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ARTICLE

A Holistic Approach to Early Warning Systems Using an Agent-Based Model

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Abstract

Developing an early warning system requires four key components: risk knowledge, hazard detection (including monitoring and forecasting), dissemination (involving decision making and warning issuance), and response (including action implementation). Early warning system (EWS) provides an integrated system to facilitate timely responses to hazards. To assess the effectiveness of an EWS, a systems-based approach that holistically captures its critical components is required. Therefore, this study used a system-based modeling tool, an agent-based model (ABM), to examine the factors influencing evacuation response in a flooding scenario. The model was tested for an area nestled within the Ba catchment in Fiji. Surveys, interviews, and previous literature underpin the development of the model. Evacuation response was examined across key social and physical factors, with the dissemination of warning information kept as the central focus. The findings indicate that timely warnings, coupled with training, substantially improve response outcomes. However, factors such as belief in the warning and flood velocity can undermine outcomes even when warnings are issued promptly. This study underscores the critical need to assess the effectiveness of EWS holistically by accounting for a range of factors, extending beyond forecast development and dissemination.

Keywords Agent-based model · Disaster response simulation · Flood risk reduction · Early warning systems · Community engagement

1 Introduction

Hydrometeorological hazards are a pressing concern, with cyclones and floods among the most frequent global hazards (EM-DAT 2023). Research demonstrates that these hazards are occurring with greater frequency and severity (Caretta et al. 2022). When compounded with conditions of vulnerability and exposure in social systems, the increased severity of these events due to climate change can lead to disasters and hinder economic growth (Alexander 2018). As the associated damages from hydrometeorological hazards continue to increase, the solution is no longer limited to hazard mitigation but rather to improving risk reduction and actionable responses, highlighting the central role of early warning systems (EWS).

According to the Sendai Framework for Disaster Risk Reduction 2015–2030, there are four core components to an effective EWS, which are (1) having knowledge of the hazard and the associated risks; (2) detecting, monitoring, and forecasting of the hazards; (3) disseminating timely and accurate warnings; and (4) initiating response at all levels

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to the information received (Akerkar et al. 2020). While all the components are equally essential for an effective EWS, studies have shown that there is a greater emphasis on the technical aspects of the forecast, with social aspects such as risk perception, community knowledge, and awareness often being undermined (Kelman and Glantz 2014; Yore and Walker 2021; Šakić Trogrlić et al. 2022). Early warning system has traditionally been conceptualized as a top-down linear process with experts developing and delivering scientific forecasts to the public (Garcia and Fearnley 2012). However, even with high forecast accuracy, the desired response may still not be achieved due to a range of social and human factors. This creates a rationale for using a holistic approach to examine how the four pillars of the EWS: risk knowledge, hazard monitoring, communication, and response capability interact to shape real-world response outcomes, rather than treating them as isolated components. Capturing these interdependencies requires a systems-based approach that observes micro- and macro-level interactions and how they channel into system-wide impacts (Anshuka et al. 2025). This is where agent-based modeling is particularly valuable. Agent-based models (ABMs) can represent heterogeneous actors (agents), their decision-making processes, and the emergent behaviors or cascading effects that arise when multiple components interact simultaneously (Anshuka et al. 2022). Consequently, ABM is an effective tool for capturing interactions between the EWS pillars and their functioning as an interconnected whole that influences disaster response. This modeling approach provides a rigorous platform for examining overall response and the targeted improvements required to enhance community safety and guide more effective policy decisions (Chandra-Putra and Andrews 2020).

Agent-based models have been successfully applied to understand evacuation response and early warning systems under flooding scenarios (Zhuo and Han 2020; Anshuka et al. 2022). A growing body of ABM-based EWS literature demonstrates that the nature of the warning information, the timing of the information, and spatial patterns influence response outcomes. In terms of the nature of warning information, studies emphasize that probability-based warnings with distinction in severity enhance response because people act when the message is clear and they understand the different levels of associated risks (Du et al. 2017; Liu and Lim 2018). Warnings that are paired with a long lead time and disseminated at regular frequency are also effective in eliciting response (Yang et al. 2018). Beyond whether evacuation occurs, the timing of evacuation is another critical factor, influenced by spatial patterns and movement dynamics. Evacuation times are generally shorter in low-density areas, but tend to increase in low-density areas with a large proportion of vulnerable agents (Wang et al. 2020). Studies also show that evacuation patterns differ by mode and relatedly time, with distinct outcomes for vehicle-based evacuations compared with on-foot evacuations (Shirvani et al. 2020, 2021). A key gap in the literature is the absence of holistic EWS framing, with a strong focus on urban contexts and vehicle-based evacuation, which has led to limited attention on rural or peri-urban contexts, non-vehicular evacuations, and locally informed simulations that critically shape EWS effectiveness.

An EWS is an integrated set of systems and processes that enables individuals, communities, and governments to take timely action to reduce risks associated with hazardous events (UNDRR and WMO 2023). Therefore, this study adopted a holistic view of EWS, using an ABM as an analytical tool to capture interactions across the different EWS pillars. By incorporating micro-level behaviors across different actors, the model enables a deeper understanding of how individual responses aggregate to shape overall disaster-response outcomes. The simulation is designed to examine evacuation response in Fiji, a Pacific Island country that experiences frequent flooding. By using on-the-ground empirical data as the basis for scenario design, the ABM enables us to examine disaster response and the effectiveness of the EWS.

2 Methodology

This section introduces the case study area, key hydrometeorological hazard characteristics, and the current EWS landscape in Fiji. It then describes the empirical data collection process, followed by the details for the development of the ABM model.

2.1 Case Study Area

Fiji is located in the South-West Pacific. The ABM was developed for an area situated in the Ba catchment in Fiji's western region (Fig. 1). The catchment is drained by the Ba River, which runs for 88.4 km and includes at least two major tributaries (McAneney et al. 2017; Metherall et al. 2021). The elevation ranges from 5 to 25 m above sea level, making the catchment extremely low-lying and hazard prone. The Ba catchment has experienced the highest proportion of hazard activity in Fiji, accounting for approximately 66% of recorded storm events and 29% of flood events nationwide (World Bank 2018). The catchment experiences at least one major flood every 3–4 years and frequent minor flood events in the wet season (McAneney et al. 2017). Devi et al. (2024) documented 43 flash flood events in the catchment within a five-year period from 2018 to 2023. Flash floods are common; however, these events are highly localized and may not always be captured in global databases. The current flood guidance system used by the Fiji Meteorological Service monitors binary flood occurrence (flood/no flood)

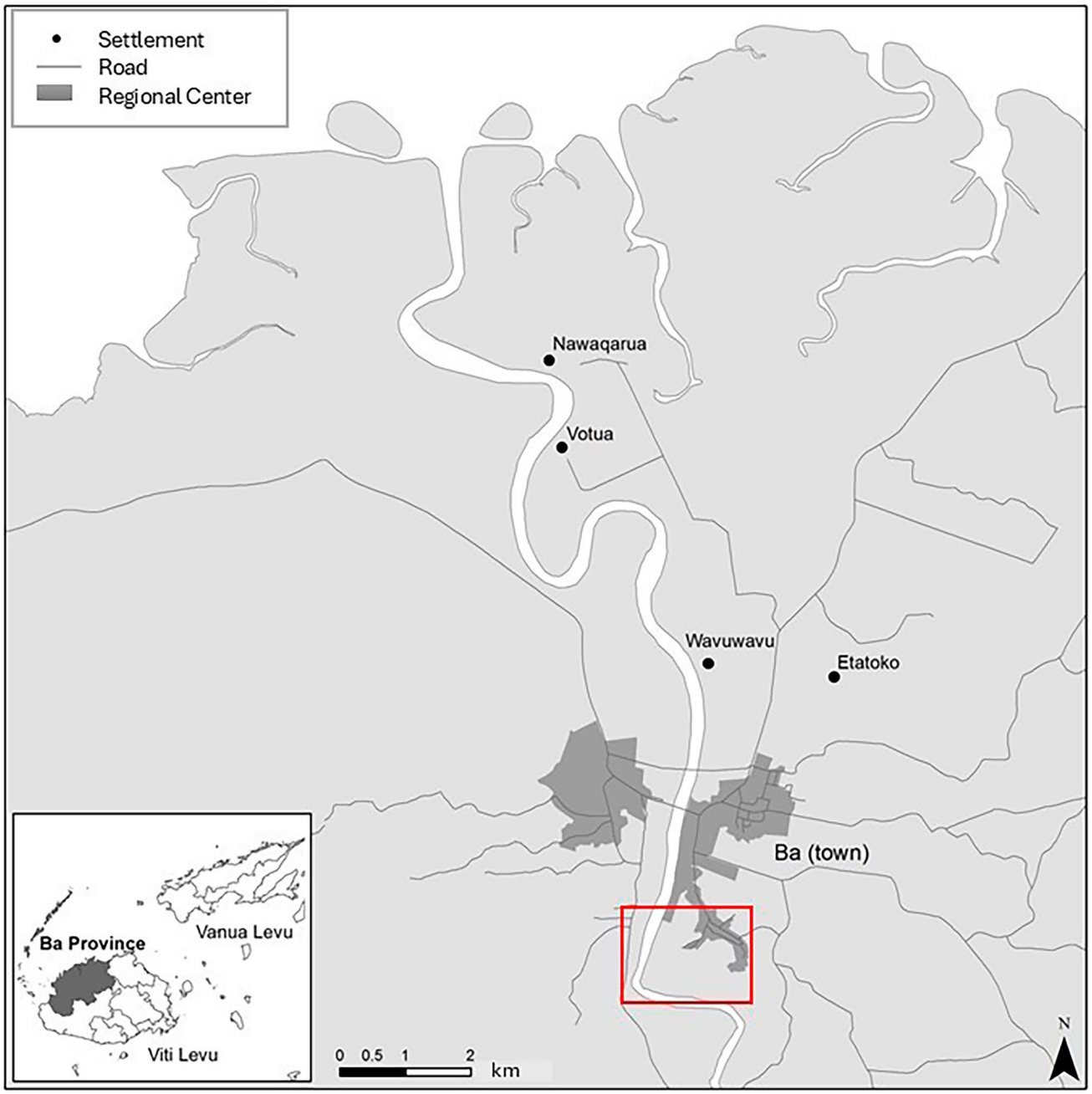

Fig. 1 Location of the Ba catchment in Western Fiji (grey shading), with the area of interest for model development indicated by a red bounding box

(Devi et al. 2024). Flood information is disseminated in two forms: alerts and warnings, and is typically updated every three hours. Importantly, these warnings rely primarily on river gauge observations and are not supported by physical models.

A review of the EWS risk landscape across the four pillars in Fiji showed multiple gaps (Dashora et al. 2024). The disaster risk knowledge is the least advanced, largely due to limited progress in conducting comprehensive risk assessments. Meteorological forecasting capabilities have improved, but hydrological monitoring remains underdeveloped due to weak flood detection systems, insufficient real-time data processing, and outdated technical equipment. Dissemination and communication mechanisms demonstrate mixed progress, with established standard operating procedures but slow advancement in impact-based warnings tailored to diverse population groups. Response capabilities require further strengthening, especially in preparedness and

public awareness. Overall, Fiji's early warning landscape is functional yet still evolving. This provides a valuable baseline for assessing the effectiveness of the current status quo and for examining how existing early warning pillars collectively shape disaster response outcomes.

2.2 Empirical Data for Model Development

Empirical data were collected through various means to support the model development. Interviews conducted with households in the Ba catchment provided information on vulnerabilities, risk perception, trust in warnings, community engagement and awareness, and intended response behaviors, as reported by Anshuka et al. (2021). This was done to develop an understanding of disaster risk knowledge within the catchment, which corresponds to the first core component of the EWS. The usefulness of any warning ultimately depends on how the end-users perceive, interpret, and act on the information provided. For this reason, understanding risk awareness, engagement, and communication processes among households is integral to developing an effective EWS. These were used to develop key parameters in the model. In addition, to further support model development with empirical data, ethics approval was obtained from the University of New South Wales, Human Research Ethics Committee (Reference number: HC220287), and key informant interviews (KII) and a Likert-scale survey were conducted. Stakeholders included experts with current or prior professional experience in disaster risk management in the Pacific. The insights gained were analyzed to identify processes related to flood monitoring, warning dissemination, and response-related decision making across the different pillars of the EWS. Together, these insights were used to develop parameters, decision rules, and the information flow (sequence of events) in the ABM, as outlined in Table 1.

2.3 Agent-Based Model Approach

The agent-based model integrates the four pillars of early warning systems by examining how warning information is disseminated, received, interpreted, and acted upon at an individual level, and how these processes shape overall evacuation outcomes. The simulation is designed to examine flood-evacuation responses in a small peri-urban community within the Ba catchment in Fiji.

2.3.1 Integration of Stakeholder Insights

To illustrate how stakeholder insights inform the model development, Table 1 summarizes the stakeholder insights and explains how they were represented in the model, either through parameters, agent attributes, or event sequencing. It also explains the rationale for their inclusion and identifies the corresponding EWS pillar they represent.

2.3.2 Agents and Attributes

The model includes two types of agents: human (individual) and a forecaster agent (meteorological service). Humans are the primary decision-making agents in the simulation. Each agent receives warning information, interprets perceived risk, and decides whether and when to evacuate, with initial positions informed by household locations. Human agents are heterogeneous and are characterized by attributes related to risk knowledge, belief in the alarm, vision, and mobility. The forecaster agent is an institutional agent responsible for issuing warnings at predefined times.

2.3.3 Environment and Spatial Representation

The model environment is spatially explicit and represents two communities situated within the Ba catchment—Wailailai and Rarawai (Fig. 2). The spatial extent of the model spans longitudes 177.67358 to 177.69252°E and latitudes −17.57415 to −17.55598°S. The study area was initialized using GIS data on buildings, elevation, the road network, and the Ba River. All spatial layers were resampled to a 20 × 20 m resolution. After resampling, the raw GIS data were discretized for inclusion in the simulation environment. The river, building, and road layers were imported as georeferenced TIFF rasters and converted into matrix formats to enable cell-by-cell manipulation. Each layer was reclassified using a categorical scheme, with river cells assigned a value of 1, building cells a value of 2, and road cells a value of 3. These layers were merged into a single matrix to create a discretized representation of the study area.

The merged matrix was then translated into a text-based grid world by mapping numeric values to symbolic characters, such as "R" for river, "B" for building, "W" for river boundary, "P" for path and "_" for empty land. Symbolic representations of shelter locations ("S") were also included. This text-based grid was exported in the simulation environment, providing a simplified, uniform-resolution representation of the real landscape for the ABM. The building data points were used to initialize the starting locations and distributions of human agents (Macal and North 2010).

2.3.4 Early Warning System Representation

The EWS is represented in the model as a set of interacting processes linking the forecaster agent and the human agent. Monitoring and forecasting, the second pillar of the EWS, are implemented by the forecaster agent. Based on information gathered from stakeholder interviews, the instantaneous warning was disseminated to the public only when

Table 1 Translation of stakeholder insights into the agent-based model (ABM) framework and the early warning system (EWS) pillars

Interview/survey insight	ABM representation	Component classification	Rationale for use in the ABM	EWS pillar
About 70% agreed that community members trust warnings.	Probability of belief in alarm	Agent attribute	Belief affects the likelihood of response.	Dissemination and communication
98% agreed that older adults and families with children take more time to evacuate.	Mobility class	Agent attribute	Mobility differences influence evacuation timing.	Response capability
60% agreed that people know shelter locations before and during floods.	Shelter awareness	Agent attribute	Knowledge of location	Risk knowledge, response capability
74% agreed that most people evacuate on foot.	Walking mode	Agent attribute	Mobility mode in rural communities	Response capability
83% agreed that neighbors inform others.	Collaboration parameter	Agent attribute: Previous experience	Social information transfer influences behavior.	Risk knowledge
96% agreed that if shelter location is unknown, people move away from water.	Retreat behavior rule	Behavior/decision rule	Represents protective instinct to avoid hazard.	Response capability
Most stakeholders agreed that prior information and training helps with planning ~ 95%	Prior information and training setting	Model parameter	Provides agents with forecast information shaping decisions.	Risk knowledge, response capability, dissemination and communication
77% agreed that people hesitate even when believing the warning.	High morale parameter	Agent attribute	Reflects behavioral hesitation before action.	Response capability
74% agreed that people take the shortest route.	Shortest path parameter	Agent attribute, behavior/decision rule	Encodes path-choice preference not necessarily along the formal road	Response capability
72% agreed that instantaneous warnings are sometimes late.	Alarm release time	Sequence of event	Timing affects response lag.	Dissemination and communication
Warning dissemination channel from the Fiji meteorological services to the national disaster management office	Warning activation pathway	Sequence of event	Represents institutional communication chain.	Response capability, dissemination and communication

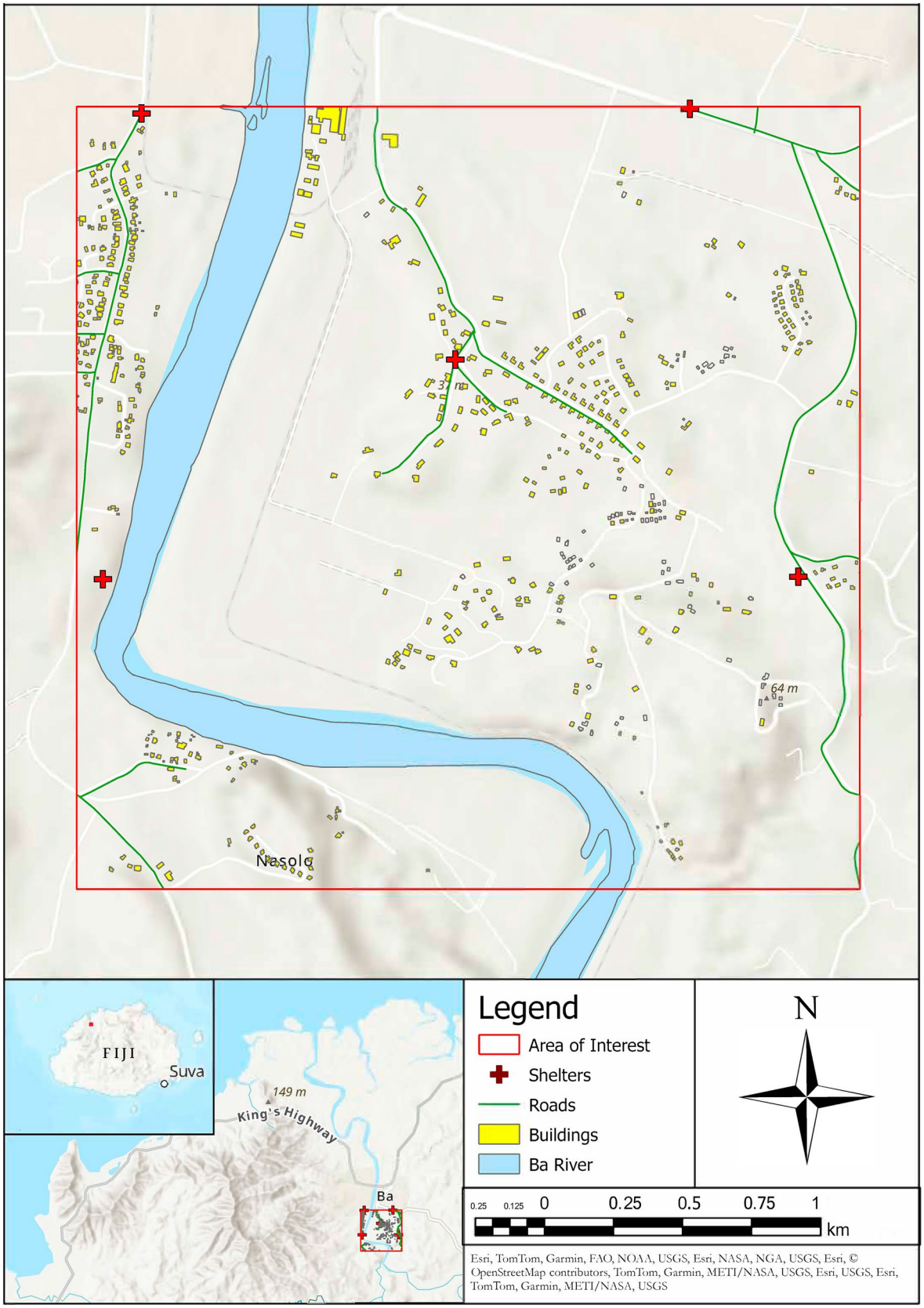

Fig. 2 Agent-based model simulation area in the Ba catchment, Fiji. The red bounding box shows the area of interest used in the simulations. Insets indicate the location of the study area within the broader Ba region and Fiji

the National Disaster Management body was activated. We captured this in our model, whereby the forecaster agent, an institutional agent, monitors flood risk but disseminates warnings only upon activation. The warnings are issued globally within the simulation environment so that all agents can access them. Building on the empirical information, households in the study area exhibit varying levels of risk perception, awareness, experience, and trust in the warning. These attributes affect the probability that an individual will believe the warning. If the human agent does not believe the warning information, they would become aware of the flood risk by assessing the environment at each timestep. Response capability is captured by household mobility and decision-making rules, which determine whether and when households evacuate in response to a warning. By representing the different EWS pillars within a single modeling framework, the model enables examination of interactions and dependencies between warning dissemination, information uptake, and behavioral response.

2.3.5 Simulation of Flood Event

The flood simulation was designed using the rule-based bathtub model (Kasmalkar et al. 2024). The bathtub inundation model assumes that an area with an elevation less than a projected water level will be flooded like a "bathtub." At each iteration, a Moore neighborhood (eight cells) was assessed to determine whether the grid cells would be inundated (Fig. 3). A cell is classified as flooded if its elevation is lower than or equal to the reference water cell. This ensures that water spreads only to cells with lower elevation and those cells that are hydrologically connected

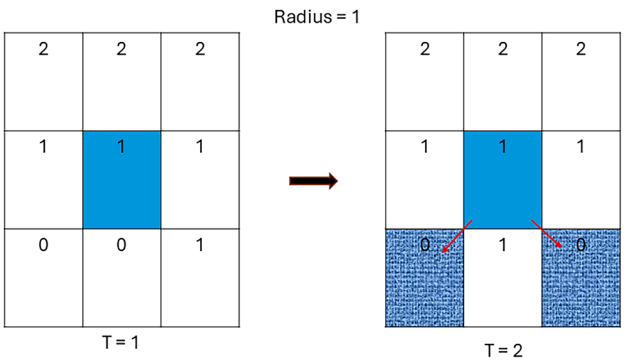

Fig. 3 Flood propagation modeling using the eight-way hydrological connectivity rule. In the left panel, only the central cell contains water. As time progresses to the second time step (right panel), the model evaluates the elevation values in the other eight neighboring cells around the reference cell (the water cell). Since the bottom-left and bottom-right cells have lower elevations than the adjacent reference water cell, they become flooded in the second time step. If radius = 1, one Moore neighborhood is considered (eight cells around a central cell)

in any cardinal or diagonal direction. We used Shuttle Radar Topography Mission data to initialize the elevation of the study area, and the Ba River shapefile to initialize the river's location in the ABM environment. At the start of the model timestep, the water would overflow from the point along the river where the elevation is lowest relative to the adjacent cells.

The radius parameter in the ABM environment determines the number of Moore neighborhoods evaluated in each time step. With a radius of 1, the model evaluates 8 cells at each time step (1 Moore neighborhood); increasing the radius to 2 expands this to include 2 Moore neighborhoods, for a total of 24 cells. In our simulation, we used a radius parameter of 1. The radius parameter influences the flood spread rate, extent, and duration. As the model employs a rule-based bathtub representation of inundation, flood extent, spread rate, depth, and duration are treated as conceptual representations.

In a 100 × 100 grid (10,000 cells), with a Moore neighborhood radius of 1, eight cells can become inundated in one time step. This corresponds to a theoretical spreading rate of 0.0008, meaning that approximately 0.08% of the total environment may become inundated per time step. However, because inundation can proceed simultaneously from multiple water cells, flood expansion occurs through parallel spreading zones rather than at a fixed rate of eight cells per step, and elevation differences further affect the rate and extent. Flood duration is represented in the model using discrete simulation steps. Under a simplified case with a spread rate of 0.0008, and where elevation differences are ignored, complete inundation of the entire grid area would require approximately 1,250 simulation steps. The spread rate governs how the flood extent evolves dynamically over time, expanding across the domain. The simulation continues until one of two termination conditions is met: (1) all agents have either successfully evacuated or become incapacitated, or (2) floodwaters have spread across the entire study area. The flood depth is implicitly governed by the underlying elevation values assigned to each grid cell. When all cells within a water cell's Moore neighborhood that have lower elevation become inundated, and remaining adjacent cells are higher than the current water surface height, the model assumes that water continues to accumulate. Conceptually, this corresponds to an increase in flood depth by one "unit," allowing the water surface level to rise and enabling inundation to proceed.

We acknowledge that the bathtub model has limitations (Sanders et al. 2024). For instance, the bathtub method does not adequately represent different surface types, terrain roughness, flow pathways, and the hydraulic aspects of floodwater movement. However, the goal of the ABM simulation is to explore response dynamics rather than simulated hydrodynamic processes.

2.3.6 Key Parameters

In our model, there are five key parameters. The first parameter is the warning release time—for example, t = 0 (immediate), t = 10 (slight delay), t = 20 (extreme delay). These time steps serve as proxies for real-world lead times between the onset of a flood and the dissemination of official warnings. For example, a warning released at t = 0 reflects an idealized instantaneous warning issued at the beginning of the flood event, whereas t = 10 or t = 20 denotes progressively delayed warnings. The belief in alarm is another key parameter, representing the likelihood that an individual agent trusts the warning upon release and acts. By modeling this probability, the ABM reflects the real-world observation that not everyone responds uniformly to warnings; instead, behavioral responses depend on various other factors.

In our model, we distinguish between gradual-onset and rapid-onset floods, making flood speed a key parameter. This distinction is particularly important for the Ba catchment, which is not only exposed to river flooding but is also highly prone to quick flash floods during intense rainfall. Furthermore, interviews indicate that many households in the Ba catchment include young children, elderly family members, or individuals with limited physical capacity, making mobility another critical parameter in the model. The collaboration parameter represents the likelihood that individuals share warning information verbally during an evacuation. This parameter is important in the Pacific context, where social networks are strong but may vary across communities and ethnic groups.

2.3.7 Human Decision-Making and Behavior Rules

The human decision-making process is underpinned by the belief desire intentions (BDI) theory (Bañgate et al. 2017). Beliefs represent knowledge of the environment, the agent's self or internal state, and desires. As such, when the warning alarm is released, whether the agent believes it and acts depends on prior knowledge and the agent's morale. The second component of the BDI theory is desire, which refers to the goal an individual tries to achieve. If the alarm has been released and the agent believes the alarm, then the agent will attempt to evacuate. Lastly, intention refers to a series of actions taken to achieve a goal. To evacuate, the agent attempts to find a shelter, takes the shortest route, and escapes the flood. Five shelter locations were considered in the study area. "Aware agents," those who believe the alarm, may encounter unaware agents and try to inform them of the alarm. This reflects the collaboration parameter.

Even when an agent does not believe the warning, they continue to detect environmental changes through its vision. The vision range follows a normal distribution to give a realistic sample within a population (Chen et al. 2021). Based on the assigned vision range, the set of visible locations for each agent is used to compute the approximate viewable area from each grid point. If the agent becomes self-warned, they may also choose to evacuate.

2.3.8 Evacuation and Mobility

Evacuation is represented as agent movement within the spatial environment following a decision to evacuate. Consistent with the rural and peri-urban context of the study area, the mode of evacuation is on-foot (Chang and Liao 2015). Each agent can only move one grid cell at a time. Grid cells in the model do not represent fixed real-world distances; rather, they serve as relative spatial units. We recognize that individuals have different walking paces, which may depend on their age or health status. To reflect this, we characterized mobility into two classes: reduced (poor) and good. People with reduced mobility had lower walking speeds than people with good mobility (Wang et al. 2016). This also accounted for the population with disabilities or functional challenges. Agents move along the road network and across accessible land cells. Movement is constrained by evolving flood conditions, with inundated cells reducing accessibility and limiting available evacuation routes over time. As such, human agents retreat when they encounter flooded cells.

2.3.9 Scenario Analysis

Table 2 presents the base-scenario settings under which the model analysis was conducted. Our initial set of scenarios is designed to examine the dynamics of warning dissemination and belief in warnings, as these are core mechanisms underlying an EWS. We subsequently wanted to investigate how other factors interact with warning information and the system-wide impact generated which influences the overall response. Therefore, we first established a consistent set of warning information-belief scenarios. We then treated these as the reference (base) conditions for subsequent simulations of other factors. This structure provides a clearer analytical progression while allowing warning information to remain the central reference point for subsequent comparisons. Results were measured based on the number of people who reached the evacuation shelter and those who became incapacitated or were surrounded by the water. The sample size used in the analysis was 100, representing the population of a small community.

2.4 Model Validation and Result Interpretation

In the ABM community and more broadly in simulation studies, model validation is complex because the behavior being simulated, for example, may never have been observed. As noted by Collins et al. (2024), numerous

Table 2 Base scenario settings used to run the simulation for 30 iterations

Scenario	Instantaneous warning alarm	Parameter to change	Degree of change
1. No prior information provided	t = 0 t = 10 t = 20	Believes alarm	10%
2. Prior information provided	t = 0 t = 10 t = 20	Believes alarm	40%
3. Prior information and training provided	t = 0 t = 10 t = 20	Believes alarm	70%

methods exist to support ABM validation, and validation must be aligned with the model's purpose and stakeholder needs. A stakeholder-centric perspective, therefore, offers an important approach to ABM validation. This validation can be conducted at both the micro level, to assess whether the behaviors and rules adequately represent real-world patterns, and the macro level, to ensure that the model outputs reflect real-world phenomena (Villamor et al. 2023). In this study, we adopted a life-cycle-based approach to model validation, whereby we assessed both the model construction and the interpretation of results. A workshop was used to engage with stakeholders to discuss and contextualize the model results. The workshop was held via Zoom in September 2023 and included stakeholders working in the disaster response sector in the Pacific. In our workshop, we used a combination of approaches, including presentations, group discussions, and brainstorming, to engage stakeholders and gather diverse perspectives. Additionally, a second form of model validation was conducted through a sensitivity analysis. This identifies the dominant factors to which the model outcomes are the most sensitive (Ligmann-Zielinska et al. 2014). We used the second-order, two-at-a-time (TAT) method to evaluate the model across a range of values for each parameter pair while holding all other parameters constant at their baseline values.

3 Results

The simulation results of the scenario testing are presented in Sect. 3.1. This is followed by model validation and an interpretation of the results in Sect. 3.2.

3.1 Scenario Testing Results

Five key parameters were tested in the simulation runs. These were belief in warning information, warning release time, flood velocity, mobility, and collaboration levels. The scenario was run with 100 agents. Each simulation consisted of 30 iterations, after which results were collated and analyzed.

3.1.1 Varying Levels of Belief in the Warning Information

Figure 4 shows evacuation outcomes under low, medium, and high degree of belief in the warning. When belief in the warning is low, the majority of agents (~ 80 agents) become incapacitated. Increasing the belief probability to a medium level substantially improves outcomes, with around 60 agents successfully reaching shelters. The most favorable outcomes occurred with a high probability of belief, in which the fewest agents were incapacitated, resulting in the highest evacuation success. Across all scenarios, variability is evident over the 30 simulation iterations, reflecting stochasticity in agent behavior and interactions.

3.1.2 Impact of Warning Release Time

Figure 5 illustrates the effect of interaction between belief in the warning (low, medium, high) and alarm release time (immediate: t = 1; delayed: t = 10; very delayed: t = 30) on evacuation outcomes. Across medium and high belief levels, the quicker the warning release time, the greater the evacuation, while progressively delayed warnings reduce the number of evacuees and increase incapacitation. In contrast, under low belief, the highest incapacitation is observed with immediate alarm release, while the evacuation response is high with delayed alarm release. This counterintuitive pattern likely reflects behavioral dynamics under low trust in warnings. When the overall belief is low among the population, warnings in general may be disregarded, and people tend to rely on their own risk perception at the onset of the flood to make evacuation decisions.

3.1.3 Effect of Rapid versus Gradual Onset Flood

Figure 6 shows the evacuation outcomes with different levels of belief in the warning alarm under two flood types: a slow-onset flood and a rapid-onset flood. In the slow-onset flood,

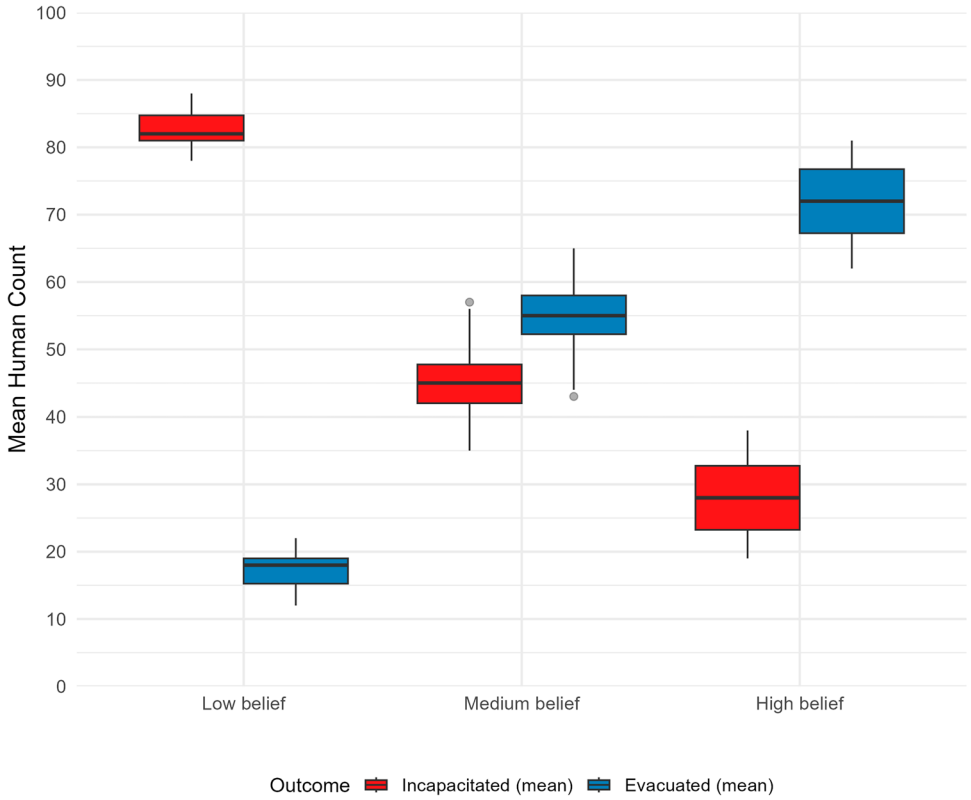

Fig. 4 Evacuation outcomes under varying levels of belief in the warning information: Low (10%), medium (40%), and high (70%)

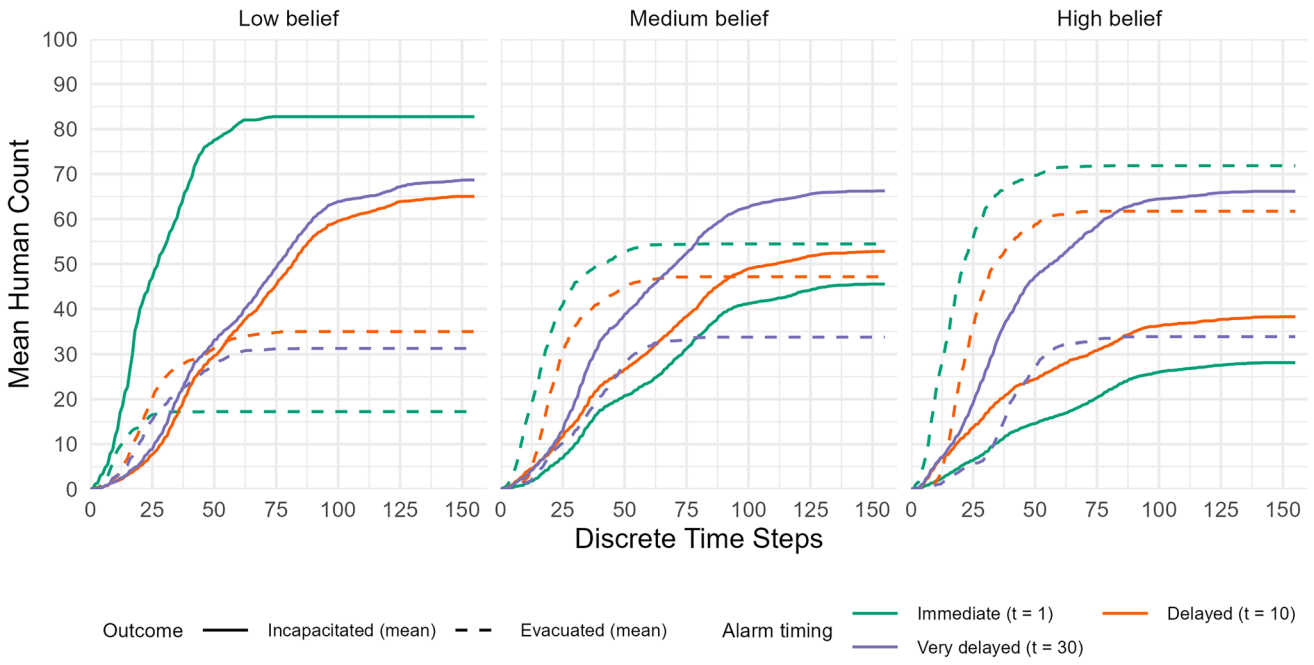

Fig. 5 Effect of alarm release timing on evacuation outcomes under varying levels of belief in the warning. The figure shows the mean number of evacuated (dashed lines) and incapacitated (solid lines) human agents over discrete time steps for low, medium, and high belief scenarios. Three alarm release timings are simulated and compared: Immediate (t = 1), delayed (t = 10), and very delayed (t = 30)

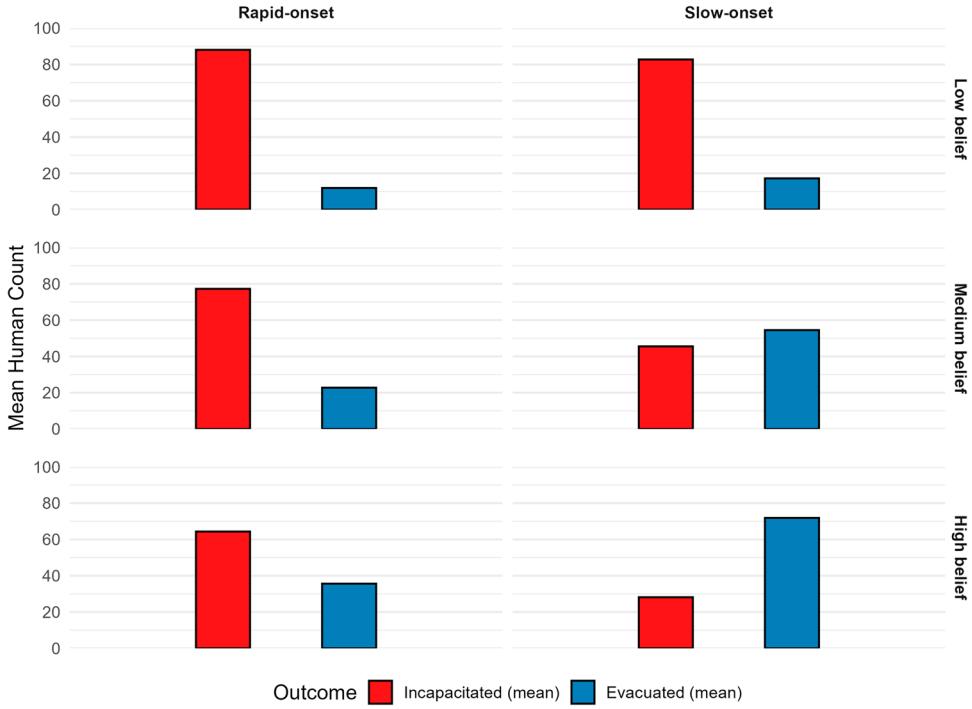

Fig. 6 The number of evacuated and incapacitated agents with different levels of belief in the warning alarm under two flood types: A slow-onset flood (right panel) and a rapid-onset flood (left panel)

as belief in the warning alarm increases, a positive effect on successful evacuation is observed. This pattern indicates that, when there is sufficient lead time, greater trust in and responsiveness to the warning can substantially reduce the number of people affected.

In contrast, in the rapid-onset flood, the benefits of higher belief in the alarm are much more limited than in a slow-onset flood. Indeed, as belief increases, the number of agents successfully evacuating increases, but the incapacitated population also remains high under medium and high belief levels. For instance, the number of agents becoming incapacitated under high belief in a rapid-onset flood is almost two times more than in a slow-onset flood (~ 30 versus ~ 65 agents). Compared with the slow-onset case, these results indicate that when the flood develops rapidly, even greater degree of belief and compliance with the warning do not translate into proportional gains in evacuation success because there is insufficient time for people to act.

In Fig. 7, we examine the effect of flood speed in greater detail. The figure shows that evacuation outcomes also differ in whether additional evacuation occurs after the early response period, defined here as step 30. Across all belief levels in a rapid-onset flood scenario, the number of people evacuated by step 30 remains largely unchanged by step 50, indicating that evacuation effectively plateaus once the flood begins to progress rapidly. In contrast, when flood progression is slow, and belief in the warning is medium or high, evacuation continues beyond the early response window. Under these conditions, a clear increase in the number of evacuated individuals is observed between steps 30 and 50, indicating that individuals continue to respond as time permits. In terms of the effectiveness of EWS, this highlights the relationship between belief in warning and available response time. Trust in warnings enables early action, but sustained evacuation depends on hazard dynamics that allow sufficient time for households to translate belief into action. Importantly, in some instances, evacuating through floodwaters may be unsafe and individuals are often aware of this risk. These underscore the importance of human factors such as risk perception and trust alongside technical forecasting capabilities.

3.1.4 Effect of Different Mobility Levels

This scenario examines the effect of different levels of mobility across population groups within a community. The scenario was adjusted to represent 70% of individuals in the system with good mobility. For comparison, a second scenario was conducted in which the percentage of the population with good mobility was reduced to 30% across the three belief levels for both groups. Figure 8 shows that, at low belief, there are minimal differences in evacuation rates between the good- and poor-mobility groups. However, when the belief in alarm increases, it becomes evident that the group with lower mobility experiences the highest incapacitation rates.

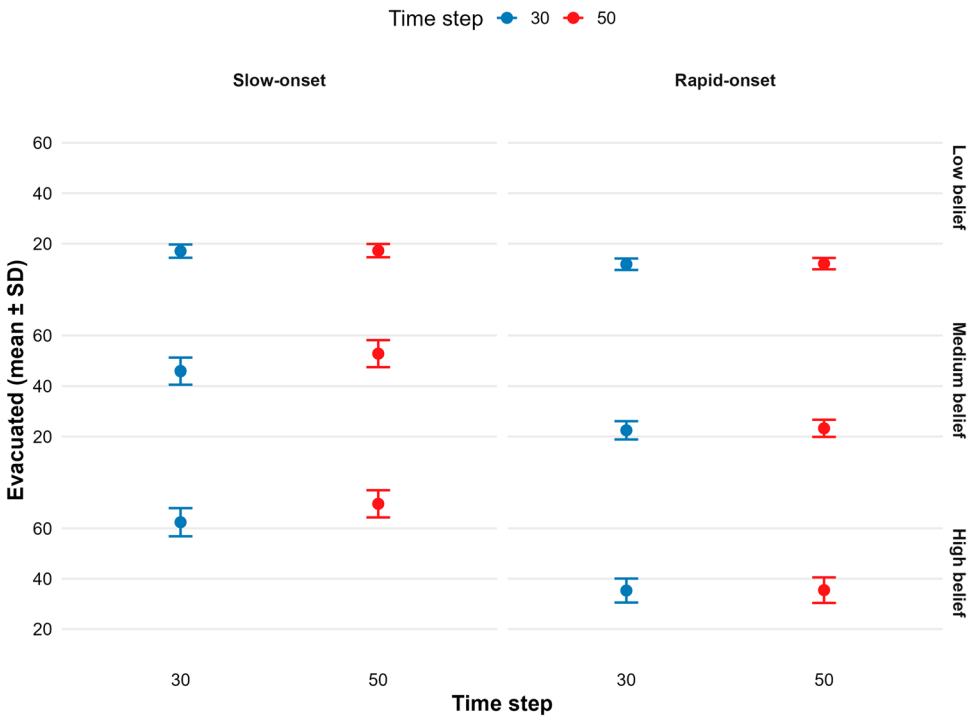

Fig. 7 Mean number of evacuated individuals at simulation step 30 and step 50, averaged across all runs, for slow-onset flooding (left panel) and rapid-onset flooding (right panel) with varying degrees of belief in warning alarm

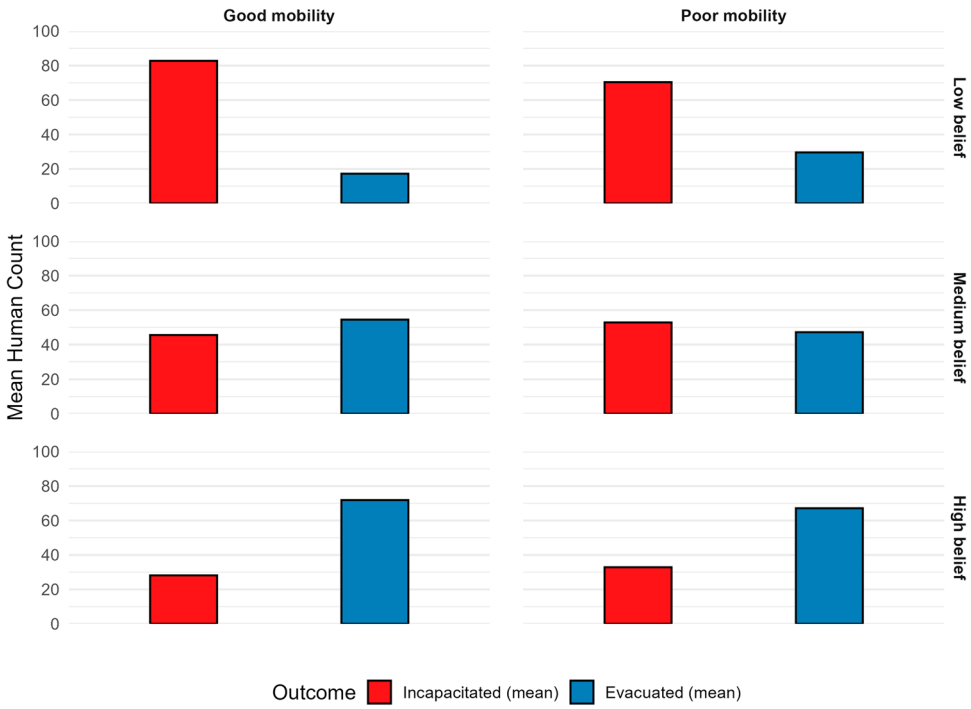

Fig. 8 Scenario analysis using an agent-based model showing evacuation outcomes for a population comprising individuals with good mobility (left panel) and reduced (poor) mobility (right panel), under varying levels of belief in the warning

3.1.5 Effect of Collaboration

Contrary to expectations, in our simulation, increasing collaboration did not lead to a corresponding increase in evacuation success (Fig. 9), with the number of agents successfully evacuating remaining broadly similar across collaborative and non-collaborative scenarios. This pattern is likely driven by the agent's experience threshold, whereby when an uninformed agent receives flood information through social interaction, their decision to act depends on prior experience. As a result, higher interaction rates do not automatically translate into earlier or more widespread evacuation.

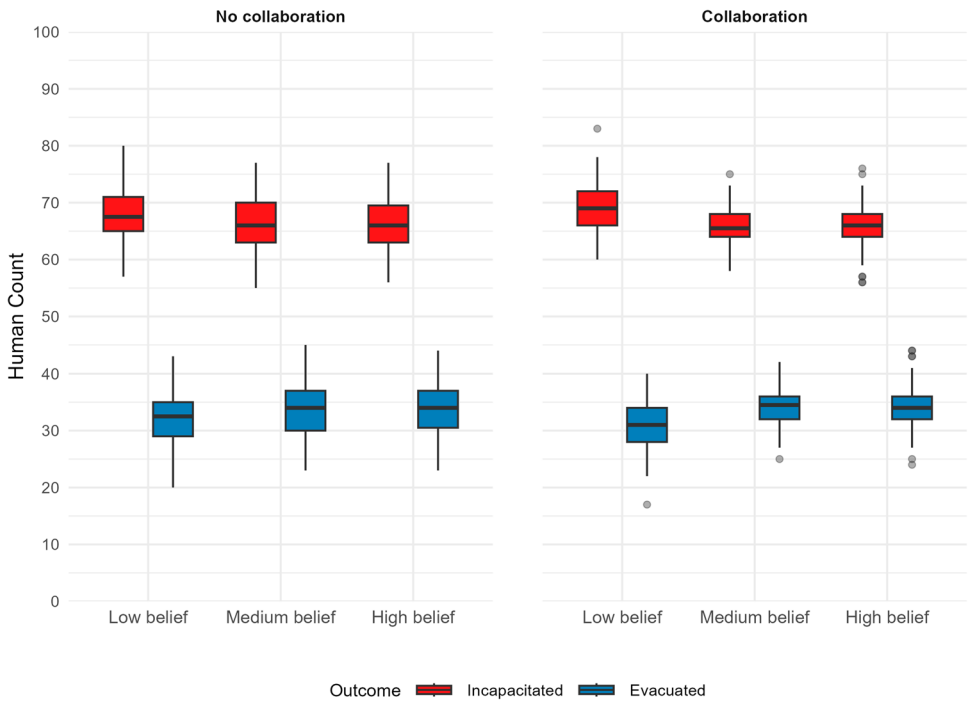

Fig. 9 Agent-based model simulation results illustrating evacuation outcomes under collaborative and non-collaborative conditions across different levels of belief in the warning alarm

3.2 Model Validation and Result Interpretation

This section discusses model validation and interpretation of results, first qualitatively through stakeholder perspectives, followed by a quantitative sensitivity analysis.

3.2.1 Stakeholder Reflections

The following draws on stakeholder discussion to contextualize the model results. A key finding from the simulations is that, as the degree of belief in the alarm increases, coupled with an earlier warning release time, successful evacuations increase. However, under rapid-onset floods, the benefits are minimal. The stakeholders emphasized that flash floods in Fiji can occur within a short time span, and even when instantaneous warnings are issued, the lag time for when the riverbanks will overflow remains unknown, putting individuals at risk.

In instances of low belief in the warning people tend to rely on environmental cues and their own risk perception. A stakeholder reported that "people who live close to the river know when the banks will overflow. In some instances, households living near the river are better prepared than those living inland" (Personal communication).

The stakeholders agreed that prior training and warning information can increase belief and improve public preparedness and awareness. "Communities that receive training are more prepared and respond better. Building capacity in the communities will mean that members are more aware of the surroundings and can better organize themselves" (Personal communication).

Participants recognized that the model's simulation of warning dissemination channel reflects the on-ground situation in Fiji. They further highlighted that the communication and warning dissemination pathway is fragmented and could be more effectively streamlined. The stakeholders also emphasized that evacuation centers are not always open in localized flood events, suggesting that real-world constraints could further reduce evacuation success compared to model assumptions. Lastly, the heterogeneity of Fijian communities was recognized, and this diversity strongly shapes how individuals and households interpret and respond to early warnings. The stakeholders agreed that an ABM, which captures this heterogeneity and is customizable to account for variation across communities, is a suitable tool for assessing EWS.

3.2.2 Sensitivity Analysis

The second-order sensitivity results (Fig. 10) indicate that the interaction between the human count parameter and all other parameters attains the highest magnitude value of 0.49. This indicates that the human count parameter has the strongest influence on the model results and has a counteracting effect with other parameters (negative). The remaining parameters show smaller positive interactions, for example, Collaboration × Flood Probability at 0.0084, suggesting that their influence on outcomes is mostly independent rather than reinforcing each other. The strong interaction between

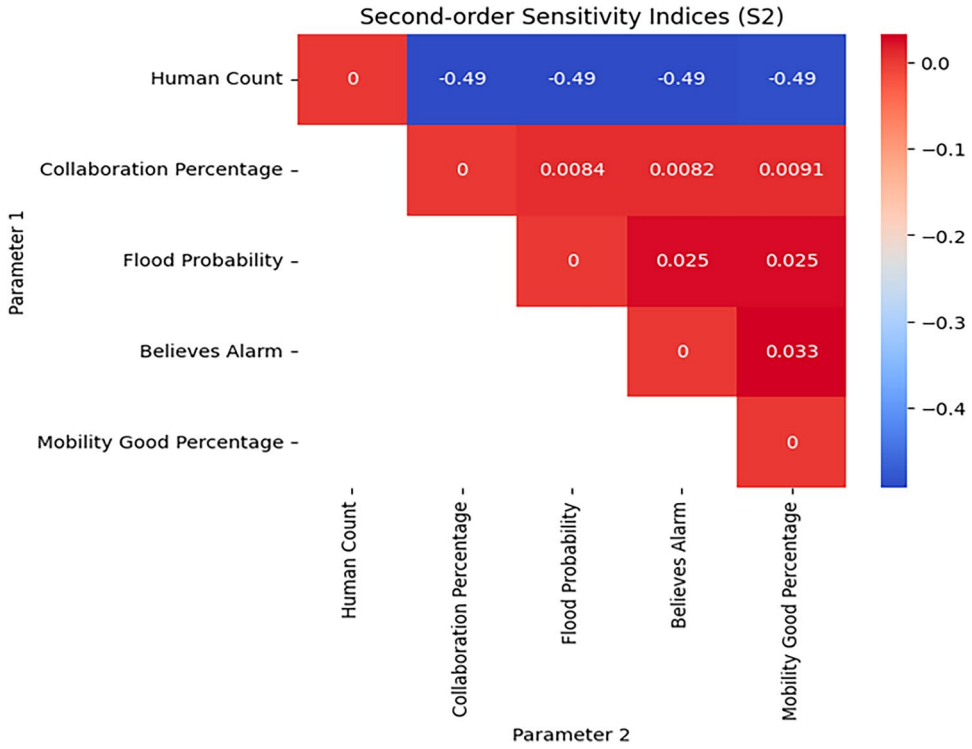

Fig. 10 Second-order sensitivity analysis of key model parameters, assessing their interaction effects on evacuation outcomes

human count and other parameters indicate that population size is one of the dominant drivers of system outcomes. This has an important implication in the real world. As more people access the same resource, the system can become sensitive to capacity constraints and much less responsive to any behavioral decisions. As such, even with prior training, timely warnings, and trust in warnings, this alone cannot compensate for the lack of adequate shelter infrastructure.

4 Discussion and Policy Implications

In this section, we discuss the simulation results, their policy implications, and directions for future research. The results from our ABM simulation showed interactions between different factors and system components in the flood evacuation scenario. These interactions between factors such as belief, mobility, collaboration, warning time, and flood speed exhibited strong nonlinearities that would not have been identifiable if these factors were considered in isolation and linearly. The emergent patterns underscore the importance of holistically capturing the different pillars of the EWS, and highlight how the ABM enables this integrated representation by linking individual behaviors, institutional processes, and system-level outcomes. A key finding from the simulation is that while warning release time is essential, it is most effective when belief levels in the population are high. When belief in the warning is low, it can significantly undermine the effectiveness of even a rapid and early alarm release. This highlights the core theme of the study that, EWS effectiveness does not stem from scientific forecasting capability alone.

Another critical finding is that higher levels of belief, coupled with earlier warning release time, influence evacuation outcomes; however, their effect may be limited during rapid-onset floods. The finding highlights the need to account for dynamic changes within the catchment, particularly amid accelerating climate change (Jenkins et al. 2017). In Fiji, the current policies are geared towards a 1-in-50-year flood event, but in the Ba catchment, 1-in-4-year flood events are becoming more common, including rapid-onset flash floods (McAneney et al. 2017). Despite advances in forecasting, flash floods remain difficult to predict with high accuracy (Collier 2007). Although this is a challenge for forecasting authorities, it simultaneously constrains individuals' capacity to perceive risk and take action. For instance, individuals may find it difficult to anticipate when and how quickly floodwaters will reach their location. Uncertainties in the predictions can also undermine trust in the warning. While accurate forecasts and trust in warnings are important, these alone do not determine response behavior. Communities with prior disaster experience and strong local knowledge have developed effective cues for responding to hazards (Gaillard et al. 2019). Therefore, risk assessments must leverage on existing cues to align forecasts with decision-making contexts, thereby reducing uncertainty and enabling appropriate and timely actions. Our results further indicated that agents with low mobility consistently became

stranded, even when alarms were issued promptly, and individuals believed the warnings and intended to evacuate. These findings highlight that without targeted systems and support for vulnerable populations, even accurate forecasts, rapid alarms, and high trust in warnings cannot ensure safe evacuation. Due to gender norms in Fiji, women are often expected to look after children, older adults, and members with a disability, which makes them more prone to becoming victims of disasters (Bizzarri et al. 2012; Yila et al. 2013). By viewing early warning systems holistically, it becomes clear that their goal should not simply be the design and dissemination of forecasts, or be based on the assumption of uniform uptake of information. Their ultimate purpose is to enable effective responses; therefore, systems should focus on inclusive strategies that support timely action for all, including vulnerable populations.

While our interviews and stakeholder workshop showed that social capital is prevalent in the communities, this was not reflected as increased effect of collaboration and interaction within our model. One reason is that a high-social-interaction setting is effective only among a small group of trusted community members (Abebe et al. 2020). Furthermore, in some instances, coping and adaptation to disasters follow a generational pass-down of behavior and knowledge (Mariam et al. 2021). As such, if family elders are resistant to evacuation, individuals may choose not to evacuate despite collaborative efforts. Moreover, of particular relevance is the need to reassess shelter locations in Fiji. Multi-hazard shelters may paradoxically elevate risk when locations fail to account for trade-offs between elevation and high-wind events. For this reason, a distinction is necessary between shelters that are safe during floods and those used during cyclones.

This study has a limitation that could be addressed in future research. The ABM does not explicitly use a pedestrian model to simulate human movement. Evacuation time can vary with the sophistication of pedestrian behavior rules (Shirvani et al. 2020). Evacuation models used in flood emergencies have mainly been for vehicular scenarios (Aalami and Kattan 2020). This limitation is due to modeling restrictions and computational complexity for agent characterization (Shirvani 2021). This area is growing in research, and further studies could simulate pedestrian behavior with more sophistication.

5 Conclusion

This study demonstrated that evacuation outcomes in a flood scenario are shaped not only by warning release time, but also, critically, by belief in the warning, mobility constraints, and the dynamic nature of the flood event. By adopting a holistic early warning systems perspective, the analysis revealed interdependencies among risk knowledge, warning dissemination, and response capability that would remain unclear under linear approaches. The agent-based modeling approach provided an effective framework for examining interactions and capturing these interdependencies. Representing heterogeneous agents, the agent-based model enables the assessment of micro-level decision making and how these decisions translate into system-wide evacuation responses. Importantly, it allows assessment not only of warning dissemination but also of whether warnings translate into timely and inclusive evacuation responses, providing clear insights for policy and early warning system design.

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