



Modeling of multi-hazard warning dissemination time distributions: An agent-based approach

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ABSTRACT

Despite the increase in frequency and intensity of disasters around the world, research on warning dissemination times is generally sparse and extremely limited. To address this gap, this study proposes an Agent-based Model (ABM) of warning dissemination time and uses this model to generate diffusion curves for two different warning systems — an official system and a peer network. The warning diffusion process is characterized by residents' patterns of official channel monitoring over the course of the day as well as influence from socio-psychological variables (e.g., warning belief and warning relay probability) of the peer network. Results show that the official warning system during a rapid-onset hazard would take 180 min to warn 92% of the at-risk residents, whereas only 73% will be notified about the hazard during a slow-onset event within the same time-period. By contrast, the peer warning network would take 13 min to warn 90% of the at-risk residents in a rapid-onset hazard but 1118 min in a slow-onset hazard. These analyses can help evacuation analysts to make more accurate assumptions about warning dissemination through the official warning system and peer warning network and can help emergency managers to improve hazard brochures and hazard awareness programs.

1. Introduction

Effective warning dissemination during a major emergency is critical to ensure that the maximum proportion of the at-risk population is warned about an imminent hazard impact, providing them adequate time to take protective actions and reach safety before the arrival of hazardous conditions. This warning process can be characterized by two chains of events — an environmental hazard chain and a community response chain (see Fig. 1). To illustrate, the National Tsunami Warning Center detects the initial indications of a far-field tsunami, produces projections of coastal residents' exposures, and provides decision information to state and local emergency managers so they can make emergency assessments and identify appropriate Protective Action Recommendations (PARs) [1]. They then issue warnings to coastal residents who mobilize and then implement protective actions such as evacuation. This process is short-circuited in the case of a near-field tsunami, in which case coastal residents must recognize earthquake shaking as their warning of an imminent tsunami [2].

Local authorities disseminate warnings within their jurisdictions through formal warning channels such as NOAA Weather Radio, National Tsunami Warning Center and local emergency management agency text alerts, sirens (electronic and mechanical), and mobile loudspeakers ("route alerting"), as well as commercial broadcast media such as TV and radio [3–5]. Formal warning systems are typically characterized by a structured and staged process for issuing warnings and communicating with the public. This process involves a management hierarchy, an inter-agency network for transmitting information, and procedures for notifying the public

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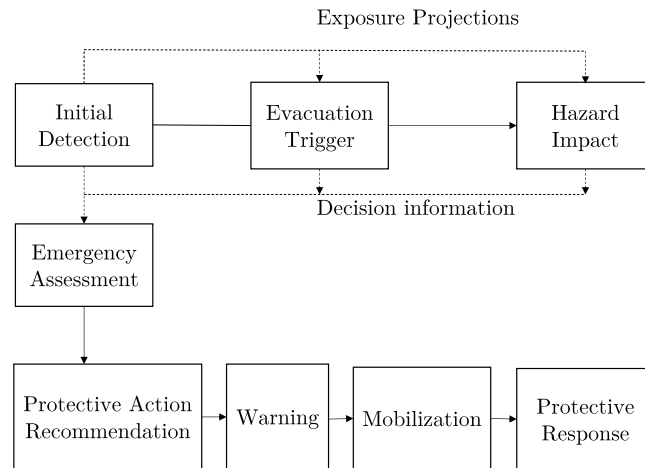


Fig. 1. Chains of events for a hazard and community response.
Source: Adapted from Lindell and Perry [4].

of potential hazards [6]. In addition to these formal warning channels, there are informal warning networks to consider. As those at risk receive warnings through either formal or informal channels, they engage in milling activities through mobilizing available resources (e.g., checking on other household members to ensure their safety, packing emergency kits, and securing the home) and, subsequently, respond by implementing PARs, such as evacuation or choosing shelter-at-place, that directly reduces their loss of lives or potential damage to property [7]. A common element of this milling process is for people to contact peers (e.g., friends, relatives, neighbors, and coworkers) to relay warnings [8–10].

The warning process can be visualized as simple and straightforward, but its practical implications can be rather complex because formal communications channels differ in their precision of dissemination, penetration of normal activities, message specificity, susceptibility to message distortion, rate of dissemination over time, receiver requirements, sender requirements, and feedback [3–5]. Recent years have seen the development of new warning channels such as short messages, micro-blogs, and news portals that are instrumental in improving public emergency responses due to their great influence and extensive coverage [11]. On the other hand, traditional media channels (e.g., TV, radio, newspaper) tend to be slower in message dissemination, although a significant portion (almost 23% of the US population) accesses such channels daily [12]. The effectiveness of the broadcast channels depends on the time of day because warning receipt is determined by whether people are watching TV or listening to radio when a warning is issued [13]. However, people can receive immediate warnings at any time of day through other channels such as sirens, tone alert radios, and text alerts.

Further challenges arise from the informal warning channel characterization as community response to emergency messages involves a complex decision analysis which lies at the interface of science, economy, and societal implications [14]. Warning message propagation through such informal warning systems are often influenced by sudden environmental changes as well as high levels of uncertainty that people experience during an emergency. To illustrate, rapid onset events are often associated with intense environmental cues (e.g., earthquake shaking greater than MMI V, dense wildfire smoke, tornado funnel cloud) occurring suddenly that cause people to experience uncertainty about their safety. In contrast, slow onset hazards provide at-risk individuals with more time to determine whether, and when, to take protective action [4].

There have been many studies of warning dissemination that have advanced the scientific understanding of the time it takes for risk area populations to receive a warning and begin to take protective action [15]. Some of these studies have discussed new communication channels for disseminating official warnings (e.g., Community Warning System (COWS) for the residents of Canon Beach, OR [16]). On the other hand, early [17] and more recent [10] reviews have summarized the findings of research on the ways that informal channels supplement formal channels of warnings. However, there remains a gap in the research literature because the rate of warning dissemination through a combined network of formal and informal warning channels remains poorly understood. Thus, the objective of this study is to create and validate a computational community-based agent-based warning simulation model that integrates (official) broadcast channels with an (unofficial) peer warning network.

1.1. Paper organization

The next section provides a review of official warning system and peer warning network that the at-risk community uses in rapid-onset hazard as well as slow-onset hazard. This is followed in Section 3, which provides a detailed discussion of the analytic model to capture warning message dissemination times and Section 4 discusses this study's major findings, considering how they correlate to those from other studies. Finally, Section 5 presents concluding remarks related to the study's limitations, and remaining challenges in providing empirical data on behavioral assumptions for the ABM analysis.

2. Literature review

A systematic review of the variation in warning dissemination time distributions that combines formal and informal channels requires an integration of technological and social factors. That is, it requires a specification of the characteristics of each channel in the official warning system with the characteristics of the network configuration and channels in the unofficial warning system [18]. This section provides a detailed discussion about previous research on each of these two components – formal and informal – of the emergency warning system, particularly related to usage pattern among different communities for different hazard events. It then identifies gaps in modeling techniques to depict the household-level warning diffusion process as well as empirical research on the elements of risk areas population response to warnings.

2.1. Formal communication channels

Most of the disaster studies related to warning diffusion through formal channels have addressed the broadcast channels of TV and radio. For example, Guillot et al. [19] identified the broadcast media that were used in Tennessee for emergency management purposes from 1997–2007. During that time, TV news was the dominant source of communication with the community. More specifically, Lindell et al. [20] reported that 58% of the survey respondents in South Carolina coastal community affected by Hurricane Floyd relied on news channels to collect continuous information about the progression of the hazard event once residents received information that hurricane was going to reach the locality within 2–3 days [21]. Although there was not any mention in the study about the frequency at which the rest of the at-risk coastal residents were accessing the news channel to collect warning information providing inadequate statistics for assessing warning diffusion times on a regional scale.

Text alerts are another form of formal communication technology that can be used to support disaster warnings. For example, Colorado's Boulder Office of Emergency Management used texts sent to mobile phones to alert people about an imminent flash flood in 2013 [22]. Those terse messages [23,24] advised people to check local news media for detailed information about the incident. A similar strategy was implemented during the Graniteville chemical gas incident in 2005 when a warning was disseminated at 5:09 AM through the Emergency Alert System (EAS), 2 h and 29 min after the chlorine tank car was breached [25]. In addition, NOAA Weather Radio, a tone alert system, was activated to achieve greater penetration among the residents who were sleeping at the time.

2.2. Informal communication channels

Unlike the official warning system that primarily uses broadcast channels (one source to many receivers in parallel), the informal communication system is generally defined by a contagion process where people who receive warning messages contact others individually in sequence [15,26]. Although informal channels are an important component of warning dissemination system, there have been few analyses of their influence on the timeliness and completeness of warning dissemination. To illustrate, summary of flood studies reported that peers ranged from 14%–89% of the first warning sources, with a median of 38% [10].

Some studies have found informal communication channel to be highly effective communication system during slow-onset hazards. To illustrate, Parker et al. [27] reported that floodplain users often monitor water levels and related conditions to assess flood risks, thus creating a “peer network” characterized with self-monitoring practices. This self-monitoring behavior is more common in communities where there is a reasonable level of hazard awareness, a high susceptibility to hazard onset, and a culture of self-protection. For example, 86% of the survey respondents in the Environment Agency's flood monitoring research [28] had heightened perceived risk due to exposure to previous flood events and therefore initiated warning message dissemination through the peer network during the 2007 flood event in England and Wales, regardless of whether they received official flood warnings. Similarly, residents in Thames Ditton Island community in the River Thames in west London reported receiving conflicting PARs from the existing official system and therefore reported the preference for such informal communication channels to achieve maximum coverage of flood warnings within the at-risk area [29].

Dissemination through peer networks is also prominent for rapid onset hazards such as near-field tsunamis. To illustrate, Harnant-yari et al. [30] observed that many of their survey respondents (46%) received warnings from neighbors about the 2018 Sulawesi earthquake/tsunami. Similarly, Wang et al. [2] examined Palu residents' warning sources for the 2018 Indonesia M7.5 tsunami and reported that the primary sources were peers - 25% of them received warnings from friends, relatives, or neighbors. On the other hand, the Siam et al. [31] study of the 2018 Mati Greece wildfire, which had a slow onset, found that many people (24%) received warnings from peers. These findings can be explained by the fact that the official warning system experiences delays due to the length of time that it takes to detect the hazard and process information about it before issuing a warning. In addition, further complexity arises during informal message passing as it is well established that not all the residents who have received information about the onset will relay this message to the neighbors [32] affecting the message propagation dynamics. For example, Parker et al. [27] observed that nearly a quarter (22%) of the respondents relayed a warning to their neighbors, whereas about 16% relayed it to family members, and nearly 40% warned other household members. The remaining respondents did not relay the warning.

3. Analytic model

The Interdisciplinary Multi-Hazard Communication Model used in this study is implemented using the NetLogo modeling environment, a high-level integrated agent-based modeling system (ABMS) [33]. This ABMS is an object-oriented modeling program that simulates actions and interactions of both independent or collective entities that produce the system's behavior [34]. The efficacy of ABMS over other modeling approaches can be summarized by three principles [35,36]: (1) ABMS captures emergent phenomena; (2) ABMS provides a natural description of a system; and (3) ABMS is flexible. ABMS has been employed in several studies of household hazard response, such as the Chen et al. [37]'s use of ABMS to simulate evacuation dynamics. Similarly, Nagarajan et al. [38] developed an ABMS to analyze the warning dissemination process. The fact that ABMS have the capacity to capture heterogeneity, randomness, and interactions at the agent level with relative ease is the primary motivation and concept behind this work.

Accordingly, this study builds upon previous work of Siam et al. [31], Wang et al. [39] and Lindell et al. [10] by introducing a communication model that better captures the dynamics of warning dissemination during an evacuation. This platform comprises five modules: the population distribution model, the transportation network, evacuation shelters, the hazard spread model, and the casualty model. The simulations are defined by evacuees' socio-technical characteristics which are translated to the evacuees' decisions about their evacuation mode, milling time (which marks their departure time), walking speed, and usage pattern for different warning channels — formal and informal.

3.1. Warning communication modeling framework

As indicated in the literature review, warning dissemination requires as an integration of two systems, (a) formal and (b) informal [26]. To model this process, risk area residents are considered as agents and their probabilities of receiving warnings through the integrated sociotechnical warning system are represented by the engineered (communication network) and social (population response) components. When the warning process begins, all residents assumed to be in the unwarned state. Once a resident receives a warning message through a formal or informal channel, the individual is recognized as being warned. The later stages of others receiving messages from warned individuals will be based on different sociotechnical factors described in the next section.

3.1.1. Warning dissemination mechanism through formal channels

We partition the population of agents ϕ within the at-risk area that broadly reflect the diversity of people in the risk area with different sociotechnical characteristics — varying usage in terms of warning communication channel. For the agent-set ϕ , we denote $W = \{\omega_1, \omega_2, \dots, \omega_k, \dots, \omega_\eta\}$ as the set of η number of available formal channels to which an agent has access at time $t \in T$. The time period T (the interval from the time a warning is issued to the time protective action is initiated) is then discretized into N steps, and for each time-step t_n , for $n = 1, 2, \dots, N$, and a mapping technique

$$\delta_{\phi, t_n} : W \rightarrow [0, 1]$$

$$\text{subject to } \sum_{k=1}^K \delta_{\phi, t_n}(\omega_k) = 1$$

represents the expected proportion of the at-risk community ϕ that has been warned through formal channel type of ω_k at time-step t_n .

The set $\Delta_\phi = \{\delta_{\phi, t_n} | n = 1, 2, \dots, N\}$ of N mappings for each individual then defines the distribution of that population's accessibility over the day. We now explain the algorithm's process per agent plan. The first step in understanding an σ_1 -agent's evacuation plan; that is, how warning about an imminent disaster reaches an individual at each time-step through the formal channels. The communication channel is drawn from the corresponding distribution table and then mapped back to an individual according to their assigned proportion of accessibility. The distributions only tell us what communication channel is accessible to an agent at a given time t , and not when they receive the warning. Therefore, the receipt times must be derived, and to do this we must know the time required for each channel to reach an individual. These durations will be some multiple of the length of each time-step $\frac{T}{N}$. We denote a duration weight $\Delta_{\phi, \omega_k} \in 1, 2, \dots, N$, such that $\frac{T}{N} \Delta_{\phi, \omega_k}$ gives the corresponding duration for population ϕ to receive a warning notification through ω_k . Then at each time-step, we can determine the number of ϕ agents who are expected to receive a warning through channel ω_k by subtracting the proportion who have already received a warning ω_k during any of the $\Delta_{\phi, \omega_k} - 1$ previous time-steps. We can then consider the recursive function

$$\psi_{\phi, t_n}(\omega_k) = \delta_{\phi, t_n}(\omega_k) - \sum_j \psi_{\phi, t_{n-j}}(\omega_k) \quad j \in (0, \Delta_{\phi, \omega_k} - 1] \cap \mathbb{N} \quad (1)$$

We consider $n \leq 0$ such that $\psi_{\phi, t_n} = 0$ to mean that no agent has received the warning notification outside the time period. Considering $\psi_{c, t_1} = \delta_{\phi, t_1}$ for all ω_k , we can recursively calculate the initial time a warning notification is received through each of the formal channels at a specific time period using Eq. (1). With such consideration, we can build a $K \times N$ matrix ζ_c for each agent σ_1 to describe all warning receipt time proportions for the at-risk population:

$$\zeta_\phi = \begin{pmatrix} \psi_{\phi, t_1}(\omega_1) & \psi_{\phi, t_2}(\omega_1) & \cdots & \psi_{\phi, t_N}(\omega_1) \\ \psi_{\phi, t_1}(\omega_2) & \psi_{\phi, t_2}(\omega_2) & \cdots & \psi_{\phi, t_N}(\omega_2) \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{\phi, t_1}(\omega_K) & \psi_{\phi, t_2}(\omega_K) & \cdots & \psi_{\phi, t_N}(\omega_K) \end{pmatrix}$$

Note that the sum of the n^{th} column in ζ_c^* means that $\sum_{j=1}^k \psi_{\phi,t_n}(\omega_j) \leq 1$, which satisfies the condition that total percentage of at-risk population being informed through formal channels will not be greater than 100, as it should. We can now normalize ζ_c as

$$\zeta_c^* = \begin{pmatrix} \frac{\psi_{\phi,t_1}(\omega_1)}{\sum_{j=1}^k \psi_{\phi,t_n}(\omega_j)} & \frac{\psi_{\phi,t_2}(\omega_1)}{\sum_{j=1}^k \psi_{\phi,t_n}(\omega_j)} & \dots & \frac{\psi_{\phi,t_N}(\omega_1)}{\sum_{j=1}^k \psi_{\phi,t_n}(\omega_j)} \\ \frac{\psi_{\phi,t_2}(\omega_2)}{\sum_{j=1}^k \psi_{\phi,t_n}(\omega_j)} & \frac{\psi_{\phi,t_2}(\omega_2)}{\sum_{j=1}^k \psi_{\phi,t_n}(\omega_j)} & \dots & \frac{\psi_{\phi,t_N}(\omega_2)}{\sum_{j=1}^k \psi_{\phi,t_n}(\omega_j)} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\psi_{\phi,t_K}(\omega_k)}{\sum_{j=1}^k \psi_{\phi,t_n}(\omega_j)} & \frac{\psi_{\phi,t_K}(\omega_k)}{\sum_{j=1}^k \psi_{\phi,t_n}(\omega_j)} & \dots & \frac{\psi_{\phi,t_N}(\omega_k)}{\sum_{j=1}^k \psi_{\phi,t_n}(\omega_j)} \end{pmatrix}$$

to calculate the probability of an σ_1 agent who has received a warning through available formal channels W at different time-steps t_N . Finally, we take the cumulative sum of each column of ζ_c^* to attain a cumulative probability matrix:

$$\Gamma_{\sigma_1} = \begin{pmatrix} \psi_{\phi,t_1,1}^* & \psi_{\phi,t_2,1}^* & \dots & \psi_{\phi,t_N,1}^* \\ \sum_{k=1}^2 \psi_{\phi,t_1,k}^* & \sum_{k=1}^2 \psi_{\phi,t_2,k}^* & \dots & \sum_{k=1}^2 \psi_{\phi,t_N,k}^* \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{k=1}^{K-1} \psi_{\phi,t_1,k}^* & \sum_{k=1}^{K-1} \psi_{\phi,t_2,k}^* & \dots & \sum_{k=1}^{K-1} \psi_{\phi,t_N,k}^* \\ 1 & 1 & \dots & 1 \end{pmatrix}$$

With such a well-defined probabilistic description of the time at which an agent will receive a warning through an informal channel, we can begin to formulate the temporal scale representation by selecting formal communication channel from Γ_c .

For a given σ_1 agent, we consider a vector $Y_{1 \times N}$ for which values are drawn from $U(0, 1)$. With such vector representation, the n^{th} values from both Γ_c and Y are compared for each t_n . Based on such comparison, a vector $\gamma_{K \times N}$ is defined as

$$\gamma_{k,n} = \begin{cases} 1, & \Gamma_{k,n} \geq Y_{1,n} \\ 0, & \Gamma_{k,n} \leq Y_{1,n} \end{cases}$$

For each column, we only have one non-zero value, so γ is a Boolean matrix representing receiving warning messages from a formal channel at each time-step t_n .

3.1.2. Warning diffusion through informal channels

In this model to formulate warning message dissemination through informal channels, a small portion β of them is introduced as warned individuals [40]. In such context, the decision of agent $i \in \sigma$ to pass a warning message through informal channel (χ) to other uninformed agents can be formulated as

$$\chi_i = \begin{cases} 1, & \Omega_i \geq \Omega_{min} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where $\Omega_{i,min}$ is agent i 's probability of relaying the warning, which is drawn from a uniform distribution $U(0, 1)$. Ω_i is dependent on two components: the ratio of informed individuals within the network (λ) and the level of warning belief (μ).¹ That is, unwarned agents will receive the warning through informal channels if there is a greater percentage of warned residents within the vicinity. That means that at time step t of the simulation, a parameter - r - is introduced to record the number of residents who have received the warning. In addition, it may happen that an agent i has received the warning from a neighbor, but does not believe the warning and so does not participate in the message propagation process [38]. This process results from the assumption that an unwarned agent will trust a warned agent to the extent that they either have pre-existing social ties (i.e., are friends, relatives, neighbors, or coworkers) or have similar personal characteristics (e.g., demographic factors) [42]. This is often observable in a peer network with lower assortativity index (closely related to "homophily" property).² On the other hand, in a community characterized with a higher assortativity index, people are likely to believe in warnings from agents with similar attributes and therefore prone to be involved in relaying the warning further.

To illustrate this process, each informed agent would evaluate their λ and μ after they receive the warning through the peer network. Agent i would pass on the warning message to others only if the inequalities $r \geq \varphi$, $\gamma \geq \rho$ hold true. The individual utility Ω_i can then be described as

$$\Omega_i = \theta \times \lambda_i + (1 - \theta) \times \mu_i \quad (3)$$

¹ "Warning belief" refers to at-risk residents' belief that the threat is real [8]. That is, there is a hazard whose impact is imminent and personal consequences are likely to be severe [41].

² In a typical social network, the similarity in attributes for individuals (e.g., age, sex, education) motivates them to form relations (i.e., friendships) and in turn the individuals are more likely to get *influenced* (putting trust in the warning messages, in this case) by these relations leading to achieving higher assortativity [43].

Table 1
Input parameters for the ABM Model.

Model parameters	Data source and mapping	Data range
Population distribution	GIS data layers - Census data	Constant
Evacuation shelters	Provided by emergency management	To the edge of hazard zone
Hazard characterization	Tsunami model [44], FARSITE [45]	Constant
Background traffic	Calculated based on Siam et al. [31]	Constant
Warning relay probability (λ_i)	–	Varied within the range of (0,1)
Warning belief (μ_i)	–	Varied in within the range of (0,1)

where θ denotes the relative weight corresponding to the ratio of informed individuals within the network (λ) and the level of warning belief (μ). In addition, here μ_i can be illustrated as

$$\mu_i = \begin{cases} 1, & \text{when greater than } \varphi_{0.5} \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

with $\mu > \varphi_{0.5}$ represents a heightened warning belief.

4. Results and discussion

The ABMS captures the dissemination of near-field tsunami warnings following the M7.5 Palu earthquake that occurred on 28 September 2018 along the Palu-koro fault (see Fig. 2(a)), such an event is typical of rapid-onset events produced in subduction zones around the world (e.g., Hikurangi Margin in north-eastern area of New Zealand [46], the Nankai and Kurile subduction zones [47]) capable of striking coastal communities in 30 min or less [39].³ The tsunami affected the regions of Palu and Donggala, as well as a few other regions in Sulawesi Tengah Province, causing 2100 deaths and 4700 injuries. In addition, tens of thousands buildings were destroyed with almost 79,000 people displaced in the aftermath [50]. Fig. 2(a) shows the locations of the Palu event characterization in ABM.

As for the wildfire scenario, the 2018 wildfire in Mati, Greece was considered which experienced the second deadliest wildfire in the Twenty First century,⁴ only exceeded by the 2009 Black Saturday bushfires in Australia [54] (see Fig. 2(b)). The Mati fire started in a forested area on the eastern slopes of Panteli mountain, about 20 km northeast of Athens (for details, please refer to Siam et al. [31]). A strong westerly wind blew for more than 10 h, creating a down-slope flow that warmed the temperatures up to 39 °C and lowered the humidity to 19% prior to the onset of the wildfire [55]. These weather conditions created ideal conditions for the fire to spread rapidly. The fire spread through the Mati area within two hours, killing 102 people and seriously injuring another 150. The fire also destroyed 3000 houses, 305 vehicles, and 1250 hectares of land [56]. The Mati wildfire is a reminder of the dangers of wildfires, especially in areas that are prone to wildfires. The fire also highlighted the need for better fire prevention and response measures.

To systematically analyze evacuation times for the rapid-onset disaster, a baseline model was run first to replicate the real Palu event — the inundation from a tsunami with approximately a 500 year return interval [57]. The characterization of the formal warning system was based on the fact that the 2018 Palu earthquake occurred at 17:05 local time. As for the parameter representing the weight between the ratio of informed individuals within the network (λ) and the level of warning belief (μ) – “ $1 - \theta$ ” – is taken as $0.70 = (\frac{49\%}{49\%+22\%})$, with 49% of the survey respondents in the peer network becoming aware of the onset through either seeing people evacuate (24%) or face-to-face interaction (25%), with the remaining 22% being able to interpret the strong earthquake as an indicator of a preceding tsunami [2]. On the other hand, the baseline model for the wildfire event includes a slow-onset disaster scenario at 13:05 local time [31]. In absence of more granular information about the informal channel usage pattern, a value of θ is taken as 0.5 providing similar weight to both of the parameters (i.e., λ , μ) related to peer network characterization.

Other model parameters related to the evacuation scenario include milling time illustrated as a Rayleigh distribution [58], 70% of the at-risk residents traveling to evacuation shelters on foot to reach the nearest shelter at a speed of 3 ft/s (or 1.5 m/s) that would be equivalent to an extremely fast running pace [59]. We include a normal distribution with standard deviation of 0.2 m/s to represent a range of walking speeds for a given population. The rest 30% of the community would use cars to travel at a speed of 25 mph in the transportation network. Such model characterizations were extracted from the results of Siam et al. [31] and Wang et al. [39]. All the analysis related to the parameters as detailed in Table 1 was followed by multiple runs of each scenario that varied each evacuation demand variable individually. Each scenario was analyzed for 10 runs to account for the randomness (or stochasticity) in the ABMS.

³ In the case of a near-field tsunami, the concentration of tsunami energy within a limited space results in coastal areas being hit by waves in a matter of minutes, leaving a short window for evacuation [48]. On the other hand, in a distant-field tsunami, the initial wave's travel time spans from 25 to 39 h, affording the vulnerable population more time to make informed decisions about protective measures [49].

⁴ Initial warning about a potential wildfire in the region of Attica was disseminated by the Emergency managers – General Secretariat for Civil Protection in Greece, in this context – in the form of a “very high” fire danger rating (i.e., class 4 in a 1–5 scale) for July 23, 2023 prior to the actual event [51]. Such rating was insinuated based on a forecast of strong-to-extreme westerly winds as well as historical pattern for the average annual temperatures in Greece during 1900–2100 [52]. This type of temporal variation in forewarning time-period is different from the rapid-onset disaster event (e.g., near-field tsunami) because they often provide only minutes to inform the at-risk residents about the onset [53].

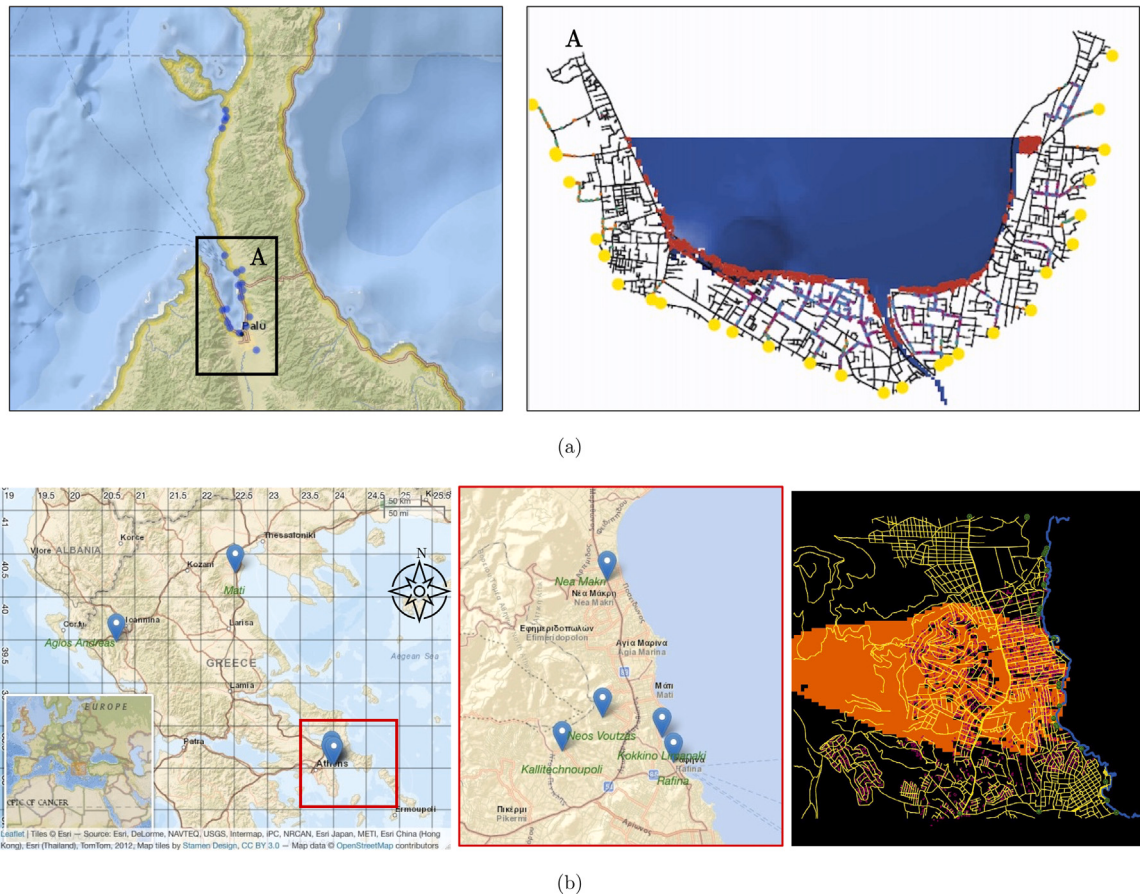


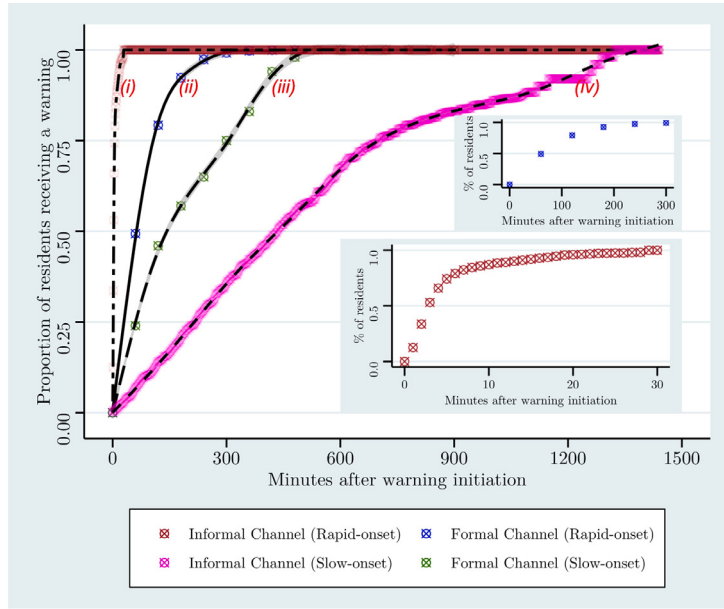
Fig. 2. (a) Map of Palu, Indonesia and ABM model to simulate tsunami event [2]; (b) overview of Mati study area with ABM characterization [31].

4.1. Warning diffusion time distributions for multi-hazard scenarios

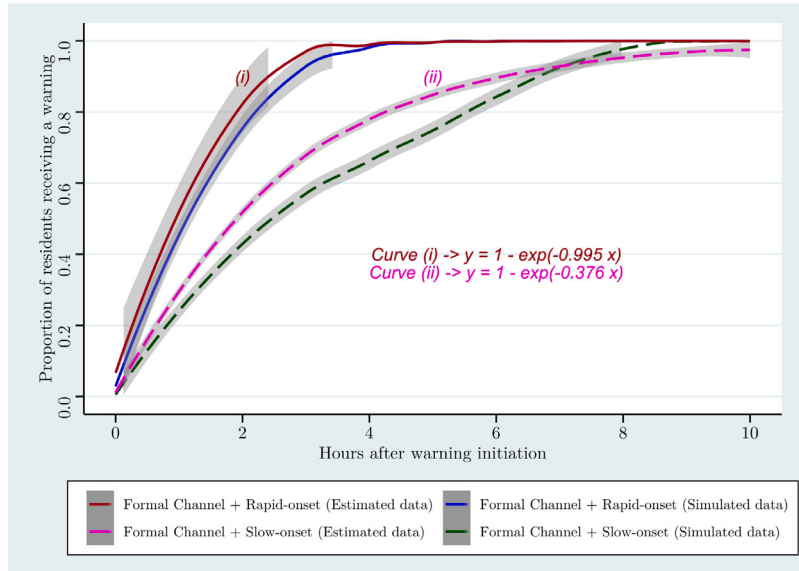
Fig. 3(a) provides results about the percentage of the residents expected to be warned about a rapid-onset disaster (e.g., near-field tsunami) or slow-onset disaster (e.g., wildfire) through informal warning systems and available formal warning systems for either types of disaster. The middle curve (i.e., curve ii) indicates that it would take 180 min after emergency managers initiate warning dissemination for 92% of residents to receive a warning through the available formal channels (e.g., TV, radio, internet). Such observation provides insights into why only 12% of the Palu received warning messages through formal channels as the tsunami waves reached the shore with height of 5–6 m [60] within approximately 20 min leading to almost 500 wireless communication towers being damaged [2]. However, this result contrasts with the Perry [61] study that reported it took around 8 h (or 480 min) for Mauritius residents become aware of the 2004 Indian Ocean Tsunami after the first wave arrived at 12:30 P.M. local time. Such variation may have resulted from the fact that although 51.4% relied on TV to hear about the 2004 tsunami, on an average 16% of the residents would have used TV as news source during the time period of 12:00 PM–3:00 PM local time [62]. This illustrates the need for emergency managers to consider residents' patterns of formal channel monitoring over the course of the day when developing warning plans.

Results depicted in curve iii of Fig. 3(a) shows that it would take almost 6 h for 83% of the at-risk population to receive warnings through formal channels about a slow-onset disaster (e.g., wildfire), with a 100% notification rate being achieved within 9 h. Such dissemination rate is similar to the diffusion process observed in Hurricanes Katrina and Rita when 80% residents of the Louisiana residents were notified about the onset within 8 h [64]. Analyses also show that warning dissemination rate during the slow-onset event is slower to that of the rapid-onset one (see curve i and iii). Such difference may have contributed to the fact that the Mati wildfire event occurred at 13:05 local time when lower percentage of people (24.9%) were using TV [12], which was the primary formal warning channel.

In case of the peer warning network for a rapid-onset event, the left-hand curve (i.e., curve i) shows that it only takes 13 min for 90% of risk area residents to receive warnings (see Fig. 3(a)). The finding that 68% of the Palu survey respondents [2] reported feeling strong earthquake shaking and seeing tsunami waves approaching them a few minutes later [65] may have contributed to warning messages disseminating through the informal network at such a greater speed.



(a)



(b)

Fig. 3. (a) Estimated warning diffusion curves for formal and informal communication channels with $\lambda = 0.5$, $\mu = 0.5$ [63], and $\beta = 30$ [40]. Here, the inset graphs provide zoom snapshots of curve i and ii.; (b) Estimated warning dissemination curve for the formal channels.

In the context of the peer network for a slow-onset disaster, the right-hand curve (i.e., curve iv) shows that it takes 1118 min (approximately 18.5 h) for 90% of the at-risk population to receive a warning. This result is consistent with the finding that the first environmental cues for the 2004 Indian Ocean tsunami reached Mauritius in the form of observable waves at approximately 12:30 PM local time — approximately 8 h after the tsunami was generated. However, only about 5% of the survey respondents had received a warning at that time and only about 20% of those who ever received a warning said that it came from a peer [61]. This pattern of warning diffusion is also similar to the curve for hurricanes illustrated in [20], which reported that it took about 20 h for just over 80% of the survey respondents to received peer warnings during Hurricane Rita in 2005. Such results, therefore, illustrate how effectively the developed ABMS captures the variation in percentage of households being informed depending on the temporal intensity (i.e., slow-onset versus rapid-onset) of the disaster event which is characterized with difference in individual's risk perception [20] and influence from peer networks [63].

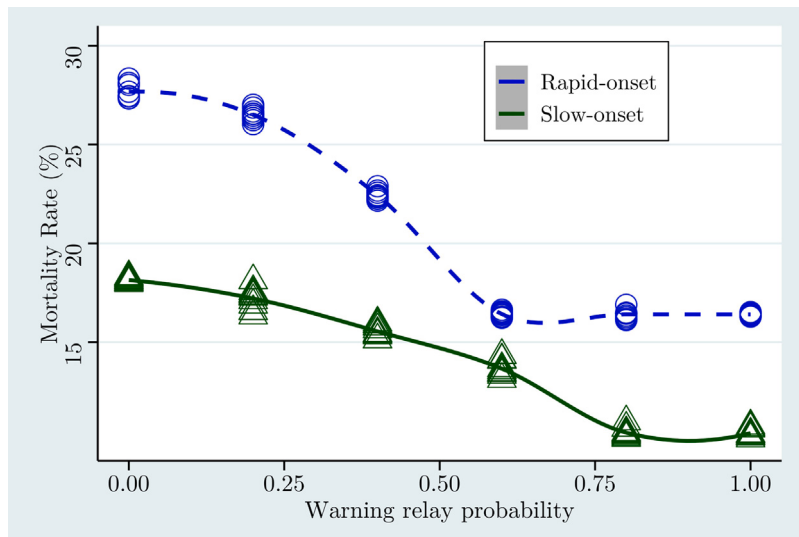


Fig. 4. Mortality rate based on ranges in warning relay probability values, with warning dissemination through the formal channels fitted on equations as illustrated in Fig. 3(b). Here, $\beta = 30$ [40].

4.2. Effect of warning relay probability on evacuation effectiveness

The results in Fig. 4 show that the warning relay probability has a positive effect on mortality rate for both of the disaster types examined in this study - a slow-onset wildfire and a rapid-onset local tsunami. Here, a warning relay probability of 0.75 denotes a scenario in which 75% of the residents have received warning messages leading to higher probability of other non-informed residents receiving information about the onset. Specifically, a warning relay probability value of 0.4 produces a 18% decrease in the mortality rate in comparison to the case in which only 20% of the at-risk population have already received warning about the rapid-onset event. Similarly, during a slow-onset disaster, mortality rate decreases from 17.2% to 13.7% when the warning relay probability changes from 0.2 to 0.6.

In addition, the mortality rate for a slow-onset disaster reaches asymptote when the warning relay probability reaches a value of 0.6 (see Fig. 4). However, the corresponding mortality rate is achieved for the rapid-onset event when 80% of the at-risk population has a warning belief, indicating that positive social influence leading to higher warning relay probability has a greater influence on disaster mortality in a near-field tsunami.

4.3. Influence of warning belief on evacuation effectiveness

Fig. 5 shows how the range of warning belief from 0–1.0 has a negative influence on disaster mortality during a near-field tsunami. Here, the warning belief value of 0.6 denotes that 60% of the community residents have a higher warning belief (i.e., $\mu_i > \varphi_{0.5}$) and therefore, are likely to pass warning messages to their peers, with other values representing corresponding percentages. The results also show that, as the percentage of residents with heightened warning belief increases, the mortality rate decreases. Specifically, as the warning belief threshold increases from 0.2 to 0.4, the mortality rate decreases from 27.7% to 21.0%—a 32.2% decrease. In addition, the mortality rate reaches asymptote when warning belief reaches a value of 0.6, which indicates that increases beyond this value yield no decrease in the mortality rate.

A similar association between mortality rate and warning belief is also observed for a slow-onset disaster (see Fig. 5). Specifically, the mortality rate decreases by 26% - from 17.4% to 13.8% - as warning belief increase from 0.2 to 0.4. However, in contrast with the rapid-onset event, the asymptotic mortality rate is achieved when 40% of the at-risk population has a higher warning belief. This difference highlights the importance of disaster education for heightened warning belief among the at-risk community during rapid-onset events as residents have less time (e.g., 15–20 min) to implement appropriate protection action before the first tsunami wave arrives [53].

5. Conclusions and future research

Disasters such as tsunamis, hurricanes, floods, and wildfires produce are frequent threats to the lives of people who live in areas at risk from these hazards. Consequently, emergency managers need to develop effective evacuation strategies to reduce loss of lives during these natural disasters [66]. In turn, effective evacuation strategies require thorough evacuation analyses based on extensive data about people's responses to environmental hazards, especially their demand for space on evacuation route systems (ERSs) [67]. One critical element of the time-dependent evacuation demand is the rate at which warnings are disseminated over

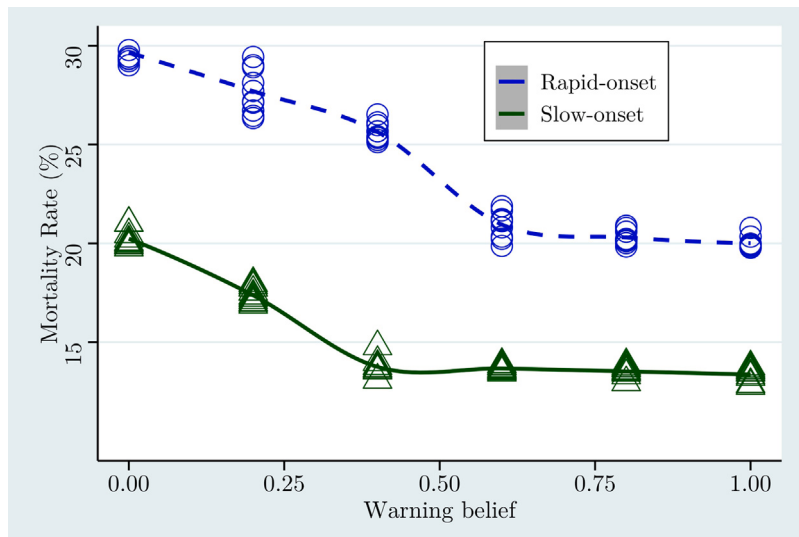


Fig. 5. Mortality rate based on ranges in warning belief threshold values, with warning dissemination through the formal channels fitted on equations as illustrated in Fig. 3(b). Here, $\beta = 30$ [40].

time. However, there is limited research on warning diffusion rates that are based on the combined effects of formal (e.g., TV and radio, NOAA Weather Radio, National Tsunami Warning Center text alerts, sirens) and informal (i.e., peer network through friends, relatives, neighbors, and coworkers) communication channels. In turn, inadequate models of these combined effects can produce inaccurate estimates of evacuation departure time distributions [68]. The resulting inaccurate estimates of departure times will produce inaccurate estimates of evacuation clearance times that can be detrimental to a community's safety [69].

In this paper, an ABM model of warning dissemination was used to generate diffusion curves for the formal and informal warning systems. To model the diffusion process through formal channels, we considered the importance of residents' channel access over the course of the day during a disaster [61]. Results show that the official warning channels during a rapid-onset hazard would take 180 min to reach 92% of the at-risk residents and only 73% will be notified during a slow-onset hazard event within the same time-period. On the other hand, the peer warning network would take 13 min to warn 90% of the at-risk residents in a rapid onset hazard, with taking 1118 min in a slow-onset hazard.

The results also show positive effects of warning belief and warning relay probability on the expected mortality rate. These findings indicate that tsunami evacuation brochures and hazard awareness programs should expand the discussion of preparedness actions described in [64] by encouraging risk area residents to believe peer warnings to evacuate, particularly if those warnings follow earthquake shaking. In addition, tsunami evacuation brochures and hazard awareness programs should encourage people to relay warnings to others in the inundation zone. This is particularly important because [70] found that US Pacific coast residents have unrealistically high expectations of being warned of a near-field tsunami by official channels such as route alert and TV or radio broadcasts.

Despite the evidence for these practical implications, this study has some limitations. For example, this ABM model will be most useful in hazard scenarios in which authorities have enough forewarning before deciding on issuing warning to the at-risk residents. That is, authorities have enough time to detect the hazard and choose a protective action recommendation so the first time component of the evacuation time estimate function, the warning issuance delay time - $t_d > 0$, Urbanik et al. [71] and Lindell et al. [10].⁵ Such forewarning would provide a longer t_w (i.e, warning receipt time distribution), which would make it possible for face-to-face communication to increase message diffusion through informal channels. In an earthquake-only event, t_p would range from 0 (i.e., no warning) to 28 s [72], which would mostly limit informal warnings to people in the same building. In addition, future research should include accurate data on the community's access to formal communication channels. For example, Fadhliah et al. [73] reported that formal warning system access was quite limited during the 2018 Palu earthquake and tsunami, with few Palu residents having access to radio (22.7%), TV (12.7%), text messages (30.9%), and internet (10.2%). Such data will help emergency managers develop accurate ETEs for the at-risk areas in different hazard scenarios [68]. Future studies should also apply this ABM to other hazards, such as hurricanes and flash floods, and in different socio-cultural contexts. Such studies could contribute to an assessment of its efficacy in addressing the dissemination of warnings about imminent threats of wider variety of environmental hazards.

⁵ The time required to complete all of these steps – an evacuation time estimate (ETE) – is a function of four ETE components: $t_T = f(t_d, t_w, t_p, t_e)$, where t_T is a household's total clearance time, t_d is the authorities' warning issuance delay time, t_w is the household's warning receipt time, t_p is the household's preparation (mobilization) time, and t_e is the household's evacuation travel time.

CRediT authorship contribution statement

M.R.K. Siam: Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing. **Michael K. Lindell:** Conceptualization, Writing – original draft, Writing – review & editing. **Haizhong Wang:** Conceptualization, Formal analysis, Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Haizhong Wang reports financial support was provided by Oregon State University. Haizhong Wang reports a relationship with Chinese Overseas Transportation Professional. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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