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Understanding the Multimodal Evacuation Behavior for a Near-Field Tsunami

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Abstract

This paper presents an agent-based tsunami evacuation modeling (ABTEM) framework in Netlogo to analyze the impact of various multimodal evacuation behaviors on life safety for a near-field tsunami. The objective of this work is to investigate how: milling time, choice of modes (i.e., walking and automobile), and critical variables involved in an evacuation scenario (e.g., walking, driving speed), affect life safety. Using the city of Seaside, Oregon, which is one of the most vulnerable cities on the Oregon coast, as a study site, different evacuation scenarios are included in the model to assess the impact of parameters involved on the mortality rate in a tsunami evacuation event. The results show that: choice of evacuation mode strongly and non-linearly influences the expected number of casualties; use of vehicles leads to the creation of congestion and bottlenecks, and thus, higher mortality rate; the mortality rate is strongly correlated with milling time; and the mortality rate is sensitive to the variations in average walking speed of the population. The results will help emergency managers, community leaders, and city and state agencies in their decision-making process for creating effective and efficient evacuation plans to increase life safety and community resilience.

The Pacific Northwest region of the U.S.A. is highly prone to a potential earthquakes resulting from the Cascadia Subduction Zone (CSZ) (*1*), which could initiate a near-field tsunami that would threaten the life safety of the coastal community (*2*). A near-field tsunami is one expected to come onshore within 20 to 40 minutes after an earthquake, as opposed to a far-field tsunami or other natural disaster which may take hours, or in some cases, days, to affect the area of interest, allowing longer lead time to issue warnings and evacuation notices (*3*). Short preparation time adds considerable complexity to the evacuation scenario, and even a well-established agency like the Pacific Tsunami Warning Center might not be able to provide sufficient warning time for the event (*4*).

In 2004, the Indian Ocean earthquake and tsunami resulted in the deaths of more than 230,000 people; and in 2011, the Tohoku earthquake and tsunami resulted in over 16,000 fatalities. These casualties resulted from a wide variety of reasons including people's inability to evacuate the affected zones and areas subject to tsunami inundation. However, since it is practically unrealistic to build all structures in a way that resists tsunami forces, evacuation is likely to be one of the most efficient and and effective protective action to reduce fatalities, especially for rapid-onset types of disasters. Tsunami evacuation modeling is a newly developing methodology to evaluate the impacts of heterogeneous decision-making on the survivability and effectiveness of evacuation plans and to set land use and construction policy in areas subjected to devastation. Although tsunami evacuation models exist, many of the current models are essentially static and there has been inadequate effort to assess the evacuation behavioral variables included in agent-based models such as milling time and choice of evacuation mode.

Near-field tsunami evacuation is a particularly vexing problem because of the multi-hazard nature of these rare events (*5*). Most tsunamis are accompanied by preceding earthquakes which severely damage infrastructure and buildings (*6*, *7*). There is generally a very short lead time following the earthquake (*6*, *8*). Thus, the uncertainties associated with milling time (*9–13*), self-initiated evacuation (*14–18*), altruistic behavior of evacuees (*19*), and multimodal transport choices (*20*) add complexities to

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the problem. The anticipation of a near-field tsunami from the CSZ is relatively new, and prior mitigation plans were based on far-field tsunami scenarios (*21–23*). The rarity of this event means there is little memory of past events or culture of tsunami preparedness in the Pacific Northwest (*12*, *24*).

Objectives

The unknowns and complexities of evacuation scenarios, both from socio-psychological and engineering perspectives, necessitates further investigation of the impact of different elements, such as evacuation mode, milling time, and walking speed on evacuation life safety. Using the city of Seaside, OR, where a sizable population is threatened by a near-field tsunami in the foreseeable future (*10*), this research aims to model the evacuees' decision-making behavior as well as the physical characteristics of the evacuees, and consequently their impact on the mortality rate of the evacuation. The results of this research will enlighten policy-makers and city planners on the behavior of the evacuation and the impacts of the factors involved in similar type of evacuation scenarios from a rapid onset disaster on the mortality rate, to inform their evacuation plans and strategies.

Contributions

One of the main contributions of this work is to show that a successful evacuation is more likely to be multimodal. In addition, this study shows the significance of such evacuation models and simulations to draw policy-level disaster mitigation insights. Moreover, this work sheds light not only on the fact that evacuation characteristics (e.g., walking speed and milling time) impact the efficiency of evacuation, but also, and more importantly, to what extent and how they affect the evacuation process and the resultant mortality rate.

Organization of the Paper

This paper begins by presenting a thorough review of the literature on related topics in the next section. Then it introduces the ABTEM framework and the methodology to achieve the defined objectives, along with a description of the study site. The results of this study are presented next, which involve a detailed explanation of the evacuation behavior and the impacts of the factors involved. Finally, following the results, the paper concludes with a section which summarizes the research and discusses the major findings from the case study, along with a description of the challenges and complexities ahead in agent-based tsunami evacuation modeling and simulation.

Literature Review

Because of the life-threatening risk posed by various disasters, evacuation is likely to be a required or often recommended protective action to improve life safety. However, the unique warning time for every hazardous event creates challenges for efficient evacuation. Evacuation time and distance vary between different disaster types, ranging from seconds and meters in earthquakes and building fires to hours/days and hundreds of miles in hurricane evacuations. This difference justifies the use of vehicles for hurricane evacuations, but not necessarily for the immediate evacuations such as earthquake and building fire. Near-field tsunamis present a complex case of multimodal evacuation because the tsunami wave arrives within 20-40 minutes after the earthquake and can travel several kilometers inland. Therefore, transportation evacuation modes may be multimodal rather than a single mode, and evacuees may face choices such as when to leave (preparation or milling time), how to leave (alone or in group), what mode of transportation to use (on foot or drive), and where to go (destinations). The multimodal choices of evacuation in these cases necessitates extensive research on the modeling of traffic flow and crowd dynamics in emergencies. In the following subsection, a comprehensive literature review is presented on current evacuation modeling techniques as well as agent-based modeling methods.

Evacuation Modeling

A mass disaster episode is the result of an interaction between two highly complex, dynamic and generally hard-to-predict phenomena: a human community and a hazard (*25*). Because of the complexity of human behaviors, the system can rarely be described as mathematical equations. Various techniques have been proposed to model this complex system. The existing efforts are summarized into the following categories (*26*, *27*):

Flow-based modeling: Flow-based models are called macroscopic models, and use the density of nodes in continuous flows. The underlying logic is derived from an analogy between the fluid and particle motions. Their characteristics are predefined; thus, all the particles behave in the same way, which is the major drawback of this approach. One example is EVACNET4 (*27*).

Cellular Automata: In this type of model, space is discretized, which differentiates it from all other modeling techniques (*27*). A matrix is created to plot areas in a two-dimensional array. In the simulation, the occupants move from one position to one of the adjacent nodes in a predefined time frame. Microscopic and macroscopic analysis are both permitted. This method is easy to implement but fails to replicate the complex movement of people, especially the

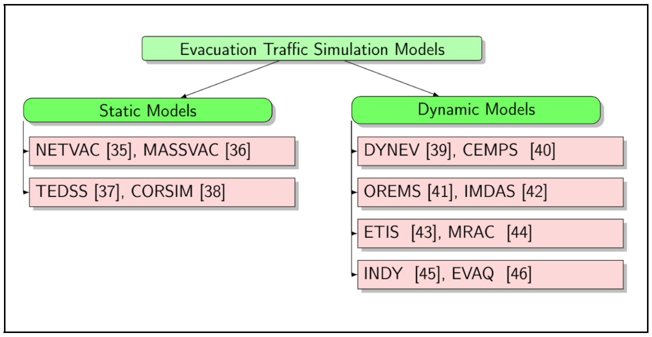

Figure 1. Evacuation traffic simulation models.

two-dimensional nature of pedestrian movements. Furthermore, due to the grid-shaped network, it is rather hard to depict the different speeds and interaction between people. One example is EGRESS (*28*).

Agent-based modeling: The multi-agent system (MAS) approach is deemed the most realistic solution due to its capability to model each individual with unique characteristics and interactions with the surrounding environment. Representative examples are SIMULEX (*27*), the latest version of EXODUS (*27*), and PedGo (*29*).

Other than the methods mentioned above, in the past decades, approaches such as static networks, dynamic networks, and dynamic traffic assignment have been widely employed to model the evacuation scenario (*20*, *30*). Wood et al. (*10*, *11*) used a least-cost distance (LCD) model, which focuses on evacuation landscape features and uses geographic information systems (GIS) to find the shortest path to safe spots from hazard zones. Similarly, GIS-aided shortest path analysis has been the centroid of most evacuation and life-safety analysis works (*4*). Along with static methods, dynamic route assignment (*31*, *32*) and mathematical modeling of evacuation (*33*) have also been implemented to minimize the evacuation time. Figure 1 highlights some of the relevant evacuation traffic simulation models (*34–46*).

Each modeling method has its pros and cons when trying to simulate real-world situations, However, the shortcoming of most of the existing static models is that they typically neglect congestion dynamics, time-of-day (*47*), and panic or herding behavior (*47*, *48*). To partially overcome these limitations, agent-based modeling and simulation (ABMS) is introduced to capture dynamic and complex systems where humans and their decision making processes are involved, especially in a near-field tsunami evacuation (*7*, *20*, *49*, *50*).

ABMS

ABMS is an object-oriented modeling technique to simulate various independent entities as well as their interactions with each other and the simulation environment to observe the behavior of the system as a whole (*51*). The benefits of ABMS over other modeling techniques can be highlighted in three statements (*52*): (i) ABMS captures emergent phenomena; (ii) ABMS provides a natural description of a system; and (iii) ABMS is flexible. The ABMS technique has already been employed in several studies. For example, Chen and Zhan (*53*) utilized ABMS to study the collective behavior of evacuee traffic flows. Nagarajan et al. (*54*) developed a multi-agent simulation model and deployed it in a warning information dissemination study. Mas et al. (*48*, *55*) proposed an evacuation model integrated with a numerical simulation of a tsunami and a casualty estimation evaluation to study life safety considering evacuees' decision-making regarding the evacuation start time. Liu et al. (*56*) formulated a dynamic route choice model in a multi-agent system, considering group evacuation. Uno and Kashiyama (*57*) proposed a multi-agent emergency evacuation simulation system. Dawson et al. (*51*) adopted a dynamic agent-based model to manage flood incidents.

Recent agent-based modeling efforts to simulate hurricane and tsunami evacuation in coastal communities, despite the observations that have shown vehicular evacuation from low-topography areas (*48*), left additional spaces for improvements to analyze the multimodal behavior in a near-field tsunami evacuation, which is the primary motivation and contribution behind this work.

Methodology: Agent-based Tsunami Evacuation Model

This study is built on top of the underlying agent-based tsunami evacuation model developed by Mostafizi et al. (*7*, *58*) and Wang et al. (*20*). The coded platform consists of five different components: the population distribution model, the transportation network, evacuation shelters, the tsunami inundation, and the casualty model. The simulations are capable to capture evacuees' socio-demographic characteristics which are related to the evacuees' decisions, such as choice of evacuation mode, milling time which marks the start time of their evacuation, and walking speed which represents the physical ability of the evacuee. The platform is capable of simulating a near-field tsunami evacuation scenario with variable tsunami and behavioral characteristics. The details of each component as well as model behavior are documented by Mostafizi et al. (*7*, *58*) and Wang et al. (*20*). In addition, the city of Seaside, OR, has been used as a case study because of its high risk of experiencing a tsunami in the foreseeable future.

Figure 2 summarizes an hour of simulation process in six steps. Figure 2*a* shows where the initial population

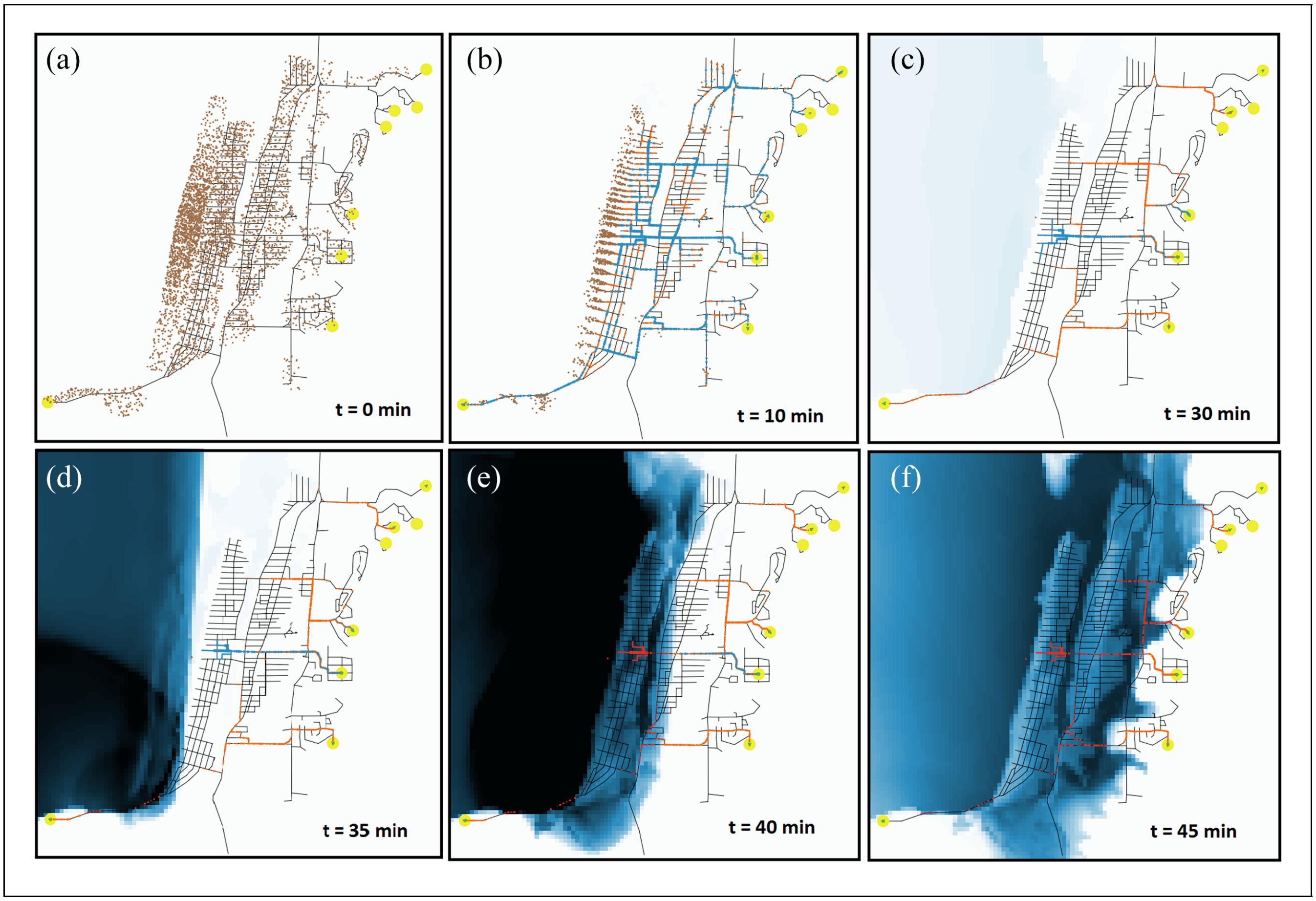

Figure 2. Example of model simulation (7): (*a*) t = 0; (*b*) t = 10; (*c*) t = 30; (*d*) t = 35; (e) t = 40; (*f*) t = 45.

(brown) are distributed at time (t) = 0. The ocean is on the left, and the evacuation shelters (yellow) are placed outside the inundation zone on the right. After the earthquake, depending on the milling time, people evacuate either by car (blue) or on foot (orange), shown at t = 10 (Figure 2*b*) and t = 30 (Figure 2*c*); and the tsunami inundates the city from about t = 35 to t = 45 (Figure 2*d–f*), causing casualties (red) (*7*).

The model can simulate several options related to human decisions and mobility characteristics. For instance, evacuation mode choice is one of the critical decisions, independently made by each agent, which have major impacts on the overall evacuation life safety. Equally important, and especially for near-field tsunami evacuations with less preparation time, milling time is another critical variable that is associated with evacuees' decision-making process. To capture the evacuation preparation time, as suggested by Mas et al. (*48*), departure times in this work follow a Rayleigh distribution where values of τ and σ respectively represent the minimum milling time and the spread of the departure times. The larger is σ, the larger the tail of the distribution towards later departure times will be.

Two other mobility characteristics affecting the efficiency of evacuation and the mortality rate of the scenario are the walking speed of the pedestrians and details of vehicular movement such as the maximum driving speed and other traffic flow variables. In this work, the movement of vehicles is governed by a classic car-following model, the General Motors model, the details of which are documented by Mostafizi et al. (*7*, *58*). In addition, it is assumed that walking speeds follow a normal distribution with varying mean.

Study Site

The city of Seaside, OR is chosen as the study site for this work, mostly because of its special geographical and topographical characteristics. The close proximity of the CSZ, which has a 7% to 12% probability of initiating a tsunami hazard by the year 2060, makes this city prone to tsunami evacuation in the foreseeable future (*2*). In addition, the existence of 10 bridges crossing two rivers, which flow from south to north, approximately 1.5 km inland from the shore, adds more complexity to the evacuation of the residents. On top of these, the flat topography of the city would allow the tsunami inundation to reach a long distance inland in a relatively short time, inundating the entire city in about 40 minutes in the extreme case. The population of Seaside is estimated to be 6,700 but is more than doubled by the numbers of tourists visiting over the summer. More detailed information about the study site is documented in the authors' previous works (*20*, *58*).

Data Quality

It should be noted that the results, and accordingly the insights drawn from these results, albeit informed by real-world circumstances and post-event surveys conducted in Samoa in 2009 (*13*) and Tohoku in 2011 (*59–61*), are simulation generated. Therefore, although the simulations are designed in such a way as to replicate real-world scenarios, the results are subject to the choice of behavioral and physical parameters in respective modeling scenarios. In addition, all the results presented in this work are averaged with a Monte Carlo simulation approach with 100 trials to account for stochasticity in the simulations.

Analysis of Evacuation Behaviors

Understanding of evacuation behavior is critical for emergency managers to develop an efficient and effective evacuation plan and consequently to minimize the loss of life. In this section, evacuation efficiency, under the influence of different control parameters, is assessed. Various factors can affect evacuation performance such as mode choices, minimum milling time, walking speed, maximum driving speed, car-following behavior, and critical tsunami inundation depth. These variables, directly and indirectly, affect the evacuation life safety. Therefore, the sensitivity analysis of the mortality rate of the evacuation against the factors affecting the efficiency of the scenario is presented.

Multimodal Evacuation: Shall We Walk or Drive?

The mode choice of the agents based on their decision-making attributes was implemented in the model by defining the percentage of agents choosing any particular evacuation mode. Studies have shown that the evacuees' mode choice has significant impacts on the mortality rate (*20*). To study the impact of driving and resultant traffic congestion on life safety, evacuation scenarios with varying percentages of pedestrians from 0% (all by car) to 100% (all on foot) were simulated. As shown in Figure 3, if it is assumed that the percentage of the agents who decide not to evacuate is minimal, an increase in the percentage of pedestrians will generally lead to much lower mortality rates. Officials generally do not recommend the use of cars for evacuation purposes since it tends to create bottlenecks and heavy congestion which will result in excessively long travel times (*62*).

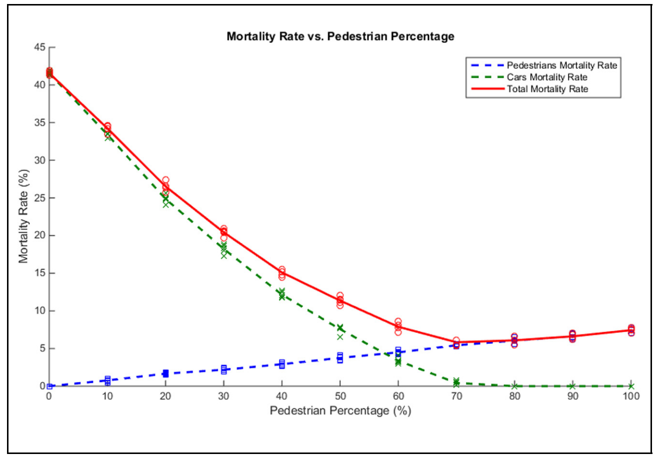

Figure 3. Impact of the percentage of pedestrians on mortality rate ($\bar{V}_{walk} = 3.5$ ft/s and $\tau = 0$).

In Figure 3, the green curve shows the contribution of use of cars to total mortality rate. It can be seen that the mortality rate of evacuees decreases exponentially as the percentage of pedestrians versus cars increases, since traffic congestion conditions are likely to increase as the number of vehicles on the road increases, especially on the roads and bridges that lead to the evacuation shelters (*62*). For example, the contribution of cars to the mortality rate increases by a factor of 5.5 if the percentage of evacuees who drive increases from 50% to 100%. On the other hand, the mortality rate of pedestrians linearly increases, shown in the blue curve, with an increase of evacuees who decide to evacuate on foot. Overall, the total mortality rate (red) reached its minimum with the percentage of pedestrians at 70%; when the percentage of pedestrians is higher than 70%, the total mortality rate changes slightly above the minimum value. This is because of the mobility advantage of vehicles over pedestrians, but only when there is no congestion. In addition, to capture the stochasticity because of the randomly drawn walking speed of the evacuees and the spatial variation agents with different decisions, the mortality rates are the average of 10 simulation runs.

Milling Time and Its Sensitivities

The milling time in this study is governed by a Rayleigh distribution which has two variables—τ and σ—where τ represents the minimum delay time and σ is the scale parameter. Although in reality both τ and σ vary based on an agent's attributes or type (e.g., resident or transient) and evacuation mode choice, only the impact of τ

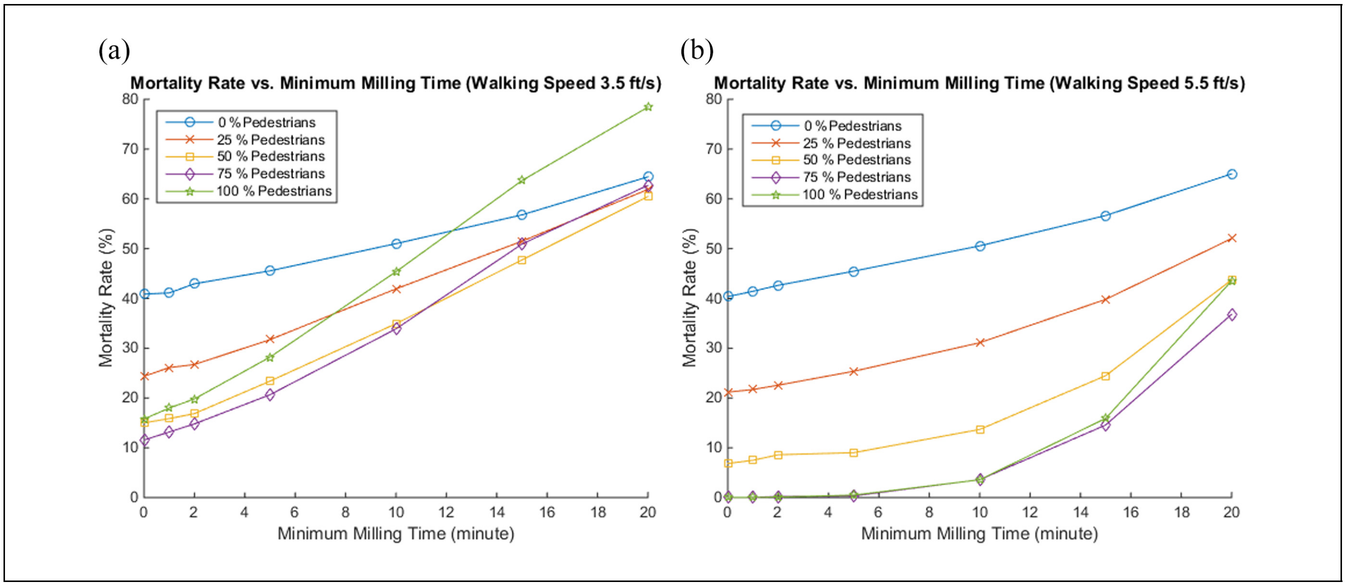

Figure 4. Impact of minimum milling time on mortality rate. Mortality rate versus minimum milling time: (*a*) speed = 3.5 ft/s, (*b*) speed = 5.5 ft/s.

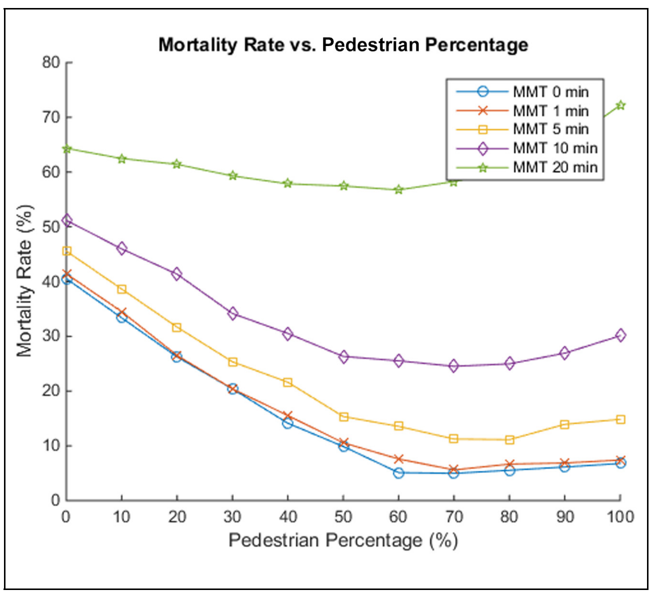

Figure 5. Impact of minimum milling time on optimal evacuation mode split ($\bar{V}_{walk} = 3.5$ ft/s).

on the efficiency of the evacuation scenario was assessed in this work, mostly because both of the parameters are expected to have a somewhat similar impact on the mortality rate.

Figure 4 shows the sensitivity of mortality rate to minimum milling time. For this scenario, σ is kept constant at 0.5 and τ varies from 0 (immediate evacuation) to 20 minutes. As expected, the mortality rate is positively correlated with the minimum milling time, regardless of the average walking speed of the population. Moreover, the effect of minimum milling time grows more significant as the number of evacuees on foot increases. Likewise, comparing Figure 4*a* and *b*, for scenarios with lower walking speeds, the impact of minimum milling time on mortality rate is higher as well.

The impact of minimum milling time on the optimal split of evacuation mode is further investigated. Figure 5 shows the variation of mortality rate because of changes in the percentage of pedestrians for different minimum milling times, where the average walking speed of the population is set to 3.5 ft/s. In general, the impact of milling time is significantly greater on pedestrians than on cars. Comparing two extreme cases: where all the evacuees evacuate by car and all the evacuees evacuate on foot, if minimum milling time increases from 0 to 20 minutes, mortality rate increases from 40% to 65% for evacuees by car and from 10% to 70% for evacuees on foot. This phenomenon causes the optimal evacuation mode split to shift according to different minimum milling times. In addition, there is a critical threshold for minimum milling time, roughly 15 minutes, beyond which fully vehicular evacuation results in lower mortality rates.

Walking Speed and Its Sensitivities

Figure 6 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 (σ). For these simulations, two different minimum milling times, $\tau = 1$ min and $\tau = 15$ min delay from the time of the earthquake to the start of evacuation with $\sigma = 0.5$ were used (i.e., 95% of the population would

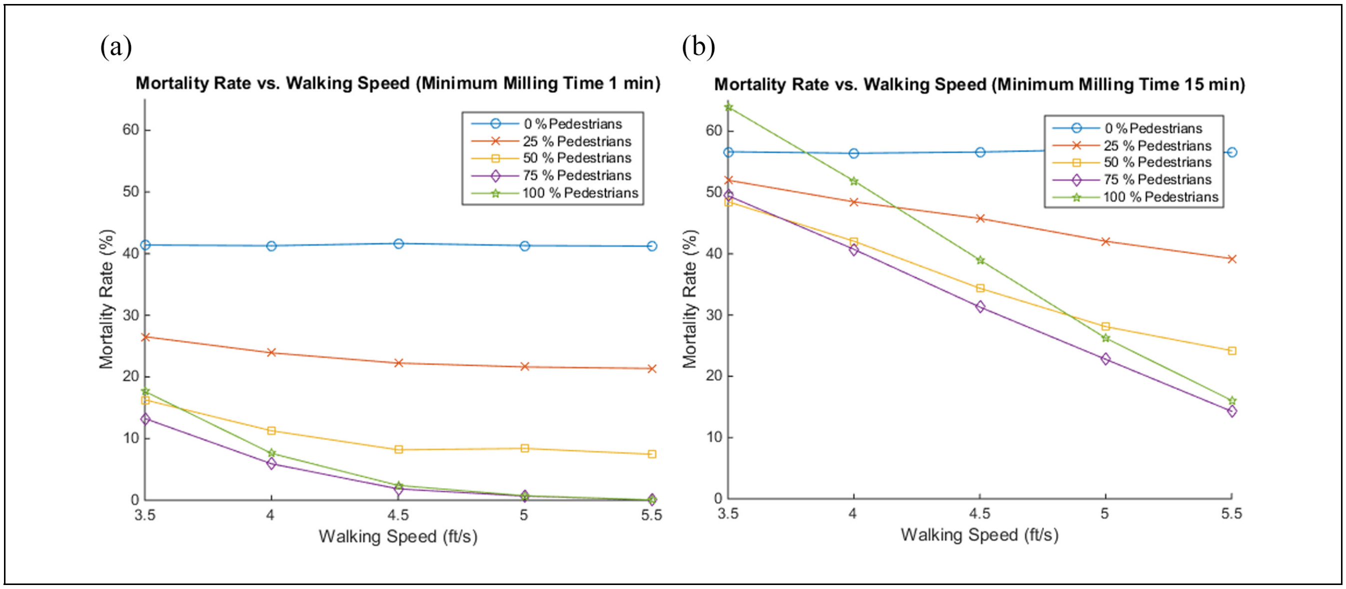

Figure 6. Impact of walking speed on mortality rate. Mortality rate versus walking speed, with (*a*) minimum milling time = 1 min, (*b*) minimum milling time = 15 min.

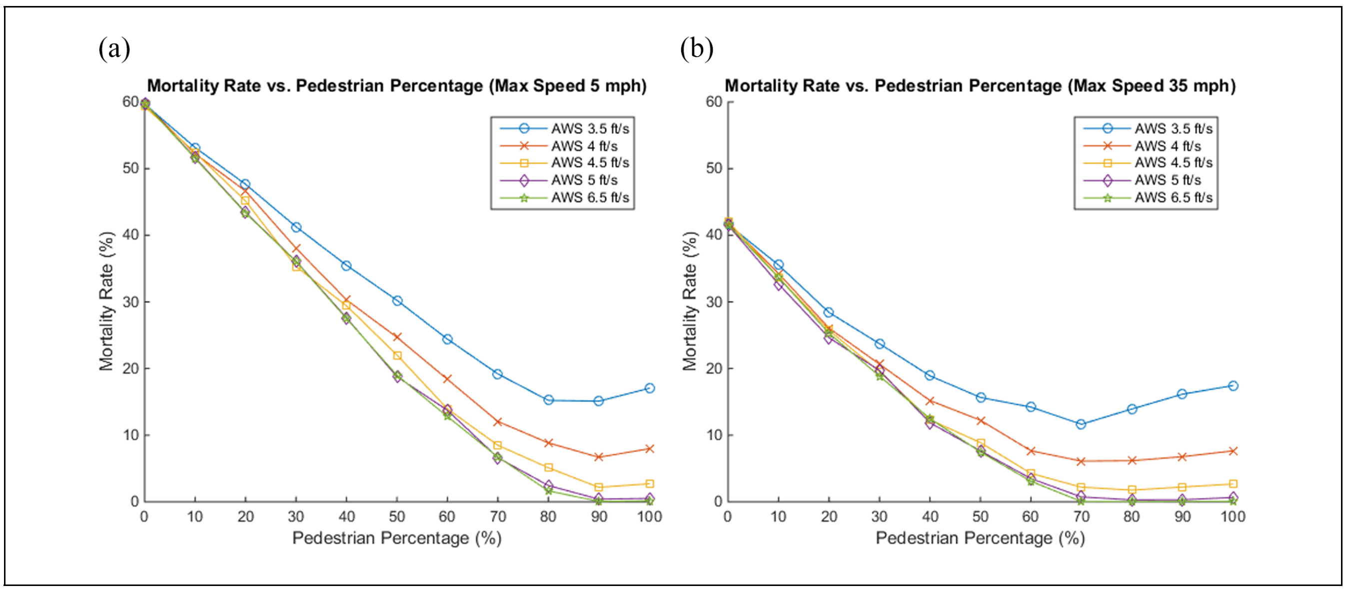

Figure 7. Impact of walking speed on the optimal evacuation mode split (τ = 1 min). Mortality rate versus pedestrian percentage: (*a*) max. driving speed 5 mph, (*b*) max. driving speed 35 mph.

have taken action approximately 5 or 20 minutes after the earthquake in either case, respectively).

Figure 6 shows that the walking speed of evacuees has a strong influence on the mortality rate. Also, as expected, the influence of average walking speed increases as the percentage of pedestrians increases in both proposed milling time cases. In addition, comparison of Figure 6*a* and *b* shows that the impact of walking speed is more significant when milling times are longer. For example, in an evacuation scenario with 100% pedestrians, an increase in walking speed from 3.5 ft/s to 5.5 ft/s decreases the mortality rate by 45% with 15 minutes minimum milling time. On the other hand, this decrease could be less than 20% if the milling time were as short as one minute. Moreover, for shorter minimum milling times, average walking speeds of 5 ft/s and higher would all have the same impact on the efficiency of evacuation. On the other hand, for longer milling times, mortality rate decreases linearly with increase in average walking speed.

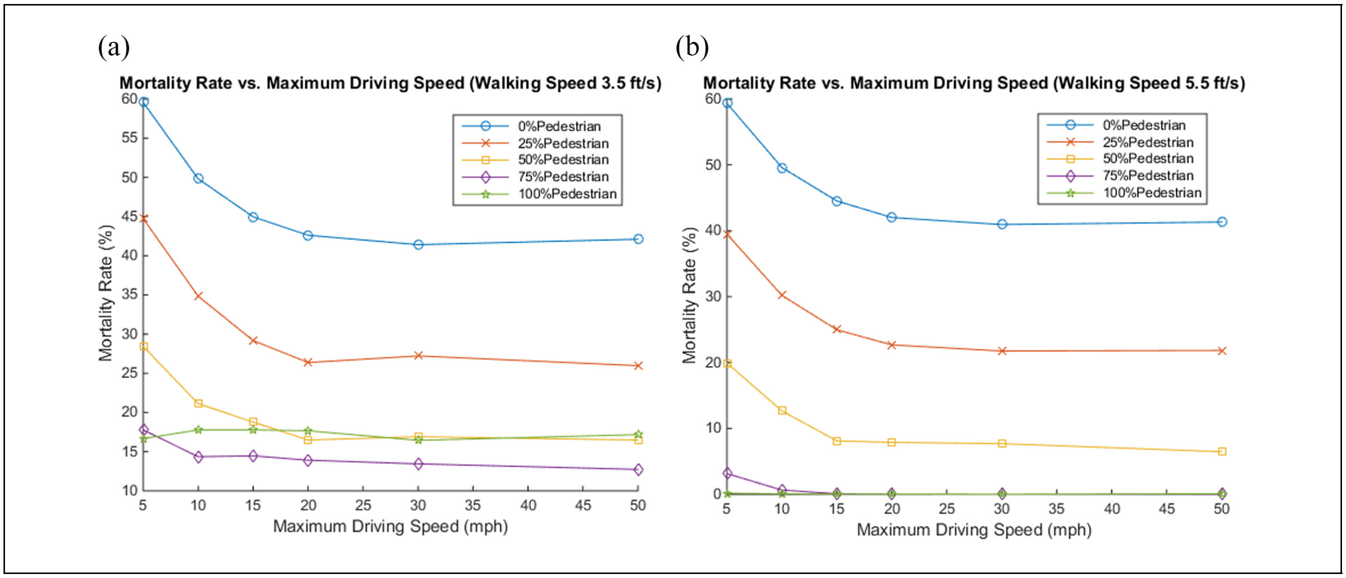

Figure 8. Impact of maximum driving speed on mortality rate (τ = 1 min): mortality rate versus maximum driving speed: (*a*) walking speed = 3.5 ft/s, (*b*) walking speed = 5.5 ft/s.

It is also of great value to assess the impact of walking speed on the evacuation efficiency, along with the maximum driving speed of the cars, which indirectly reflects the advantage of cars in relation to pedestrians. Figure 7 shows the impact of walking speed for two evacuation simulation scenarios with two different driving speeds. Here, minimum milling time is set at one minute. As expected, increase in average walking speed moves the optimal split of evacuation mode toward pedestrians; the optimal split shifts from 100% pedestrians to 80% pedestrians as average walking speed decreases from 5.5 ft/s to 3.5 ft/s. Also, comparing Figure 7*a* and *b*, it can be seen that the optimal percentage shifts very minimally toward cars, even though maximum driving speed increases from 5 mph to 35 mph. This phenomenon again emphasizes the importance and efficiency of evacuation on foot. At the same time, increase in maximum driving speed decreases the mortality rate when the majority of the population evacuate with cars.

Maximum Driving Speed

The maximum driving speed of the cars, reflecting the speed limit, could be an important parameter which not only affects the mortality rate of a specific scenario but also shifts the optimal evacuation mode choice split toward either higher or lower percentages of pedestrians. Figure 8 shows the effect of the driving speed limit on mortality rate for two different evacuation simulation scenarios with different average walking speed for pedestrians. Both Figure 8*a* and *b* confirm that the effect of a maximum driving speed of 20 mph and above is negligible for almost all the evacuation mode splits. This is mainly because of the fact that in a congested network where cars do not get to reach the speed limit, unrealistically high speed limits are not influential to the mobility of the network. However, for maximum driving speed lower than 20 mph, the mortality rate of the scenario increases as the maximum driving speed decreases, and as expected, the effect goes to zero as the percentage of cars goes to zero.

Comparing these two figures, it can also be stated that the impact of an increase in maximum driving speed is slightly greater for the scenarios with a lower average walking speed of pedestrians. In addition, Figure 9 shows the impact of maximum driving speed on the optimal evacuation mode split, coupled with different average walking speeds. Figure 9*a* suggests that the optimal split shifts toward pedestrians as the speed limit decreases to 5 mph and vice versa in the scenarios with lower walking speeds. Similarly, from Figure 9*b*, simulations with higher average walking speeds showed that the mortality goes to zero earlier with the increase in percentage of pedestrians for cases with a higher maximum driving speed for the cars.

Car-Following Behavior and Parameters

Another significant parameter which indirectly affects the mortality rate is the sensitivity coefficient in the car-following model, α. As this coefficient directly correlates with the range of acceleration and deceleration of the cars, this variable cannot take a value higher than 0.14 mile^2/h since any higher value leads to the assumption of

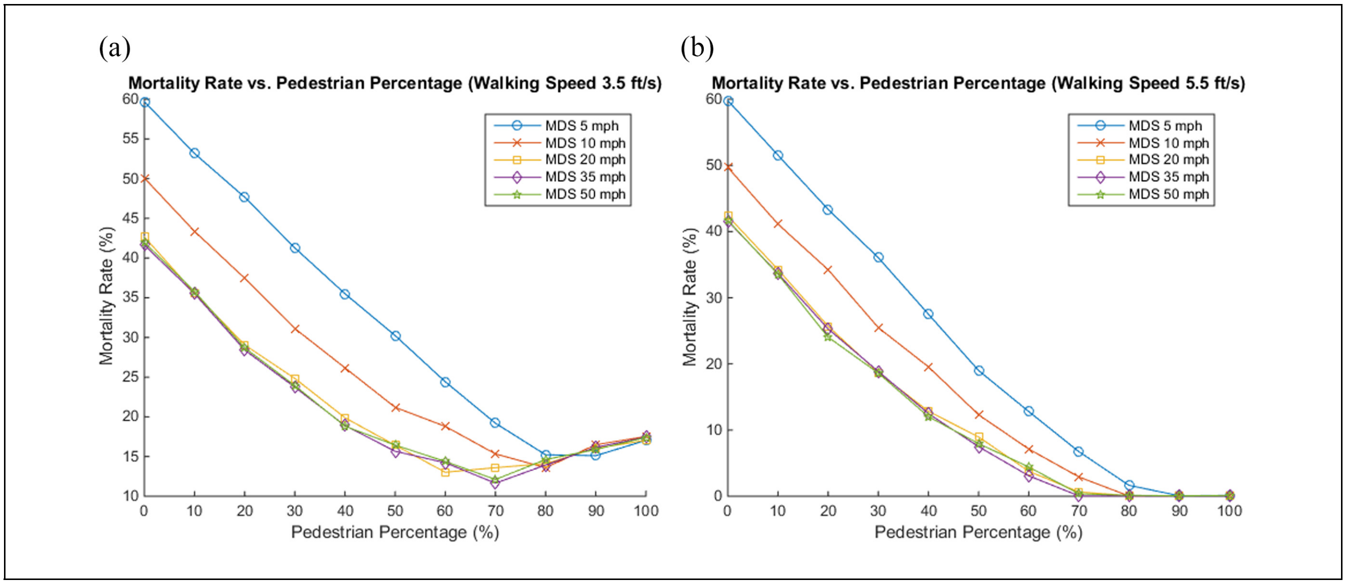

Figure 9. Impact of maximum driving speed on the optimal evacuation mode split (τ = 1 min). Mortality rate versus pedestrian percentage: (*a*) walking speed = 3.5 ft/s, (*b*) walking speed = 5.5 ft/s.

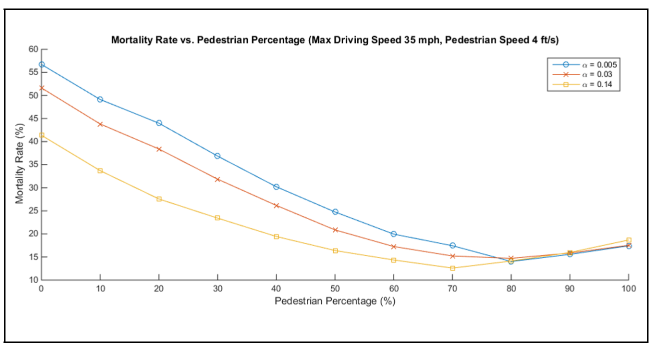

Figure 10. Impact of car-following model sensitivity parameter.

jam density lower than 250 veh/mile/lane or free flow speed of higher than 35 mph which is unrealistic. On top of this, any value of α higher than 0.14 results in extreme acceleration and deceleration rates (*7*).

Despite the low variability range of α, Figure 10 displays the sensitivity of mortality rate over change in α for the scenario where maximum driving speed is set to 35 mph, mean walking speed is set to 4 ft/s, and minimum milling time is set to one minute ($\tau = 1$ and $\sigma = 0.5$). The results show that lower sensitivity coefficients, which lead to lower acceleration and deceleration rates, meaning that the cars lose their agility, cause higher mortality rates when a significant portion of evacuees are evacuating by car. In addition, with the decrease of parameter α, the optimal evacuation mode split moves toward pedestrians since cars lose their advantage because of lower acceleration and deceleration rates.

Critical Depth

Critical depth, the minimum depth of the wave that causes fatality to the population, can represent the physical vulnerability of the would-be evacuees to the tsunami inundation. For instance, a community with higher number of elderly people and children could be more sensitive to the impact force of tsunami inundation, and in that case, the critical depth can be adjusted to lower values (*7*, *20*, *58*).

Figure 11 shows the mortality rate as a function of critical depth, h_c, used as the criteria to determine the fatality of an agent. For this simulation, which shows the impact of critical depth coupled with mode choice split and minimum milling time, walking speed of 4 ft/s, maximum driving speed of 35 mph, and minimum milling time of one minute (τ = 1, = 0.5 ($\tau = 1, \sigma = 0.5$) were set. In this scenario, it is shown that generally mortality rate very insignificantly decreases as the critical depth increases. The effect of critical depth increases with the increase in the percentage of pedestrians. In addition the effect of critical depth is also positively related to minimum milling time, meaning that the effect of critical depth increases for higher milling times. This is mainly because of congestion of evacuees on the shoreline because of high milling times when the first waves hit the shore. However, it may be concluded that the effect of critical depth on mortality rate is not comparable with other factors such as walking speed and milling time. Such analysis done in this work can help to improve our understanding of the near-field tsunami, and more generally of rapid onset disasters and evacuation scenarios,

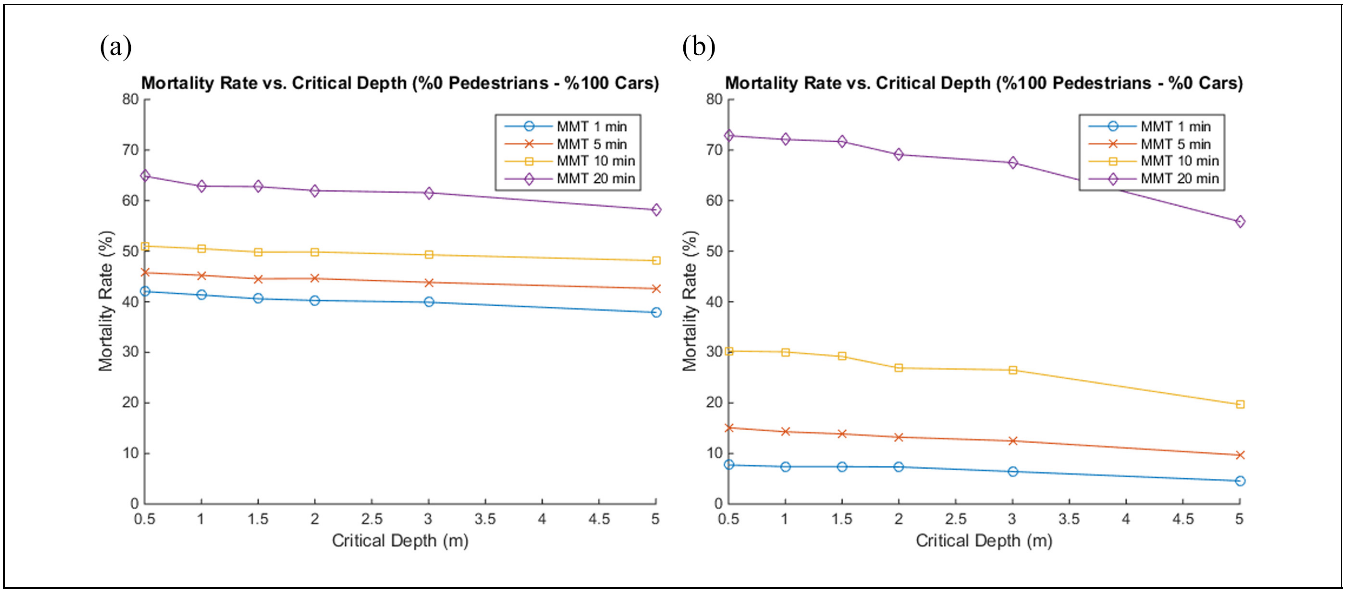

Figure 11. Impact of critical depth on mortality rate: (*a*) 0% pedestrians, 100% cars; (*b*) 100% pedestrians, 0% cars.

and will help emergency planners, decision-makers, and officials to devise more efficient and effective evacuation plans and strategies.

Discussion

The results of this study can be translated into policy-level insights for designing effective evacuation plans and strategies. One key takeaway is that, although it appears that the minimum mortality is achieved in a multimodal scenario (Figure 3), the difference between this minimum value and the mortality rate when the entire population evacuates on foot is minimal, especially for higher walking speeds (Figure 7) and lower milling times (Figure 5). To avoid the complications associated with multimodal evacuation, this finding supports advocacy for evacuation on foot instead with a consideration of the facts there were vehicle uses in tsunami evacuations from both the American Somoa in 2009 and the Tohoku event in 2011. In addition, the milling time is the most important variable when the entire population evacuates on foot (Figure 4). Thus, as walking speed is constrained by the physical ability of the evacuees, immediate evacuation has to be greatly emphasized. In addition, immediate evacuation could possibly compensate for low walking speeds and decrease the impact of slower walking crowd on the efficiency of evacuation (Figure 6). Moreover, in case of vehicular evacuation, speed limits above 20 mph have no impact on the efficiency of evacuation (Figure 8).

Model Extensions

The underlying model used in this study is a multimodal and agent-based evacuation model initially developed by Wang et al. (*20*) and Mostafizi (*58*). This model is designed with a modular programming paradigm and has several components: (a) transportation network, (b) population distribution, (c) hazard model, (d) safe zones, and (e) casualty model. Each of these components can be changed with minimal effort to investigate another setting or another type of disaster evacuation. Thus, this tool can be used in any other geographic location and any other type of disaster as long as it has a clear propagation and casualty model which explains how the disaster spreads and how it interacts with the evacuees and possibly causes of casualties.

Conclusion and Future Directions

This research presented a near-field multimodal tsunami evacuation study through an agent-based modeling environment. This work was designed to study how variations in decision-making time, choices of transportation modes, and general influential factors in an evacuation scenario affect the life safety (i.e., mortality rate) of coastal communities to provide a better understanding of the multimodal evacuation behavior. Using the city of Seaside, Oregon as a case study, an agent-based modeling environment was developed in NetLogo to assess the sensitivity of mortality rate to the factors involved in the evacuation scenario. The results show that: (i) mortality rate is sensitive to the minimum milling time such that a slight increase in minimum milling time can lead to a significant increase in mortality rate, especially where the average walking speed of the community is low; (ii) walking speed has significant effects on the estimation of the number of fatalities; (iii) maximum driving speed is also influential when the speed limit is lower than 20 mph; and, most importantly, (iv) mortality rate is highly correlated with evacuation mode choice, such that there is an optimal mode split which leads to the lowest mortality rates and is typically when between 100% and 75% of evacuees are pedestrians. The results of this work can potentially be used by city planners and officials to devise well-informed evidence-driven evacuation plans and strategies.

Future work will involve modeling of coalescing behavior, car-abandoning (evacuation mode transfer), and communications (information provision and propagation strategies) which could possibly affect the efficiency of evacuation and must be considered in a realistic evacuation platform. Population distribution also has a great impact on mortality rate, and analyzing different population distributions reflecting day-time or night-time conditions would be beneficial to this study.

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Author Contributions

The concept of this study has been proposed and implemented by AM. In addition, AM has been the primary developer of the agent-based tsunami evacuation platform that has been utilized to carry out this research. Literature Review, Simulations, and Data Collection have been done by SD. The analysis and interpretation of results have been done by HW and AM. All authors reviewed the results and approved the final version of the manuscript.

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