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The variety of natural disasters provide different sets of characteristics and properties with unique challenges. One significant difference between hazard types is prewarning lead time, the amount of time individuals have from a potential warning to the disaster occurring. Rapid onset disasters may not provide an official warning about a hazard at all; social cues such as others evacuating or environmental cues such as an earthquake may be the only indication of an incoming tsunami for many individuals. Slow onset disasters such as hurricanes may provide much more of an official broadcast, allowing the public to plan and warn others. When individuals from the public warn others, they produce a "contagion process" which allows for people who would otherwise be uninformed to become informed and potentially spread the information themselves. However, since not everyone communicates to their connections when they learn new information, there is some average probability of spreading information which may be below a necessary critical percolation threshold to guarantee network permeation. This can be mitigated in part with a significant initial official broadcast process. This paper addresses the relationship between the official communication size and the probability of the public to share information, identifying approximate probabilities which are significantly affected by the broadcast process. I develop an interdisciplinary agent-based simulation of a multiplex social network with Monte Carlo iterations to model this relationship. This simulation takes a novel approach to the problem by considering social networks in a multiplex context, where different forms of communication have unique attributes associated with them. Each agent in the simulation is an individual from the hazard-affected community who, once informed, potentially informs others in their social network. The probability of an individual informing others is based on who has told them the information previously and the lead time to the disaster, among others. Simulation parameter values are chosen from previous literature along with the spatial aspects of the Coos Bay, OR and Seaside, OR communities. Results indicate that the initial broadcast size has a negative correlation with the critical percolation threshold. The threshold varies from approximately 1–5%, depending on the size of an initial broadcast. A sensitivity analysis on simulation parameters indicates that, along with sharing probability and initial broadcast size, prewarning lead time and confidence in information significantly affect the total number of informed individuals in the public. The results generated from this study will inform officials and community leaders with the behavior of community characteristics on their response to hazards and natural disasters specific to the community.

# An Agent-Based Simulation for Emergency Warning Dissemination in a Multiplex Social Network

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I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Charles Koll, Author

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# AN AGENT-BASED SIMULATION FOR EMERGENCY WARNING DISSEMINATION IN A MULTIPLEX SOCIAL NETWORK

## 1. INTRODUCTION

### 1.1. Emergency Warnings and their Sources

A critical component of protecting the public as a hazard nears, an emergency warning serves as a method to inform the public about the hazard and provide guidance in avoiding its negative effects. There are two primary components to the spread of an emergency warning among the public: a broadcast process and a contagion process [41, 51, 74, 75, 76]. The broadcast process, also known as the vertical process or formal warning, is a unified effort to inform others; this is commonly performed by officials or other community leaders. Conversely, the contagion process, also known as the horizontal process or informal warning, is a distributed effort of individuals in the community to inform those in their social circles [53]. While ideally every community member could be informed by the broadcast process, due to time constraints and community resources this goal is nearly always intractable. The contagion process can "fill in the gaps", but due to its informal and distributed nature, as well as its delayed pace, it cannot be assumed that everyone will become informed prior to the disaster.

Not every individual will receive information about a hazard and decide to share it with others. That may be due to prioritizing other steps to prepare for the hazard, not having suitable resources to reach out to others, or even lack of confidence in the information provided [51, 75]. To account for this, a simulation attempting to model the contagion process must include some probability that an individual will not share their received information with others.

While some information may come directly from credible sources such as officials or community leaders, often it will come from other news sources such as radio or television. Since these other sources are not targeted to specific individuals, I consider them in this study as part of the broadcast process. Some sources may be trusted more than others. However, this paper considers a complete trust of all information from the broadcast process; details are covered in the 5.1.1 Discussion subsection.

Emergency "warnings" have a connotation of originating from an individual or organization, but that is not the only way the public can become informed about an impending hazard. Environmental cues, such as visuals, sounds, or smells of the hazard, can indicate a threat even without other people nearby. Social cues, such as businesses closing and people evacuating, can also prompt people to seek more information. Finally, social warnings are purposeful warnings from authorities, news media, and other public which are what has been discussed previously [47]. This paper examines in particular the social warning aspect of emergency warning sources; details are covered in the 5.1.2 Discussion subsection.

### 1.1.1 Considered Hazards

Not all hazards have similar characteristics: some may be predicted days in advance, such as hurricanes, while some may have mere minutes, such as tsunamis. Due to these differences, many papers consider only a single type of hazard [14, 22, 46, 53, 54, 57, 74, 83, 93]. In this paper, I attempt to generalize several of the characteristics into variables in a multi-hazard approach. However, the wide range of characteristics does place some limitations on which types of hazards are considered. Accordingly, the primary focus of this paper is around short-term natural hazards, with tsunamis in the shortest rapid onset case and hurricanes in the longest slow onset case. Some man-made disasters such as chemical accident spills may be applicable [37, 46, 76], but they may contain additional characteristics which this study does not consider.

## 1.2. Statement of the Problem

Emergency warning broadcast processes may reach a sizeable number of the population, but the remainder of the population must be informed by a contagion process of informed individuals sharing with others in their social networks. Not all informed individuals will choose to share with others, so if the broadcast process and probability to disseminate are small, there is a high likelihood the informed sample of individuals within the range of a hazard will be in the minority. As the broadcast process and/or probability to disseminate increases, there is a critical threshold where the majority of the network of individuals will become informed [101]. This is due to percolation theory. I develop a simulation to model the interactions of individuals after the broadcast process, identifying an approximate relationship between the initial broadcast size and the likelihood of informed individuals to share information with others. [45] developed a framework to identify this relationship, but did not provide a simulation to model it.

## 1.3. Organization of this Thesis

This thesis is organized into six parts: 1.) the introduction, where I detail the problem; 2.) the background, covering relevant and related topics and include a literature review of previous work; 3.) methods, detailing the design of the simulation; 4.) results and examples, including a simplified example and a full set of results from the simulation; 5.) a discussion covering limitations, assumptions, and possible future work; and 6.) a conclusion, summarizing key results and the importance of the topic.

# 2. BACKGROUND

## 2.1. Percolation Theory

Percolation theory indicates that for a percentage $p$ of nodes removed from a network, there exists a critical threshold $p = p_c$ above which a large connected component exists and below which it does not exist [23]. Emergency warning networks can model this behavior by providing an informed individual a probability $p$ of not sharing their information with their neighbors. This produces site percolation, and a critical threshold of dissemination probability can be found above which the majority of the network will eventually become informed and below which only a minority will. The percolation of emergency warnings can be extended to social networks in general; [18] used site percolation to analyze advertising of firms in social networks. This study attempts to find the relationship between the number of initially informed nodes in the network and the critical threshold $p_c$ where the majority of the network eventually becomes informed.

### 2.1.1 Site and Bond Percolation

There are two primary approaches to percolation: site percolation and bond percolation. As described previously, site percolation involves removing $p$ nodes from a network. Conversely, bond percolation involves removing $p$ edges from a network. While this difference may appear minor, each type can produce different results [70]. Information dissemination can be modeled as site percolation since a node not disseminating information produces the same information propagation results on its neighbors as if it did not exist in the network.

## 2.2. Agent-Based Simulations

Agent-based simulations (ABSs) are used in a wide field of research where individual actors or agents interact with each other over time [31, 42, 55, 69, 71]. They have been used specifically in information dissemination [1, 24, 33, 72] due to their ability to model complex interactions between agents and identify the roles agents play in disseminating information [94]. While ABSs are commonly contrasted with discrete-event simulations, they are not necessarily exclusive [20, 56, 80]; a system can contain components of each type, such as the simulation detailed in this paper. An ABS is most useful modeled as discrete events rather than continuous events [16].

## 2.3. Random Networks

Random networks, also called random graphs, are networks where some attribute of their structure is probabilistic. "Random networks" commonly refer to Erdős–Rényi (ER) networks, but in this paper I distinguish between ER and random networks in general. I use ER, small-world (SW), scale-free (SF), and random geometric (RG) networks, with ER as a basic simulation example and the remainder in the more detailed simulation.

### 2.3.1 Erdős–Rényi

ER networks are the most commonly applied networks in social simulation [3], likely due to their easily analyzable nature. An ER network can be constructed by the probability of an edge connecting each pair of nodes in the network. Another version randomly selects a graph out of all possible graphs of $n$ vertices and $m$ edges. An advantage of ER networks is they have an easily identifiable average degree; this along with a known percolation critical threshold provide several tools for researchers to analyze their simulations [3].

### 2.3.2 Small-World

SW networks are an extension of ER, with an addition of clustering. Clustering allows the network to follow the small-world property, where there is a relatively small path length between any two nodes in the network. The most commonly used SW model is the Watts-Strogatz model (WS) [3, 91], which is applied in this simulation. To create a WS model, an ER network is created then modified by "rewiring" a proportion of edges $\beta$. By doing so, the WS is able to hold the clustering property of regular lattice networks while containing the randomness of an ER network. Several real-world networks have been shown to follow the small-world property, allowing them to be modeled by an SW network. Short message service (SMS) is one of these [58].

### 2.3.3 Scale-Free

Many real-world networks have been shown to have a power-law distribution of node degree [7]. A common model, the Barabási–Albert (BA) model [2], uses preferential attachment to generate a network following this property. This simulation uses a BA model as the application of a scale-free network.

### 2.3.4 Random Geometric

Spatial networks are networks which have an underlying spatial property. Social networks can have spatial characteristics [25, 95], meaning the spatial properties of a network can inform structure. The most simplistic spatial network is a Random Geometric Graph (RGG), where two nodes are connected if and only if their distance is less than a given cutoff value. While RGG commonly have nodes distributed across a space according to a probability distribution, in this simulation I use two real-world communities to inform location.

## 2.4. Multiplex Networks

Multiplex networks are a subset of multilayer networks. A multilayer network consists of multiple layers, where each layer is a network. Interlayer edges connect the layers together. A multiplex network includes two additional conditions: 1) that the set of nodes on each layer is the same; and 2) that interlayer edges only connect the same node between layers [15]. A unique property held by multiplex networks not shared with other multilayer networks is they can be represented as a multigraph, where there is a single set of nodes with potentially several edges joining two nodes together. Figure 2.1 is an example of a multiplex network. There is a single set of nodes, A – E, which exist on each layer. Interlayer edges, the dotted connections, only exist between identical nodes. Figure 2.2 indicates how Figure 2.1 could be represented as a multigraph.

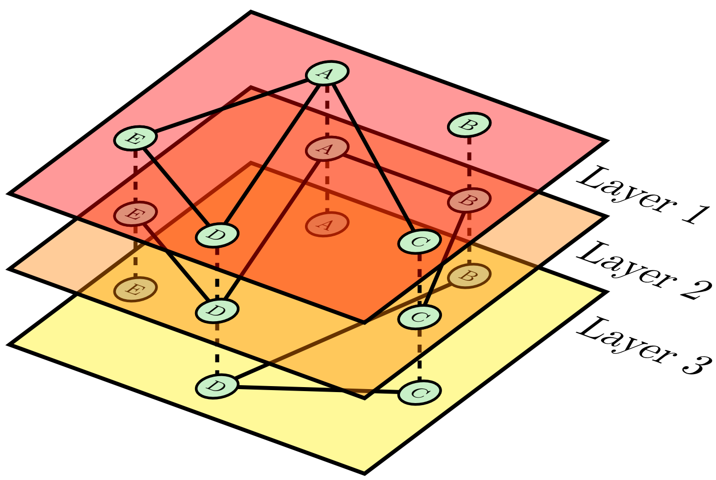


FIGURE 2.1: Example of a multiplex network.

### 2.4.1 Applications to Social Network Analysis

The qualities of multiplex networks enable them to be particularly useful in social network analysis (SNA). Each node can be treated as an individual and each intralayer edge as a connection between individuals. If each layer is treated as a type of social con-

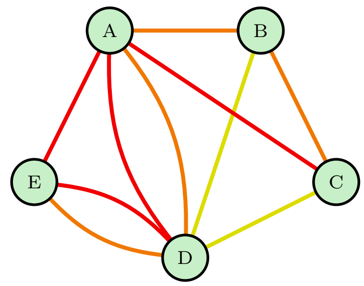


FIGURE 2.2: Multiplex networks can be represented as multigraphs.

nection or manner of communication between people, this allows the network to represent many different types of interactions which would be overly simplified in a single-layer network [6, 8, 15, 26, 35, 77]. [87] indicates that adult friendships have much of these different types of interactions, which emphasizes the need for a complex network. It has been found that attempting to analyze a multiplex network as individual simplex (single-layer) networks produces results without additional nuances of the multiplex network [29, 59].

### 2.4.2 Network Properties

Since the different layers of a multiplex network are interdependent during information diffusion, an important aspect of initializing the network is deciding the number of layers. Modeling every type of connection as a unique layer may be intractable, increasing computational complexity while having a minimal impact on network entropy, especially for similar connection types [30]. However, combining connection types into a single layer may obscure the nuance of communities in the network [63]. Some research analyzes the correlation of network edges between layers [9, 13, 15]. This correlation can cause layers to appear similar, potentially allowing them to be joined into a single layer with minimal effects [30].

Percolation in multiplex networks has been studied extensively [19]. One aspect analyzed has been the minimal set of initially informed nodes needed for percolation criticality [64], which has applications to emergency warning. However, in this study I randomize the set of initially informed nodes, since the broadcast process may not be able to target a certain set of individuals specifically, either due to constraints in the communication medium or due to officials not knowing who the minimal set of individuals in their community is. Another aspect that affects percolation in a multiplex network is the structure of each layer. [96] compared ER, scale-free, and small-world random networks as different layers of a duplex (two-layer) network as it applies to innovation diffusion. This concept has also been generalized to multilayer networks, comparing structures of random graphs as they affect information diffusion [90]. In addition to percolation regarding diffusion of information, percolation of node failures has been conducted on multiplex networks [28, 86]. While there may be some overlap of results with information diffusion, the largely stochastic nature of diffusion and differences in assumptions likely produces quite different results. Similarly, [21] analyzed the synergistic effects of multiple contagions in a multilayer network, but did not consider interlayer contagion, preventing an exact mapping to information diffusion.

## 2.5. Discrete-Event Simulations

Discrete-event simulations (DES) are simulations which model time as discrete events. This can be contrasted with continuous simulations, which model time on the basis of a set of continuous equations. DES time progression can be separated into two types: fixed-increment and next-event. Fixed-increment time progression models each time step in the course of the simulation, allowing for consistent updates as the time increases. Next-event time progression models time in a series of events, skipping forward to the next event after completing the previous one. This allows for reduced computation in situations where updates would not occur at each time step with fixed-increment time progression. This simulation uses next-event time progression due to a potentially long latency in a node receiving information and then sharing with others.

## 2.6. SEIR Epidemiological Model

The SIR epidemiological model is a compartmental model used to identify the spread of infectious diseases. Each component – S: susceptible, I: infectious, R: recovered – can be used as the state of an individual. A variant of the SIR model, the SEIR model, also includes E: exposed. The order of the letters indicates the transitions between them. Following SEIR, an individual will start out susceptible to an infection. If they become infected, there may be a time before they can spread it to others. This is the exposed (E) stage. They will then transition to infected (I), where they can spread the disease to others. Finally, the individual will transition to recovered (R), at which point they cannot become reinfected or continue to spread the disease.

### 2.6.1 Similarities to Emergency Warning Dissemination

While SEIR was originally applied to epidemiology, it can also be applied to information dissemination [11, 97]. Each component of SEIR can be mapped to an individual's state during emergency warning dissemination. Table 2.1 indicates a possible mapping. The transitions between information dissemination states are performed in the same order as SEIR.

| | |
|---|---|
| Susceptible | Uninformed |
| Exposed | Informed – not sure about warning others |
| Infectious | Informed – warning others |
| Recovered | Informed – done warning others |

TABLE 2.1: Mapping of SEIR to information dissemination.

## 2.7. Protective Action Decision Model

The Protective Action Decision Model (PADM) is a framework to investigate how individuals commonly respond to environmental hazards. It consists of a cue stage where individuals learn of a threat, an analysis stage where they determine the level of the threat and how it could potentially affect them, and a decision stage where they behave according to the analysis [51]. This study primarily responds to the cue and analysis stages, where people learn of a hazard and decide whether to tell others. However, I also include an evacuation variable to account for the potential effect of the decision stage on being able to inform others.

## 2.8. Related Work

This study attempts to find the relationship between the number of initially informed nodes in the network and the critical threshold where the majority of the network becomes informed. To do so, I develop an agent-based simulation which uses a multiplex social network to model emergency warning dissemination. While previous literature has touched on several aspects of this topic, as far as I am aware, this is a unique approach to the problem.

[39] developed an agent-based simulation to compare two types of nodes with a trust differential in emergency warning dissemination. ER, BA, and WS networks were used, analyzing the differences in information dissemination between them. [38] conducted a similar study, focusing on an ER network. Other studies have conducted emergency warning dissemination simulations using household grids; both [65] and [66] used a grid of 1000 households, with the contagion process of [66] being a spatial network.

# 3. METHODS

## 3.1. Dissemination Framework

The structure of interactions between individuals in the network and their decisions can be described with a dissemination framework. I provide a flowchart of this framework with Figure 3.1. At the beginning of the simulation, a broadcast process occurs where a set number of nodes are randomly selected from the network to be informed. Following this, the contagion process supplies logic for each newly informed node until they choose to do nothing further.

## 3.2. Simulation Variables

For the research of this study I have developed an agent-based simulation in Julia to model emergency warning dissemination. I include eight simulation parameters which can be modified to fit a given community, along with other possible adjustments made by changing values in the code. Some simulation parameters are functions which rely on other parameters and simulation state changes. Table 3.1 describes two state variables which are parameters to some simulation parameter functions; their values change as the simulation progresses.

| State Variable | Description |
|---:|---|
| $t_s$ | Current time step |
| $c_s$ | Number of times node has been informed |

TABLE 3.1: State variables and descriptions.

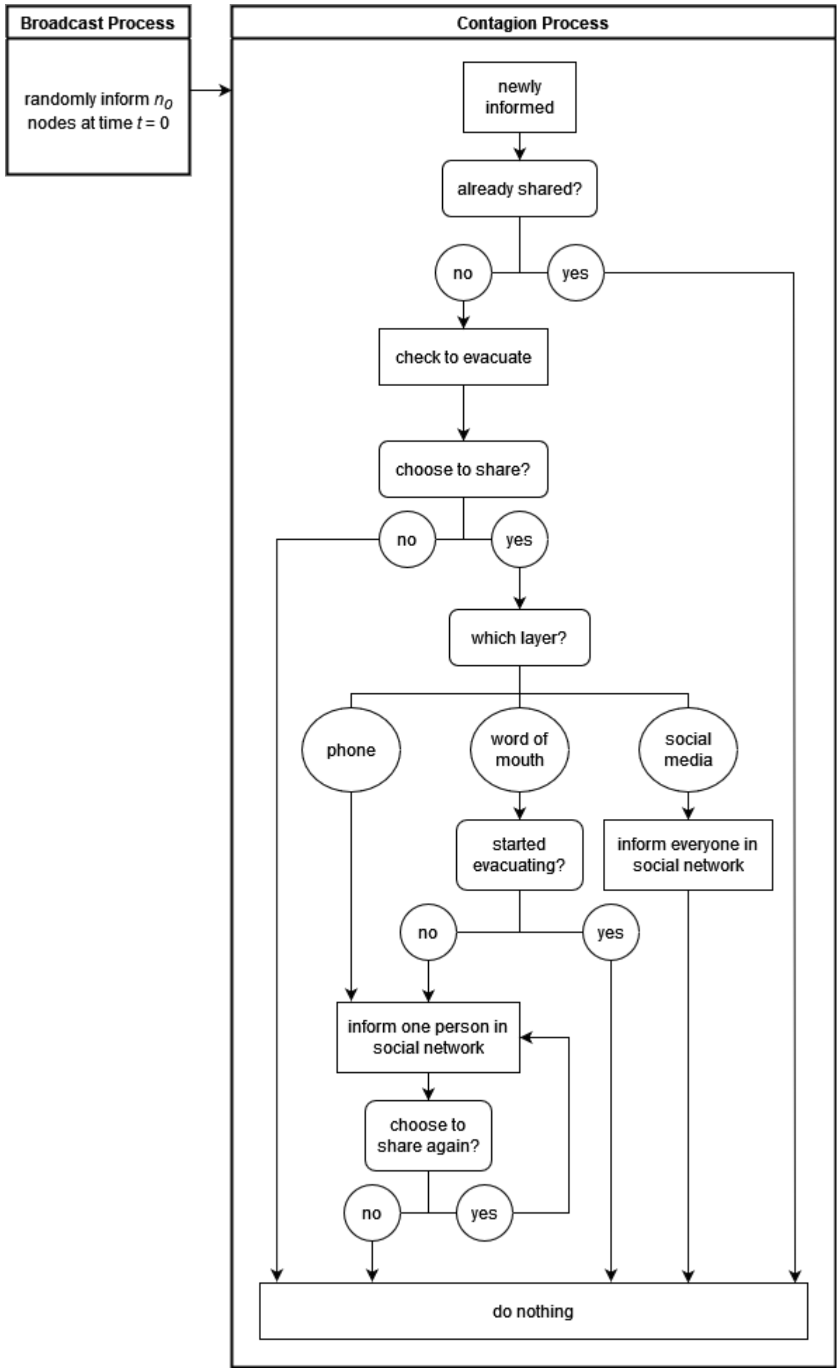


FIGURE 3.1: A dissemination framework for the simulation.

### 3.2.1 Broadcast Size ($n_0$)

The broadcast size is the initial number of nodes informed at the beginning of the simulation, prior to the contagion process. Previous research has provided broadcast sizes for a wide range of hazards including flash floods, water contamination, hurricanes, and volcanoes. However, since the relationship of this variable is to be compared with the probability of an individual to share information, I test a wide range of values. Table 3.2 provides a brief summary of $n_0$'s properties.

| | |
|---|---|
| Parameter | $n_0$ |
| Description | Broadcast size |
| Type | value |
| Range | [1, $n$] ($n$ being number of nodes) |

TABLE 3.2: $n_0$ properties.

For the Mount St. Helens (MSH) eruption [50] identified 6% and 0% who received information from official sources in two locations and 58% and 47% who received information from their social network in those locations. These MSH numbers do not add to 100%, which indicates that many individuals were informed by other means such as environmental cues. While this may indicate a possible concern with assuming only social warnings in this simulation, many hazard types will not have as obvious environmental cues, and the sudden nature of the broadcast process indicates it could include those other types of information sources as well. Table 3.3 summarizes these literature values and others.

### 3.2.2 Probability to Share Information ($p$)

The probability of an informed individual to share information with others is a very significant parameter of the simulation since it plays a major role in percolation. This simulation parameter is a function which takes four parameters: $t_s$ (current time), $d$ (total prewarning time), $t_l$ (time to share information), and $c$ (confidence in information). $d - t_s$ determines how much time is left before the disaster occurs. This value affects an

| Values | Hazard Type | Information Source | Source |
|---|---|---|---|
| 14% min, 38% median, 89% max | flash floods | peers | [47] |
| 31.8% | floods | primarily neighbors | [93] |
| 7%, 0% | hurricanes | peers | [54] |
| 6%, 0% | volcano | officials | [50] |
| 58%, 47% | volcano | social network | [50] |

TABLE 3.3: $n_0$ literature values.

individual's probability to share information because an individual learning information a very short time before the disaster will cause them to tend to their own safety before warning others. $t_l$ plays a role in the probability to share information because a series of informing options which take a long time will affect how much time an individual has to prepare themselves prior to the disaster. Finally, $c$, the confidence in the information, affects the value because an individual less confident in information will be less likely to share it. Table 3.4 provides a brief summary of $p$'s properties.

| | |
|---|---|
| Parameter | $p$ |
| Description | Probability to share information |
| Type | function |
| Function Parameters | $t_s$, $d$, $t_l$, $c$ |
| Output | value/distribution |
| Output Range | [0, 1] |

TABLE 3.4: $p$ properties.

Based on these assumed parameters, I construct a function $p$ to use for results; however, the simulation allows for an easy change of function for this simulation parameter.

Equation 3.1 describes this function:

$$p(t_s, d, t_l, c) = c \times p_0 \times \max\left(1 - \frac{\min(t_l)}{\max(d - t_s, 0)}, 0\right) \quad (3.1)$$

where $\max(x, 0)$ ensures no negative numbers, $\min(x)$ returns the smallest value in $x$, and $p_0$ is an initial starting probability.

This function has the property where a confidence of 0 or a time to communicate longer than the time remaining returns a result of 0. A returned value of $p_0$ occurs when confidence is 100% and time to communicate is 0. I include the $p_0$ for percolation purposes; since probability appears to vary widely among different communities, percolation changes drastically with small adjustments of $p$, and the relationship with $n_0$ is based on $p$, I select a wide range of values and narrow them to determine the relationship.

While much literature does not provide information regarding what percentage of people informed someone else, several surveys identify how many told others via different forms of communication. These can help guide starting values for this parameter before narrowing it down. One study which did have general information of how many people informed others identified 1.1% and 2.4% told someone else during two hazardous materials transportation accidents (HMTA) [76]. Other studies which are more specific to communication types are detailed in 3.2.3 and Tables 3.6 and 3.7.

### 3.2.3 Weight to Share Information on Layers ($p_l$)

The weight to share information on different layers determines how often each layer is used to share information. A higher value in one element of the vector increases the use of the given layer while decreasing the use of the others; in other words, the vector is the set of weights in the multiple layers. This simulation parameter is a function which takes three parameters: $t_s$, $d$, and $t_l$. $d - t_s$ determines how much time is left before the disaster occurs. This value affects a layer's weight for the same reason as it affects $p$: an individual learning information a very short time before the disaster will cause them to tend to their own safety before warning others. This combined with $t_l$ identifies the effect that the time it takes to spread information on a given layer has on deciding to use it. Table 3.5 provides a brief summary of $p_l$'s properties.

| | |
|---|---|
| Parameter | $p_l$ |
| Description | Weight to share information on layers |
| Type | function |
| Function Parameters | $t_s$, $d$, $t_l$ |
| Output | list of values/distributions – one per layer |
| Output Range | [0, 1]; sum of values/sampled distributions = 1 |

TABLE 3.5: $p_l$ properties.

Based on these assumed parameters, I construct a function $p_l$ to use for results; however, the simulation allows for an easy change of function for this simulation parameter. Equation 3.2 describes this function:

$$p_l(t_s, d, t_l) = \text{norm}\left(b \times \max\left(1 - \frac{t_l}{\max(d - t_s, 0)}, 0\right)\right) \tag{3.2}$$

where $\max(x,\ 0)$ ensures no negative numbers, all operations are element-wise across vectors, $\text{norm}(x)$ normalizes the vector $x$ so its elements sum to 1, and $b$ is an initial starting probability vector whose elements sum to 1.

I include $b$ to emphasize variation. Some communities may be predisposed towards certain forms of communication where time remaining and time to communicate play negligible roles. In these cases, $b$ allows for returning values which may appear closer to the community's characteristics.

Communication probabilities with different types are much more common in emergency warning literature than general communication probabilities. I separate them into two groups: probabilities of informed individuals sharing with others via different types of communication (Table 3.6) and probabilities of individuals receiving information via different types of communication (Table 3.7). The latter group does not exactly correspond to the intent of $p_l$; however, they can provide guidance on the values of the former group. "HMTA" represents "hazardous materials transportation accidents".

| Values | Hazard Type | Communication Type | Source |
|---|---|---|---|
| 22% | floods | neighbors | [67] |
| 27% | emergencies in Europe; survey | social media | [73] |
| 48% | emergencies in Europe; survey | social media in future | [73] |
| 0.1% | wildfire | retweets (Twitter) | [81] |
| 0.1% | tsunami | retweets (Twitter) | [22] |
| 57.7% | tsunami | face-to-face | [68] |
| 26.9% | tsunami | phone call | [68] |
| 5.8% | tsunami | SMS | [68] |

TABLE 3.6: $p_l$ literature values – communication types of individuals.

### 3.2.4 Time to Share Information ($t_l$)

The time an individual takes to share information can vary based on their chosen form of communication. In the real world there is also time it takes for an individual to receive information; depending on the form of communication, if an individual is away from their home or device to communicate, that can increase time before they are informed. To simplify, in this study I include that additional time into $t_l$. It is expected to have a minimal effect combined as opposed to separated, since individuals only attempt to communicate once. However, it could play a role in simulation parameters which use this variable in their functions if the effect of this variable is significant. The simplification of the parameter of time to share information also allows for fewer limitations on literature

| Values | Hazard Type | Communication Type | Source |
|---|---|---|---|
| 1.84 (1–5 Likert scale) | hurricane | internet | [49] |
| 36% | flash flood | face-to-face | [61] |
| 31.8% | floods | neighbors | [93] |
| 1.1% | floods | SMS | [93] |
| 10.5% | floods | not neighbors or SMS | [93] |
| 26% | tornado | word of mouth | [74] |
| 51% | tornado | cell phone | [74] |
| 8% | tornado | social media | [74] |
| 17% | tornado | internet | [74] |
| 18.3% | HMTA | friends, neighbors, relatives | [76] |
| 11.8%, 29.7% | HMTA | door-to-door | [76] |
| 24% | volcano | face-to-face | [50] |
| 13%, 14% | volcano | telephone | [50] |

TABLE 3.7: $p_l$ literature values – sources of communication.

values to be used. This is especially noticeable with social media, since many people may not receive a notification of the update. Table 3.8 summarizes $t_l$'s properties.

Table 3.9 summarizes previous literature values. [100] did not explicitly provide the values included in the table except for the oral communication type, although it seems they were a part of their data; I compute the values based on equations and tables. Delay time of the microblog communication type was computed with Equation 7 and Table 1 of the paper. Delay time of the oral communication type was said to be 1 minute, although this appears to be an assumption. The delay time of SMS and cell was indicated to be 99.2% closer to oral communication than microblog; based on this statement and the computed values of oral and microblog communication, SMS and cell communication was computed

| | |
|---|---|
| Parameter | $t_l$ |
| Description | Time to share information |
| Type | list of values/distributions – one per layer |
| Range | $[0, \infty)$ |

TABLE 3.8: $t_l$ properties.

to be 17 minutes. "HMTA" represents "hazardous materials transportation accidents".

| Values | Hazard Type | Communication Type | Source |
|---|---|---|---|
| 3.36 hrs | disasters in Beijing; survey | microblog | [100] |
| 1 min | disasters in Beijing; survey | oral | [100] |
| 17 mins | disasters in Beijing; survey | SMS, cell | [100] |
| 49 mins | HMTA | friends, neighbors, relatives | [76] |
| 70 mins, 66 mins | HMTA | door-to-door | [76] |

TABLE 3.9: $t_l$ literature values.

### 3.2.5 Confidence in Information ($c$)

Information confidence plays a significant role in informed individuals deciding to share with others. Many individuals will choose to confirm information before trusting it, which lends to a slower and less effective percolation process. An individual's confidence in information depends on how many times they have received it previously, by whom, and their trust in that source. Based on these aspects, the simulation parameter $c$ is a function which takes $c_s$ and $w_l$ as parameters. Table 3.10 provides a summary of its properties.

Based on these assumed parameters, I construct a function $c$ to use for results;

| | |
|---|---|
| Parameter | $c$ |
| Description | Confidence in information |
| Type | function |
| Function Parameters | $c_s$, $w_l$ |
| Output | value/distribution |
| Output Range | [0, 1] |

TABLE 3.10: $c$ properties.

however, the simulation allows for an easy change of function for this simulation parameter. Equation 3.3 describes this function:

$$c(c_s, w_l) = \text{clamp}\left(\frac{\text{trust}(c_s, w_l)}{c_n + 1}, 0, 1\right) \tag{3.3}$$

where clamp($x$, 0, 1) enforces results between 0 and 1, trust$(c_s, w_l)$ retrieves the sum of trust weights for the number of times/layers the node has been informed through, and $c_n$ is the expected number of times a node will need to confirm information before sharing it if they completely trust their sources.

I include $c_n$ as the number of times an individual wishes to confirm information with others. Trust levels have a linear relationship with this value.

Previous research regarding confidence and confirmation is minimal. One paper specified an average number of confirmations, which is the most helpful for determining a range of values for $c$, but others regarded confirming through types of communication and waiting for additional information, without any data provided regarding how much confirmation was necessary. Confidence data is challenging to acquire, since it requires public surveys to gather information which may rely significantly on trust levels. Table 3.11 details some of the previous literature regarding confidence and confirmation. “HMTA” represents “hazardous materials transportation accidents”.

| Values | Hazard Type | Communication Type | Source |
|---|---|---|---|
| confirmed with on avg 1.37 (std dev 0.65) | flash floods | N/A | [47] |
| confirmed with on avg 1.76 different warning channels | water contamination | N/A | [48] |
| 11.0%, 11.2% waited to see | HMTA | N/A | [76] |
| 31.3% confirmed | tsunami | face-to-face | [68] |
| 4.1% confirmed | tsunami | telephone | [68] |
| 3.8% confirmed | tsunami | internet | [68] |

TABLE 3.11: $c$ literature values.

### 3.2.6 Evaluation Probability ($r$)

Since safety actions by the public involve evacuating for many types of hazards, including an evacuation probability accounts for this likely scenario. [49] found that peers were the reason for evacuation from a hurricane in 6.6% and 7.8% of the population. In a wildfire context, individuals considered others telling them to leave when deciding for themselves as a 3.50 on a 1–5 Likert scale [57]. A decision to evacuate involves the time remaining until the disaster occurs ($d - t_s$) and confidence in the information ($c$), so the simulation parameter $r$ is a function. Table 3.12 summarizes the properties of $r$.

Based on these assumed parameters, I construct a function $r$ to use for results; however, the simulation allows for an easy change of function for this simulation parameter. Equation 3.4 describes this function:

$$r(t_s, d, c) = c \times \left(1 - \text{clamp}\left(\frac{d - t_s}{t_r}, 0, 1\right)\right) \tag{3.4}$$

where clamp($x$, 0, 1) enforces results between 0 and 1 and $t_r$ is the maximum time at which anyone would evacuate.

| | |
|---:|---|
| Parameter | $r$ |
| Description | Evacuation probability |
| Type | function |
| Function Parameters | $t_s$, $d$, $c$ |
| Output | value |
| Output Range | [0, 1] |

TABLE 3.12: $r$ properties.

This function has the property where the probability to evacuate is 0 if the time remaining until the disaster is greater than $t_r$ and the probability is 1 if the time remaining until the disaster is 0 or has already passed. I include $t_r$ as the maximum time at which anyone would evacuate.

Previous literature does not detail the probability of an individual evacuating at any given time; rather, it provides results of times that they leave. The literature is best suited for validating evacuation results, although it can guide potential testing values. The majority of evacuation literature considers hurricanes. Much hurricane literature has determined evacuations to follow a Rayleigh distribution, with studies using $\beta$ parameters of 40, 45, 62, 74, 117, and 181 [52].

### 3.2.7 Prewarning Time Before Disaster ($d$)

The prewarning time before a disaster plays a major role in information dissemination. An extremely short prewarning time causes individuals to look after their own safety rather than informing others as well as limits the length of the chain of becoming informed and informing others. A longer prewarning time allows for flexibility on both of these fronts. Since prewarning time before a disaster is fixed at the start of the contagion process, the simulation parameter $d$ is a singular value. Table 3.13 summarizes $d$'s properties.

| | |
|---|---|
| Parameter | $d$ |
| Description | Prewarning time before disaster |
| Type | value |
| Range | $(0, \infty)$ |

TABLE 3.13: $d$ properties.

While prewarning time literature primarily details tsunami and hurricane hazards, their corresponding prewarning times are expected to be on the shortest and longest ranges of hazard values, respectively. Table 3.14 summarizes several study values.

| Values | Hazard Type | Source |
|---|---|---|
| 9 mins | tsunami | [22] |
| 12 mins | tsunami | [4] |
| 72 hrs | hurricane | [54] |
| 42 hrs | hurricane | [49] |
| 36 hrs | hurricane | [85] |

TABLE 3.14: $d$ literature values.

### 3.2.8 Trust of Layers ($w_l$)

To determine confidence in a piece of information, an individual will evaluate their trust in the source. While a source will be another individual, the type of social connection the two people have may be correlated with their communication channel. Several studies have grouped trust into communication types [82, 98, 100], allowing for a simplified manner of adjusting trust levels. This simulation does the same, with a simulation parameter $w_l$. Table 3.15 summarizes its properties.

| | |
|---|---|
| Parameter | $w_l$ |
| Description | Trust of layers |
| Type | list of values/distributions – one per layer |
| Range | [0, 1] |

TABLE 3.15: $w_l$ properties.

Table 3.16 details literature on trust in social networks. All studies except for source [76] group trust by communication type. [98] do not indicate where their values originate; presumably a survey was conducted.

## 3.3. The Julia Programming Language

This simulation is written in the Julia programming language. Julia is a high-level dynamically typed language designed for high performance numerical computing [12]. Used heavily in academic research, it provides high-level language features similar to Python with lower-level features such as parallelism.

The simulation uses several dependencies which make the core simulation much simpler:

- LightGraphs [17]: mathematical graphs and utility functions
- MetaGraphs: functionality on top of LightGraphs to support node properties
- Distributions [10]: probability distributions and utility functions
- DataFrames: tabular data storage similar to R's dataframes
- DataStructures: tree and queue data structures
- CSV: importing and exporting data to/from CSV files

| Values | Value Location | Communication Type | Source |
|---|---|---|---|
| 81.3%, 58.6% disregarded information | hazardous materials transportation accidents | N/A | [76] |
| 2.74 trustworthy (1–5 Likert scale) | news in Singapore | social media | [82] |
| 45% | disasters in Beijing | email | [98] |
| 50% | disasters in Beijing | microblog | [98] |
| 41.3% | disasters in Beijing; survey | SMS | [100] |
| 43.3% | disasters in Beijing; survey | cell phone | [100] |
| 38.91% | disasters in Beijing; survey | oral | [100] |
| 48.3% | disasters in Beijing; survey | microblog | [100] |

TABLE 3.16: $w_l$ literature values.

- JLSO [34]: importing and exporting data to/from JLSO files (compressed data type)
- Makie: plotting
- Colors: colorschemes for plotting
- ProgressMeter: progress tracking on the terminal

## 3.4. Network Structure

An advantage of a multiplex network is the ability to customize each layer with unique properties. I use a multiplex network with three layers representing three different communication types: phone, word-of-mouth, and social media. When looking at the literature summarized in the tables of 3.2., it appears there are generally three types of communication: 1) physical interaction, such as neighbors, oral, face-to-face, and word of mouth; 2) one-to-one virtual interaction, such as phone calls, SMS, and email; and 3) one-to-many virtual interaction, such as social media, retweets, microblog, and internet. Because of these three generalized types of communication, I have grouped them into word-of-mouth, phone, and social media respectively. Each layer has additional properties associated with its usage which are detailed in subsections 3.4.2, 3.4.3, and 3.4.4.

### 3.4.1 An Undirected Network

Each layer of the multiplex network is modeled as an undirected network. Uninformed networks have been assumed in previous contagion process studies [36, 78] and a reciprocal relationship can be assumed for all layers but social media. While a form of social media may be designed such that "following" others might not be reciprocal, I assume that these cases are somewhat rare.

One unique case of an undirected network is that there is a possibility a newly informed node could attempt to share with their source. However, I assume the unrealistic effects of this possibility are negligible because the newly informed individual may choose to discuss the topic more with their source anyway, the probability of sharing with their source is fairly low (1/social network size), and resharing will not affect the source's decision making because they have already shared their information.

### 3.4.2 Phone Layer

I set the phone layer of the simulation as a network with the small-world property using the Watts-Strogatz (WS) model. Phone-type networks have been shown to have the small-world property [3, 60, 89]. Coverage is very high, with one study citing 97.2% for SMS and 99.0% for cell phone [100]. The same study also provided the average number of people forwarded to for different communication types: 11.8 on SMS and 9.7 on cell phone. [89] identified a phone network as a WS network with an average node degree of 3 and rewiring probability of 0.7. Contrastingly, [60] identified an average node degree of 20. To account for these widely varying values, for this layer I choose a rewiring probability of 0.7 and an average node degree of 10, which splits 3 and 20 and is approximately the same as the average number of people forwarded to.

The number of people shared to depends on previous sharing success. If an individual decides to share, they do so and check their probability again, repeating until they do not share. If they do not share, then they are done attempting. This is the same behavior as for the word-of-mouth layer. The expected number of people shared to is $\frac{p}{1-p}$ since the behavior is the inverse of a geometric distribution. Note that like the undirected network case there is a possibility the individual will attempt to contact the same person twice. I allow this behavior for simplicity and possible further topic sharing.

### 3.4.3 Word-of-Mouth Layer

I set the word-of-mouth layer of the simulation as a random geometric graph (RGG) based on real-world data. Previous studies have used spatial networks for social networks [3]. Coverage is essentially perfect, with one study citing 100% for oral communication [100]. Real-world data is drawn from two sources: a possible population distribution of Seaside, Oregon [88] and household locations approximated by 2020 census data for Coos Bay, Oregon [84]. Both of these locations are coastal, with a high likelihood of impact from a Cascadia Subduction Zone tsunami. Using real-world data allows for a spatial network with a realistic clustering structure. The cutoff value used for the RGG is 60 meters. [100] found the distribution of oral communication was entirely within 90 meters, with the vast majority, 93.6%, within 60 meters. Based on this I allow for connections between any individuals within 60 meters apart but no further. However, this distance could be easily adjusted for future analysis.

While the real-world data is based on households, I aggregate each household into a single individual. Considering households instead of individuals would likely increase information dissemination speed due to a more rapid communication between household members and an increased social network of the household, so individuals are a worst-case scenario. When learning new information individuals will likely inform other household members prior to the rest of their social network which may delay their contagion process, but communication is likely to be much faster and nearly instantaneous if all household members are at home. Considering households versus individuals could be a future research direction.

For a stable diffusion process, studies have used 600 [38], 1000 [65, 66, 92], 10000, and 20000 [32] nodes. Based on these values, the node sizes of 26363 for Coos Bay and 4502 for Seaside appear suitable for the diffusion process.

The word-of-mouth layer works closely with the evacuation parameter $r$. When an individual decides to evacuate, they are removed from this layer. This is because, having evacuated, an individual can no longer discuss with neighbors but they can likely still communicate virtually via cell phone or social media. The phone and social media layers are not affected by the evacuation.

The number of people shared to depends on previous sharing success. If an individual decides to share, they do so and check their probability again, repeating until they do not share. If they do not share, then they are done attempting. This is the same behavior as for the phone layer. The expected number of people shared to is $\frac{p}{1-p}$ since the behavior is the inverse of a geometric distribution. Note that like the undirected network case and phone case there is a possibility the individual will attempt to contact the same person twice. I allow this behavior for simplicity and possible further topic sharing.

### 3.4.4 Social Media Layer

I set the social media layer of the simulation as a scale-free network using the Barabási–Albert (BA) model. Social media and internet networks have been shown to be scale-free [3, 5, 97]. Coverage is much lower than that in phone and word-of-mouth networks: 66.5% [100], 63% [73], 47.7% [79], 24.7% [79], and 12.5% [68]. Because of this wide range of values, during testing I consider a case of no social media. The average number of people forwarded to is much higher than that of the phone-like networks [99] because social media is a form of broadcast media. The parameters of the BA model are the number of initial nodes in the network before adding edges and the number of edges added for each new node. I choose values of $0.374n$ and 105 respectively, with $n$ being the total number of nodes (26363 or 4502). To select these values I chose a range of possible parameter values and compared resulting coverage and average node degree. These values give approximately 63% coverage and an average node degree of 132, which match coverage and forwarding numbers in the literature.

When an individual decides to share information via social media, they broadcast it to everyone in their social media network. This allows for matching forwarding number and average node degree and provides an advantage of social media over other personal communication types. The broadcast which occurs in social media has similar properties as the broadcast process by community leaders and officials which occurs at the beginning of the simulation.

# 4. RESULTS AND EXAMPLES

## 4.1. Simplified Example

To clarify my search for a relationship between $n_0$ and a critical value of $p$, I provide a simplified example of the simulation using a lattice grid and ER network. In this simplified example, the only two variables are $n_0$ and $p$, there is a single layer of the network, and sharing only occurs with two connected nodes. Based on these properties, a lattice grid network has a theoretical critical percolation threshold of 50%. Figure 4.1 shows results of the simulation where $n_0 = 10$ (out of 10000 nodes). To gather results for the figure, a sensitivity analysis was performed over different values of $p$ (probability to share with a neighbor), with a Monte Carlo method of 100 iterations per $p$ value. It appears that the simulated critical threshold matches the theoretical value. Figure 4.2 shows the same results over different levels of $n_0$. One can see that as $n_0$ increases, the critical percolation threshold decreases.

The tests for the lattice grid were replicated with an ER network. The ER network has a node size of 10000, the same as the lattice grid, and an average node degree of 4. Based on these properties, this ER network has a theoretical critical percolation threshold of 25%. Figure 4.3 shows results of the simulation where $n_0 = 10$. It appears that the simulated critical threshold matches the theoretical value. Unlike the lattice grid network, for low $n_0$ values there are some results that are close to 0 even with relatively high $p$ values. The likelihood of this happening is due to the nature of the random network; with only 10 initially informed nodes, there is a chance that several have a low degree, increasing the chances that all of them will not spread the information. The lattice grid network could have the same occurrence, but with only 100 Monte Carlo iterations it is relatively rare. Figure 4.4 shows the same results as Figure 4.3 over different levels of $n_0$.

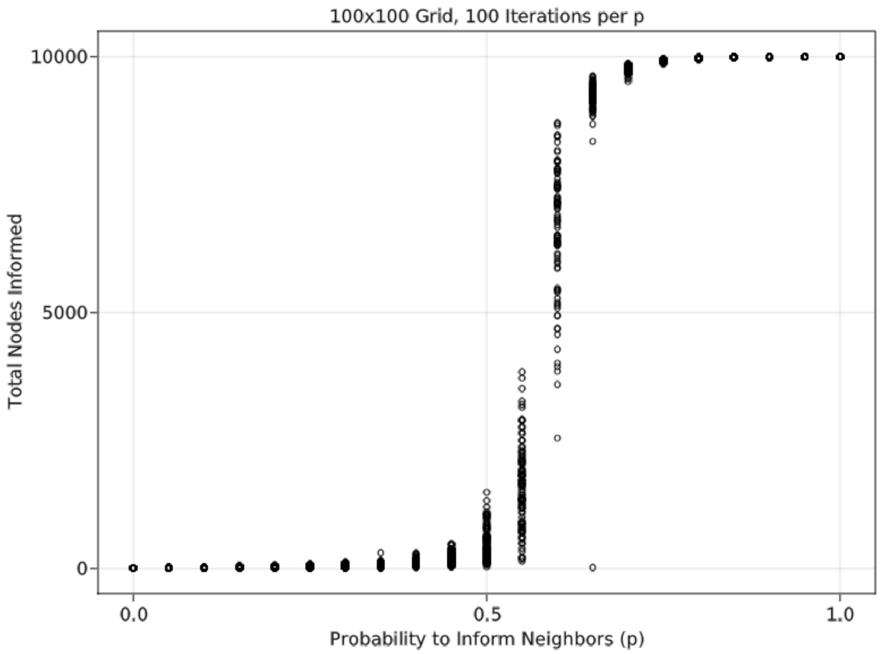


FIGURE 4.1: Lattice grid simulation results with $n_0 = 10$.

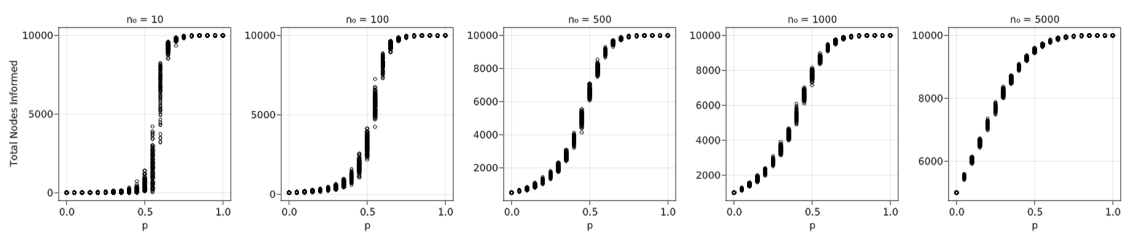

FIGURE 4.2: Lattice grid simulation results with $n_0 = 10$, 100, 500, 1000, 5000.

Like the lattice grid network, as $n_0$ increases, the critical percolation threshold decreases.

## 4.2. Full Simulation

I start with an exploratory sensitivity analysis of all simulation parameters then provide a more narrowed and detailed view of a few key parameters. For simplicity, in this section the values for the simulation parameters $p$, $p_l$, $c$, and $r$ are initial starting

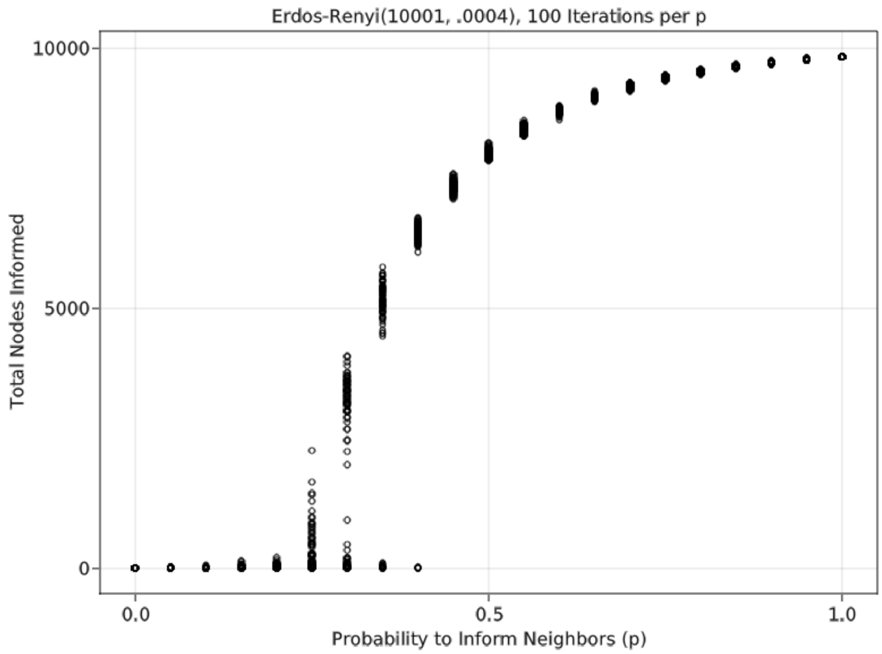


FIGURE 4.3: ER network simulation results with $n_0 = 10$.

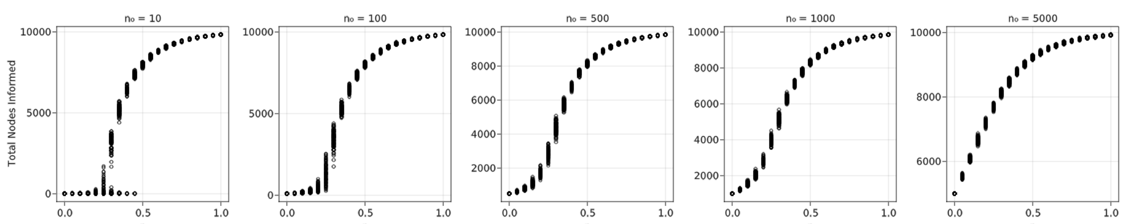

FIGURE 4.4: ER network simulation results with $n_0 = 10$, 100, 500, 1000, 5000.

parameters I designed for the provided functions: $p_0$, $b$, $c_n$, and $t_r$. Additional information on these initial starting parameters can be found in equations 3.1, 3.2, 3.3, and 3.4. Table 4.1 details the range of values used for the first exploratory analysis of the Coos Bay dataset. The total number of individuals in the simulation for this dataset is 26363. Each combination of parameter values has four Monte Carlo iterations. The ordering of the values in the lists of simulation parameters $p_l$, $t_l$, and $w_l$ are [phone, word-of-mouth, social media], corresponding to the three layers of the simulation. The values chosen originate from the literature values detailed in section 3.2.; I select values within the range of those provided by the literature and center around the most common to have consistent coverage of the simulation parameter space. The third value of $p_l$, [30%, 70%, 0%], does not originate from the literature. I select those values in the list to account for a scenario where social media is unavailable or internet coverage is sparse. The values of $c$ also do not appear obvious in the literature; I select values two standard deviations away from a mean of 1.37, from [47]. If $c$ is a random variable following a normal distribution, that encompasses approximately 95% of the population.

| Simulation Parameter | Description | Range of Values |
|---|---|---|
| $n_0$ (Section 3.2.1) | broadcast | 1582, 7909, 13182, 18454, 24518 (6%, 30%, 50%, 70%, 93%) |
| $p$ (Section 3.2.2) | probability | 5%, 20%, 35%, 50%, 65%, 80% |
| $p_l$ (Section 3.2.3) | layer probability | [50.5%, 25.5%, 24%], [2.5%, 73.3%, 24.2%], [30%, 70%, 0%] |
| $t_l$ (Section 3.2.4) | sharing time | [17 mins, 1 min, 120 mins], [120 mins, 70 mins, 201.6 mins] |
| $c$ (Section 3.2.5) | confidence | 0.07, 2.67 |
| $r$ (Section 3.2.6) | evacuation | 15 mins, 60 mins, 360 mins, 3600 mins (60 hrs), 5760 mins (96 hrs) |
| $d$ (Section 3.2.7) | prewarning time | 9 mins, 60 mins, 180 mins, 1440 mins (24 hrs), 4320 mins (72 hrs) |
| $w_l$ (Section 3.2.8) | trust | [43%, 39%, 48%] |

TABLE 4.1: Range of Simulation Parameter Values for Exploratory Sensitivity Analysis.

When looking at a range of $n_0$ values between 1582 (6%) and 24518 (93%) out of 26363, Figure 4.5 indicates that while there is variation within the $p$ values, across the $p$

values there is mostly a linear trend. This, combined with a very large variation of total nodes informed at the smallest $p$, 5%, indicates a closer look needed at smaller values of $n_0$ and $p$.

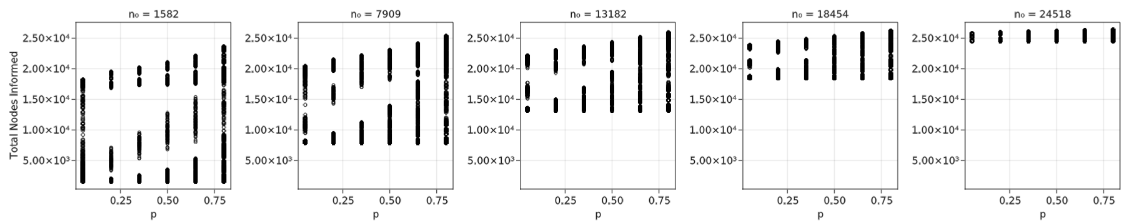


FIGURE 4.5: Effects of $n_0$ and $p$ on total nodes informed.

Figure 4.6, with 100 Monte Carlo iterations per combination, $n_0 = 5$, 100, 500, and $p = 1$–10%, begins to show more of a curve as expected. Particularly $n_0 = 500$ looks somewhat similar to Figure 4.3, although with much more variation. This figure has most variables fixed to single values for computational time purposes, unlike Figure 4.5.

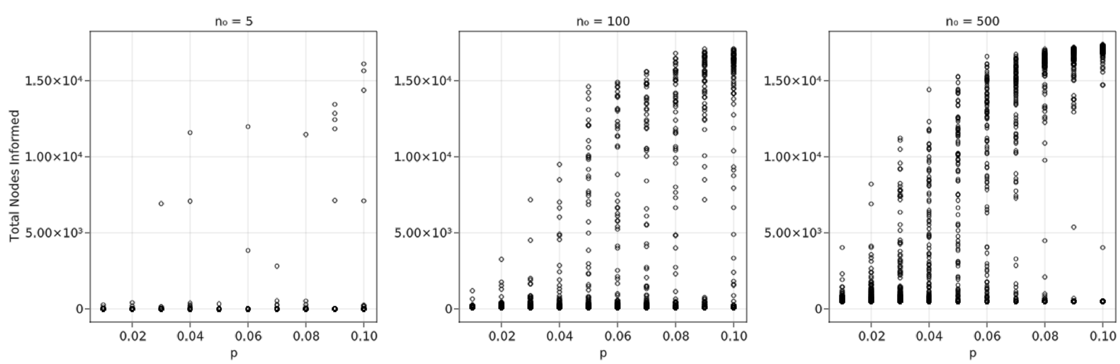


FIGURE 4.6: Effects of small $n_0$ and $p$ on total nodes informed.

Using the exploratory data, I analyze sensitivity of simulation parameters besides $n_0$ and $p$. I begin with $d$, prewarning time before the disaster. Figure 4.7 indicates that the contagion process when $d = 9$ mins performs poorly, even with high $n_0$. The largest difference between the initial number of informed nodes and final number is 7268, approximately 28% of the total. This suggests extremely rapid onset hazards such as tsunamis may not be able to rely on a contagion process and will likely perform better with immediate broadcast methods such as tone alert radio or SMS notification. Environmental and social cues may be able to mitigate some of the broadcast effort. Continuing in this paper I use a $d$ value of 1440 mins (24 hrs) since it is shorter than uniquely hurricane times but long enough to show the contagion process. I also use $n_0 = 1582(6\%)$ and $p = 5\%$ because of Figure 4.6's indication of the critical percolation threshold at low $n_0$ and $p$ values.

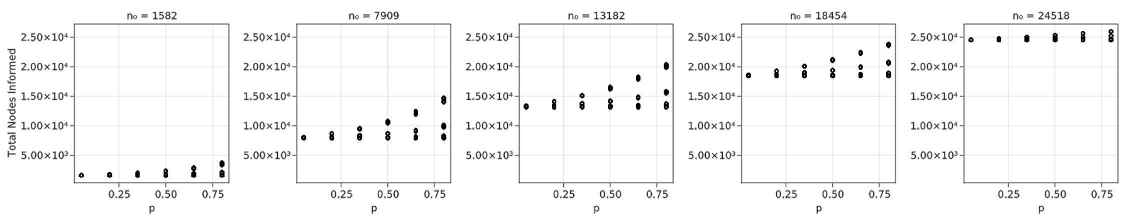


FIGURE 4.7: Total nodes informed with $d = 9$ mins.

The value of $c$ impacts total nodes informed significantly. Table 4.2 shows approximately tripling final dissemination values for the lower $c = 0.07$, indicating a lower requirement for information confirmation increases information sharing. While there is a significant difference in the values, continuing in this paper I use $c = 0.07$ since lack of trust in a source may additionally lower confidence. Literature summarized in Table 3.11 states a final average number of confirmations during dissemination, which implicitly includes trust levels.

| $c$ Value | Min | Mean | Median | Max |
|---|---|---|---|---|
| 0.07 | 1608 | 10461 | 13814 | 17596 |
| 2.67 | 1613 | 4158 | 3617 | 14318 |

TABLE 4.2: Total nodes informed with $c = 0.07$ and $c = 2.67$.

While not impacting total informed nodes nearly as significantly as variation in $c$, values of $t_l$ still provide some difference. This is likely because every value in the second list for $t_l$, [120 mins, 70 mins, 201.6 mins], is longer than the corresponding value in the first list. This means the minimum value in the first list is considerably smaller than the one in the second list, affecting $p$ as shown in Equation 3.1. Table 4.3 summarizes the differences in values. Note that the order of layers in the list is [phone, word-of-mouth, social media]. For further analysis in this paper I use $t_l$ = [17 mins, 1 min, 202 mins] because those values are more directly pulled from the literature and, with the word-of-mouth value being considerably smaller, are likely more sensitive to evacuations.

| $t_l$ Value | Min | Mean | Median | Max |
|---:|---:|---:|---:|---:|
| [17 mins, 1 min, 120 mins] | 1616 | 11460 | 16993 | 17596 |
| [120 mins, 70 mins, 201.6 mins] | 1608 | 9463 | 12328 | 16399 |

TABLE 4.3: Total nodes informed with $t_l$ = [17 mins, 1 min, 120 mins] and $t_l$ = [120 mins, 70 mins, 201.6 mins].

As indicated in Table 4.4, changes in $r$ do not appear to impact the total number of informed individuals. This is surprising considering the impact evacuation has on word-of-mouth dissemination. It implies the driving forms of communication are phone and social media. For additional analysis I use $r$ = 3600 mins (60 hrs) because it is not the largest value but it is greater than $d$. A value greater than $d$ means that some individuals will choose to evacuate immediately, following previous research [52].

Table 4.5 displays a significant difference in total informed individuals when social media is approximately 24% and when it is 0. Note that the order of layers in the list is [phone, word-of-mouth, social media]. The two results when social media is approximately 24% are quite similar, although it appears the one with a larger phone percentage is slightly more. This table indicates social media plays a large role in information dissemination and phone communication plays a somewhat larger role than word-of-mouth.

| $r$ Value | Min | Mean | Median | Max |
|---:|---:|---:|---:|---:|
| 15 mins | 1647 | 11810 | 16778 | 17579 |
| 60 mins | 1642 | 11836 | 17057 | 17596 |
| 360 mins | 1648 | 10916 | 17071 | 17539 |
| 3600 mins (60 hrs) | 1622 | 12008 | 17054 | 17587 |
| 5760 mins (96 hrs) | 1616 | 10727 | 16897 | 17432 |

TABLE 4.4: Total nodes informed with $r$ = 15 mins, 60 mins, 360 mins (6 hrs), 3600 mins (60 hrs), 5760 mins (96 hrs).

Communities with limited internet access may need to supplement the contagion process with additional official communication or provide resources to increase effectiveness of the contagion process. For further analysis in this paper I use $p_l$ = [50.5%, 25.5%, 24%]. The values in the list originate from previous literature and the differences between values are smaller than the other two lists.

| $p_l$ Value | Min | Mean | Median | Max |
|---:|---:|---:|---:|---:|
| [50.5%, 25.5%, 24%] | 17161 | 17343 | 17312 | 17587 |
| [2.5%, 73.3%, 24.2%] | 16982 | 17053 | 17054 | 17123 |
| [30%, 70%, 0%] | 1622 | 1629 | 1630 | 1634 |

TABLE 4.5: Total nodes informed with $p_l$ = [50.5%, 25.5%, 24%], $p_l$ = [2.5%, 73.3%, 24.2%], and $p_l$ = [30%, 70%, 0%].

Since reference values for all variables have been identified, I analyze $n_0$ and $p$ in additional detail. Figure 4.8 shows 50 different combinations of $n_0$ and $p$, with $n_0$ = 1, 5, 50, 500, and 100 and $p$ = 1–5%. Due to the low probabilities and highly stochastic nature of the problem, results vary significantly across each run of the simulation. I simulate a much larger number of iterations to identify a curve when there are low values of $n_0$ and

$p$. Each permutation has 1000 Monte Carlo iterations. One can see with $n_0 = 1$ that the vast majority of results are very close to 0; only a few approach larger numbers similar to those seen with larger $n_0$. Based on this graph, it appears a critical percolation threshold may be around 3.5–4%. As $n_0$ increases, the critical threshold appears to shift to the left, toward smaller $p$. For example, $n_0 = 50$ the threshold appears to be around 1.5% and at $n_0 = 1000$ it is closer to 0.5–1%. While these differences appear significant in determining a necessary initial broadcast size, the critical threshold cannot necessarily be relied upon; with such small $p$, the variation is large and there are still many simulation runs where results are close to 0 even with larger $n_0$. $n_0 = 1000$ in Figure 4.8 indicates there is a steady range of results within each $p$ value even with the smaller critical percolation threshold.

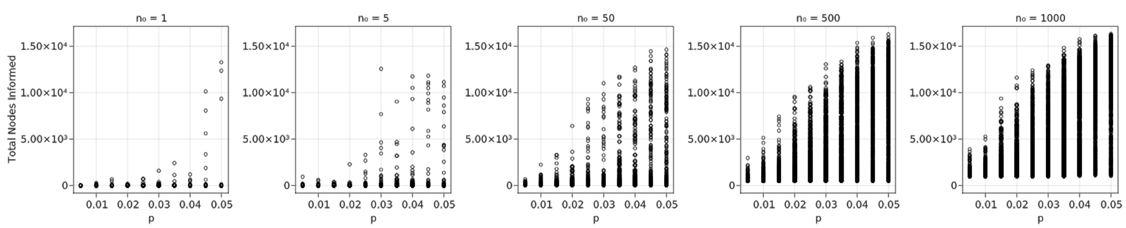


FIGURE 4.8: Total Coos Bay informed individuals with $n_0 = 1, 5, 50, 500, 1000$ and $p =$ 0.5–5%.

The data collected for Figure 4.8 was replicated with Seaside data for Figure 4.9. While the exact critical thresholds may not be quite as obvious, it seems to follow the same trend as the Coos Bay data. Note that while the $n_0$ values are the same between the two datasets, they are different percentages of the total population since Coos Bay is 26363 individuals and Seaside is 4502.

### 4.2.1 Validation

Some simulation parameters, being functions, do not have direct connections to existing literature. In this section I analyze values produced during the simulation to determine similarity to previous studies' results.

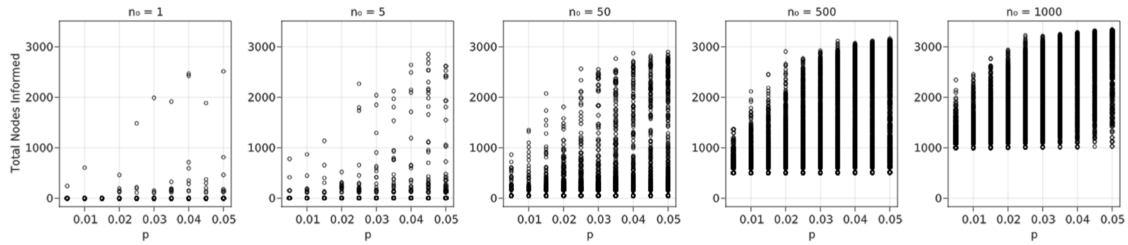


FIGURE 4.9: Total Seaside informed individuals with $n_0$ = 1, 5, 50, 500, 1000 and $p$ = 0.5–5%.

I first look at differences in real probability values from the initial starting $p$. Since the initial starting $p$ is used for analysis in section 4., any results drawn from those conclusions would need to be adjusted for these differences. The differences are provided in Table 4.6 for $p$ = 0.5–5% in the Coos Bay dataset. Note that the real probability values are always less than $p$ due to the function detailed in Equation 3.1. As $p$ increases the differences in probabilities also increase, greater than a constant fraction of $p$. The differences are small, with the greatest being three-quarters of 1%. This indicates that while the $p$ values shown in figures 4.8 and 4.9 are not exact, they are close enough that the trends discovered are still there.

While relatively small $p$ values have been identified for the critical percolation threshold, when analyzing hurricane dissemination times I use larger ones. [54] determined peers as the first source of warning in 7% and 0% of the population in two different hurricanes. Because of this, I use the exploratory $p$ = 5%, 20%, 35%, 50%, 65%, 80%. In a hurricane scenario ($d$ = 1440 mins (24 hrs), 4320 mins (72 hrs)), the average percentage of the population informed after 8 hours is 87%, quite a bit higher than the identified 70% in the literature [54]. The average percentage informed after 24 hours is 89%, fitting the $>$ 80% found in the same study. An additional study found that 50% were notified by 15 mins and 95% were informed by 2.25 hrs [49]. The simulation finds an average 51% informed by 15 mins and 79% by 2.25 hrs. The combination of over- and under-estimation of the simulation when compared with previous studies shows that the results are within

| Initial Starting $p$ | Mean Difference in Real Value from $p$ (always less) |
|---|---|
| 0.005 | 0.0001 |
| 0.010 | 0.0005 |
| 0.015 | 0.0010 |
| 0.020 | 0.0017 |
| 0.025 | 0.0027 |
| 0.030 | 0.0034 |
| 0.035 | 0.0046 |
| 0.040 | 0.0056 |
| 0.045 | 0.0065 |
| 0.050 | 0.0075 |

TABLE 4.6: Mean differences in real probability values from initial starting $p$ values.

acceptable bounds.

[49] found that approximately 53.6% evacuated from Hurricane Lili. The simulation identifies an average of 35% evacuated in hurricane prewarning times ($d = 1440$ mins (24 hrs), 4320 mins (72 hrs)). This appears quite a bit smaller than the literature value; however, the simulation produces a range of 30–94%, showing a difference of 18.6% may not be as large as it originally appears.

An information dissemination curve of individuals informed by phone was provided by [99]. They do not provide many specific parameters of their model, so I select a range of $n_0 = 1582$, 7909, 13182, 18454, 24518 (6%, 30%, 50%, 70%, 93%), $p =$ 5%, 20%, 35%, 50%, 65%, 80%, $d = 9$ mins, 60 mins, 180 mins, 1440 mins (24 hrs), 4320 mins (72 hrs), and $r = 15$ mins, 60 mins, 360 mins, 3600 mins (60 hrs), 5760 mins (96 hrs). These are all from the exploratory values of Table 4.1. Figure 4.10 provides a visual view of the results. The results do not seem to match the telephone dissemination curve of [99], which appears sigmoidal. This is likely due to differences in behavior. In this study's simulation, an individual continues to contact others until failure, which has an expected value of $\frac{p}{1-p}$ contacts, since it is inverse of a geometric distribution. In the study by [99], they have an individual attempt to contact 150 others, regardless of failure. In addition, this simulation has a phone layer working alongside word-of-mouth and social media layers, so those may play a significant role in the results.

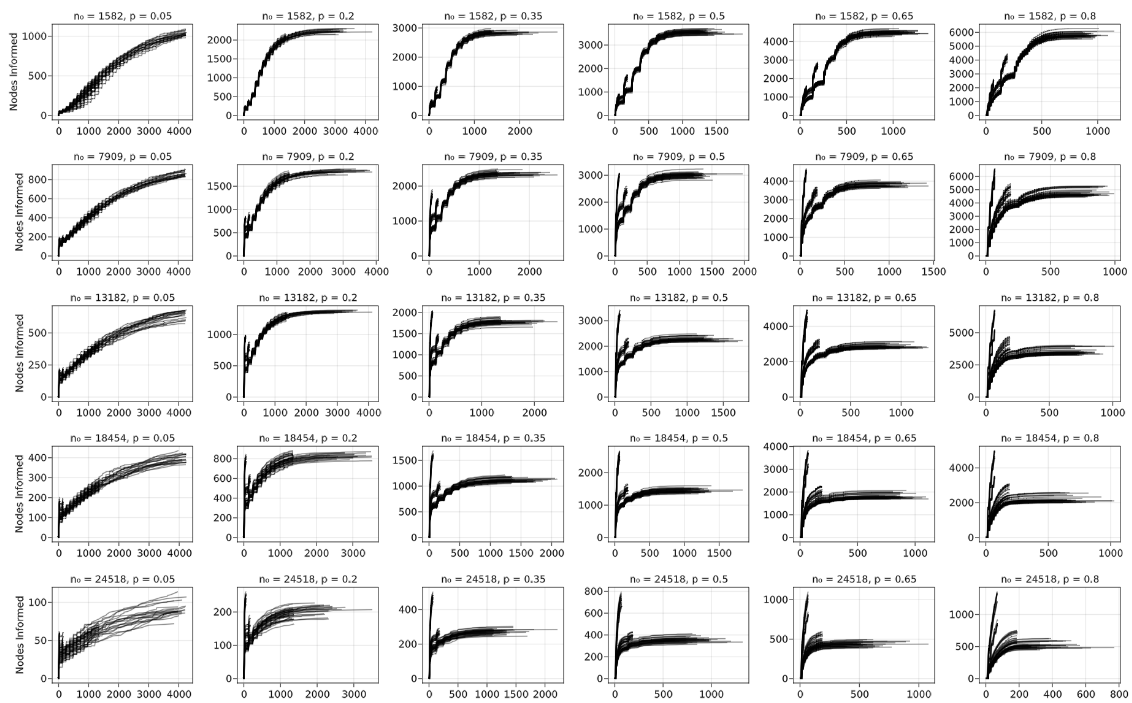


FIGURE 4.10: Total individuals notified by phone with $n_0$ = 1582, 7909, 13182, 18454, 24518 (6%, 30%, 50%, 70%, 93%) and $p$ = 5%, 20%, 35%, 50%, 65%, 80%.

# 5. DISCUSSION

While the methodology and results of this study are unique, there are assumptions made, often due to complexity constraints, which could be addressed by future research. I address limitations and assumptions in 5.1. and possible future work in 5.2.

## 5.1. Limitations and Assumptions

Due to the agent-based simulation aspect of this research, there are many implicit assumptions made when developing the simulation. However, there are several assumptions which were consciously made and could be adjusted in future work. There are nine primary assumptions made which are not addressed in subsections 5.1.1 and 5.1.2: 1) ignoring environmental and social cues; 2) limiting to eight simulation parameters ($n_0$, $p$, $p_l$, $t_l$, $c$, $r$, $d$, and $w_l$) and determining the relationships between them (for more details, see section 3.2.); 3) assuming reciprocal relationships with an undirected network; 4) combining time to communicate and time before receiving information – especially problematic with word-of-mouth because it is not easy to "leave a message" if the recipient is not there; 5) assuming trust is on a per-communication type level rather than individual level; 6) assuming the type of disaster requires evacuation and the provided information suggests that; 7) evacuation only affecting the word-of-mouth communication type; 8) assuming households behave like individuals; and 9) ignoring interactions between different official sources and pieces of information.

### 5.1.1 Broadcast Process

The broadcast process has two primary assumptions which could be focused on in future research: 1) perfect trust in the official source, regardless of the communication type or message format; and 2) an instant receipt of official information, where every individual in the broadcast process receives the information at the same time.

### 5.1.2 Warning Sources

This study does not touch on information sources, whether from the broadcast process or the contagion process. It assumes there is exactly one piece of information from one official source, which may not be realistic with an approaching hazard. It also assumes that individuals may share information with whomever gave it to them; this may not be realistic, especially when those individuals are still sharing with others.

## 5.2. Future Work

Future work could add environmental and social cues to determine their effects with social warnings. In addition, the possible effects of directed networks could be tested with different types of network structures such as regular or ER networks. If choosing to use different data sources for the word-of-mouth layer, locations which are not coastal and more rural may provide additional insights.

Regarding a broadcast process, there are several components to study which have not been covered by this simulation. The effects of a message format or communication type on an official broadcast's effectiveness could provide guidance on best practices for community leaders to successfully reach the public. Multiple news sources may also play a role, especially if there are generally different levels of trust for each source. Since it is unlikely a community leader will be able to reach everyone at a single time, repeating messages at periodic intervals over time could simulate information reception from other news sources such as television and radio [62]. Updated information regarding the hazard could also play a role. Independence of different information could be investigated to aid in identifying how incorrect information works against public safety.

The time of day an emergency warning is delivered can affect the length of time before individuals receive it [43]. Accounting for this as well as separating out the time it takes to send a communication and reception time may significantly increase realism. Finally, adjusting the current simulation parameter functions would be useful for determining the sensitivity of the variables.

The seemingly discrete curves of Figure 4.10 indicate there may not be enough variation in the simulation parameters for smooth curves. Future work could determine the variation in parameters necessary for curves more suitable for regression analysis.

# 6. CONCLUSIONS

The initial official broadcast of an emergency warning plays a significant role in the following informal spread of the information by newly informed individuals. While several characteristics of the situation such as prewarning time before the disaster occurs, the likelihood of individuals to confirm new information, and the amount of time it takes to share information affect the dissemination of information, the most significant is the probability of an individual to share with others. To find these results I developed an agent-based simulation which modeled information dissemination in a multiplex social network where each layer is a different communication channel. I collected data from previous literature to inform suitable parameter values for the simulation and provide verification of its results. Providing real-world data as a context for a potential hazard, I used a dataset for Seaside, OR [88] and 2020 census data to inform a dataset of Coos Bay, OR [84].

Providing a simplified example for clarification of methods, I showed that its simulated results matched theory. When applying all considered variables in the model to a more complex simulation, the results indicated that, as expected, initial broadcast size has a negative correlation with the critical percolation threshold. The threshold ranges from approximately 1–5%, where a larger initial broadcast lowers the value. Significant variables, along with probability to share and initial broadcast size, are primarily confidence in the information and amount of time before the disaster occurs. Social media appears to play a large role in dissemination as well, suggesting a possibly highly effective method for rapid information sharing, provided it is checked often and remains trustworthy.

This study will inform officials and community leaders on their community's response to natural disasters and other hazards, provided unique characteristics of their community. This paper also provides a groundwork for future studies. Focus on the official broadcast process, types of cues besides social warnings, specific hazards, or information confidence could provide more specific results and policy suggestions for various communities with different characteristics. The field of emergency warning dissemination will become increasingly more relevant as communities have to manage increasingly challenging hazards [27, 40, 44].

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