flood vulnerability in urban settings is influenced not only by environmental factors but is deeply connected with socio-economic factors, urban planning legacies and infrastructural constraints.

In this context, Evacuation Plans (EPs) are a key component of non-structural mitigation strategies aimed at disaster risk reduction. The main goal is to reduce the people exposure during hazardous events, by guiding individual and collective movement toward safe areas. Efficient and realistic EPs require accurate modelling of hazard evolution, precise estimation of available warning time, and understanding of how the population is distributed, mobilised, and able to respond under stress. The increasing complexity of urban environments and the rapid onset of many flood events require EPs to incorporate adaptive approaches and spatial-temporal precision that are achievable only through the integration of modelling tools, real-time data and well-defined operational frameworks.

In literature it is well known that these mentioned complexities regard several aspects ([8], and references herein):

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- River flood events can suddenly and severely occur, with a limited warning, and hydraulic structures like dikes can fail due to a combination of high-water loading, wave attack and flood duration [9]. Consequently, unpredictability in floodwater can alter evacuation routes and render some pathways and emergency facilities impassable.
- Moreover, human factors in flood evacuation play a crucial role: education level, age, and gender can significantly influence judgment, decision-making, and evacuation destinations [10–14]. Additionally, emotional and behavioral factors such as altruism and irrational responses significantly affect evacuation processes [15].
- Furthermore, the limitations of emergency facilities further complicate flood evacuation scenarios. Evacuation routes and shelters may be inadequate or become quickly overwhelmed, particularly in large-scale disasters [16–20].

Over the last decades, advances in computational capacity, high-resolution digital elevation data, and open-access geospatial datasets have enabled the development of Evacuation Models (EMs), capable of simulating evacuation at different spatial and behavioural scales [21–23].

Specifically, when focusing on pedestrian behaviour—which is of primary relevance in operational settings where general vehicular traffic is typically restricted to facilitate emergency response and avoid the complexities of mixed pedestrian–vehicle interactions—evacuation models are commonly classified into macroscopic and microscopic approaches.

Macroscopic models describe evacuation dynamics at an aggregated scale, accounting for the influence of flood propagation on the accessibility of pedestrian routes and the availability of shelters [24], and are often employed to estimate evacuation times [25,26]. They have also been widely used to investigate optimal evacuation strategies [27] and to identify evacuation pathways [28–31], among other applications. However, due to their aggregated nature, these models do not explicitly capture detailed pedestrian behaviours, instead focusing on large-scale evacuation patterns.

On the other hand, microscopic models aim to reproduce individual-level dynamics by explicitly simulating pedestrian movement and their interactions with floodwaters. Through the integration of hydrodynamic modelling and behavioural representations, these approaches have enabled the analysis of key aspects of flood evacuation, including pedestrian decision-making [32], evacuation processes [33–37], and evacuation efficiency [38,39]. Such studies have also supported the development of advanced methodologies for flood hazard assessment [40].

Focusing on the specific mathematical structure, Evacuation Models (not only for Floods) can be broadly classified into three families:

1. A first class of modelling approaches conceptualises pedestrian movement as a continuous flow. Known as Flow Dynamics (FD, [41, 42]) models, these approaches borrow heavily from fluid mechanics and continuum descriptions. Pedestrians are treated as particles within a compressible medium whose density and velocity fields evolve according to macroscopic flow laws. In evacuation contexts, FD models effectively describe the emergence of congestion, shock waves and density-driven slowdowns. However, the primary limitation of FD models lies in their inability to capture the discrete, individual-level decisions that often govern routing under stress. FD models tend to assume homogeneous movement and rational route selection, which may not reflect actual human behaviour under conditions of panic or uncertainty.
2. Cellular Automata (CA, [34,35]; [43,44]) discretize the spatial domain into a grid, where each pedestrian occupies a cell and moves from this according to specific transition rules. Interactions among pedestrians, in terms of bottleneck formation, lane development, competitive versus cooperative behaviour, are modelled. However, CA models strongly depend on grid resolution and cell neighbourhood assumptions, and their ability to represent fine-scale behavioural complexity remains limited. Moreover, their discrete representation may limit the accuracy of evacuation path modelling in urban road networks, whose geometry is inherently anisotropic and heterogeneous.
3. Agent-Based Models (ABMs, [31,45–48]) are a third class for EMs, and they emerged as a response to the need for greater behavioural realism. In ABMs, each individual is represented as an autonomous agent with attributes, perception limits, decision heuristics and adaptive responses. ABMs can model the influence of partial information, environmental cues, social dynamics, panic transmission and fatigue [49]. They allow explicit simulation of heterogeneity within the population and can capture complex crowd behaviour that arises from interactions between individuals and with the environment [50]. In flood evacuation scenarios, ABMs have demonstrated the ability to replicate non-standard routing, risk aversion, group dynamics and variable compliance with instructions [51]. Despite their versatility, ABMs are characterized by significant computational costs, and they require an extensive calibration against empirical data, which is not always available. Their sensitivity to parameter choices and the need for high-quality behavioural datasets often limits their operational use [52].

These three families of models (FD, CA and ABM) represent the major pillars of contemporary research on EMs. Each provides a different approach through which pedestrian movement and hazard interactions can be analysed.

Despite these advancements, a significant disconnection persists between sophisticated research models and the operational tools used by civil protection authorities, mainly in flood contexts:

- First of all, most advanced models (particularly ABMs and 2D/3D hydraulic simulations) are characterized by prohibitive computational burdens, complex parameterization, and extensive data requirements [53]. This makes them difficult to implement for real-time emergency planning at the local level, where authorities often lack the necessary technical expertise or high-performance hardware. Consequently, EPs often rely on static maps or prescriptive route choices that fail to capture dynamic

aspects of hazard evolution and human mobility. This gap limits the practical applicability of evacuation modelling in real-time emergency planning.

- A second gap concerns the limited integration of evacuation and hazard models [54,55]. Although detailed flood models exist, and evacuation models separately advance behavioural realism, very few approaches systematically integrate these components in a way that reflects their joint uncertainty. The timing of flood arrival relative to pedestrian movement is one of the most critical determinants of successful evacuation, yet it is rarely represented probabilistically.
- A third gap lies in the scarcity of uncertainty-aware evacuation assessments. Most evacuation studies employ deterministic assumptions, i.e. fixed walking speeds, predefined routes or deterministic hazard arrival times [56]. Such simplifications severely constrain their ability to anticipate worst-case scenarios, which are the most relevant for practical risk reduction. In other words, such simplifications ignore the inherent uncertainty of flood emergencies [57]: i) warning times often depend on hydrological forecasts that carry significant uncertainty; ii) human behaviour under stress is also variable, and iii) road networks themselves may be partially or entirely compromised, with accessibility changing dynamically as conditions evolve [58]. Any realistic approach to evacuation assessment must therefore embrace uncertainty as a fundamental component.
- A fourth gap relates to the rapid rise of Digital Twin (DT) paradigms [59,60], which promise real-time environmental monitoring, continuously updated hazard forecasts, and adaptive guidance for the population. However, most existing evacuation models are not readily integrable into such real-time systems due to their computational demands or limited modularity.

Recent systematic reviews [46,52,61] confirm that state-of-the-art joint flood-evacuation modelling remains broadly divided between two operational paradigms:

- **High-Fidelity Coupled Models (ABM/CA + 2D Hydrodynamics):** Outstanding frameworks such as FlooPEDS [37], MIKE 21 + MATSim [62], GAMA-based flood ABMs [51], Opinion Dynamics + HEC-RAS [31], SFM + Hydraulic coupling [38], and Macroscopic 2D SWE coupling [32] provide rich physical interactions (e.g., body sliding/toppling, social force modifications, dynamic surface roughness). However, because these models numerically solve 2D shallow water equations alongside agent interactions, they require high-performance computing (HPC/GPU), heavy dataset parameterization, and long runtimes (hours to days). Consequently, they are typically applied to single deterministic scenarios or a small set of predefined cases, making massive uncertainty propagation unfeasible [46].
- **Fast Conceptual Arrival-Time Models:** Recent advances in lightweight flood modeling [63] execute in milliseconds to enable rapid probabilistic risk evaluation (analysing about 100 scenarios). However, these models focus strictly on the flood hazard front and do not simulate pedestrian routing choices, human behavioural variability, or crowd movement persistence.

Our proposed framework fills this methodological gap by serving as a **complementary, screening-level joint probabilistic tool**. Rather than replacing physically based 2D hydrodynamic codes or microscopic ABMs, it abstracts micro-scale mechanics into stochastic distributions, enabling **1,000,000 joint Monte Carlo realizations per node** to run in seconds on standard hardware (more details about computational costs are provided in Sect. 3).

In this context, the proposed study arises from the recognition that emergency planners often need tools that are fast and capable of generating meaningful insights even under significant uncertainty. Its novelty lies in the development of a computationally lightweight probabilistic evacuation assessment framework that integrates uncertainties in pedestrian mobility, routing behaviour and flood propagation within a unified Monte-Carlo simulation environment. Unlike traditional evacuation models that aim to reproduce detailed physical processes, the proposed approach focuses on the rapid identification of relative evacuation risk patterns across urban networks. This perspective allows the methodology to be used as an operational screening tool for emergency planning, particularly in data-scarce contexts where detailed hydrodynamic simulations may not be available.

As explained in the following sections, this proposed tool can clearly integrate more detailed information from hydrodynamic simulations (when available), in order to better estimate pedestrian–floodwater interaction probabilities and detail the impacts in terms of sliding, toppling, and floating ([64] and references herein). On the contrary, without availability of hydrodynamic simulations and/or measured data, the obtained results from the proposed framework constitute "relative risk indicators" rather than absolute predictions.

Rather than modelling the detailed behaviour of individuals, the approach focuses on generating large ensembles of plausible evacuation paths, capturing variability in route choice, movement speed, and hazard arrival. This ensemble-based logic mirrors stochastic approaches used in many fields of environmental modelling and allows the estimation of probability distributions rather than deterministic outputs.

Consequently, the methodology here proposed is intended to be complementary to (and not to replace) Agent-Based Models (ABMs) and complex hydraulic simulations, offering a faster, first-level assessment tool. Compared to fully coupled hydrodynamic–agent based models, the proposed approach significantly reduces computational demand by several orders of magnitude, enabling large Monte Carlo ensembles that would otherwise be infeasible in operational timeframes.

As better specified in Section 3, the model:

- generates probability distributions of evacuation times from any point in an urban network. By modelling thousands of simulations per node, the method moves beyond deterministic estimates and captures a spread of possible outcomes under uncertain routing and movement conditions;

- estimates flood arrival times, based on a simplified hydraulic representation. Instead of simulating full hydrodynamics (which can be clearly considered as well, if available), the approach reconstructs flood propagation using probabilistic velocity distributions, providing an accessible yet physically plausible approximation;
- evaluates the compatibility of evacuation times with hazard arrival by quantifying the probability of encounters between pedestrians and floodwater. This interaction probability provides a meaningful measure of safety that integrates movement dynamics and hazard evolution;
- tests the methodology on a real case study, producing actionable insights for emergency planning and discussing its potential for future integration into Urban Digital Twin (UDT) architectures.

The tool is implemented into a user-friendly Microsoft Excel file with embedded VBA (Visual Basic for Application) macros, to ensure maximum accessibility for practitioners. The obtained output tables are then imported in QGIS software for map representation. Authors also developed a python script (nowadays in beta version) for QGIS 3.40.12.

The proposed model was applied to Ostia, a coastal district of Rome (Italy). It is characterised by a combination of fluvial and pluvial hazard, high population density and complex infrastructural layout. Its proximity to both the sea and the Tiber River creates interactions between hydrological processes that may accelerate flood propagation and/or reduce the effectiveness of drainage systems. The presence of multiple local depressions and a highly articulated street network further complicate the identification of safe evacuation routes. These factors make Ostia a compelling case study and an ideal context in which to test simplified modelling approaches.

2. Materials

2.1. Study area description

The selected study area concerns the north-western zone of Ostia (Fig. 1), a densely populated coastal area located in Rome (Italy). It lies within the floodplain of the Tiber River, and its flood vulnerability arises from the combined effects of environmental and infrastructural factors. The total extension is approximately 15 km², with about 90,000 residents, and then an average density of 6000 inhabitants/km². Over 30,000 residents live in areas officially categorized as Flood Hazard Area (FHA, see also Sect. 2.2).

First, the very low topographic elevation of the area (generally below 5–6 m above sea level) may induce widespread flooded areas even if limited hydraulic forcings occur.

In addition, the intense urbanization resulted in large impermeable surfaces and a street layout organised in a regular orthogonal grid. While efficient from a planning perspective, this configuration restricts natural drainage, accelerates surface runoff, and can exacerbate the impacts of heavy rainfall beyond the capacity of the existing drainage system.

Flood risk is furtherly influenced by the drainage infrastructure (comprising reclamation canals and pumping stations) which was designed according to historical climatic and hydraulic conditions [65]. Consequently, mainly due to climate change effects, during periods of high river levels or marine backwater effects these systems may be unable to discharge water into the Tiber. Under such circumstances, the infrastructure can shift from its intended role of drainage to inadvertently facilitating the inflow of floodwaters into the urban area.

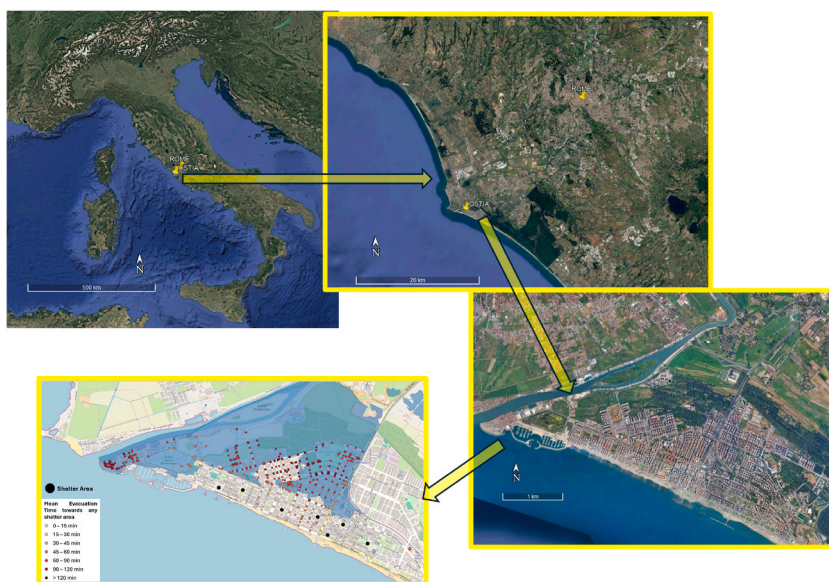


Fig. 1. The investigated study area.

The fluvial behaviour of the Tiber River introduces additional uncertainty. Severe flood events can cause embankment overtopping, particularly along the outer bends of river meanders [66]. When these events coincide with tidal influences and storm surges, flooding can produce widespread inundation that propagates through the urban environment in highly unpredictable patterns [7].

In this context, the high population density and diverse land use make Ostia an especially relevant case for assessing evacuation feasibility under changing flood conditions. Its selection as a case study reflects the complex interaction between flood hazards, infrastructural limitations, and the practical need for effective, time-sensitive evacuation modelling.

In this work, only river flood (and not also pluvial flood) risk is considered.

2.2. Datasets

Four key datasets underpin the modelling framework and provide the basis for its implementation: i) the road network, extracted from OpenStreetMap (OSM), ii) the Shelter Areas from the official Civil Protection Plan of Municipality of Rome (<https://www.comune.roma.it/web/it/informazione-di-servizio.page?contentId=IDS1154428>, in Italian), iii) the official Flood Hazard Area (FHA) maps for Italy, from the IdroGEO/ISPRA website (<https://idrogeo.isprambiente.it/app/>); for these maps, the H2 scenario was considered, corresponding to flood events with a return period of 100–200 years; and iv) the digitised riverbank polyline.

In detail, from the road network, 609 nodes were selected. Each node represents either a road intersection or a key directional change. A topological matrix was defined into the MS-Excel file, in which each node is associated with attributes that include (Table 1):

- o X-Y coordinates (m), based on projected coordinate reference system (in this work the EPSG 3004 was adopted);
- o a set of up to three admissible neighbouring outgoing nodes, describing the possible directions a pedestrian can move toward at each step. All outgoing neighbour nodes pointing towards the river were excluded from the choice set, as they are inconsistent with evacuation logic. Routing algorithm is detailed in Sect. 3.1;
- o a first flag indicating proximity to officially designated shelter areas (i.e., Flag = 1) or not (i.e., Flag = 0). This flag ensures that a specific pedestrian path terminates (clearly if no interaction occurs with floodwater, as specified in Sect. 3) once a designated safe location is reached (i.e., a pedestrian reaches a node with Flag = 1);
- o a second flag indicating whether the node lies inside (i.e., FlagINSIDE = 1) or outside (i.e., FlagINSIDE = 0) the Flood Hazard Area (FHA) map of interest. This flag clearly identifies the nodes which must be considered for the interaction between a pedestrian and the floodwater along a multi-segment path;
- o the Euclidean distance from the left riverbank (useful for evaluation of hydraulic distance, as reported in Sect. 3.2). If the node is outside the FHA map (i.e., FlagINSIDE = 0), then the distance is set equal to –9999.

3. Methods

Starting from the topological structure described in Sect. 2.2, the proposed approach combines:

- a probabilistic modelling of pedestrian velocity under emergency conditions (Sect. 3.1),
- a simplified estimation of floodwater arrival times (Sect. 3.2),

Table 1

Structure of the adopted topological matrix. For each node ID: i) X and Y are coordinates (m), based on projected coordinate reference system (in this work the EPSG 3004 was adopted), ii) the Flag indicates the proximity to officially designated shelter areas (i.e., Flag = 1) or not (i.e., Flag = 0), then iii) at most three admissible neighbouring outgoing nodes (in terms of ID) are provided together with their number (Num Choices), iv) the presence of the node inside or outside the Flood Hazard AREA (FHA) is detailed as inside (i.e., FlagINSIDE = 1) or outside (i.e., FlagINSIDE = 0), v) the Euclidean distance (m) from the left riverbank is reported. If the node associated to the path is outside the FHA map, the associated values are set to –9999.

ID	X (m)	Y (m)	Flag	ID Choice1	ID Choice2	ID Choice3	Num Choices	FlagINSIDE	Distance from river (m)
...	...	...	...	...	...	...	...	...	...
20	273656.63	4624056.31	0	30	28	12	3	1	1446.21
21	273541.41	4623811.35	0	39	599	14	3	0	–9999.00
22	273508.56	4623737.54	0	23	41		2	0	–9999.00
23	273498.37	4623717.9	0	24	15		2	0	–9999.00
24	273468.14	4623654.88	1				0	0	–9999.00
25	273450.12	4623660.9	1				0	0	–9999.00
26	273841.68	4624227.39	0	27	43	18	3	1	1414.69
27	273801.51	4624137.93	0	28	47	19	3	1	1459.15
28	273746.19	4624015.83	0	29	48	20	3	1	1527.65
29	273690.96	4623896.45	0	31	30		2	1	1601.65
30	273600.31	4623938.78	0	21	29	13	3	1	1519.61
31	273730.9	4623877.94	0	49	32	29	3	1	1637.68
32	273710.93	4623836.84	0	33			1	1	1663.23
33	273693.03	4623817.9	0	131	34		2	1	1670.64
...	...	...	...	...	...	...	...	...	...

to evaluate the probability of pedestrian-floodwater interaction (Sect. 3.3).

As already mentioned in the Introduction, a user-friendly Microsoft Excel file with embedded VBA (Visual Basic for Application) has been implemented, to ensure maximum accessibility for practitioners. The obtained output tables are then imported in QGIS software for map representation.

Authors also developed a python script (nowadays in beta version) for QGIS 3.40.12. The script runs on an Intel(R) Core(TM) Ultra 7 265K processor (3.90 GHz) with 96.0 GB RAM, 64-bit Windows operating system, x64-based processor. By using Numba, the open-source Just-In-Time (JIT) compiler for Python, the developed script is able to run 1,000,000 simulations for all the 609 analysed nodes in about 25 s.

Fig. 2 illustrates the flowchart of the methodology, in order to help readers to better understand the overall workflow and the relationship among the components, detailed in the following sections.

In detail:

- the Module 1 (Sect. 3.1) is exclusively focused on generating pedestrian travel time distributions under diverse conditions, such as varying crowd densities and panic levels. This is achieved by treating the parameters of the adopted AR(1) model for the pedestrian velocity as random variables. For any k -th starting node, N simulations are generated concerning plausible paths (compatible with the topological structure in Sect. 2.2) to reach any shelter area. At this stage of the framework, travel times are estimated independently of the flood wave propagation to establish a baseline of movement variability, i.e. the requested time to reach any shelter area;
- the Module 2 (Sect. 3.2) concerns estimation of floodwater arrival times of the flood water at any node inside the FHA from the riverbank;
- then, if Modules 1 and 2 are simultaneously run, the pedestrian travel times generated in Module 1 (Sect. 3.1) are compared with the flood arrival times derived in Module 2 (Sect. 3.2). For each simulation, the time a pedestrian takes to reach any given j -th node from a specific starting k -th node is evaluated against the floodwater arrival time at that same j -th node from the riverbank (Fig. 3). This comparison allows the framework to account for the spatio-temporal interaction between human movement and hazard evolution. In other words, the proposed model employs a conservative 'first-arrival' logic. If the floodwater arrival time at any node along the evacuation path is found to precede the pedestrian's arrival, the simulation is immediately flagged as "with pedestrian-floodwater interaction" for that k -th starting node. In such cases, the "interaction" counter for the specific starting node is incremented, and the algorithm terminates the current path analysis to proceed with the next simulation.
- Consequently, the pedestrian-floodwater interaction probability $P_{w,k}$ (also more briefly indicated as interaction probability) for each starting k -th node is calculated as the percentage of total simulations in which at least one interaction occurs along the route (Sect. 3.3). As soon as the first j -th node with this characteristic is identified (Fig. 3), the analysis for that specific simulation path

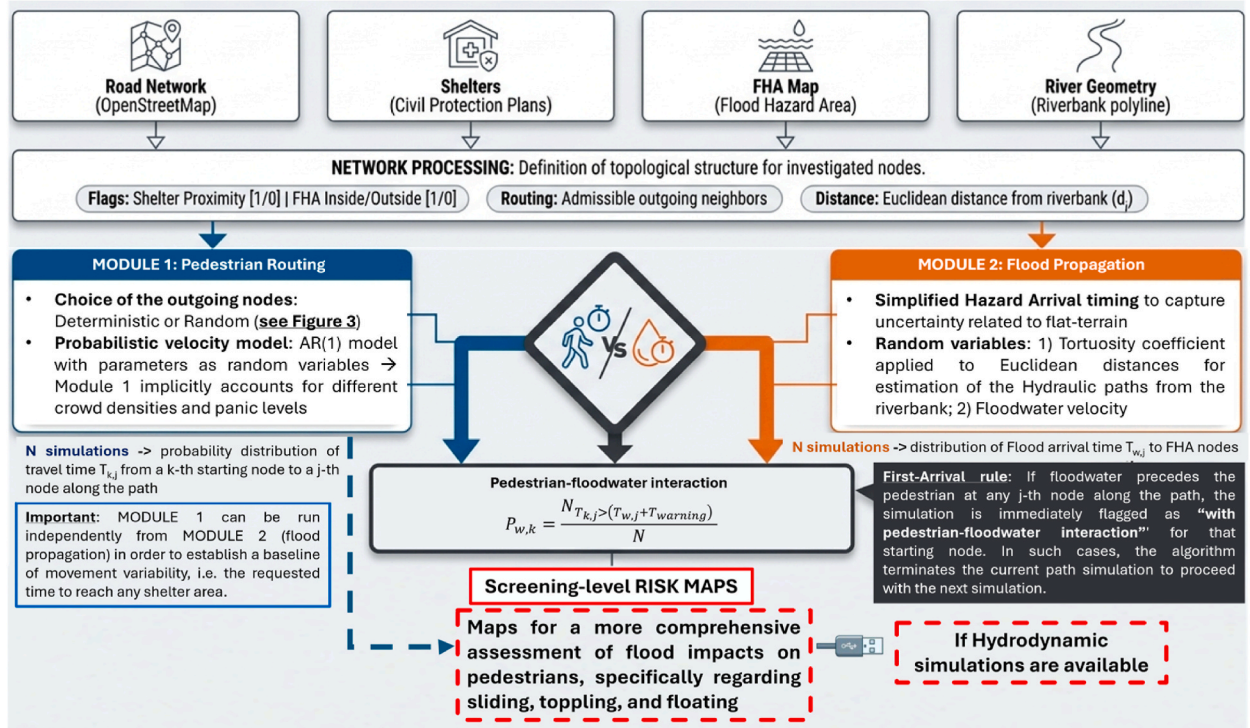


Fig. 2. Flowchart of the proposed framework.

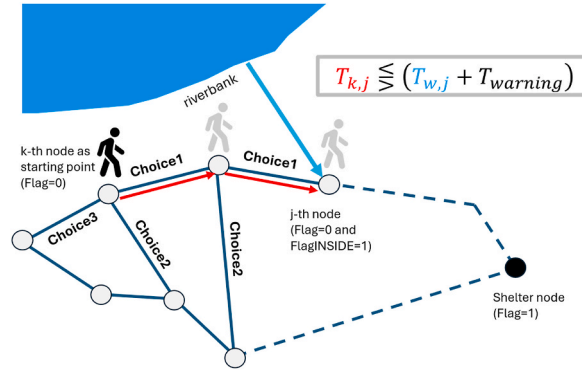


Fig. 3. Conceptual representation of pedestrian–floodwater interaction along an evacuation path, comparing evacuation time and flood arrival time in investigated nodes.

from a starting k -th node is concluded, ensuring that the risk assessment focuses on the earliest point of potential compromise along the evacuation route. Clearly, $P_{w,k}$ can be also evaluated by considering a warning time $T_{warning}$ (Eq. (7) in Sect. 3.3)

Authors remark that all the inherent simplifications described in the following Sects. 3.1–3.3 are not omissions, but deliberate modelling choices aligned with the need (by emergency planners) of tools that are fast and capable of generating meaningful insights even under significant uncertainty. Then, the main contribution in this work is the development of a computationally lightweight probabilistic evacuation assessment framework that integrates uncertainties in pedestrian mobility, routing behaviour and flood propagation within a unified Monte-Carlo simulation environment (as also highlighted in Introduction and Sect. 5). This framework allows for the rapid identification of relative evacuation risk patterns across urban networks, unlike traditional evacuation models that usually aim to reproduce detailed physical processes (which are not of main interest in real time). Consequently, the proposed framework:

1. constitutes an operational screening tool for emergency planning, particularly useful in data-scarce contexts where detailed hydrodynamic simulations may not be available. As better discussed in Sects. 3.2 and 5, the proposed framework can perform very well in flat, low-gradient coastal and deltaic urban floodplains (such as Ostia, the analysed case study);
2. is intended to be complementary to (and not to replace) Agent-Based Models (ABMs) and complex hydraulic simulations. Compared to fully coupled hydrodynamic–agent based models, the proposed approach significantly reduces computational demand by several orders of magnitude, enabling large Monte Carlo ensembles that would otherwise be infeasible in operational timeframes;
3. does not aim to simulate full hydrodynamic impact on pedestrian (sliding, toppling), or water depth evolution, but only evaluates potential interaction with floodwater. It is a conservative first-arrival timing model, not an impact model. This is obviously aligned with the requirements of a screening-level application, where reduced computational costs and ease of use are prioritized over micro-scale behavioural accuracy;
4. can clearly integrate more detailed information from hydrodynamic simulations (when available), in order to better estimate pedestrian–floodwater interaction probabilities and detail the impacts in terms of sliding, toppling, and floating ([64] and references herein). On the contrary, without availability of hydrodynamic simulations and/or measured data, the obtained results from the proposed framework constitute "relative risk indicators" (rather than absolute predictions), intended to support screening and prioritization in emergency planning, rather than predictive measures of actual evacuation performance.

3.1. Module 1 - probabilistic modelling of pedestrian path and velocity along the path

3.1.1. Model description

As outlined in Sect. 2.2, each non-shelter k -th node (i.e., with $\text{Flag} = 0$) in the topological network matrix is assigned a choice set of up to three admissible outgoing neighbouring nodes, which define the potential directional steps a pedestrian can take. Outgoing neighbouring nodes directed toward the riverbank are systematically excluded from the choice set to maintain consistency with basic evacuation logic. To capture behavioural variability under emergency conditions, two standardized routing strategies are implemented:

1. **Deterministic routing** (also referred to as *Choice1 routing*), where pedestrians strictly select the primary, safest, or shortest route designated in local emergency plans;
2. **Random routing** (the *random-routing scenario*), where pedestrians probabilistically choose among all available outgoing nodes at each intersection. In this strategy, besides the node labelled as Choice 1, a pedestrian could also select the node Choice 2 or Choice

3; they represent the alternative neighbouring outgoing nodes and allow however to reach any shelter area, but redundancy in evacuation planning can occurs (i.e., evacuation times can significantly increase with respect to Choice1)

Along any selected evacuation route composed of sequential street segments, the pedestrian walking velocity v_l along the l -th segment of each chosen polyline (which connects a starting node with a shelter) is modelled as a first-order Autoregressive stochastic process AR(1) [67]; [68]:

$$v_l = \mu_v + \phi \cdot (v_{l-1} - \mu_v) + \epsilon \quad (1)$$

where.

- v_{l-1} is the pedestrian velocity corresponding to the previous ($l-1$)-th segment,
- μ_v is the mean value of pedestrian velocity,
- ϕ is the autoregressive persistence parameter, with the well-known property $|\phi| < 1$ for the respect of stationarity [67], and
- $\epsilon \sim \mathcal{N}(0, \sigma^2)$ is a zero mean gaussian noise, characterized by a standard deviation σ .

The adopted autoregressive model allows to generate evacuation time distributions with smoother transitions, reflecting realistic persistence in movement speed. This mirrors behavioural inertia documented in empirical evacuation studies [69–72], in which evacuees rarely change velocity abruptly between successive segments. Parameter definition and justification of assumptions are detailed in the next Sect. 3.1.2.

3.1.2. Parameter definition and justification of assumptions

As already mentioned in the previous Sect. 3.1.1, Eq. (1) models pedestrian movement as a process where each step is influenced by the previous direction while incorporating random deviations that represent individual decision-making during evacuation.

In a single simulation, μ_v, ϕ, σ are assumed to be constant along the full extent of the associated polyline which connects a starting node with a shelter. Obviously, μ_v, ϕ, σ are context-dependent parameters, usually on i) density of walking/corridor population, ii) panic-like conditions, iii) presence of elderly/mobility-limited population, iv) presence of obstacles, slope and step along the path, and so on.

Consequently, due to the significant uncertainty associated to these AR(1) parameters, μ_v, ϕ, σ are generated (from a simulation to another one) by using uniform probability distributions inside specific ranges, according to literature review ([64,73–76] and references herein, [77]). In detail:

$$\mu_v \sim U\left(0.5 \frac{m}{s}; 1 \frac{m}{s}\right)$$

$$\phi \sim U(0; 1)$$

$$\sigma \sim U\left(0.05 \frac{m}{s}; 0.25 \frac{m}{s}\right)$$

In particular, the experiments in the recent work of Li et al. [77] demonstrated that μ_v values inside the range $\left(0.5 \frac{m}{s}; 1 \frac{m}{s}\right)$ can be associated with pedestrian densities from 2.0 ped/m² to 3.0 ped/m² when water depth is null. Moreover, the maximum value for σ , i.e. $0.25 \frac{m}{s}$, is also consistent with the error-bar plots of the pedestrian speed–densities in Li et al. [77].

This allows for considering the outputs of this specific Module 1 of the proposed simplified model as suitable for significant ranges of pedestrian densities when floodwater has not already arrived. In other words, this first module could implicitly account for different crowd interaction scenarios (also panic levels, which can clearly induce low pedestrian velocity, mainly in a random routing scenario) from a simulation to another one.

The underlying statistical assumptions are justified as follows:

- **Uniform routing probabilities in random routing:** In the random-routing scenario, all the n outgoing nodes (with $n \leq 3$) can be randomly chosen by a pedestrian, according to a uniform distribution. In detail, in each simulation, for each node with Flag = 0 and $n = 3$, a random number $R \sim U(0; 1)$ is generated, and a pedestrian selects the Choice1 if $R \in (0; 1/3]$, the Choice2 if $R \in (1/3; 2/3]$, the Choice3 if $R \in (2/3; 1)$. Obviously, the thresholds $1/3$ and $2/3$ can be modified if a user prefers to apply not-uniform distributions. Clearly, if $N = 2$ then a pedestrian selects the Choice1 if $R \in (0; 1/2]$, the Choice2 if $R \in (1/2; 1)$, while Choice1 is the only allowed outgoing node when $n = 1$. A uniform distribution is mainly justified by the principle of maximum entropy in data-scarce urban environments. Scientifically, random routing could also reflect unguided, panic-driven spatial behaviour where evacuees experience acute cognitive stress, loss of spatial legibility, or environmental disorientation (e.g., due to floodwater or smoke). However, panic does not necessarily imply a random movement: human evacuation behaviour is influenced by (1) familiarity, (2) signage, (3) social interactions, (4) following crowds, (5) Visual cues, (6) previous experience;
- **Uniform distributions for all AR(1) parameters:** also in this case, assumption of uniform distribution for all the AR(1) parameters, managed as random variables from a simulation to another, serves as a non-informative prior in data-scarce contexts, to encompass the intrinsic demographic heterogeneity of evacuating crowds—including variations in age, physical capability, group

size, and luggage loads—without imposing unverified demographic biases during screening-level risk assessments. Clearly, the framework allows for using different and specific probability distributions for each parameter when the informative content of the investigated case study is not scarce.

3.1.3. Implementation

The computational workflow of Module 1 (which can be also run independently from Module 2) is executed within a Monte Carlo simulation framework. For each starting k -th node, a total ensemble of $N = 1,000,000$ independent stochastic realization runs is performed. In each simulation run $i \in \{1, 2, \dots, N\}$, an individual evacuation path is generated from node k step-by-step until a designated shelter node (Flag = 1) is reached. The magnitude of N is obtained by generation of 1000 3-parameter sets of values for (μ_v, ϕ, σ) and, for each, 1000 plausible polylines towards any shelter node.

For each traversed street segment l , the physical segment length d_l (m) is extracted from the GIS spatial network, and the segment travel time t_l (s) is obviously calculated as $t_l = d_l/v_l$. Concerning Eq. (1), related to pedestrian velocity v_l along the l -th segment, it is well-known from the theory of stochastic processes [67] that, for a specific set of values for parameter (μ_v, ϕ, σ) associated to a polyline,

$v_l \sim \mathcal{N}\left(\mu_v, \frac{\sigma^2}{1-\phi^2}\right)$. However, in order to avoid unrealistic negative or excessive values for pedestrian velocity, we furtherly applied the following filter:

$$v_l = \begin{cases} 0.01 \text{ m/s} & \text{if } v_l < 0.01 \frac{\text{m}}{\text{s}} \text{ from Eq. (1)} \\ \mu_v + \phi \cdot (v_{l-1} - \mu_v) + \epsilon & \text{if } v_l \in \left[0.01 \frac{\text{m}}{\text{s}}; 2 \frac{\text{m}}{\text{s}}\right] \text{ from Eq. (1)} \\ 2 \text{ m/s} & \text{if } v_l > 2 \frac{\text{m}}{\text{s}} \text{ from Eq. (1)} \end{cases} \quad (2)$$

Application of Eq. (2) allows to obtain (without considering interaction with floodwater, i.e. without simultaneously using Module 2) the total pedestrian evacuation travel time $T_k^{(i)}$ for the i -th realization, starting at k -th node, by accumulating the segment travel times along the complete path:

$$T_k^{(i)} = \sum_{l=1}^m \frac{d_l}{v_l} = \sum_{l=1}^m t_l \quad (3)$$

Aggregating all the $T_k^{(i)}$, with $i \in \{1, 2, \dots, N\}$, achieves the estimation of probability distribution of evacuation-time T_k for each node (with Flag = 0) considered as starting point towards any shelter area.

3.2. Estimation of floodwater arrival times

Module 2 evaluates the propagation of the flood front in the flood plain, from the riverbank to every j -th node located inside the official Flood Hazard Area (FHA). This section is organized in the following four subsections:

- Sect. 3.2.1 – Brief literature overview about floodwater propagation in the flood plain;
- Sect. 3.2.2 – Model description;
- Sect. 3.2.3 – Justification of parameter assumptions and model applicability;
- Sect. 3.2.4 – Implementation.

3.2.1. Brief literature overview about floodwater propagation in the flood plain

Flood wave evolution in evacuation models can be simulated using approaches of varying complexity, from simplified representations to physically based models, because the key objective in this context is to assess the impact on human behaviour rather than to model fluid dynamics in detail.

The modelling of flood propagation is generally characterized by a delicate equilibrium between the need for a complete physical representation and the need for fast calculation [78]. Concerning some models (Life Safety Model, MassMotion Flood, Pathfinder Flood, AnyLogic), the flood wave is first simulated using a 2D hydraulic model (HEC-RAS, LISFLOOD-FP, TELEMAC, MIKE21 and so on) and then imported as input in terms of time-dependent raster maps for flood depth h and velocity v_w . From these raster maps it is possible to evaluate, in each cell, the product $h \cdot v_w$ providing a useful metric for assessing flood impacts on pedestrians and vehicles in terms of sliding, toppling, and floating ([64] and references herein). However, these models entail substantial computational costs—often requiring hours or days to simulate large domains—and are characterized by significant uncertainty due to their high demand for accurate initial boundary conditions and high-resolution input data, which are often difficult to meet in data-poor regions [79]. This uncertainty arises mainly from the following characteristics of the case study area:

- spatial variability of hydraulic roughness;

- extensive low-gradient flood plains (as in the present study case), for which high-resolution Digital Terrain Models (DTMs) may contain systematic errors [80] which may be misinterpreted as false channels or obstructions when deriving flood propagation direction with TauDEM (Terrain analysis using DEM) algorithms.

Additionally, the computational burden grows substantially when an ensemble of scenarios must be simulated, like in this proposed work.

For other EMs (for example, GAMA, [81]), several simplified/low-complexity approaches for flood propagation have been introduced to bridge this gap, each with distinct trade-offs. For examples, we can mention:

- Local Inertia Approximation (LIa): while faster than full shallow-water equations, LIa models exhibit severe physical limitations such as the development of unphysical shocks at wetting fronts and the inability to simulate receding fronts (drying), which are forbidden by the model's mathematical structure [78].
- Rapid Flood Spreading Models (RFSM)/Safer RAIN: these models are highly efficient for mapping the final hydrostatic state of a flood at high resolutions (e.g., 1 m) but typically disregard the temporal evolution and timing of the phenomenon [82,83]
- Conceptual Regression Models: these can estimate flood arrival times based on terrain slope and discharge, proving accurate for the first phase of an event, but they are often restricted to a single flow path and struggle with bifurcations or complex spreading [63].

In this context, the proposed framework introduces a new simplified and probabilistic approach for flood wave evolution, in order to reduce the computational costs and to take into account the significant uncertainty for floodwater velocity and hydraulic path in flat floodplains.

3.2.2. Model description

The estimated floodwater arrival time $T_{w,j}$ at any j -th node inside the FHA map (i.e., with $\text{FlagINSIDE} = 1$) is evaluated as:

$$T_{w,j} = \frac{d_{w,j}}{v_w} \quad (4)$$

where $d_{w,j}$ is the estimated hydraulic path length between the j -th node and the nearest riverbank flood-entry point (see also Fig. 3), and v_w is the floodwater propagation velocity across the floodplain. The main core of Module 2 regards the evaluation of $d_{w,j}$ and v_w :

- To represent the physical obstruction caused by urban micro-topography, building footprints, wall barriers, and non-straight flow paths, the hydraulic path length $d_{w,j}$ is calculated stochastically by perturbing the straight-line Euclidean distance d_j from the j -th node to the nearest riverbank source as:

$$d_{w,j} = d_j \cdot (1 + \delta) \quad (5)$$

where $\delta \sim U(0;1)$ is a tortuosity coefficient, treated as a random uniformly distributed variable (Sect. 3.2.3).

- Floodwater velocity v_w in the flood plain is assumed as spatially constant and generated, in each simulation, from a statistical uniform distribution, according to ranges from literature ([64] and references herein), i.e. $v_w \sim U\left(0.5 \frac{m}{s}, v_{w,max}\right)$, in which $v_{w,max} \sim U\left(1.5 \frac{m}{s}, 3 \frac{m}{s}\right)$.

3.2.3. Justification of parameter assumptions and model applicability

The assumption about the tortuosity coefficient δ – i.e., the hydraulic distance $d_{w,j}$ can be up to two times the Euclidean value (see Eq. (5)) – can be justified by several critical factors, mainly related to the specific study area:

- **Micro-topographic and Urban Obstructions:** In flat, low-gradient floodplains like Ostia, water propagation is highly non-Euclidean due to built-up features. As highlighted by Li et al. [84], traditional flood modeling frequently struggles because it fails to capture reshaped surface topography and micro-topographic variations commonly seen in urban environments. Furthermore, Chebika et al. [85] note that built-up areas (buildings, infrastructure) typically cover at least 20% of the land surface, acting as impassable barriers that obstruct and redirect flow. This forces floodwaters to propagate along highly circuitous street networks rather than straight lines;
- **Grid Resolution and Numerical Limitations:** Even high-resolution DTMs in flat areas often contain systematic errors that algorithms may misinterpret as false channels or non-existent obstructions, making deterministic path prediction unreliable [80]. Consequently, Standard Single Flow Direction (SFD) algorithms struggle in regions without clear confinement, as water does not naturally drain in only one of eight directions [79]. Even high-fidelity 2D hydrodynamic models are subject to path distortions due to cell discretization. As shown by Dazzi et al. [86], grid resolutions frequently lead to the 'fictitious enlargement of embankments' and artificial blockages at bottlenecks. Since resolving these sub-grid features deterministically is computationally prohibitive for screening-level Monte Carlo simulations, our probabilistic multiplier $(1 + \delta)$ in Eq. (5) can act as a physically justified, stochastic proxy to represent this path length uncertainty;

- **Grid Topology Geometry:** In highly structured orthogonal urban layouts (such as Ostia), flow paths naturally conform to street grids rather than Euclidean routes. Geometrically, orthogonal (Manhattan) routing on a grid is mathematically up to $\sqrt{2} \cong 1.41$ times longer than Euclidean distance [85]. When combined with the 20% (or more) building blockages and micro-topographic variations [84] mentioned above, a maximum hydraulic path length of 2.0 times the Euclidean distance appears as a highly realistic physical upper bound for water tortuosity in flat urban environments.

Moreover, as already discussed in Sect. 3.1, the general assumption of uniform distribution, for δ , v_w and for all the defined parameters of the whole proposed framework, is grounded in the principle of maximum entropy (non-informative prior) for data-scarce screening contexts. Focusing on v_w , when specific breach hydrographs or growth rates are unmeasured prior to an event, assuming a uniform distribution avoids imposing unverified Gaussian clustering or arbitrary modal biases. Furthermore, uniformly sampling across [0.5 m/s, 3.0 m/s] creates a multi-scenario hazard envelope—encompassing slow overland filling (0.5–1.5 m/s) up to fast breach/flash dynamics (1.5–3.0 m/s), corresponding to 10- to 500-year return periods—within a single Monte Carlo ensemble (10^6 realizations per node) at minimal computational cost (compared with Physically based 2D hydrodynamic codes, which would require a heavy separate run for each realization/scenario). This parameter range directly reflects velocities observed in 2D hydrodynamic floodplain simulations [37,63,86].

Consequently, as also discussed in Sect. 5, this simplified formulation can perform exceptionally well in flat, low-gradient coastal and deltaic urban floodplains (such as Ostia), where floodwaters propagate gradually through interconnected street networks. However, the model is not applicable to steep mountainous catchments or steep river valleys. In high-gradient terrain, flood dynamics are governed by strong gravity-driven momentum, supercritical flows, hydraulic jumps, and severe bathymetric contractions, which require full 2D hydrodynamic solvers to capture depth and velocity dynamics.

Further, we emphasize that the proposed framework is intended as a screening-level probabilistic tool, to capture (especially for low-gradient flood plains, like Ostia) the uncertainty in flood paths when full 2D hydrodynamic models are not available or computationally feasible for real-time screening. Thus, it is not a substitute for physically based hydrodynamic or high-fidelity evacuation models. While the current proposed approach facilitates rapid assessments under high uncertainty (i.e., only evaluates a potential interaction between pedestrian and floodwater, because it is a conservative first-arrival timing model), future validation against 2D hydrodynamic models (e.g., LISFLOOD-FP) is recognized as a necessary successive step of this research (obviously by considering flood scenarios with several return periods). In fact, the availability of detailed hydrodynamic simulations would allow for a more comprehensive assessment of flood impacts on pedestrians and vehicles, specifically regarding sliding, toppling, and floating. Consequently, this tool is designed to modularly integrate high-resolution data from such simulations when available, thereby enhancing the estimation of interaction probabilities and detailing micro-scale physical impacts [64].

3.2.4. – Implementation

The computational workflow of Module 2 is executed within the same Monte Carlo simulation framework of Module 1, when this latter module is not independently run.

In detail, in each simulation run $i \in \{1, 2, \dots, N\}$ (with $N = 1,000,000$) related to the starting k -th node (Figs. 2 and 3):

- the value of floodwater velocity v_w is generated from the related uniform distribution (Sect. 3.2.2), and then assumed as spatially constant for the specific simulation;
- for each j -th node (and its associated Euclidean distance d_j to the nearest riverbank flood-entry location) within the FHA along the i -th generated evacuation path, the specific value for δ is generated from $U(0; 1)$ (Sect. 3.2.2), and then the correspondent hydraulic path length d_{wj} and flood arrival time T_{wj} are computed (by using Eqs. (4) and (5)). Moreover, the pedestrian travel time T_{kj} (from the k -th starting node to the same j -th node) is also computed (Sect. 3.1.3);
- as soon as the first j -th node (along the i -th simulated path related to the starting k -th node) is found with the condition $T_{kj} > T_{wj}$, then the specific simulation is immediately flagged as “with pedestrian-floodwater interaction” (Fig. 3). In this case, the algorithm terminates the current i -th path simulation and proceeds with the next simulation (always related to the k -th starting node);
- on the contrary, if no j -th node is characterized by $T_{kj} > T_{wj}$, then the algorithm terminates the analysis of the i -th path simulation when pedestrian reaches a shelter node (Flag = 1).

The overall analysis of the simulations ensemble allows to obtain the Probability of pedestrian-floodwater interaction $P_{w,k}$ for each k -th starting node, as better specified in the next Sect. 3.3.

3.3. Probability of pedestrian-floodwater interaction

Starting from the procedures described in Sects. 3.1–3.2, for each k -th node with Flag = 0 and considered as starting point for a pedestrian, the Probability of pedestrian-floodwater interaction $P_{w,k}$ (which can be also more briefly indicated as interaction probability, as reported in Sect. 3) is evaluated as:

$$P_{w,k} = \frac{N_{T_{kj} > T_{wj}}}{N} \quad (6)$$

where N is the total number of simulations, and $N_{T_{kj} > T_{wj}}$ is the number of simulations for which the evacuation time T_{kj} , from the k -th

node to any j -th node along the path, is greater than flood arrival time $T_{w,j}$ related to the same j -th node (Fig. 3).

If a warning time $T_{warning}$ (which allows population to anticipate the evacuation) is taken into account, Eq. (6) is modified as:

$$P_{w,k} = \frac{N_{T_{k,j} > (T_{w,j} + T_{warning})}}{N} \quad (7)$$

4. Results

To provide a comprehensive evaluation of the proposed framework, the results are organized into four thematic subsections:

- Sect. 4.1 establishes a baseline for pedestrian mobility by comparing mean evacuation times and travel distances under deterministic and random routing strategies, excluding floodwater interactions;
- Sect. 4.2 introduces the flood hazard component, quantifying for both routing strategies the pedestrian–floodwater interaction probability $P_{w,k}$, and evaluating practical civil protection implications;
- Sect. 4.3 analyses the impact of different warning lead times (from 0.5h to 3h) in mitigating pedestrian–floodwater interaction within the random-routing scenario;
- Finally, Sect. 4.4 presents a sensitivity and robustness analysis, examines internal model consistency, discusses parameter interactions, outlines future validation strategies using published datasets.

4.1. Baseline evacuation times and distances: deterministic vs. random routing

In the first step (as already highlighted in Sect. 3) pedestrian–floodwater interactions are not considered from the implemented framework. Estimation of travel/evacuation times independently of the flood wave propagation is aimed to establish a baseline of movement variability, i.e. the requested time to reach any shelter area.

Under these baseline conditions, a direct comparison (Figs. 4 and 5) is conducted between the spatial distributions of mean evacuation times obtained using **deterministic routing** (where pedestrians consistently follow Choice1 in Fig. 3, representing the safest, shortest, or official evacuation route toward a shelter) and **random routing** (where pedestrians choose among admissible outgoing nodes uniformly at random, that could implicitly reflecting unguided or panic-influenced behaviour). As expected, random routing yields systematically higher mean evacuation times across the entire urban network, with the most severe delays occurring in the north-western sector due to its greater topological distance from official shelter locations. To complement the spatial GIS maps, Figs. 6 and 7 allow for numerical comparison analysis between the routing strategies:

- **Difference in Mean Evacuation Time (Fig. 6):** Switching from deterministic routing to random routing causes a substantial increase in travel duration across the study area. Across all analysed nodes, the random routing strategy induces an average delay of approximately 25 min compared to the baseline deterministic paths. The most pronounced time increases are concentrated in

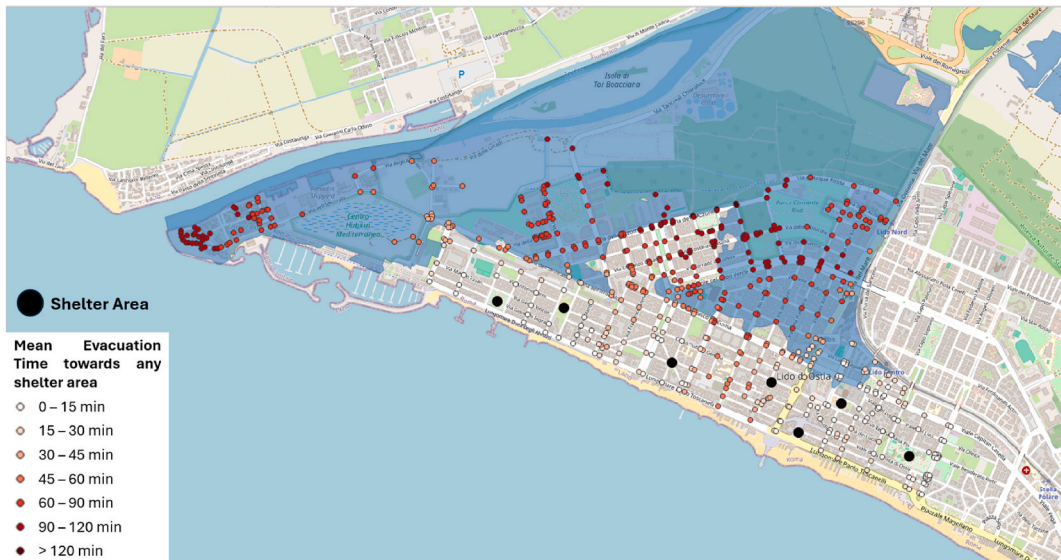


Fig. 4. Spatial distribution of mean evacuation time under random routing. The blue polygon delineates the official Flood Hazard Area (FHA) for the H2 scenario (100–200 year return period). The colour scale ranges from light (0–15 min) to dark red (>120 min); darker shades indicate longer mean evacuation times required to reach designated shelters.

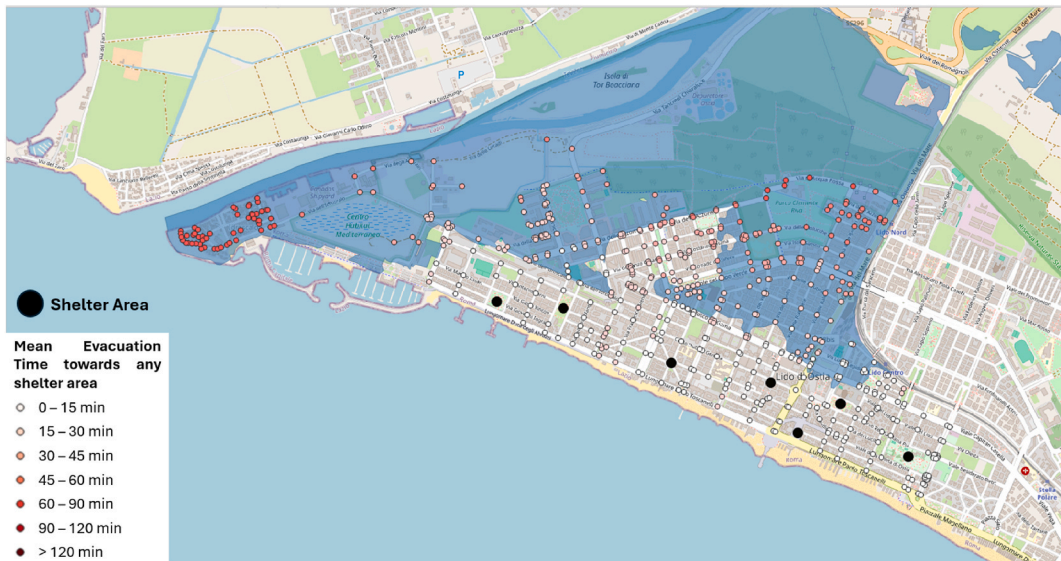


Fig. 5. Spatial distribution of mean evacuation time under deterministic routing. The blue polygon represents the H2 FEMA scenario. Comparison with Fig. 4 highlights the efficiency gain achieved when evacuees strictly adhere to primary (Choice1) routes.

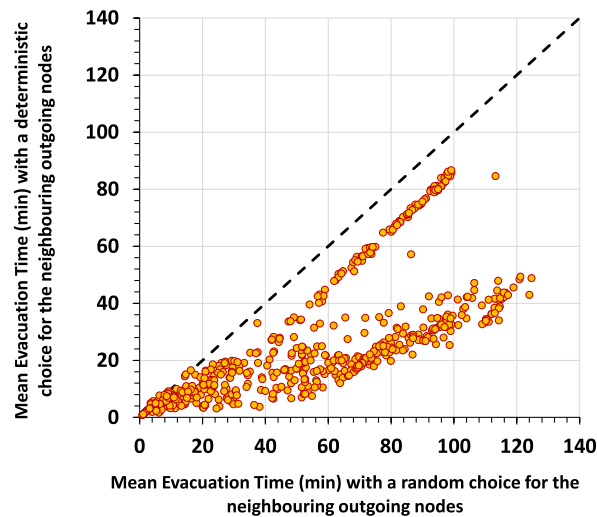


Fig. 6. Node-level difference in mean evacuation time between random routing and deterministic routing strategies.

network sub-regions characterized by high node degree and multiple branching intersections, where non-deterministic choices lead to cumulative detours.

- **Difference in Travelled Distance** (Fig. 7): In terms of physical path length, random routing results in an average excess travel distance of approximately 700 m relative to the deterministic shortest paths. This structural path lengthening demonstrates that spatial detours are an inherent outcome of unguided junction choices in regular grid or complex branching networks.

The same comparison is analysed from a probabilistic perspective as well (Figs. 8 and 9): travelling distances in all simulations from each node to any shelter area are reported along the horizontal axes, while the vertical axes represent the probability that evacuation times exceed selected thresholds (15, 30, 45, 60, 90 and 120 min). Under random routing, a wide dispersion in the distance–probability relationship emerges, capturing the cumulative variance introduced by stochastic junction decisions. Conversely, under deterministic routing, the distance–probability variance is strictly zero because path selection is fixed and invariant across Monte Carlo runs.

4.2. Pedestrian–floodwater interaction probability under random and deterministic routing

In the second stage of the framework, floodwater propagation (Module 2) is explicitly coupled with pedestrian movement (Module

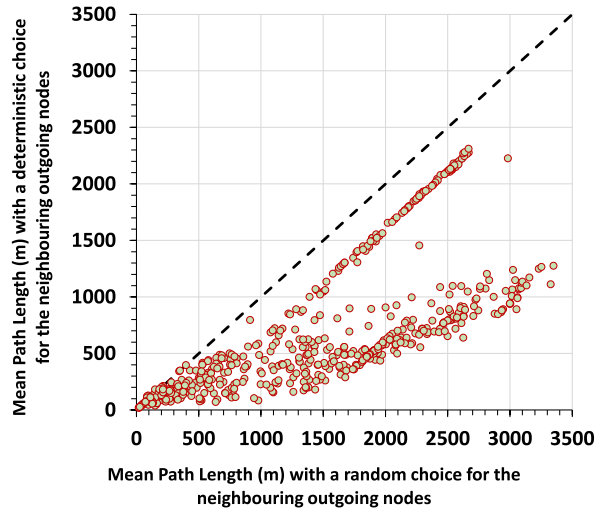


Fig. 7. Node-level difference in total travelled distance between random routing and deterministic routing strategies.

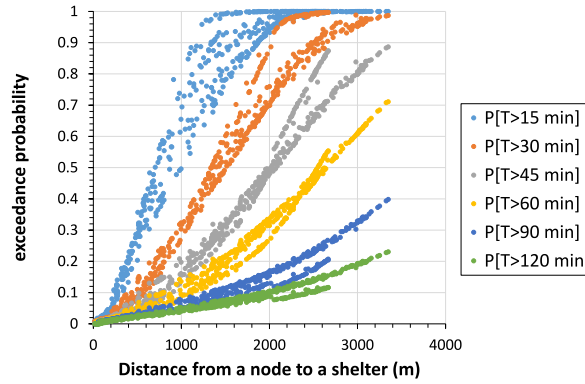


Fig. 8. Exceedance probability of evacuation time thresholds (15 to 120 min) as a function of travelled distance under random routing.

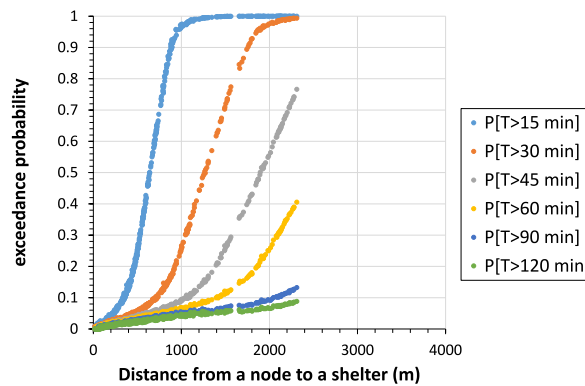


Fig. 9. Exceedance probability of evacuation time thresholds as a function of travelled distance under deterministic routing.

1) to evaluate the spatio-temporal overlap between evacuees and the advancing flood front. For each starting k -th node, the pedestrian–floodwater interaction probability $P_{w,k}$ is calculated by using procedure discussed in Sect. 3.3. It is important to emphasize that $P_{w,k}$ quantifies the probability that a pedestrian encounters floodwater along their evacuation path prior to reaching safety, and it does not automatically imply life loss, as hazard severity (i.e. the simultaneous analysis of flood depth and velocity) is not explicitly modelled in this screening stage. To provide clear readability and distinguish key findings, the interpretation of the interaction

probability maps (Figs. 10 and 11) is structured into four distinct subsections.

4.2.1. Deterministic routing results

Under deterministic routing (Fig. 11), where evacuees follow optimal Choice1 pathways, interaction probabilities are minimized across large portions of the urban grid. Nodes located in the central and eastern sectors exhibit low interaction values ($P_{w,k} < 0.2$), as fixed pathways allow evacuees to reach safe shelter nodes before the simulated flood wave arrives.

4.2.2. Random routing results

When evacuees exhibit random routing (reflecting possible panic, lack of wayfinding, or obstructed paths), interaction probabilities increase sharply across the entire domain (Fig. 10). The spatial distribution demonstrates that branching uncertainty creates severe vulnerabilities, causing even nodes located relatively close to shelter boundaries to exhibit moderate-to-high interaction risks ($P_{w,k} \in [0.4, 0.8]$) due to cumulative detours.

4.2.3. Comparative analysis: deterministic vs. random routing

Comparing both strategies (Fig. 12) demonstrates that route determinism yields substantial $P_{w,k}$ reductions in central sub-areas. However, in the far north-western sector, characterized by larger spatial distances from shelters, $P_{w,k}$ exceeds 0.80 under both deterministic and random routing. This indicates that certain network zones are structurally critical: topological distance alone prevents timely escape, and route guidance alone is insufficient to guarantee safety without early warning or alternative mitigation strategies.

4.2.4. Operational implications for emergency management

As more generally discussed in Introduction and Sect. 5, the identification of high- $P_{w,k}$ nodes and spatial $P_{w,k}$ hotspots provide actionable intelligence for municipal civil protection authorities and emergency planners. Specifically for Ostia, rather than serving merely as theoretical outputs, the obtained probabilistic indicators can directly inform specific emergency planning interventions:

- **Prioritizing Infrastructure and Drainage Improvements:** High- $P_{w,k}$ nodes highlight priority street segments where urban drainage upgrades, local flood barriers, or elevated walkways should be constructed to delay inundation along key escape routes.
- **Relocating or Adding Shelter Areas:** Critical hotspots in the north-western sector ($P_{w,k} > 0.8$ under both routing strategies) demonstrate the need to designate additional safe shelter zones or vertical refuge facilities closer to these population clusters.
- **Optimizing Evacuation Routes and Wayfinding Signage:** In areas where random routing significantly elevates $P_{w,k}$ compared to deterministic baseline paths, municipal authorities should install physical direction signs, dynamic message displays, or mobile app guidance to steer evacuees along primary Choice1 routes.
- **Deploying Early Warning Resources & Public Campaigns:** Hotspot maps identify priority zones for deploying localized acoustic sirens, targeting automated SMS emergency alerts, and conducting community preparedness campaigns.

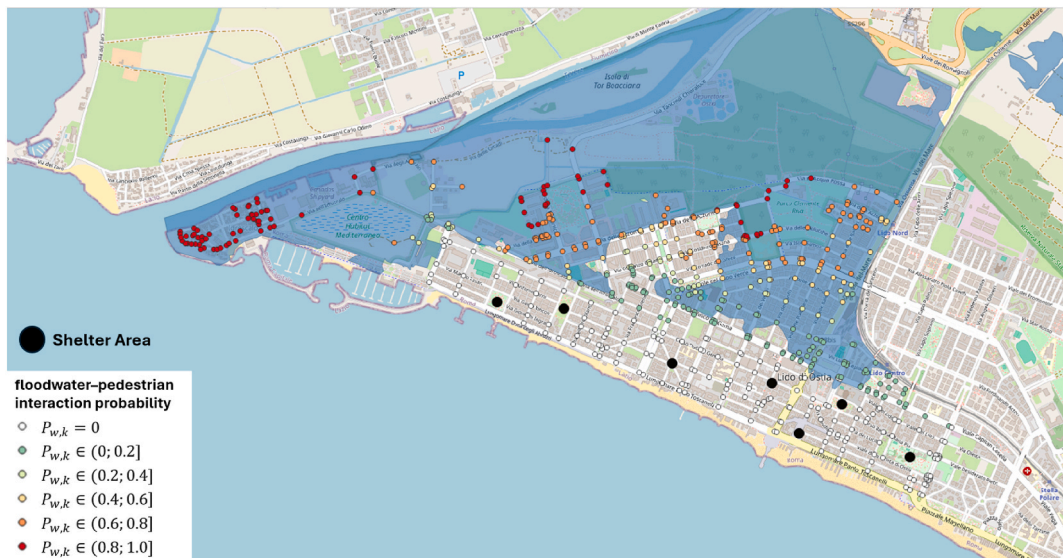


Fig. 10. Spatial distribution of pedestrian–floodwater interaction probability $P_{w,k}$ under random routing. Probabilities are derived from Monte Carlo simulations; higher values (dark red) indicate a greater likelihood of pedestrian–floodwater interaction along the path. The blue polygon represents the H2 flood scenario.

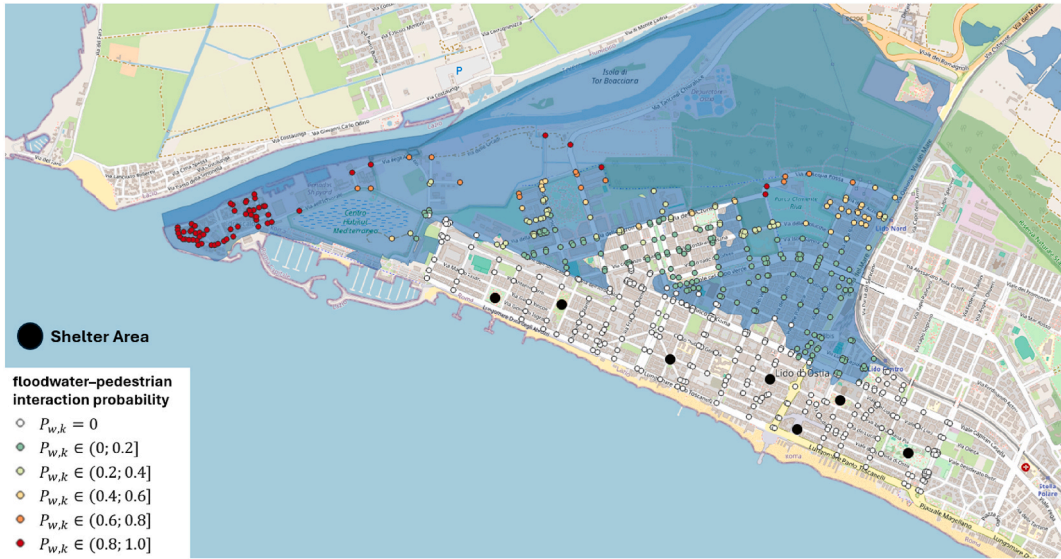


Fig. 11. Spatial distribution of pedestrian–floodwater interaction probability $P_{w,k}$ under deterministic routing. Probabilities are derived from Monte Carlo simulations; higher values (dark red) indicate a greater likelihood of pedestrian–floodwater interaction along the path. The blue polygon represents the H2 flood scenario.

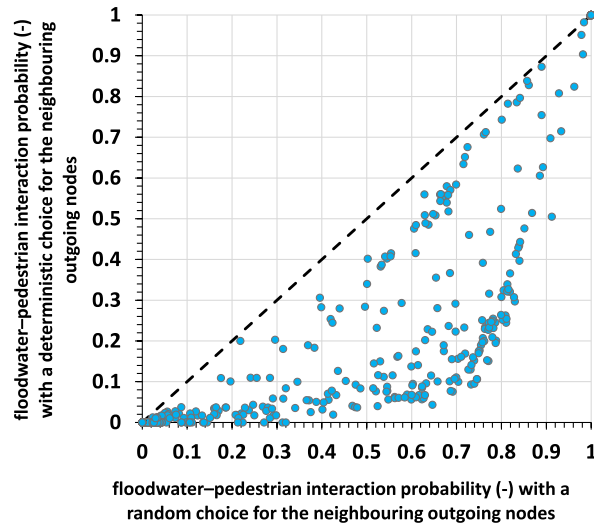


Fig. 12. Node-by-node comparison of pedestrian–floodwater interaction probabilities $P_{w,k}$ between random and deterministic routing strategies.

4.3. Influence of warning lead time under random routing

Focusing on the random-routing scenario only (which could implicitly capture panic-driven or unguided behaviour), this section evaluates the influence of warning lead time $T_{warning}$ on interaction probability $P_{w,k}$ (Eq. (7) in Sect. 3.3); $T_{warning}$ values equal to 0.5h, 1h, 1.5h, 2h and 3h were considered.

Figs. 13 and 14 show the spatial distribution of $P_{w,k}$ with 1h and 2h warning lead time, respectively.

Overall, the dispersion plot in Fig. 15 and the histogram in Fig. 16 highlight the reduction of $P_{w,k}$ values for each analysed warning lead time.

In detail, the comparative analysis across different lead times shows a progressive and significant migration of nodes from high- $P_{w,k}$ to low- $P_{w,k}$ categories. As shown in the histogram of Fig. 16:

- the distribution of $P_{w,k}$ is strongly bi-modal in the no-warning scenario, with a high concentration of nodes in the class $P_{w,k} > 0.8$;
- a warning time of just 30 min already initiates a notable reduction in these high- $P_{w,k}$ peaks: no node presents $P_{w,k} > 0.6$;

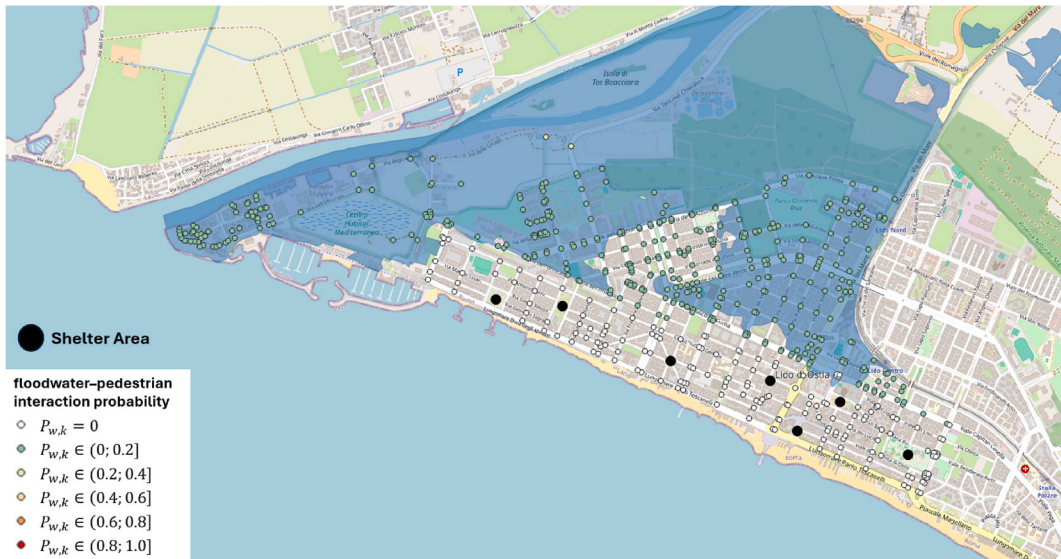


Fig. 13. Spatial distribution of pedestrian–floodwater interaction probability $P_{w,k}$ under random routing with 1-h warning lead time. The blue polygon represents the official Flood Hazard Area (FHA) related to H2 scenario (return period of 100–200 years).

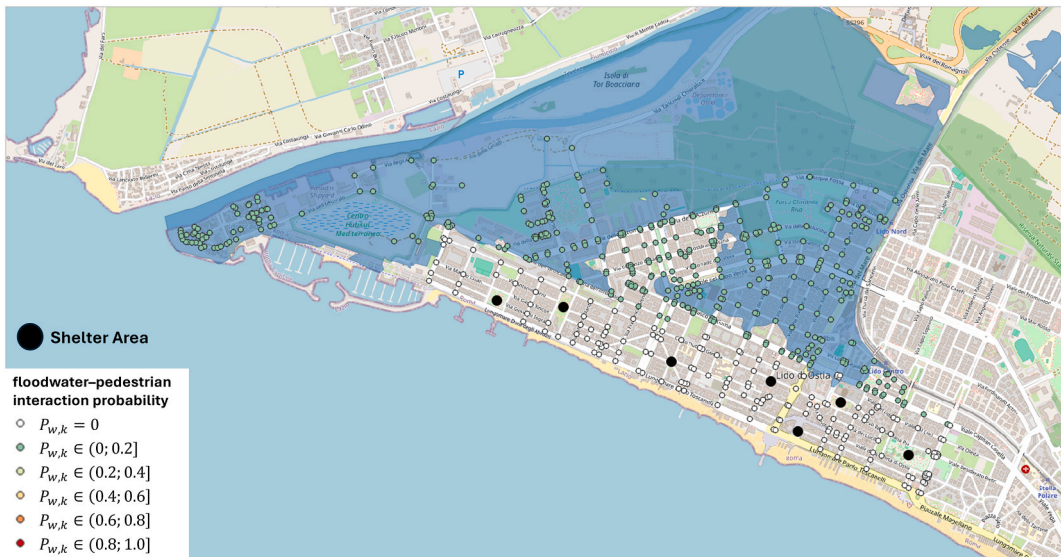


Fig. 14. Spatial distribution of pedestrian–floodwater interaction probability $P_{w,k}$ under random routing with 2-h warning lead time. The blue polygon represents the official Flood Hazard Area (FHA) related to H2 scenario (return period of 100–200 years).

- a warning time of 1h is sufficient to reduce interaction probabilities below 25%, even for the most critical nodes in the north-western sector (sector, as already partly inferable from the evacuation times reported in Fig. 4), which is the area furthest from shelters;
- when the lead time reaches 2–3 h, the interaction probabilities drop below 10% across the entire study area, suggesting that 2 h can be considered a 'critical warning time' for this specific urban topology to ensure near-complete evacuation success despite behavioral routing randomness.

4.4. Sensitivity analysis, model consistency, and validation outlook

In the absence of observed evacuation datasets and high-resolution hydrodynamic simulations for the study area, the assessment of the proposed framework was carried out through sensitivity and robustness analyses (Sect. 4.4.1).

Moreover, an indirect validation is discussed (Sect. 4.4.2), by comparing our framework's outputs with those produced by existing

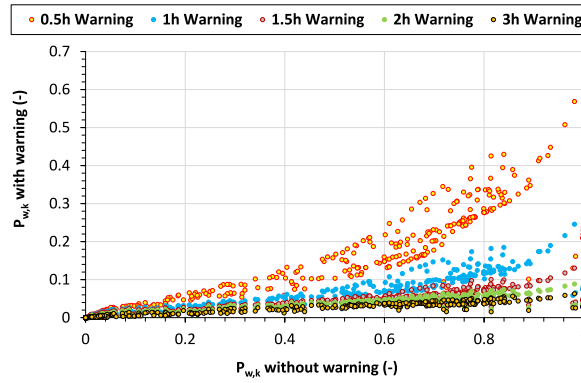


Fig. 15. Dispersion comparison of pedestrian–floodwater interaction probabilities $P_{w,k}$ across varying warning lead times (0.5 h to 3 h) relative to the no-warning baseline.

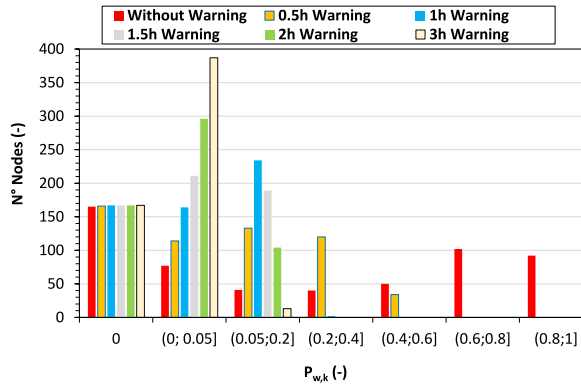


Fig. 16. Categorical histogram displaying the number of network nodes within specific interaction probability $P_{w,k}$ classes for different warning lead time.

ABM and 2D hydraulic models in literature and applied to case studies like Ostia. Although such comparisons do not constitute a full empirical validation, they can provide an additional confidence in the proposed framework and help position its performance relative to established evacuation modelling approaches.

The robustness and internal consistency of the proposed framework were already assessed in Sects. 4.1 and 4.2 through the comparison between deterministic and random routing configurations, and in Sect. 4.3 through the analysis of different warning-time conditions. Building upon these previous analyses (which provided expected results), the present section further extends the robustness assessment by investigating the sensitivity of the model responses to additional assumptions concerning pedestrian mobility and flood propagation. The overall objective is not to validate absolute predictions, but rather to evaluate whether the proposed probabilistic framework produces plausible responses under varying evacuation and hazard conditions.

More specifically, the following analyses investigate how variations in the main uncertain parameters affect pedestrian–floodwater interaction probabilities $P_{w,k}$. Particular attention is devoted to the internal consistency of the framework, namely whether the model reproduces the expected monotonic trends under more critical or less critical evacuation condition.

Authors considered as benchmark parameter configuration the sets described in the previous sections, i.e.

- $\phi \in [0; 1]$, $\mu_v \in [0.5 \text{ m/s}; 1 \text{ m/s}]$ for pedestrian velocity,
- $v_w \in [0.5 \text{ m/s}; 3 \text{ m/s}]$ for floodwater velocity,
- $d_{w,j} \in [d_j; 2 \cdot d_j]$ for hydraulic distance from the riverbank to a generic j -th node with a Euclidean distance equal to d_j ,

and a 'One-At-a-Time' (OAT) methodology was adopted. Specifically, the range of one single parameter was varied while maintaining all other parameters invariant at their reference benchmark values (Sect. 4.4.1). This approach allowed for isolating the individual contribution of each source of uncertainty to the final interaction probability $P_{w,k}$. Obviously, OAT approach ignores parameter interactions (e.g., non-linear joint coupling between crowd density-driven speed reduction and flood wave acceleration). Future extensions will incorporate Global Sensitivity Analysis (GSA) techniques [87], to capture higher-order parameter interactions. However, the obtained results with OAT in this work allows for similar considerations with respect to GSA analysis in other works [63]

4.4.1. Parameter sensitivity findings

The results, illustrated in Figs. 17 and 18, clearly demonstrate that the most significant factors influencing the interaction probability are the mean value of pedestrian velocity μ_v and floodwater velocity v_w , which exert a much greater impact on node risk classification than the hydraulic distance. The histograms in Fig. 18 reveal that variations in these velocity parameters trigger the most substantial shifts in node distribution across risk classes, highlighting how the 'window of escape' is critically defined by the relative ratio between human movement and flood front propagation. The number of nodes in the highest class ($P_{w,k} > 0.8$) more than doubles in two specific scenarios: when the mean pedestrian velocity μ_v is lowered to the 0.25–0.5 m/s range, or when the floodwater velocity v_w is concentrated in the upper range of 1.5–3 m/s. The impact of reduced walking speed is particularly significant because it represents conditions of high crowd density (exceeding 3 ped/m²), as reported in the experimental studies of Li et al. [77]

In contrast, the influence of the tortuosity coefficient δ , which regulates hydraulic distance $d_{w,j}$, and the autoregressive persistence ϕ appears to be secondary. Focusing on hydraulic distance $d_{w,j}$, Figs. 17 and 18 reveal that modifying the ranges induces, when compared to the benchmark configuration, a detectable difference in the number of nodes belonging to the highest class ($P_{w,k} > 0.8$). However, the magnitude of this variation is not comparable to the substantial shifts triggered by velocity parameters.

The performed sensitivity analyses provide a first-level credibility assessment of the framework in the absence of evacuation datasets and high-resolution hydrodynamic simulations. The model systematically reproduces expected trends across different uncertainty scenarios, supporting its applicability as an operational screening probabilistic tool for flood emergency planning. In particular, higher flood propagation velocities systematically increase evacuation failure probabilities, whereas higher pedestrian velocities reduce the likelihood of pedestrian–floodwater interaction.

Moreover, the results suggest that, for a screening-level assessment in flat urban environments like Ostia, the 'speed gap' between the two moving actors (pedestrian and floodwater) appears as the dominant driver of evacuation failure, outweighing the uncertainty related to the exact hydraulic path.

4.4.2. Framework verification vs. validation outlook

Although the sensitivity analysis confirms the internal consistency and logical responsiveness of the model (reproducing expected monotonic risk trends under adverse parameter bounds), it cannot substitute for formal model validation. To establish absolute predictive accuracy in future research, the framework can be validated by:

- testing model predictions against published empirical evacuation datasets and historical disaster trajectories from comparable urban flood events;
- benchmarking the simplified hazard arrival module against high-fidelity 2D hydrodynamic simulation models (e.g., LISFLOOD-FP, HEC-RAS) across multiple return period scenarios;
- calibrating pedestrian velocity distributions using empirical field experiment data under shallow water conditions

However, we detail how our model's findings, parameter choices, and sensitivity responses are indirectly validated by state-of-the-art literature related to other similar study cases.

- **Dominance of the "Speed Gap" over Hydraulic Path Length:** Our sensitivity analysis revealed that the "speed gap" (the relative ratio between human movement speed and flood propagation velocity) is the dominant driver of evacuation failure, whereas

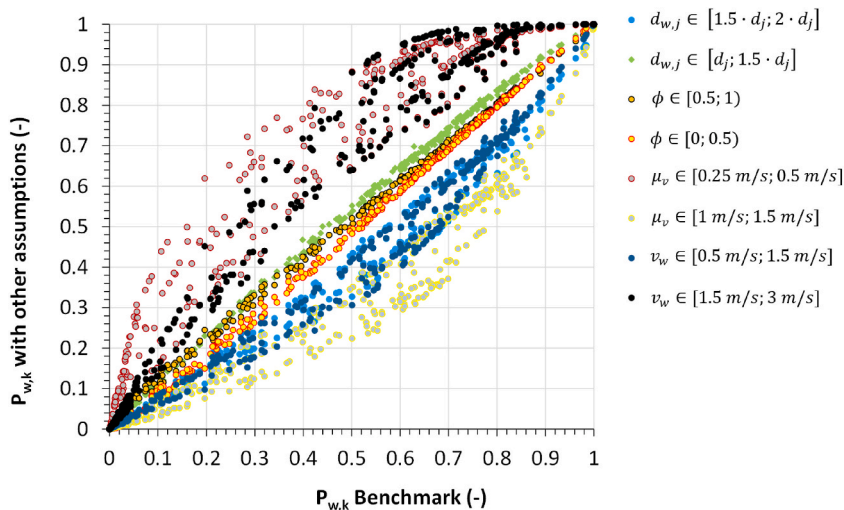


Fig. 17. Sensitivity Analysis: scatter plot of $P_{w,k}$ under several parameter configurations with respect to the benchmark setup.

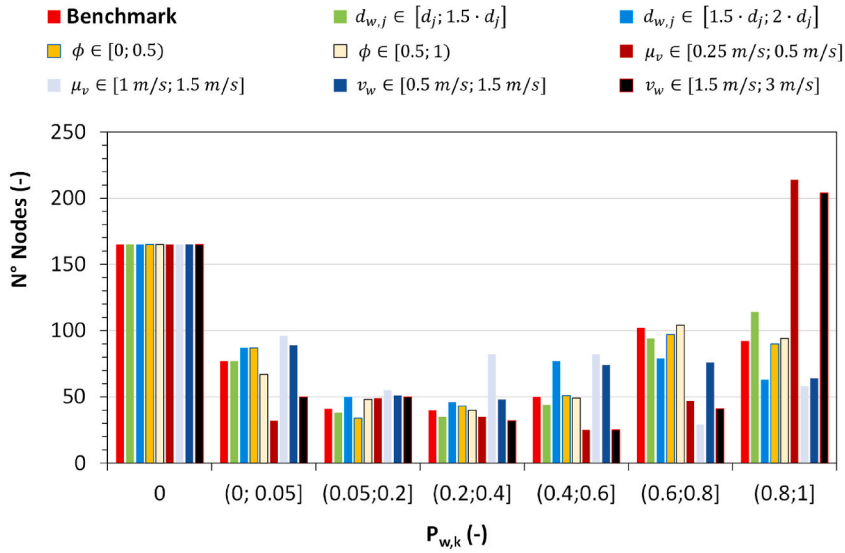


Fig. 18. Sensitivity Analysis: $P_{w,k}$ -class node distributions comparing benchmark and other parameter configurations.

hydraulic path tortuosity exerts a secondary effect. This finding is strongly corroborated by advanced 2D hydrodynamic and ABM literature:

- o **Flood Arrival Time Sensitivity:** Besseling et al. [63] performed global sensitivity analyses on flood propagation across flat delta floodplains, demonstrating that arrival timing at downstream locations is governed primarily by front propagation velocity, whereas spatial path perturbations along local drainage routes play a secondary role;
- o **Hydrodynamic Velocity vs. Distance:** 2D shallow water simulations of lowland levee breaches by Dazzi et al. [86] showed that flood arrival times at urban nodes are far more sensitive to flow velocity and friction dynamics than to minor spatial path deviations;
- o **Ablation of Speed Mechanisms:** In a coupled pedestrian-hydraulic model, Shi et al. [38] conducted parameter sensitivity and ablation analyses on coupled pedestrian-hydraulic models. They proved that velocity deceleration mechanisms (the speed gap) exert a large effect size on evacuation clearance timing, whereas spatial distance adjustments produce lower relative shifts.
- **Consistency of Parameter Ranges with Experimental and Numerical Literature:**
 - o **Mean Pedestrian Velocities:** Our assumed benchmark range [0.5 m/s, 1.0 m/s], low-speed range due to congestion/flood [0.25 m/s, 0.5 m/s], and unhindered range [1.0 m/s, 1.5 m/s] match empirical experimental records. Controlled experiments [88,89] confirm that walking speed drops from 1.2 to 1.4 m/s in dry conditions down to 0.7 – 0.9 m/s at knee depth, 0.3–0.6 m/s at waist depth, and 0.25 – 0.5 m/s under high crowd density ($>3\text{ped/m}^2$) [77,90].
 - o **Flood Propagation Velocities:** Our assumed range [0.5 m/s, 3.0 m/s] is consistent with 2D hydrodynamic breach and floodplain simulations. For instance, Besseling et al. [63] reported median flood arrival propagation speeds of 0.5–0.6 m/s (up to 1.25 m/s) across flat delta floodplains, while 2D shallow water simulations [37,86] report mean urban floodplain velocities of 0.2–1.5 m/s, rising up to 3.0 m/s near breach sites or major channel bottlenecks.
- **Hydraulic distance up to twice the Euclidean distance:** already discussed in Sect. 3.2.3. The cited references confirm that the bounds of tortuosity factor are strongly grounded in both the physical geomorphology of urban floodplains and the numerical constraints of hydrodynamic modelling.

5. Discussion

This section comprises: results interpretation (Sect. 5.1), innovative aspects compared to recent literature (Sect. 5.2), practical implications in civil protection contexts (Sect. 5.3) and limitations (Sect. 5.4).

5.1. Results interpretation

Although detailed validation against observed flood propagation data and real evacuation trajectories is not currently possible due to the absence of suitable datasets for the investigated area, the proposed framework was assessed through sensitivity and robustness analyses, as discussed in Sect. 4.4. The obtained results indicate that the model reacts coherently to variations in the governing parameters, producing spatial and temporal patterns that are plausible for screening-level evacuation assessment.

Specifically:

- *Evacuation feasibility depends far more on the topological constraints of the urban network and on the branching uncertainty encountered by evacuees than on straight-line distances to safety.* This observation is consistent with findings from the evacuation modelling literature, particularly ABM studies that emphasize the critical role of decision points. While ABMs typically attribute route divergence to complex perception, cognition or panic-related dynamics, the proposed simplified model does not explicitly represent psychological behaviours. These effects could be considered as implicitly included into the random choice of the neighbouring outgoing node. This suggests that simplified models may, in many contexts, be sufficiently informative for identifying structural weaknesses in evacuation plans, and that behavioural models are more suited to later, more refined analyses rather than for initial screening;
- *Path inefficiency is not a rare exception but a structural outcome of network complexity, which can induce large variances in evacuation times* (see Fig. 9). In areas where multiple branches have similar geometric characteristics, small deviations in movement decisions at successive intersections accumulate, producing extended detours and substantial increases in evacuation times;
- *Uncertainty plays a crucial role.* Traditional EMs usually adopt deterministic assumptions: a single travel time, a single hazard scenario, and a single representation of the network. Such approaches inherently narrow the range of possible outcomes, risking failure under worst-case conditions. In contrast, the present model incorporates uncertainty directly through stochastic path generation, speed variability and (albeit modelled in simple way but clearly improvable with outputs from hydrodynamic models) flood arrival perturbation. This ensemble-based logic aligns with modern probabilistic risk assessment practices and highlights how uncertainty propagation can reveal vulnerabilities invisible to deterministic evaluations. The heavy-tailed evacuation-time distributions observed in several network sectors illustrate how low-probability but high-impact outcomes—long detours, extremely slow speeds, delayed mobilisation—can significantly affect risk, even when average outcomes appear not so dangerous;

Overall, the results reinforce evidence from prior studies that evacuation strategies cannot rely solely on static maps or prescriptive routing but must account for the variability introduced by human behaviour and network structure. Where inefficiencies emerge, even in well-connected areas, the results suggest that emergency planners should consider interventions such as physical signage, improved wayfinding, real-time routing support and heightened communication strategies, especially for areas with high branching. Moreover, planners should also consider alternative strategies (including vertical evacuation), when evacuation times are persistently incompatible with flood propagation.

5.2. Innovative aspects compared to recent literature

To position the proposed methodology within the broader landscape of recent flood evacuation research and highlight its novelty relative to existing probabilistic models, Table 2 provides a comparative synthesis across key functional, computational, and modeling dimensions.

The core methodological innovations of the framework are synthesized as follows:

1. **Stochastic Pedestrian Routing Ensembles:** Unlike static shortest-path algorithms that assume perfect rationality [85,91], our model implements stochastic path generation (comparing deterministic safest routes with random uniform choices). As already reported in Sect. 3.1, this could implicitly capture panic-driven, unguided routing behavior and topological branching uncertainty across urban street networks.
2. **AR(1) Velocity Persistence Model:** Rather than assuming static walking speeds or abrupt velocity jumps between street segments, pedestrian velocity along polyline segments is modelled using a 1st-order Autoregressive process. This formulation mathematically can capture behavioural inertia and velocity persistence across connected network links under stress [70,71], generating smooth, realistic travel-time distributions without the computational overhead of microscopic agent-tracking algorithms.
3. **Probabilistic Flood Arrival-Time Formulation:** To represent hazard evolution without the prohibitive runtime of solving full 2D shallow water equations, floodplain propagation velocity and hydraulic path tortuosity are probabilistically modelled. This allows the model to encompass multiple flood return periods and dike breach scenarios within a single stochastic framework.
4. **Lightweight Monte Carlo Interaction Screening Engine:** By evaluating a conservative "first-arrival" condition across 1,000,000 simulations per node, the framework produces evacuation-time distributions and spatially explicit pedestrian-floodwater interaction probabilities in about 0.04 s per node (about 25 s with 609 analysed nodes, see Sect. 3). This ultra-fast computation makes the tool directly integrable as a real-time module within emerging Urban Digital Twin (UDT) decision-support architectures [63, 92].

5.3. Practical implications in civil protection contexts

We articulate how civil protection agencies and municipal authorities can operationalize the framework across five key emergency management pillars (see also Table 3).

5.3.1. Evacuation planning and dynamic route guidance

Traditional civil protection plans frequently rely on static maps assuming deterministic, shortest-distance routes. However, literature demonstrates that shortest-path routing during active inundation often directs evacuees into advancing floodwaters, significantly increasing risk [85,91]. Furthermore, simultaneous uncoordinated departures trigger severe network congestion and traffic bottlenecks [62,98].

Table 2

Comparative Synthesis Matrix: Positioning the Proposed Screening Framework relative to Existing Joint Modelling Paradigms.

Feature	Microscopic Coupled 2D-ABMs (e.g., Ref. [37,62])	Fast Conceptual Models (e.g., Ref. [63])	Proposed Probabilistic Screening Framework
Primary Scope	Micro-scale physical process & behavioural reproduction	Millisecond flood arrival estimation	Joint human-hazard interaction & risk screening
Computational Burden	High to Prohibitive (hours/days; HPC required)	Extremely Low (milliseconds)	Extremely Low (0.04 s for 10⁶ runs/node)
Pedestrian Routing	Microscopic rules/Social Force/Heuristic	None (no human mobility module)	Stochastic path ensembles (deterministic vs. random routing)
Movement Dynamics	Individual body force/speed reduction in water	N/A	AR(1) autoregressive velocity persistence & inertia
Flood Modeling	Dynamic 2D Shallow Water Equations	Linear regression/terrain filling	Probabilistic propagation velocity & tortuosity
Uncertainty Analysis	Highly constrained (1 or few deterministic scenarios)	Flood arrival uncertainty only	Full joint Monte Carlo propagation (10⁶ realizations per node)
Operational Niche	Detailed pre-event research & design	Rapid flood arrival forecasting	Operational spatial screening & Digital Twin integration

Table 3

Operational integration of the proposed framework.

Operational Domain	Civil Protection Challenge	Integration of Proposed Framework
Evacuation Planning	Congestion from simultaneous departures; unsafe shortest paths [62,91].	Identifies network bottlenecks to design safe-routing detours and staged evacuation schedules.
Shelter Allocation	Suboptimal shelter placement and overcrowding trap points [62,93].	Maps $P_{w,k}$ to optimize shelter catchment areas and pre-allocate resources.
Early Warning Systems	Uncertainty in warning trigger timing and delay-induced casualties [31,51].	Establishes "critical lead times" (e.g., 2-h threshold for Ostia) to calibrate EWS trigger protocols.
Emergency Exercises	Lack of realistic spatial scenarios for community drills [91,94].	Supplies stochastic worst-case path ensembles to parameterize DIGs, drills, and Virtual Reality training [95].
Infrastructure & UDTs	Prohibitive runtimes of 2D/ABM codes for real-time decision support [63,96].	Acts as a millisecond simulation module within Urban Digital Twins to prioritize signage, handrails, and cables [97].

- **Operational Application:** Civil protection authorities can use maps of interaction probabilities $P_{w,k}$ and random-routing ensembles to identify structural bottlenecks and unsafe corridors. Rather than prescribing static routes, planners can establish **dynamic safe-routing protocols** (e.g., inundation-avoidance detour networks as demonstrated by Ref. [91]). Furthermore, mapping travel-time distributions across urban sectors allows managers to design **staged (phased) evacuation orders**, releasing at-risk sectors sequentially to prevent systemic network gridlock [62].

5.3.2. Strategic shelter allocation and catchment optimization

Decisions regarding temporary emergency housing must account for network topology and flood propagation. As demonstrated in recent socio-hydrological studies, establishing a higher number of shelters does not inherently improve evacuation clearance times if those shelters are not strategically located relative to advancing hazard fronts [62]. Furthermore, uncoordinated shelter planning often leads to scheduling failures, overcrowding, and neglect of vulnerable groups or pet accommodations, causing residents to refuse evacuation [93].

- **Operational Application:** Civil protection planners can leverage $P_{w,k}$ maps to define **dynamic shelter catchment boundaries**, ensuring evacuees are directed to shelters reachable prior to flood arrival. This helps identify "shelter-overcrowding trap points" and optimizes the allocation of specialized resources (e.g., medical support, frailty assistance, or pet-friendly accommodations) before an event.

5.3.3. Early warning systems (EWS) and lead-time calibration

Setting warning trigger thresholds is a major operational challenge. Disseminating warnings too late drastically increases casualties—studies show that a 30-min delay in warning release can multiply exposure exponentially [51]—while false alarms or uncalibrated early alerts cause loss of public trust. Moreover, improving warning reception and response probability is particularly critical for rapid-onset flash floods [31].

- **Operational Application:** In Section 4.3, our framework quantifies how warning lead times alter risk distributions across urban sectors. Planners can use these probabilistic curves to **establish objective operational trigger thresholds**. For instance, in Ostia, our results confirm that a 30-min lead time removes nodes with $P_{w,k} > 0.6$, whereas a 2-h lead time is required to reduce $P_{w,k}$ below 10% network-wide. Emergency managers can thus calibrate Cell Broadcast and app-based alert systems to ensure the required "critical lead time" is met.

5.3.4. Scenario-based emergency exercises and preparedness

Effective emergency response depends heavily on community risk perception, self-efficacy, and routine preparedness drills.

- **Operational Application:** The stochastic path ensembles and evacuation-time distributions generated by the Monte Carlo framework (1,000,000 runs per node) capture realistic worst-case detours and mobilization delays. Local authorities can use these spatial scenarios to parameterize **Disaster Imagination Games (DIG, [91])**, tabletop exercises, and community-level drills. Furthermore, these data can feed into **Immersive Virtual Reality (IVR) serious games [94,95]** to train residents on identifying safe alternative routes and enhancing spatial self-efficacy under stress.

5.3.5. Infrastructure prioritization and Urban Digital Twin (UDT) integration

Municipalities operate under strict budget constraints and require screening tools to prioritize non-structural and structural interventions. High-fidelity 2D hydrodynamic simulations are computationally prohibitive for real-time operations, highlighting the necessity of fast, conceptual arrival-time models [63,96].

- **Operational Application:** Because our framework executes 1,000,000 simulations for 609 nodes in about 25 s, it is built to serve as a computational module (see also Sect. 6.1) within **Urban Digital Twin (UDT) architectures [63]**. Coupled with real-time IoT river-stage sensors or rainfall forecasts, the model dynamically updates exposure maps during an event. Pre-event, authorities can use the $P_{w,k}$ maps to prioritize physical retrofits at critical bottlenecks—such as installing directional signage, raised floor walkways, handrails, or low-cost physical guiding cables at high-exposure intersections [97,99].

5.4. Limitations

Notwithstanding its strengths, the modelling framework presented here entails limitations and aspects that can only be addressed implicitly, due to its simplified structure:

- A first limitation concerns the representation of flood propagation, when hydrodynamic simulations are not available. In fact, when this information is absent, the model does not capture the full complexity of inundation processes, such as variable water depths, topographic depressions, surface roughness, hydraulic connectivity or interactions between fluvial and pluvial components. As a result, while flood arrival times provide a useful approximation for assessing evacuation feasibility, they cannot substitute for detailed hydrodynamic modelling when high precision is required. In fact, as already mentioned in Sect. 3.2, availability of hydrodynamic simulations (obviously related to flood scenarios with several return periods) allows to assess flood impacts for pedestrians and vehicles, in terms of sliding, toppling, floating. Clearly, this proposed tool can integrate more detailed information from hydrodynamic simulations (when available), in order to better estimate pedestrian–floodwater interaction probabilities and detail the impacts in terms of sliding, toppling, and floating ([64] and references herein). Moreover, as already highlighted in Sect. 3.2, the developed Module 2 can perform exceptionally well in flat, low-gradient coastal and deltaic urban floodplains (such as Ostia), but it is not applicable to steep mountainous catchments or steep river valleys. In high-gradient terrain, flood dynamics are governed by strong gravity-driven momentum, supercritical flows, hydraulic jumps, and severe bathymetric contractions, which require full 2D hydrodynamic solvers to capture depth and velocity dynamics.
- A second limitation pertains to the routing model. The probabilistic routing scheme adopted here assumes that evacuees select among possible directions uniformly at random, thereby not explicitly representing real behavioural tendencies such as following signage, seeking the shortest familiar route, imitating others or avoiding perceived danger zones. It may overestimate detours relative to real-world expectations when guidance is available. However, this aspect can be clearly managed by modifying the choice probability associated to the neighbouring outgoing nodes.
- The model does not explicitly incorporate congestion, and/or presence of children, elderly individuals, tourists unfamiliar with the area and persons with disabilities who may exhibit markedly different behavioural responses than those assumed in the model. In real evacuations, crowd density can significantly reduce effective walking speeds or block access to certain routes. Nevertheless, these features are implicitly taken into account when the adopted autoregressive model generates with low (or very low) values of pedestrian velocity.
- The model also omits the influence of vehicles, which can both facilitate and impede evacuation. Mixed pedestrian–vehicle interactions are common in urban flood events and can substantially alter evacuation timing. Accordingly, “ideal” scenarios that limit traffic to emergency and rescue vehicles should be prioritized and promoted.
- Finally, the framework does not account for the possibility of vertical evacuation, such as seeking temporary refuge on upper floors of buildings. Evacuation is modelled exclusively as horizontal movement along the road network toward designated safe areas, which are limited to the official shelters identified in civil protection plans. While this assumption is consistent with standard evacuation planning practices, it may underestimate coping capacity in dense urban areas where vertical refuge is feasible.

6. Conclusions and future developments

This study introduces a simplified probabilistic model to evaluate flood evacuation feasibility in urban areas and demonstrates its application through a case study in the coastal district of Ostia in Rome (Italy). By integrating routing uncertainty, pedestrian velocity variability, and simplified flood arrival times into a Monte Carlo framework, the tool provides a rapid, screening-level assessment of

urban safety.

Despite its simplicity and limitations (discussed in Sect. 5), the obtained results provide compelling evidence of the framework's operational value. Overall, uncertainty modelling plays a crucial role. EMs based on deterministic assumptions could underestimate evacuation delays or overestimate the time available before flood impact. On the contrary, ensemble-based approaches allow planners to better analyse worst-case scenarios and design interventions that remain robust under a variety of conditions. The baseline analysis (Sect. 4.1) reveals that random routing increases mean evacuation times by approximately 25 min and travel distances by 700 m compared to deterministic strategies. However, routing efficiency alone is insufficient in structurally critical areas. As discussed in Sect. 4.2, in the western sector of Ostia, the average value of pedestrian–floodwater interaction probability $P_{w,k}$ remains above 80% regardless of whether deterministic or random routing is adopted (Figs. 10 and 11), highlighting a physical incompatibility between the network's topology and flood propagation speeds in those zones.

A key contribution of this work is the identification of a "critical warning time" for emergency management (Sect. 4.3). In a no-warning scenario, the risk distribution is strongly bi-modal, with a high concentration of nodes in the highest risk class ($P_{w,k} > 0.8$). The study quantifies the mitigation potential of early warnings: a lead time of 30 min is sufficient to ensure that no node in the network presents $P_{w,k} > 0.6$, while a 2-h warning effectively mitigates 100% of high-risk nodes, bringing interaction probabilities $P_{w,k}$ below 10% across the entire study area.

Furthermore, the sensitivity analysis (Sect. 4.4) establishes that the "velocity gap" between pedestrians and floodwater is the dominant driver of pedestrian–floodwater interaction. Specifically, reducing mean pedestrian speed to 0.25–0.5 m/s (typical of high crowd densities) or increasing flood velocity to the 1.5–3 m/s range more than doubles the number of nodes in the highest risk category ($P_{w,k} > 0.8$), far outweighing the impact of topographical tortuosity (Eq. (4)) or movement persistence (ϕ parameter in Eqs. (1) and (2)). These findings reinforce the need for emergency plans that move beyond static maps. In sectors where path inefficiency is a structural outcome of network complexity, planners should prioritize physical signage and real-time guidance to push behaviour toward deterministic paths. When evacuation times remain persistently incompatible with hazard arrival, alternative strategies—such as vertical evacuation—must be considered.

As an outlook for future work, given its lightweight structure and limited computational requirements, the proposed approach presents potential for integration into Urban Digital Twin (UDT) frameworks (Sect. 6.1). UDTs aim to combine real-time sensing, dynamic modelling and interactive decision support into unified systems for managing the urban built environment—capabilities that are particularly valuable during emergencies. The simplified evacuation model presented in this study can serve as a computational module within such systems, providing rapid estimates of evacuation feasibility under evolving conditions and enabling authorities to adjust strategies dynamically.

6.1. Toward an Urban Digital Twin framework for flood evacuation management

In recent years, growing recognition of the value of Digital Twin paradigms for managing complex built environment systems has driven increasing interest in their development and application across multiple scales, including the urban scale. Urban Digital Twins are increasingly considered as dynamic, data-driven representations of urban systems that integrate real-time observations with predictive modelling and decision-support capabilities [100,101]. Within this context, EMs should not be treated as standalone analytical exercises, but rather as adaptive components that can be updated to reflect evolving hazard conditions, infrastructural changes, and behavioural signals.

A first direction for future developments concerns coupling of the proposed evacuation model with real-time or near-real-time hydrological and hydraulic information. While the current implementation relies on a simplified representation of flood arrival times, the approach adopts a modular structure, enabling the integration of externally derived estimates from forecasting chains, such as rainfall nowcasting, river stage predictions or 2D hydrodynamic simulations. Within a comprehensive UDT framework, these inputs—processed by a dedicated module—could be updated as new data become available, allowing for a continuous evaluation of evacuation-time distributions and pedestrian–floodwater interaction probabilities. This would enable local authorities and civil protection organisations to move beyond static evacuation plans toward adaptive assessments that reflect the evolving event.

A second development concerns integrating heterogeneous sensing technologies and crowd-sourced data streams [102,103]. Existing UDT applications show that information from fixed IoT sensors deployed in the urban environment can be supplemented with other sources, such as citizens' mobile devices, cameras, and social media content, which can provide proxy indications of population presence, movement patterns and compliance with evacuation orders. Even if the proposed model does not explicitly consider individuals, its probabilistic structure allows to aggregate indicators, such as reduced walking speeds due to congestion, partial network obstructions or delayed mobilisation in specific sectors. These data could be used to dynamically model parameters (e.g., velocity distributions, routing probabilities), improving the accuracy and operational value of the resulting outputs without compromising computational efficiency.

Another critical aspect concerns decision support and what-if scenario exploration. Within an UDT framework for flood evacuation management, the evacuation module based on the integration of the proposed approach could be used to support both real-time emergency response and pre-event preparedness and planning. Authorities could rapidly test alternative scenarios, such as different warning lead times, modified shelter locations, temporary road closures or the installation of additional signage, and immediately visualise their effects on evacuation feasibility and risk distribution. In this context, the proposed model is well suited for extensive what-if scenario analysis, as it reduces the computational burden typically associated with agent-based approaches.

From an operational perspective, effective integration within UDT frameworks requires EMs to rely on open standards, easily

interpretable inputs and outputs, and assumptions that can be clearly communicated to decision-makers. Leveraging widely available datasets (e.g., OSM networks, official hazard maps) and producing probabilistic indicators, rather than opaque optimization outputs, supports transparency and facilitates scenario comparison. In this respect, the proposed model provides a practical way to represent uncertainty in a form that is directly useable for decision support.

Finally, building on preliminary insights from related work by the authors [92], a long-term evolution of this framework involves a more participatory, citizen-centred UDT for flood risk management. While the current approach abstracts behavioural complexity into probabilistic routing and speed variability, future research could progressively incorporate differentiated population profiles, vulnerability classes and adaptive responses to warnings, without sacrificing tractability. When embedded in an UDT, such extensions could support targeted communication strategies, identify priority areas for assistance and improve equity in evacuation planning. In this perspective, the simplified probabilistic evacuation model proposed in this study represents an important step towards the realization of UDT-based flood evacuation management. The integration of this approach with real-time data, forecasting models and interactive decision-support tools, paves the way to more resilient, adaptive and informed responses to urban flood emergencies.

CRedit authorship contribution statement

Davide Luciano De Luca: Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mara Lucantonio:** Software, Methodology, Data curation, Conceptualization. **Daniela Biondi:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization. **Francesco Cruscomagno:** Validation, Software, Methodology. **Francesco Napolitano:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization. **Elena Ridolfi:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Vito Getuli:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization. **Alessandro Bruttini:** Writing – review & editing, Writing – original draft, Supervision, Methodology. **Federico Cinquepalmi:** Writing – review & editing, Writing – original draft, Validation, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Authors dedicate this work to Prof. Pasquale Versace (Emeritus Professor c/o University of Calabria, Italy), who passed away on 6th December 2023. His studies about flood evacuation plans in Italy were very useful for the development of this work.

E.R. and F.N. acknowledge the RETURN Extendend Partnership which received funding from the European Union NextGenerationEU (National Recovery and Resilience Plan – NRRP, Mission 4, Component 2, Investment 1.3 – D.D. 1243 2/8/2022, PE0000005 – Spoke TS2).

Data availability

Data will be made available on request.

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