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An agent-based model of a multimodal near-field tsunami evacuation: Decision-making and life safety

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ABSTRACT

This paper presents a multimodal evacuation simulation for a near-field tsunami through an agent-based modeling framework in Netlogo. The goals of this paper are to investigate (1) how the varying decisn time impacts the mortality rate, (2) how the choice of different modes of transportation (i.e., walking and automobile), and (3) how existence of vertical evacuation gates impacts the estimation of casualties. Using the city of Seaside, Oregon as a case study site, different individual decision-making time scales are included in the model to assess the mortality rate due to immediate evacuation right after initial earthquake or after a specified milling time. The results show that (1) the decision-making time (τ) and the variations in decision time (σ) are strongly correlated with the mortality rate; (2) the provision of vertical evacuation structures is effective to reduce the mortality rate; (3) the mortality rate is sensitive to the variations in walking speed of the evacuee population; and (4) the higher percentage of automobile use in tsunami evacuation, the higher the mortality rate. Following the results, this paper concludes with a description of the challenges ahead in agent-based tsunami evacuation modeling and simulation, and the modeling of complex interactions between agents (i.e., pedestrian and car interactions) that would arise for a multi-hazard scenario for the Cascadia Subduction Zone.

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1. Introduction

1.1. Near-field tsunami hazard

The Cascadia Subduction Zone (CSZ) is a major source for near-field tsunami through mega-thrust earthquake raptures threatening the costal community life safety in the Pacific Northwest region (Goldfinger et al., 2012). A near-field tsunami is likely to come onshore within 20–40 min after the initial earthquake, while a far-field tsunami (eq. distant-source) is typically 1000 km away from the area of interest which can take hours to reach seashores. Near-field tsunamis pose a greater risk for coastal communities because the first waves can move on shore in minutes (40 min or less).

Essentially, tsunami warning times are much shorter than other natural disasters such as hurricanes and floods, and even a well established system such as the Pacific Tsunami Warning Centre (PTWC) may not provide sufficiently long lead time for evacuation before a disaster happens, especially for locally-generated tsunamis (Katada et al., 2006). The near-field tsunami

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event is particularly devastating because the tsunami arrives in a very short time after the earthquake. Under such circumstances, evacuation is the most important and effective method to save human lives because it is impractical to construct all building to resist tsunami forces. The large-scale evacuation represents a complex system for transport operation and planning to minimize casualties, including the potential for critical infrastructure and communication systems to be damaged from the earthquake (Lammel, 2011).

1.2. Evacuation modeling from natural hazards

Fig. 1 shows the length and time scales from the perspective of an evacuee for several types of natural hazards. Evacuation plans for earthquakes and building fires generally occur over short time scales, seconds to a few minutes, and evacuees are on foot to shelter in place or nearby. For example in the case of an earthquake, an evacuee might take refuge under a desk within a few seconds of feeling the strong shaking of the building. On the other hand, evacuations from hurricanes often have several hours to days of advanced warning, and evacuees rely on vehicles to seek shelter several miles away beyond the hazard zone. Nearfield tsunamis present a complex case of multi-modal evacuation because the tsunami arrives within several minutes of the earthquake and can travel several kilometers inland. Moreover, evacuees may be faced with choices of sheltering near place (vis-a-vis vertical evacuation) on foot or to travel outside of the inundation zone typically by car.

There is extensive emergency evacuation modeling research due to its significance to human life safety, and advances in technology as is shown in Fig. 2. We are not planning to review each paper listed in Fig. 2 in this work, however interested readers are directed to the original papers/reports for more information. Fig. 2 presents five distinct hazard groups whose warning time increase from seconds level (i.e., earthquake) to hours range (i.e., hurricane) as is revealed in the hazard length and time scales in Fig. 1. For earthquake and building fire with very short warning times, the mode of evacuation is primarily on foot. However, for wildfire and hurricane with relatively longer warning time, people generally drive to evacuate the affected areas to safer places. Near-field tsunami represents the middle range of the five hazard groups in terms of warning time scales which is typically in the range from 20 min to 40 min. Therefore, transportation evacuation modes, may be multimodal rather than a single mode.

1.3. Tsunami evacuation modeling

Recent research efforts have begun using agent-based modeling frameworks for hurricanes and coastal community tsunami evacuation (Mas et al., 2011); however the existing tsunami evacuation research models typically assumes 100% pedestrian walking with little consideration of other modes of transportation such as auto-mobiles or bicycles. This is despite recent work where it was observed that a large number of evacuees left from low-topography areas by car (Mas et al., 2011).

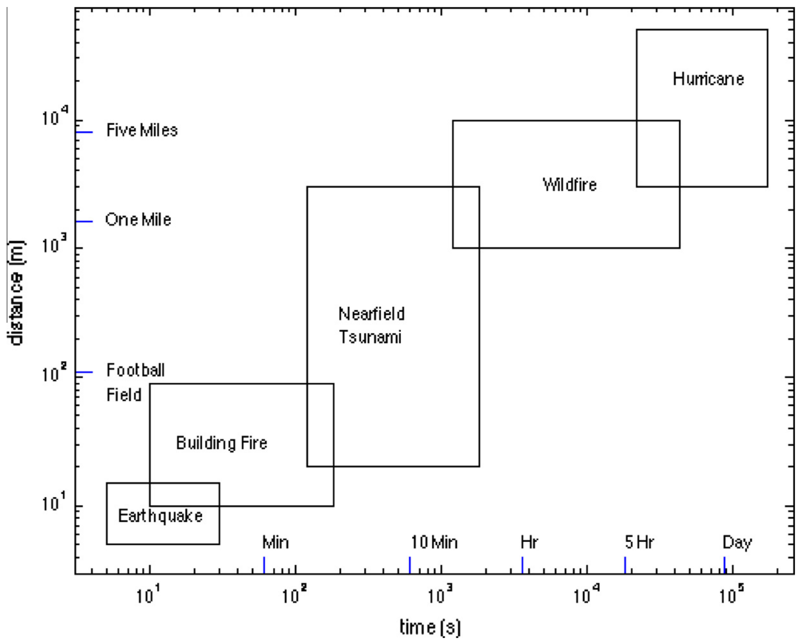


Fig. 1. Time and length scales from evacuees perspective for different hazards.

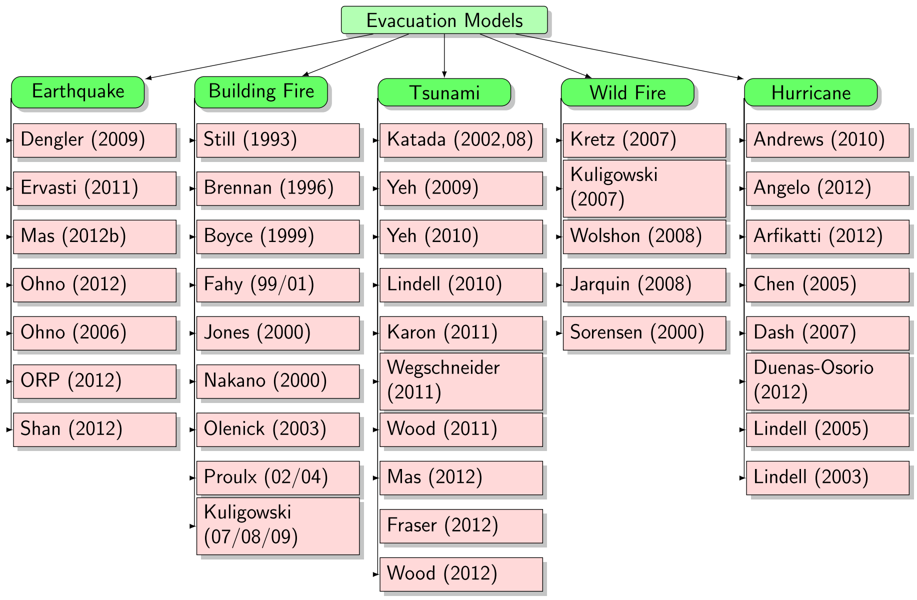


Fig. 2. A brief summary of evacuation models for varying hazards (the warning time increases from left to right).

In the past decades, approaches to model the evacuation scenarios such as static networks (shortest path, minimum cost network flow, or quickest path), dynamic networks, and traffic assignment have been widely employed to model the evacuation scenario (Hamacher and Tjandra, 2002). Wood and Schmidtlein (2012) used a least cost distance to assess pedestrian-evacuation potential from CSZ-related tsunamis in the US Pacific Northwest. A typical example of evacuation simulation based on static concepts is MASSVAC (Hobeika et al., 1994). An integrated GIS-based simulator framework, which employed the shortest-path algorithm, was developed by Katada et al. to improve evacuation efficiency (Katada et al., 2006). Chalmet et al. (1982) suggested using the dynamic network to model the circumstance that many occupants evacuated in minimum time. Sheffi et al. (1982) proposed the NETVAC model for simulating the traffic pattern under an emergency evacuation scenario. Lovs (1998) presented the way-finding problem in emergency evacuation using various models in a mathematical setting, providing various models. However, these methods bear the flaws that it is hard to be implemented in the real world. For example, shortest path solution does not consider congestion effects, which tend to underestimate the travel times, and the shortcoming of static assignment is that it does not possess the consideration of the time-of-day dynamics (Lammel, 2011). They neglect central behavioral aspects like panic or herding behavior as well (Lammel, 2011). Traditional methods lack the capacity to describe the individuals decision-making behavior in that circumstance, nor fully incorporate the potential interaction effects between evacuees. Human behavior is highly complex, and is the most difficult aspect of the evacuation process and hard to model in mathematical equations (Mas et al., 2011). The desired approach for the evacuation problem is an iterative learning method, which could be improved by agent-based modeling and simulation (ABMS) (Lammel, 2011). ABMS is situated to offer meaningful insights to the mechanisms and preconditions for decision making processes under pressure and panic.

An agent-based modeling and simulation (ABMS) is an approach to simulate the interactions and actions of the autonomous decision-making entities, assessing the effect as a whole to capture the emergent phenomena. Hundreds of agents operate concurrently to investigate the connection between the macro and micro level individuals behavior (Mas et al., 2011). Each agent individually assesses its situation and makes an evacuation decision on the basis of a set of rules (Dawson et al., 2011). The ABM has demonstrated it can provide insights that are not available from other methods and captures both the natural and human system dynamics (Dawson et al., 2011). For example, Chen and Zhan (2006) introduced an agent-based technique to model the traffic flow and investigate collective behavior of evacuees. Liu et al. (2009) proposed a dynamic route decision model based on multi-agents by considering group evacuation. Mas et al. (2011, 2012) presented a new method for start time evacuation decision-making modeling under tsunami scenarios. An agent-based simulation model of multi-agents in a hypothetical community to study the influence of behavior on warning dissemination is suggested by Nagarajan et al. (2012). Similarly, Dawson et al. (2011) employed the dynamic agent-based model to manage flood incidents. Uno and Kashiyama (2008) proposed an emergency evacuation simulation system based on multi-agent models. Karon et al. (2011) presented a simulation of tsunami inundation in Oregon area as well. Efforts to model the tsunami evacuation process have also included the least-cost-distance (LCD) models. LCD model focuses on evacuation landscape features (Wood and Schmidtlein, 2013) and uses geographic information system (GIS) to find the shortest path to safe spots from hazard zones (Wood and Schmidtlein, 2012). Agent based modeling focuses on the evacuees behavior and incorporates the dynamic travel costs when deciding travel speed and the location of evacuees. Further, agent-based models may serve practitioners who are developing preparedness plans for a site-specific tsunami scenario.

1.4. Agent-based modeling in transportation

Agent-based modeling and simulation is widely used in transportation (Zheng et al., 2013). Multiple platforms have been introduced as applications of agent-based modeling in transportation. One example is the MATSim (Multi-Agent Transport Simulation project (Lammel et al., 2010)) which was initially developed for the simulation of vehicular traffic flow for large cities or even regions (Lammel et al., 2010). Agent-based models are also used in travel demand modeling (Zhang and Levinson, 2004) and freight transport analysis combining with macro-level traffic models Holmgren et al. (2014). TRANSIMS (TRansportation Analysis and SIMulation System) is an activity-based travel demand modeling and simulation tool which was initially developed to simulate individual travelers in a regional transportation network as well as transit system through activity-based travel demand modeling and it can also be used for planning the evacuation of metropolitan areas (Zheng et al., 2013). Zheng et al. (2013) also reviewed a few other multi-agent activity-based platforms including Sacramento Activity-Based Travel Demand Simulation Model (SACSIM) (Bradley et al., 2010), Simulator of Activities, Greenhouse Emissions, Networks, and Travel (SimAGENT) (Goulias et al., 2011), Open Activity–Mobility Simulator (OpenAMOS) (Pendyala et al., 2005), and Integrated Land Use, Transportation, Environment (ILUTE) (Salvini and Miller, 2005). In addition, Yin et al. (2014) presented an agent-based travel demand model system for hurricane evacuation to simulate six household activity-travel decision-making strategies and evaluated their effectiveness. Recently, Xiong et al. (2015) developed an agent-based en-route diversion model to evaluate the dynamic behavioral responses and network performance through macroscopic fundamental diagrams for real-time operational applications, while Ma et al. (2015) used an agent-based optimization model and a lagrangian relaxation-based heuristic within a mesoscopic dynamic traffic simulator to evaluate the personalized real-time traffic information provision strategies such as when and where to provide the information and what are the alternative routes.

Interested readers are referred to (Bazzan and Klugl, 2013) and references therein for a detailed review of the agent-based modeling techniques for traffic and transportation applications. The authors of this research chose to use NetLogo (Wilensky, 1999) mainly because under evacuation circumstances, drivers and pedestrians act in an unexpected panic situation and the traditional driver behavior models such as car-following and lane-changing behavior might fail to capture the conditions in emergency. NetLogo (Wilensky, 1999) offers flexibility to model the agent-to-agent interactions and the heterogeneous decision-making behavior and how that combination impacts life safety.

1.5. Social vulnerability

Compounding the challenges of simulating individual decision-making behavior is the extent of social vulnerability across a geographic region. Social vulnerability to natural hazards is not constant throughout a community and varies due to the unique conditions, needs, and constraints of the subcultures that exist within that community. Factors that may interfere with the evacuation capacity surrounding a disaster include: single female-headed households, being elderly, racial/ethnic minority, living in a rural region, living in institutions or congregate care, suffering from a physical or mental disability, requirement for ongoing medical assistance, and having limited transportation options (Beaulieu and Tootle, 2010). Integrating the perspectives and contributions of these populations into evacuation simulations is especially important because the chances for greater victimization during a disaster are unevenly distributed in society, as are opportunities for enhanced safety (Tierney et al., 2001; Morrow, 2008). At the same time, the resilience of vulnerable populations and the perspective that they can bring to disaster risk reduction cannot be underestimated (Cramer, 2012; Schoch-Spana et al., 2008).

It is not population and socio-economic characteristic per se that indicate vulnerability; rather it is the extent that such features limit access to resources necessary to prepare, respond and recover from a disaster (NRC, 2006; NRC, 2012). Social science research has demonstrated that gender (Fothergill, 1996; Enarson and Morrow, 1998; Fordham, 1999), race and class (Perry and Lindell, 1991; Peacock et al., 2000; Cutter et al., 2001), and age (Ngo, 2001) are among the most important indicators of vulnerable individuals and social groups (NRC, 2006). To the extent that evacuation modeling can begin to capture the diversity of evacuee socio-demographic characteristics, as well as decision-making modeling, the more precise will be the predictions.

Unfortunately, due to social and technological complexities and the state of modeling technology, some important factors have been omitted by researchers when simulating the tsunami evacuation. Developing an effective evacuation strategy requires not only understanding spatial differences in geophysical risk, but also social vulnerability (Chakrabority and Montz, 2005). The connection to place, household evacuation logistics (Lindell et al., 2011), and personal familiarity with evacuation routes (Dow and Cutter, 2002) would significantly influence the decision making time. Furthermore, it was found that transient residents (i.e., tourists) were more likely to evacuate faster than the permanent residents (Charnkol and Tanaboriboon, 2006). Thus, differential reaction times would lead to different evacuation and transportation impacts. Also, research from a survey for the 1995 Kobe earthquake shows that residents with local knowledge may choose a different route and the mode of evacuation (walk, auto-mobile) (Liu et al., 2009). Rational choice approaches (Bogard, 1988) suggest that people behave in a rational manner based on their knowledge, efficiency and resources; therefore, every evacuee will choose the optimal evacuation strategy under their given circumstance, which would lead to a, so called, Nash equilibrium (Lammel, 2011). In addition, different from existing transportation simulations, since any location outside the inundation zone is regarded to be safe and could therefore be a possible destination, the destinations of evacuation are not known in advance (Lammel, 2011). The ability to choose a route to safety, directly instead of seeking a safe location aimlessly is crucial to evacuation efficiency. In the case of an anticipated detour, forecasting technologies should have the capacity to model the logistical impacts in order to aid disaster preparations.

1.6. The motivation

The goal of this research is to investigate the impacts of different evacuee decision-making times on the estimation of casualties in a multi-modal tsunami evacuation. The motivations are three folded: (1) a real evacuation is most likely to be multi-modal instead of a single mode; (2) the length of the decision-making process regarding when and how to evacuate; and (3) existence of vertical evacuation sites is crucial to life safety benefits (i.e., mortality rate). Another motivation is to develop a framework that can include a more comprehensive multi-hazard and multi-modal evacuation scenario for the CSZ event, however we are only focusing on tsunami in this research. In particular, this research will model the evacuees decision-making behavior during the near-field tsunami evacuation event which can lead to a better comprehension of transportation impacts under various evacuation scenarios (e.g., whether to evacuate or not? Which mode of transportation? Which route to take?). According to a survey in Mas et al. (2011), 57% of the interviewees evacuated immediately after the earthquake while 37% had delayed their evacuation. A general evacuation model may provide the regional perspective, but site-specific case studies are useful for emergency planning at those specific locations (Wood and Schmidtlein, 2013). Thus, this study plans to use the city of Seaside, Oregon as a case for the multi-modal agent-based evacuation model, where tourists and sizeable residential population are constantly threatened by near-field tsunamis (Wood and Schmidtlein, 2012).

2. Tsunami evacuation model

2.1. Agent-based modeling environment

Our tsunami evacuation model was constructed using NetLogo modeling environment which is a high level integrated modeling platform through agent-based programming language (Wilensky, 1999). This modeling environment enables the exploration of emergent phenomenon in a multi-agent system, and it allows users to modify parameters through sliders and visualize the simulation environment. This feature has turned NetLogo into an increasingly popular tool for research due to its extensive documentation, the existence of good tutorials, and a large library of preexisting models (Klugl and Bazzan, 2012). The main part of complexity in evacuation modeling is caused by interactions between agents. Since NetLogo is a high-level platform for simulating complex and stochastic systems, the model is developed in this platform. The model uses GIS data as input for transportation network. Fig. 3 shows a screen capture of the tsunami evacuation model as an example.

We note that for this simulation we are modeling only the consequences of the tsunami hazard, and we do not include direct consequences of the earthquake on the population or the constructed environment. We assume that there are not casualties or injuries resulting from the earthquake or any damage to surface streets, bridges or buildings. For the agent behavior, we assume that all agents are autonomous, that their choices are not influenced by the behavior of others, and that their behavior does not change with time. In other words, an agent that initially chooses "no action" cannot change this behavior even if neighboring agents are evacuating.

2.2. Model components

The model requires a number of precomputed data files containing the population distribution, street grid, evacuation destinations, and the inundation hazard. Each of these data files are discussed briefly.

2.2.1. Population density model

There can be a high spatio-temporal variability of community population density based on factors such as the weather, time of day, week, or season. Moreover, a given population will contain a number of different segments such as residents or transients (i.e., tourists) who will respond differently for a given hazard. There are also wide distributions in age as well as other factors affecting social vulnerability as discussed earlier. For this simulation, we represent two population classes (residents, tourists) and place the population across several zones, with the population density increasing at the waterfront and beach area. For the simulations presented here, this would represent a crowded peak summer weekend which is considered the worst case scenario with approximately the same number of tourists and residents which adds up to 2500 evacuees.

2.2.2. Road network

The evacuation road network was constructed using the open street map by cutting out the area of interest (i.e., Seaside, OR in this case) and saving as an OSM file. The road network is extracted from the OSM file with their coordinates. In the simulation, it is assumed that all the agents (i.e., residents and tourists) have to follow the road network to the tsunami shelters. The use of other alternatives such as swimming across the river or cutting through fields or parking lots are prohibited. In addition, a conservative assumption has been made. All of the roads are considered as a one-way one-lane street with 30 mph speed limit towards outside of the inundation zone.

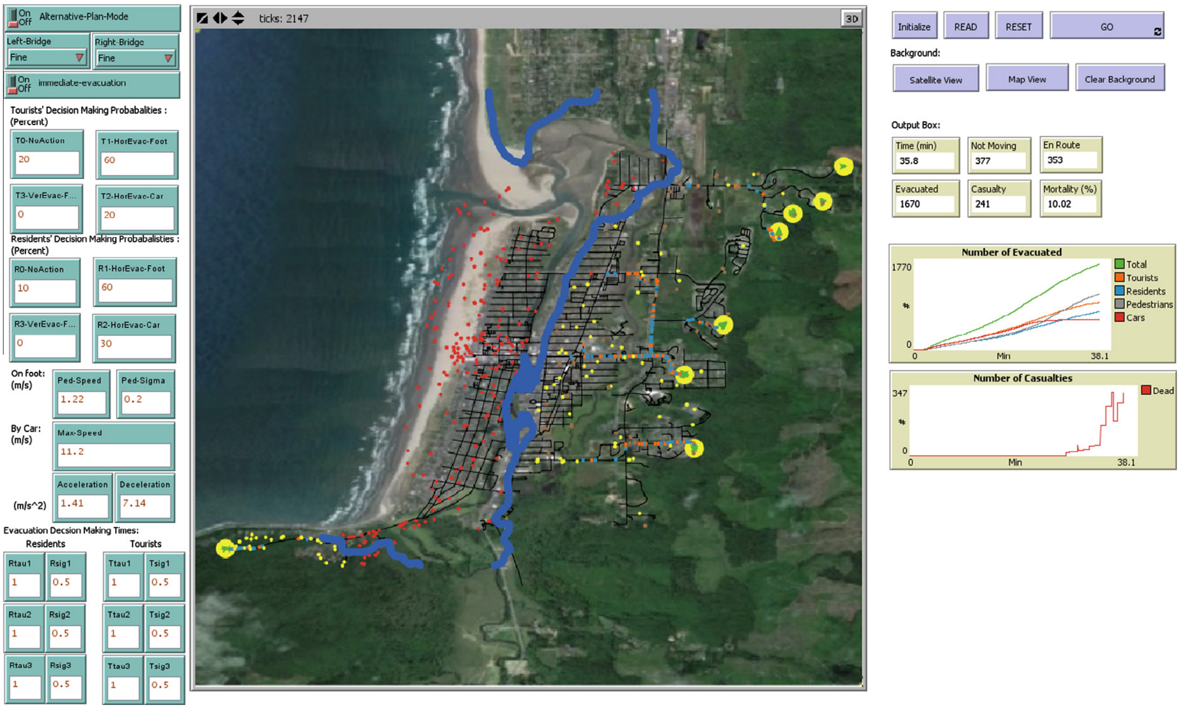


Fig. 3. The NetLogo tsunami model of Seaside, Oregon.

2.2.3. Tsunami shelters

For this simulation, we identified eight evacuation areas located outside of the tsunami inundation zone based on the horizontal evacuation maps provided by the Oregon Department of Geology and Mineral Industries (Priest et al., 2013). For these simulation, we assume that there is unlimited capacity for people and cars at the shelter areas. In addition to these eight locations, we include three fictitious vertical evacuation structures within the inundation zone for some simulations. Vertical evacuation shelters have been placed in the areas where population of evacuees were concentrated the most. Here, we assume an unlimited capacity for sheltering and that the shelter is of sufficient height and strength to withstand the tsunami forces (FEMA, 2008).

2.2.4. Tsunami inundation

For the tsunami inundation, we simulate the Cascadia Subduction Zone event using the ComMIT/MOST model developed by NOAA and used for tsunami evacuation mapping in the US (Titov and Gonzalez, 1997). For this simulation, the maximum extent of inundation is consistent with estimates of the inundation for a probable event with approximately a 500 year return interval (Venturato et al., 2007). The model provides time variation of the flow depth and speed throughout the model domain. We note that these simulations use a ‘bare earth model, meaning that the influence of large roughness features such as buildings and groups of buildings are not included in the flow. It is likely that the constructed environment would increase flow speeds along evacuation routes running parallel to the main flow direction (Park et al., 2013).

2.3. Agent decisions

For a given population, road network, tsunami shelter, and inundation scenario, the model can be run with several options related to the human decisions and are described below.

2.3.1. Agent choices: Options 0, 1, 2, and 3

Each agent can make one the following choices. Option 0 is no action where the agent chooses not to evacuate. We assume that the agent is located at ground level and outside. In other words, we assume they are not in their car, nor are they in a building that would provide them shelter if no actions were taken. Option 1 is horizontal evacuation on foot. For this option, we assume that the agent is knowledgeable of the most efficient route to the nearest tsunami shelter outside the inundation zone. Option 2 is horizontal evacuation by car. Similar to Option 1, we assume that the agent knows the most efficient route. We also assume that the car is located nearby and the time that it takes to go to the car is modeled in the differences in milling time as discussed in the next section. Option 3 is vertical evacuation. For this option, an agent may choose to seek refuge in a vertical evacuation structure if that is a closer alternative. For the case of Seaside, OR, an agent assigned Option 3 will not cross the river toward the hazard area and instead will seek refuge via horizontal evacuation.

The probability for choosing an option can be specified for each simulation for the two population classes. For example, for a given simulation, the resident population may have 5% who choose no action (Opt 0), 50% who choose horizontal evacuation on foot (Opt 1), 25% who choose horizontal evacuation by car (Opt 2), and 20% who choose vertical evacuation on foot (Opt 3). The tourist population can have a different distribution to account for differences in tsunami awareness, access to vehicles, local route knowledge or other factors. It is possible to assign a 100% probability to both classes to limit only one option. This could be used to force, all agents to choose horizontal evacuation to test the current evacuation plan for a community (Opt 1 = 100%). As mentioned earlier, we assume that agents act independent of others (there are no social groups).

2.3.2. Decision time with variations

One of most important decisions that evacuees should make is the departure time. We continue to confront important challenges regarding evacuation lead times, the accuracy and reliability of the information that is being communicated, and in our ability to elicit the appropriate response from decision makers and the general public (NRC, 2006). While much research has been done related to hurricane and flood preparation time (Lindell et al., 2002; Kang, 2004), research is needed to assess the extent to which evacuation preparation time has occurred for rapid-onset hazards, such as tsunamis (NRC, 2006). The timing of evacuee responses can have a significant effect on traffic congestion and bottlenecks during an evacuation (Naser and Birst, 2010). The model simulates the evacuation time in two different ways:

- Immediate evacuation: in which evacuees start the evacuation immediately after the Tsunami alarm.
- Delayed evacuation: in which evacuees postpone their departure time. In this work, as suggested by Mas et al. (2011), agents follow a Rayleigh distribution for deciding their evacuation departure time.

The total decision time for an evacuee is a complex process involving psychological preparation for the emergency evacuation involving a series of stages to confirm whether there is an immediate threat and what action should be taken (Sorensen, 2000). For this model, we simplify and combine these processes by specifying a delay time (τ) and a probability of action using a Rayleigh distribution (Tweedie et al., 1986; Lindell and Prater, 2007) with a scale parameter σ given as

$$P(t) = \begin{cases} 0 & \text{if } 0 < t < \tau \\ 1 - e^{-(t-\tau)^2/(2\sigma^2)} & \text{if } t > \tau \end{cases}$$

where t is the time in minutes after the earthquake. Both τ and σ can vary for each option and can vary between population class, allowing the model to evaluate mortality as a function of the decision time for a fairly wide range of conditions. Fig. 4 shows an example with $\tau = 5$ min (that is, the decision making process takes at least 5 min for all agents) and a range of values for σ. As the value of σ increases, the distribution times of agents taking action increases. For example, when $\sigma = 1.0$, it takes $\tau + 3.0$ min for 99% of the agents to have taken action. When σ increases to 4.0 to initiate an action, only 50% of the agents will have taken action after $\tau + 4.7$ min and 99% will have taken action after $\tau + 12.1$ min. Table 1 summarizes the variation in time required as a function of σ.

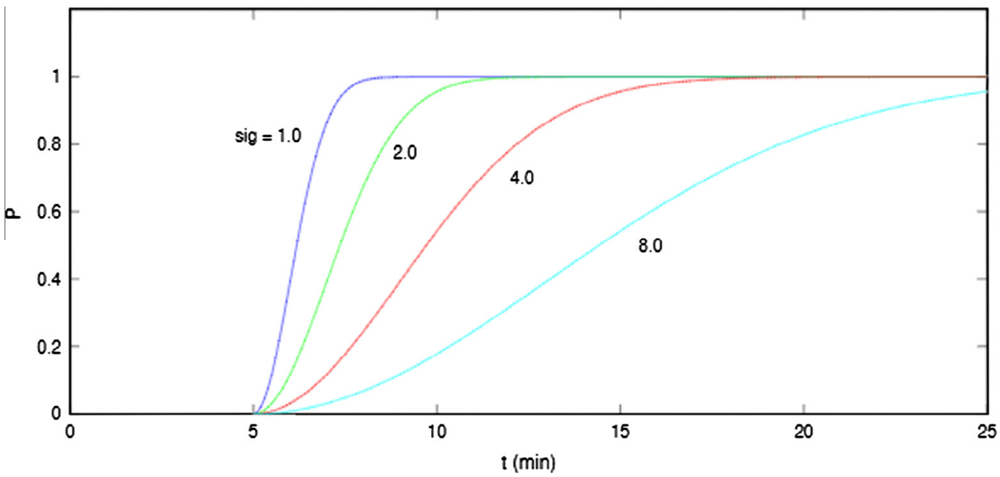


Fig. 4. Use of τ and σ to represent milling time and variation in milling time. For this example, τ = 5 min.

Table 1
Time in minutes required for agents to initiate an action after the initial delay time as a function of sigma assuming a Rayleigh distribution.

σ	Percent of agents initiating actions		
	50%	95%	99%
1.0	1.2	2.4	3.0
2.0	2.4	4.9	6.1
4.0	4.7	9.8	12.1
8.0	9.4	19.6	24.3

2.3.3. Evacuation speed

Evacuation speed is a critical parameter to estimate mortality rates for near-field tsunamis (Wood and Schmidtlein, 2012). For agents traveling on foot, we assign a mean speed u, of $u = 1.5$ m/s for a fast walk (Knoblauch et al., 1995). We include a normal distribution to represent a range of walking speeds for a given population in Fig. 5. When sig = 0.2 m/s, this would cover a range from slow walk (1 m/s) to slow run (2 m/s). Typical jogging paces range from 15 min/mile (1.8 m/s) for a slow run to 10 min/mile (2.7 m/s) for a moderate run (TRB, 2010). An extremely fast running pace would be equivalent to a 7 min/mile (3.8 m/s). The agent is assigned a constant walking speed, and there is no effect from topography or influence from the speed of other agents.

In modeling the evacuation by car, we assume that the time required to get to their car is a function of the τ and σ. One exception would be for agents not on a grid such as agents on the beach at the start of the simulation. In this case, agents are assigned the walking speed and take a direct path to the road network after which time their classification changes and the agents speed is governed by the car model. In this model, we set the maximum speed limit, and acceleration and deceleration limits. We assume that there is no damage from the local earthquake (the roads are clear), no accidents, and unlimited capacity in the evacuation areas.

In this work, we considered a variable maximum speed for cars. To incorporate car–car interaction, cars speeds are calculated regarding how dense the cars are surrounding you. Cars speed up with the variable acceleration, which can be adjusted in the model, if there is no car ahead. Otherwise, they slow down to the speed of their adjacent car. According to previous efforts regarding traffic flow simulation in NetLogo (Wilensky, 1999), the state of panic in evacuation simulation correlates with acceleration and deceleration of cars. In case of evacuation, acceleration and deceleration are much higher than the average, which typically results in much greater average evacuation time and traffic congestions.

2.3.4. Casualty model

The casualty model is based on a critical water depth, h_c, defined as the water depth above the local grade. If the water depth exceeds h_c at an agents location, then the agent is counted as a fatality. Although studies have shown that many factors

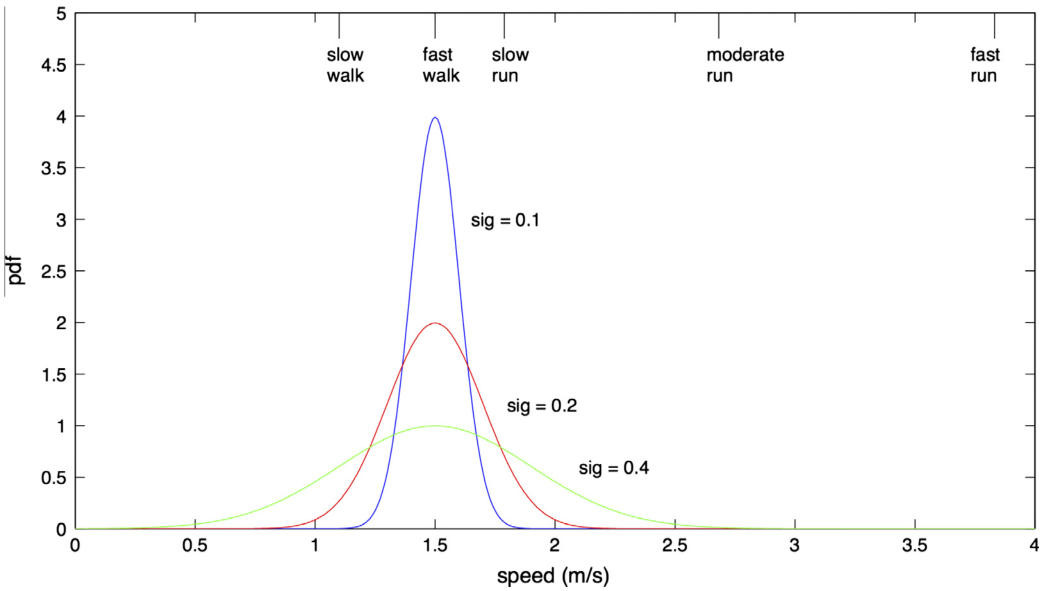


Fig. 5. Normal distribution of pedestrian walking speed.

determine the probability of drowning, including age, water temperature, mental well-being (Yeh, 2010), the critical depth is a reasonable first approximation for the purposes of this model. Future iterations may contain a more complex casualty model involving a persons shape and the flow speed conditions (Yeh, 2010).

3. Study area

3.1. CSZ scenario

For this project, we model the nearfield tsunami arising from the Cascadia Subduction Zone (CSZ) shown in Fig. 6(a). The Cascadia Subduction Zone (CSZ) measures 1000 km in length and extends from the Mendocino Ridge off the coast of northern California to northern Vancouver Island, British Columbia (Fig. 6). A near-field event generated from the CSZ is expected to cause widespread damage to the northwest Pacific coast of North America with the first waves arriving in the tens of minutes. The last great CSZ event occurred more than three centuries ago on 26 January 1700 and was a full length rupture. The event is estimated to have had a moment magnitude (M_W) between 8.7 and 9.2, and a slip of 19 m (Satake et al., 2003). The average recurrence interval between full length CSZ events is 530 years, and the next event is estimated to have a 7–12% probability of occurrence by 2060 (Goldfinger et al., 2012).

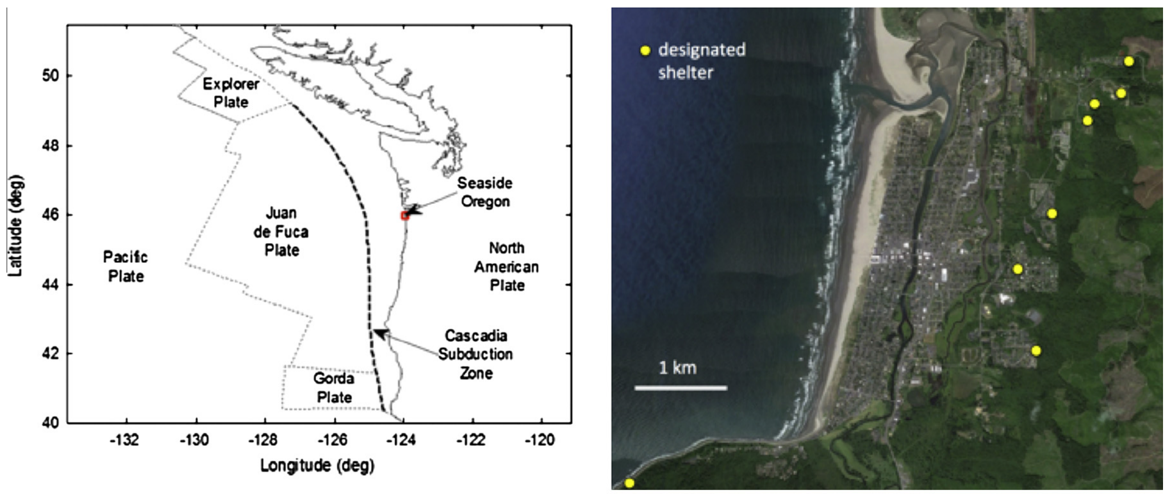
3.2. Seaside, OR

The city of Seaside (Fig. 6(b)) was chosen for this study because it has been identified as having a high risk to the CSZ tsunami (Wood, 2007). This is due, in part, to the proximity to the CSZ (Fig. 6(a)), fairly flat topography, and the location of the tsunami shelter areas at more than 1.5 km from the shoreline. The Necanicum River which flows from south to north, bisecting the city, is spanned by 5 bridges and creates additional complexity for the multi-modal evacuation. The current tsunami evacuation plan for the area calls for horizontal evacuation on foot, and the option of vertical evacuation has only be discussed in recent years as a possible option. No comprehensive studies exist which explore the feasibility of vertical evacuation. In addition to Seaside, there are several other towns along the coast with a high risk to nearfield tsunamis, including Ocean Shores, WA, and Long Beach, WA (Wood and Schmidtlein, 2013).

4. Model results

4.1. General behavior of model

Fig. 7 shows an example of the model simulation starting with time $t = 0$ representing the end of the initial shaking due to the earthquake. For this simulation, we assume that no evacuation takes place during the earthquake itself. Fig. 7(a) shows the initial population divided between residents (yellow) and tourists (brown). The agents have the 4 options as described earlier, and they evacuate to either vertical evacuation structures within the inundation zone or to designated shelter outside the zone. Agents change color depending on their option and mode of transportation (Fig. 7(b) and (c)). After approximately



(a) (b)

Fig. 6. (a) Location of Cascadia Subduction Zone in North Amerak and Seaside study area; (b) overivew of Seaside study area with designated horizontal evacuation shelters.

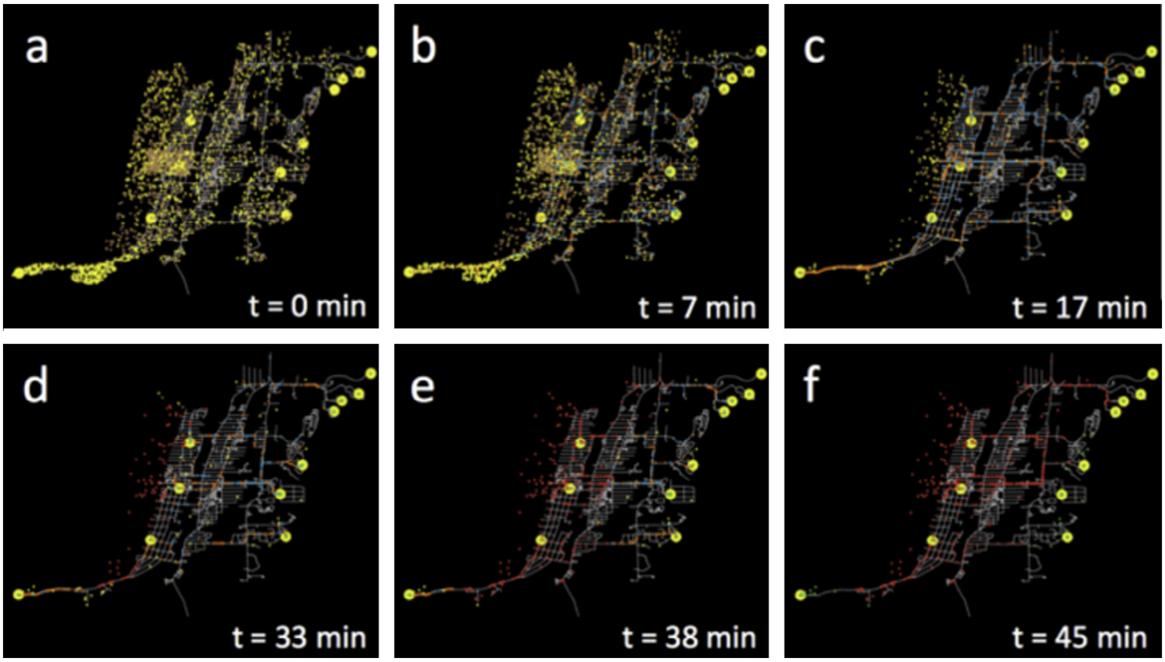


Fig. 7. Example of model simulation.

30 min, the tsunami reaches the shore and fatalities occur when the inundation level exceed 0.5 m (Fig. 7(d)). The tsunami has inundated the first part of Seaside after 38 min, crossing the Necanicum River (Fig. 7(e)), and finally the tsunami reaches the runup limit approximately 1 km inland, 12 min after reaching the shoreline.

4.2. Model sensitivity

4.2.1. Model sensitivity to critical depth

Fig. 8 shows the mortality rate as a function of critical depth, h_c, used as the criteria to determine the casualty of an agent. For this simulation, all agents were prescribed Option 1 (horizontal evacuation on foot), with a walking speed of 1.1 m/s and immediate evacuation ($\tau = 0, \sigma = 0$). Under this scenario, the models predicted similar results for a range of depths from $0.5 < h_c < 3$ m. Although our model results were not sensitive to the choice of h_c, we can seek improvements to the model by considering alternative casualties models that consider age and gender (Yeh, 2010), hydrodynamic forces (Koshimura et al., 2006), and other factors (Jonkman et al., 2008).

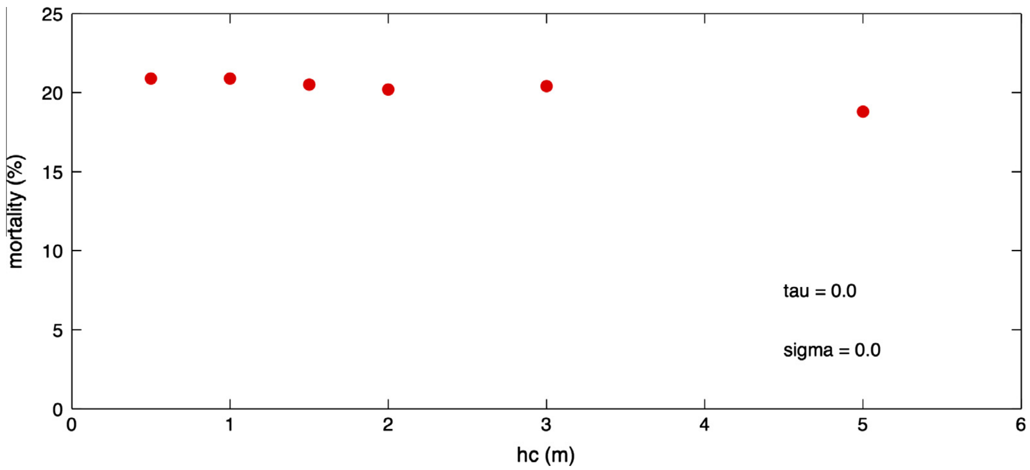


Fig. 8. Mortality rate as a function of critical depth h_c (m).

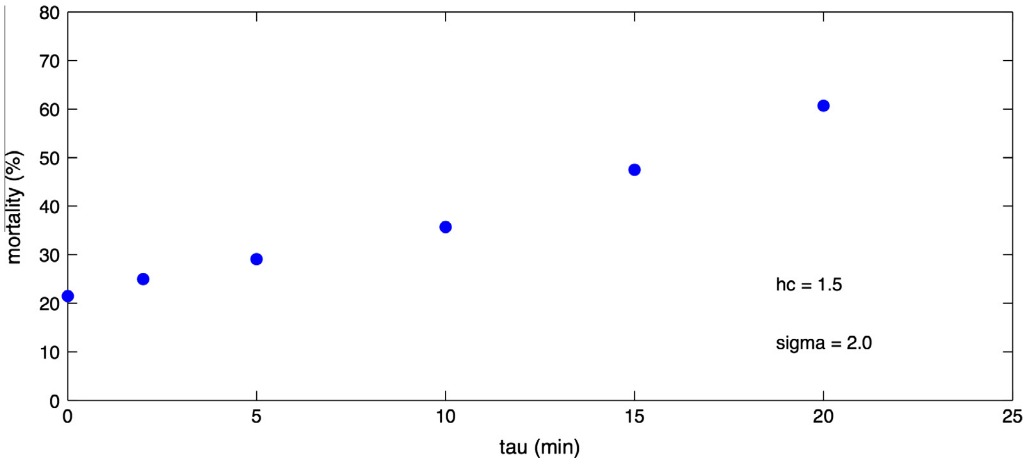


Fig. 9. Influence of delay time (τ) on mortality rate with fixed scale parameter ($\sigma = 2.0$).

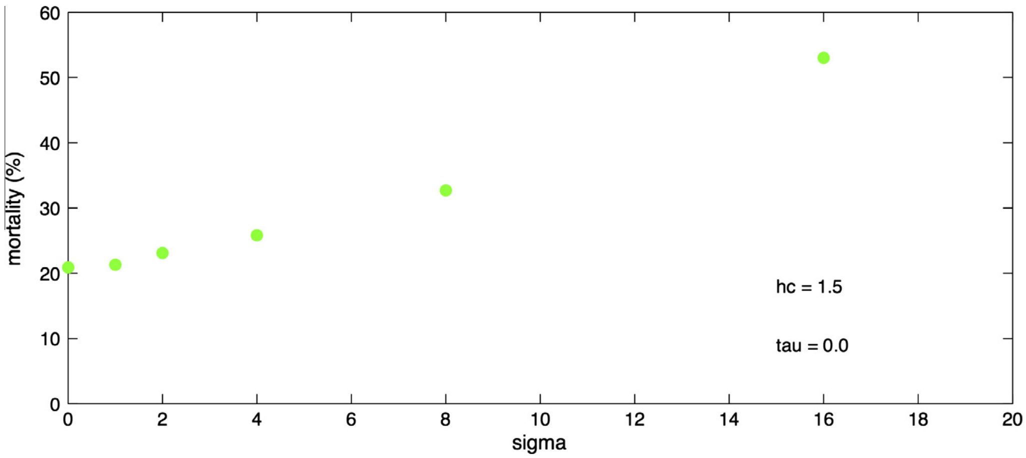


Fig. 10. Influence of scale parameter (σ) on mortality rate with fixed delay time ($\tau = 0$).

4.2.2. Model sensitivity to τ and σ

As discussed in Section 2.3.3, we model the decision time with two parameters τ and σ, where τ represents the delay time (no agents evacuate for $t < \tau$) and σ is a scale parameter representing the variability in the cumulative probability distribution based on a Rayleigh distribution.

Fig. 9 shows the model sensitivity to τ. For this scenario, σ is kept constant ($\sigma = 2.0$) and τ varies from 0 (immediate evacuation) to 20 min. As expected, the mortality rate increases significantly as the delay time increases. Fig. 10 shows the model sensitivity to σ. Here, τ is set to zero, and σ varies from 0 (immediate evacuation) to $\sigma = 16$. As expected, Fig. 10 shows a large increase in mortality rate as the variability in departure times increases. In reality, both tau and sigma can be varied based on an agents classification (e.g., resident or transient) and evacuation choice.

4.3. Evacuation options

4.3.1. Option 1: Horizontal evacuation on foot

Fig. 11 shows the effect of the walking speed on mortality rate where the walking speed is modeled as a normal distribution with mean speed u and standard deviation sigma (sig). For these simulations, we use $\tau = 5$ min delay from the time of the earthquake to the start of evacuation with a $\sigma = 2$ (e.g., 95% of the population would have taken action approximately 10 min after the earthquake). There were $N = 2405$ agents and we assumed no difference between tourists and residents. In this figure, the mean walking speed varies from 1.0 to 2.25 m/s and three values of sig were used: sig = 0.1 (circles) representing a low variance (that is, most evacuees will move near the mean speed), sig = 0.2 (square), sig = 0.4 (diamond).

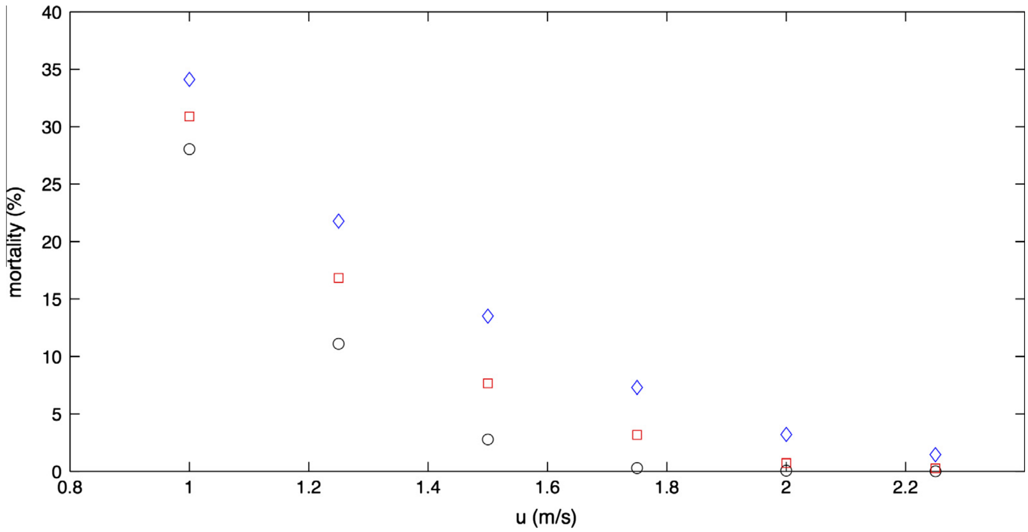


Fig. 11. Influence of mean and variance of walking speeds on mortality rates considering horizontal evacuation on foot. Circles (sig = 0.1), squares (sig = 0.2), diamonds (sig = 0.4).

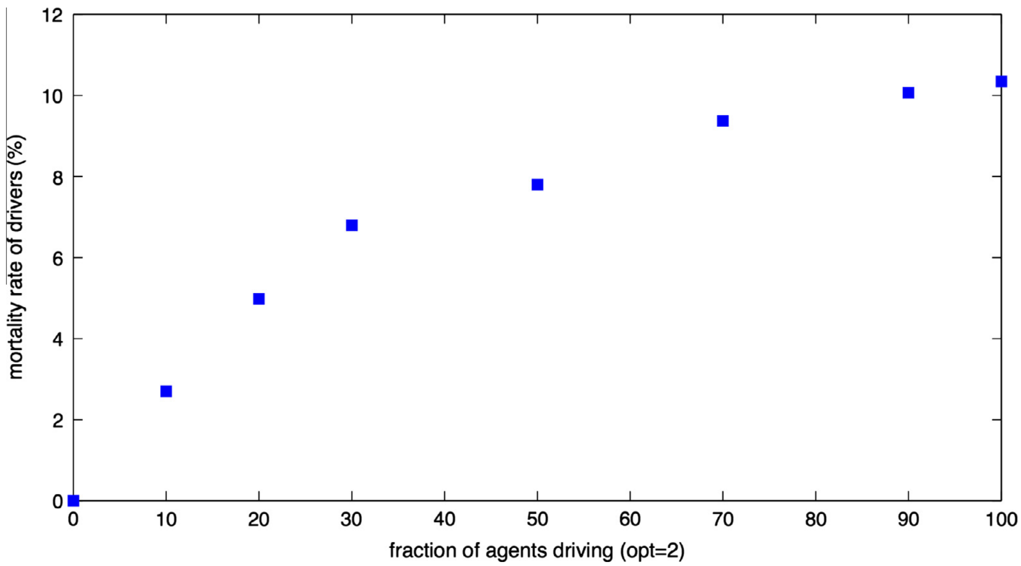


Fig. 12. Mortality rate of drivers as a function of percent of agents choosing to evacuate by car.

As expected, Fig. 11 shows that the walking speed has a strong influence on the mortality rate. For walking speeds in excess of 2.5 m/s (running), the mortality rate was near 0%, and then the mortality rate increases sharply to above 25% when the speed drops to 1.0 m/s (slow walk). Moreover, the variability in walking speed has a strong effect. For example, at $u = 1.5$ m/s in the top figure, there is about a 5-fold increase in mortality if there is a wide range of walking speeds (i.e., sig is increasing from 0.1 to 0.4). This highlights the need to look at mobility issues for effective tsunami evacuation planning.

4.3.2. Option 2: Horizontal evacuation by car

Traffic congestion conditions will likely increase as the number of vehicles on the road at any one time increases (Spiess, 1990). To test the capability of the model to simulate traffic congestion using NetLogo model library: Traffic Basic, we considered agents choosing horizontal evacuation by either foot (Option 1) or by car (Option 2), varying the percentage from 0 (on foot) to 100% (by car). Fig. 12 shows the mortality rate of agents who evacuated by car as a function of the percent of agents choosing that option. The figure shows that the mortality rate of drivers increases significantly as more and more agents choose to evacuate by car because congestion increased on several of the roads leading to the evacuation shelters.

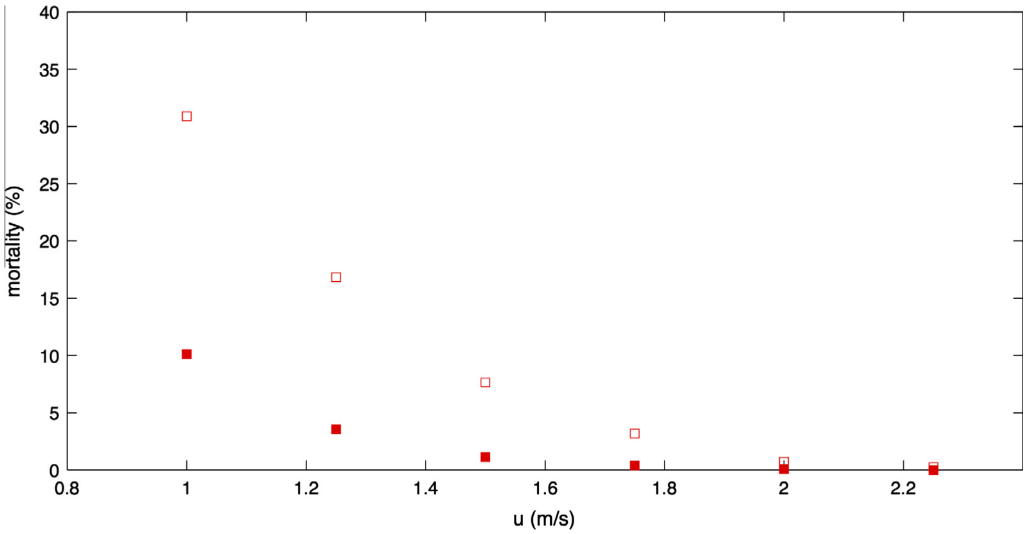


Fig. 13. Influence of vertical evacuation options on mortality rates as a function of walking speed. Open symbols for horizontal evacuation (Opt 1), solid symbols for vertical and horizontal evacuation (Opt 2).

For example, the mortality rate of drivers increases by a factor 3.5 as the percent of agents evacuating by car increases from 10% to 70%.

We note that in this scenario, we made several assumptions that minimized congestion and increased survivability of agents traveling by car, including unlimited car capacity at each tsunami shelter and basic interaction of cars and pedestrians. Furthermore, we did not include a probability of accidents or breakdowns that would increase delays, nor did we attempt to model agents who would abandon their cars and continue on foot. Factors such as bridge failure and landslides due to the earthquake or other technological failures such as signal timing that would affect surface transportation were not included. Future efforts will have to consider these factors to develop realistic scenarios for multi-modal tsunami evacuation.

4.3.3. Option 3: Horizontal and vertical evacuation

For the case of $u = 1.5$ m/s, there is a 7-fold decrease in the mortality rate with the inclusion of vertical evacuation structure. Fig. 13 shows the influence that three vertical evacuation structures would have on the mortality rate for walking speeds in the range $1 < u < 2.25$ m/s for the case of $\tau = 5$ and $\sigma = 2$ as seen previously in Fig. 11. This dramatic decrease in the mortality rate with the inclusion of vertical evacuation structures highlights the need to further investigate the role that the vertical evacuation option may play in Seaside and other coastal communities threatened by near-field tsunami hazard. Vertical evacuation, where evacuees seek refuge in a structure within the inundation zone, has been shown to be effective during the 2011 Tohoku tsunami for cases where the evacuation structure was of sufficient height to avoid overtopping and sufficient strength to withstand the hydrodynamic forces (Chock et al., 2013).

5. Summary, conclusions and future work

This paper presented a near-field multimodal tsunami evacuation study through an agent-based modeling environment. The research questions were how variations in decision-making time (i.e., τ and σ) and the choices of transportation modes impact the coastal community life safety (i.e., mortality rate) using Seaside, Oregon as a case study. We used an agent-based modeling environment NetLogo to model and simulate the (1) the sensitivity of mortality rate to the tsunami wave critical depth (h_c); (2) the mortality rate to variations in decision-making time (τ and σ); and (3) the mortality rate to the choice of evacuation options (i.e., horizonal evacuation on foot, horizontal evacuation by car, and both horizontal and vertical evacuation).

The results show that (1) the mortality rate is sensitive to the decision-making time τ which is a "delay time" or "milling time" and the scale parameter σ; (2) the variations in walking speed has significant impacts on the number of casualties in the horizontal evacuation on foot; (3) the provision of vertical evacuation structures is very effective to reduce the mortality rate; and (4) the mortality rate increases as the number of evacuee who used automobile to evacuate increases as a result of congestion and bottleneck effects.

Future research will be based on current work and extended to include (1) partial damage to the transportation network (i.e., single bridge failure or combination of bridge failures after an earthquake) considering bridge vulnerability; (2) transportation behavioral models such as a modified Greenshields model to better capture the bottleneck effects; (3) realistic interaction rules among agents (i.e., pedestrian and car interaction) to provide more accurate representation of the multimodal evacuation; (4) how mortality rate varies when the population (residents and tourists) distribution is different (i.e., an earthquake happens over the day or during night); (5) incident scenario analysis such as people who used their cars to evacuate at the beginning but abandon the car in the middle of congestion and changed to horizontal evacuation on foot; (6) different information provision and propagation strategies (i.e., communication tower or mouth to mouth) to increase the evacuation efficiency and congestion mitigation strategies (i.e., contra-flow lanes); and (7) validation of the agent-based model using empirical data from 2011 Tohoku event for multiple cities in Japan.

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