JASSS ODD Protocol

Charles Koll, Michael K. Lindell

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The model description follows the ODD (Overview, Design concepts, Details) protocol for describing individual- and agent-based models [9], as updated by [10].

1 Purpose and patterns

The model's purpose is to identify the effect of 1) initial broadcast size; 2) likelihood of informed individuals to relay a warning with others and by which method; 3) time it takes to relay the warning with different communication channels; 4) warning belief; 5) likelihood to evacuate; and 6) forewarning of the disaster on the total number of people who receive an emergency warning.

The model is based on the following empirically based principles: 1) initial broadcast size, likelihood of informed individuals to relay the warning with others, belief in the received warning, and forewarning of disaster impact are positively correlated with the total number of people warned; and 2) the time it takes to relay the warning and the likelihood to evacuate are negatively correlated with the total number of people warned.

2 Entities, state variables, and scales

The model's unit of analysis is the *individual*, representing a household as a single entity. Analyzing each household as multiple individuals instead of as single individuals would likely increase information dissemination speed due to more rapid communication between household members and an increased social network of the household, so individuals are a worst-case scenario. When receiving a warning, individuals typically warn other household members prior to the rest of their social network. This may delay the contagion process, but communication is likely to be much faster and nearly instantaneous if all household members are at home.

This simulation does not model the spatial distribution of the agents except for initialization of the word-of-mouth graph, described in a later section.

Timesteps are continuous, handled as discrete events. This allows for entities to easily affect each other while also allowing for more flexible variation in event times. The simulation ends when there is no more communication between

Variable	Description	Dynamic/static	Type	Range
ID	My unique identifier.	Static	Any	At least as many values as the number of individuals.
comm	If I've started communicating.	Dynamic	Boolean	true/false
evac	If I've started evacuating.	Dynamic	Boolean	true/false
informed	The collection of individuals who have informed me.	Dynamic	Set	Each element of the set is a tuple of *(ID, channel)* where *channel* is the communication channel.
trust	How much I trust neighboring individuals for each communication channel.	Static	Dictionary	Each key is a tuple of *(ID, channel)* where *channel* is the communication channel. Each value of the dictionary is a real number between 0–1.

Table 1: Individual agent characteristics.

individuals. The scale of the timestep variable is minutes because rapid-onset hazards such as flash floods, hazardous materials releases, and local tsunamis can strike with little forewarning so models of warning processes for these hazards need to operate within this short time frame.

3 Process overview and scheduling

This simulation is run as a series of discrete events, so it is an iteration of events. To reduce complexity, each individual transmits a maximum of one warning, which means each new event targets a new individual. Each event has the following timeline:

1. Add communication source (ID, channel) to *informed*.
2. Assess warning confidence.
3. If an individual decides to evacuate, remove them from the word-of-mouth network and set *evac* to true.
4. If an individual decides to relay the warning:
   (a) Pick a communication channel: phone, word-of-mouth, or social media.
   (b) Use the communication channel to determine who should be contacted at which times and add them to the event queue unless they're already being contacted by someone else.
   (c) Set *comm* to true.
5. Select the next event nearest in time.

No individual modifies a variable which is accessed by others, so in cases where multiple individuals are informed at the same time and the communications started at the same time, it is left to the language's implementation of tuple sorting.

4 Design concepts

4.1 Basic principles

This model integrates several elements of the emergency warning literature into a single simulation: probability to relay the warning, communication channels, warning time, warning belief, probability to evacuate, and forewarning. Detailed background and literature on these elements can be found in Section 7: Submodels. These elements are combined into a multiplex network which agents (*individuals*) use to communicate with others in warning dissemination.

4.2 Emergence

The model produces the number of warned individuals with varying probabilities of relaying the warning, which yields a sigmoidal curve. This shape results from percolation theory's critical percolation threshold. Other simulation parameters produce primarily linear results.

4.3 Adaptation

All adaptive behavior is performed after an individual receives a warning. They have some probability of evacuating if they haven't already done so and some probability of relaying the warning to others if they haven't already done so. Both, exactly one, or none of these actions can be performed immediately following warning reception but not any time after that.

4.4 Objectives

The objective measure of an individual is the importance of the warning they receive. The more important the warning, the more likely they are to relay it to their social network. The importance of the warning is computed from a base probability to relay the warning, the time it takes to relay, warning belief, and the amount of forewarning.

4.5 Learning

Learning is not implemented.

4.6 Prediction

Individuals explicitly predict when the disaster will strike. This time remaining until the disaster strikes affects their decisions to relay the warning and to evacuate.

4.7 Sensing

Individuals receive warnings from other individuals in the multiplex social network. Each individual receives a warning through a specific communication channel. The warning receiver's confidence in the warning is entirely based on the channel through which it was received. Each individual then chooses a network layer for warning others.

4.8 Interaction

Individuals directly interact by relaying the warning over a communication channel. Each channel is a layer of the multiplex social network.

4.9 Stochasticity

Connections within the multiplex network are primarily determined stochastically. The network's phone and social media channels are represented by Watts-Strogatz and Barabási-Albert networks, which are inherently stochastically initialized. This is useful to represent connections between individuals which would be challenging to represent otherwise. The network's word-of-mouth communication channel is entirely deterministic, based on distances between individuals.

Other stochastic processes in the model are relaying the warning, choosing a communication channel, and evacuation. These "choices" made by the individuals represent complex decisions which would be overly complex to model. Further details of these choices are detailed in Section 7.

4.10 Collectives

Each of the three communication channels (phone, word-of-mouth, and social media) in the multiplex social network can be thought of as a collective. Individuals are a part of all of these collectives and they can only communicate with others that are also connected to the collective. This collective behavior emerges from interactions between the individuals, although the connections for each channel were initialized together as a unique network type (Watts-Strogatz, Barabási-Albert, and Random Geometric). These networks cannot be modeled independently due to the ability of individuals to relay the warning over a channel different from the one on which they received it. This creates a dependence between the networks.

4.11 Observation

The simulation produces four dataframes of model data. Table 2 identifies the columns of each dataframe and their meanings. No other analysis data is produced from the model.

5 Initialization

The multiplex social network must be initialized as an array of graphs prior to running the model. This initialization can occur by generating a multiplex graph with "makenet()", which uses default network parameters from the literature. These values are detailed below in Section 7. An additional parameter which does not come from literature is location data for the individuals in the network. The default name of this file is "wom_coords.csv", located in a "data" directory under the simulation's directory; however, this can be changed to any other file name or location. The file consists of two columns, "x" and "y", which are assumed to be in meters. The coordinates provided in this file represent locations of the individuals who are connected in the word-of-mouth communication channel.

6 Input data

The model does not use input data to represent time-varying processes.

Dataframe	Column Name	Meaning
dissem	t	Minutes after the beginning of warning dissemination
dissem	dissem	Number of individuals informed of warning up until and including the current moment in time
probs	prob	Probabilities of an individual relaying the warning
probs	informed	Number of individuals warned up until and including the current moment in time
layers	t	Minutes after the beginning of warning dissemination
layers	phone	Number of individuals warned by phone up until and including the current moment in time
layers	wom	Number of individuals warned by word of mouth up until and including the current moment in time
layers	sm	Number of individuals warned by social media up until and including the current moment in time
evac	t	Minutes after the beginning of warning dissemination
evac	evac	Number of individuals having started to evacuate by the current moment in time

Table 2: Results as dataframes returned by the simulation.

7 Submodels

Submodels to the simulation consist of parameters influenced by emergency warning literature and structure of the multiplex social network. These are described in this section.

7.1 Broadcast size (n_0)

The broadcast size n_0 is the 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. Table 3 provides a brief summary of n_0's properties.

For the Mount St. Helens (MSH) eruption, [15] 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

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

Table 3: n_0 properties.

informed by other means such as environmental cues that include personal observation of the ash plume. While this may indicate a possible concern with assuming only social warnings in this simulation, many hazards such as radiological materials releases 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 4 summarizes these literature values and others.

Values	Hazard Type	Information Source	Source
14% min, 38% median, 89% max	flash floods	peers	[12]
31.8%	floods	primarily neighbors	[35]
7%, 0%	hurricanes	peers	[17]
6%, 0%	volcano	officials	[15]
58%, 47%	volcano	social network	[15]

Table 4: n_0 literature values.

7.2 Probability to relay the warning (p)

The probability that a warned individual will relay a warning to 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 forewarning), t_l (time to relay the warning), and c (warning belief). The difference $d - t_s$ determines how much time is left before the disaster strikes. This value affects an individual's probability to relay the warning because an individual receiving a warning only a very short time before the disaster strikes will cause them to tend to their own household's safety before warning others outside the household. t_l plays a role in the probability to relay the warning because warning channels which take a long time will reduce the time individuals have to prepare themselves. Finally, c, warning confirmation, affects the value of p because an individual who has not confirmed a warning will be less likely to relay it. Table 5 provides a brief summary of p's properties.

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

Parameter	p
Description	Probability to relay a warning
Type	function
Function Parameters	t_s, d, t_l, c
Output	value/distribution
Output Range	[0, 1]

Table 5: p properties.

simulation parameter. Equation 1 describes this function:

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

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

This function has the property that 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. We include the p_0 for percolation purposes; since this 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, we select a wide range of values and narrow them to determine the relationship.

While few empirical warning studies have provided information regarding the percentage of people who warned someone else, several of them report how many people warned others via different communication channels. These studies 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 reported that 1.1% and 2.4%, respectively, told someone else during two hazardous materials (hazmat) transportation accidents [26]. Other studies which are more specific to communication channels are detailed in 7.3 and Tables 7 and 8.

7.3 Probability to relay the warning on different communication channels (p_l)

The weight to relay the warning on different layers (communication channels) determines how often each layer is used in warning dissemination. The simulation parameter p_l is a normalized vector comprising the set of weights associated with the multiple layers. A higher value in one element of the vector increases the use of the given layer while decreasing the use of the others. The parameter p_l is a function that is defined by three parameters: t_s, d, and t_l. The difference $d - t_s$ determines how much time is left before the disaster strikes. This value affects a layer's weight for the same reason as it affects p; receiving a warning shortly before the disaster strikes will cause people to tend to their own household's safety before warning others outside the household. This difference, combined with t_l, computes the effect that the time it takes to relay a warning via a given communication channel has on deciding to use it. Table 6 provides a brief summary of p_l's properties.

Parameter	p_l
Description	Probability to relay the warning on different communication channels
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 6: p_l properties.

Based on these assumed parameters, we construct a function p_l; however, the simulation allows for an easy change of function for this simulation parameter. Equation 2 describes this function:

$$p_l(t_s, d, t_l) = \text{norm}\left(b \times \max\left(1 - \frac{t_l}{\max(d - t_s, 0)}, 0\right)\right) \tag{2}$$

where $\max(x,\ 0)$ ensures no negative numbers, all operations are conducted 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.

We include b to emphasize variation among communities because some may be predisposed towards certain communication channels where time remaining before the disaster strikes and the time required to transmit a message play negligible roles. In these cases, b allows for returning values which may appear closer to the community's characteristics.

Communication probabilities for different types of communication channels are much more common in emergency warning literature than other communication domains. We separate these probabilities into two groups: probabilities of warned individuals relaying the warning to others via different communication channels (Table 7) and probabilities of individuals receiving the warning via different types of communication channels (Table 8). The latter group does not exactly correspond to the intent of p_l; however, these values can provide guidance on the values of the former group. "Hazmat" represents "hazardous materials transportation accidents".

7.4 Warning time (t_l)

The time an individual takes to relay the warning can vary based on the communication channel they choose. In actual emergencies, there is also the time it takes for an individual to receive information; depending on the communication channel, an individual who is away from their home or communication device can take longer to be warned. To simplify, this version of the model incorporates

Values	Hazard Type	Communication Channel	Source
22%	floods	neighbors	[22]
27%	emergencies in Europe; survey	social media	[24]
48%	emergencies in Europe; survey	social media in future	[24]
0.1%	wildfire	retweets (Twitter)	[29]
0.1%	tsunami	retweets (Twitter)	[6]
57.7%	tsunami	face-to-face	[23]
26.9%	tsunami	phone call	[23]
5.8%	tsunami	SMS	[23]

Table 7: p_l literature values – communication types of individuals.

Values	Hazard Type	Communication Channel	Source
1.84 (1–5 Likert scale)	hurricane	internet	[14]
36%	flash flood	face-to-face	[21]
31.8%	floods	neighbors	[35]
1.1%	floods	SMS	[35]
10.5%	floods	not neighbors or SMS	[35]
26%	tornado	word of mouth	[25]
51%	tornado	cell phone	[25]
8%	tornado	social media	[25]
17%	tornado	internet	[25]
18.3%	Hazmat	friends, neighbors, relatives	[26]
11.8%, 29.7%	Hazmat	door-to-door	[26]
24%	volcano	face-to-face	[15]
13%, 14%	volcano	telephone	[15]

Table 8: p_l literature values – prevalence of communication channels.

that additional time into t_l. It is expected to have a minimal effect combined as opposed to separated if individuals only attempt to relay a warning 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 warning time also allows for fewer limitations on literature values to be used. This is especially noticeable with social media, since many people may not receive a notification of the update. Table 9 summarizes t_l's properties.

Table 10 summarizes previous literature values for t_l. [40] did not explicitly provide the values included in the table except for the word-of-mouth communication channel, although it seems they were a part of their data; we compute the values based on equations and tables. The delay time for microblog communication was computed with Equation 7 and Table 1 of [40]. Delay time

Parameter	t_l
Description	Warning time
Type	list of values/distributions – one per layer
Range	[0, ∞)

Table 9: t_l properties.

for word-of-mouth was said to be 1 minute, although this appears to be an assumption. The delay time for SMS and cell was indicated to be 99.2% closer to word-of-mouth communication than microblog; based on this statement and the computed values for word-of-mouth and microblog communication, SMS and cell communication was estimated to be 17 minutes.

Values	Hazard Type	Communication Channel	Source
3.36 hrs	disasters in Beijing; survey	microblog	[40]
1 min	disasters in Beijing; survey	oral	[40]
17 mins	disasters in Beijing; survey	SMS, cell	[40]
49 mins	Hazmat	friends, neighbors, relatives	[26]
70 mins, 66 mins	Hazmat	door-to-door	[26]

Table 10: t_l literature values.

7.5 Warning confirmation (c)

Warning confirmation plays a significant role in the warning contagion process. Many individuals will choose to confirm a warning before trusting it, which produces a slower and less effective percolation process. An individual's warning confidence depends on how many times they have received it previously, from which source, 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 11 provides a summary of its properties.

Parameter	c
Description	Warning confirmation
Type	function
Function Parameters	c_s, w_l
Output	value/distribution
Output Range	[0, 1]

Table 11: c properties.

Based on these assumed parameters, we construct a function c; however, the simulation allows for an easy change of function for this simulation parameter. Equation 3 describes this function:

$$c(c_s, w_l) = \text{clamp}\left(\frac{\text{trust}(c_s, w_l)}{c_n + 1}, 0, 1\right) \tag{3}$$

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 warned, and c_n is the expected number of times a node will need to confirm a warning before sharing it if they completely trust their sources.

Previous research regarding warning confidence and confirmation is minimal. One paper reported an average number of confirmations, which is the most helpful for determining a range of values for c, but others reported the communication channels from which confirmation was sought without providing any data regarding how much confirmation individuals required. Table 12 details some of the previous literature regarding warning confirmation.

Values	Hazard Type	Communication Channel	Source
confirmed with on avg 1.37 (std dev 0.65)	flash floods	N/A	[12]
confirmed with on avg 1.76 different warning channels	water contamination	N/A	[13]
11.0%, 11.2% waited to see	Hazmat	N/A	[26]
31.3% confirmed	tsunami	face-to-face	[23]
4.1% confirmed	tsunami	telephone	[23]
3.8% confirmed	tsunami	internet	[23]

Table 12: c literature values.

7.6 Evacuation Probability (r)

For many hazards, evacuation is common but this protective action prevents people from relaying warnings by word-of-mouth. Consequently, warning models need to include an evacuation probability to account for these “dead ends” in the warning process. For a hurricane, peers were the reason for evacuation in 6.6% and 7.8% of the population [14]. For a wildfire, individuals rated the influence of others telling them to evacuate as 3.50 on a 1–5 Likert scale [19]. A decision to evacuate involves the time remaining until the disaster occurs ($d - t_s$) and warning confirmation (c), so the simulation parameter r is a function. Table 13 summarizes the properties of r.

Based on these assumed parameters, we construct a function r; however, the simulation allows for an easy change of function for this simulation parameter. Equation 4 describes this function:

$$r(t_s, d, c) = c \times \left(1 - \text{clamp}\left(\frac{d - t_s}{t_r}, 0, 1\right)\right) \tag{4}$$

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

Table 13: r properties.

where clamp(x, 0, 1) enforces results between 0 and 1 and t_r is the earliest time at which anyone would evacuate. This function yields a probability to evacuate of $r = 0$ if the time remaining until the disaster strikes is greater than t_r and a probability of $r = 1$ if the time remaining until the disaster strikes is 0 or has already passed. We include t_r as the maximum (i.e., the earliest) 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. Some evacuation departure time studies have reported that hurricane evacuations follow a Rayleigh distribution, with studies using β parameters of 40, 45, 62, 74, 117, and 181 [16].

7.7 Forewarning (d)

The amount of forewarning before a disaster strikes plays a major role in warning dissemination. An extremely short forewarning causes individuals to look after their own household's safety rather than informing others, and also limits the length of the chain of receiving a warning and then relaying it to others. Since forewarning before a disaster strikes is fixed at the start of the contagion process, the simulation parameter d is a constant value. Table 14 summarizes d's properties.

Parameter	d
Description	Forewarning before disaster
Type	value
Range	$(0, \infty)$

Table 14: d properties.

While the warning dissemination time literature is primarily based on tsunami and hurricane hazards, their corresponding forewarning times are the shortest and longest values, respectively, across the range of environmental hazards. Table 15 summarizes several study values.

Values	Hazard Type	Source
9 mins	tsunami	[6]
12 mins	tsunami	[2]
72 hrs	hurricane	[17]
42 hrs	hurricane	[14]
36 hrs	hurricane	[32]

Table 15: d literature values.

7.8 Warning confidence (w_l)

To determine warning confidence, individuals evaluate their trust in the source from which they receive a warning. While a source is another individual, the type of social connection the warning source and receiver have may be correlated with their communication channel. Several studies have defined trust by communication channel [30, 38, 40], allowing for a simplified manner of adjusting trust levels. This simulation does the same, with a simulation parameter w_l. Table 16 summarizes its properties. Table 17 details literature on trust in social networks. All studies except for [26] group trust by communication channel. [38] do not indicate where their values originate; presumably a survey was conducted.

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

Table 16: w_l properties.

7.9 Network Structure

An advantage of a multiplex network is the ability to customize each layer with unique properties. The literature summarized in the earlier tables of this section suggests that there are generally three types of communication channels: 1) one-to-one physical interaction, such as face-to-face (word of mouth) communication with neighbors; 2) one-to-one virtual interaction, such as voice phone calls and, to a lesser extent, SMS and email; and 3) one-to-many virtual interaction, such as social media, retweets, microblog, and internet. We have labeled these three generalized types of communication word-of-mouth, phone, and social media, respectively. Each layer has specific characteristics that are detailed in subsections 7.9.2, 7.9.3, and 7.9.4.

7.9.1 An Undirected Network

Each layer of the multiplex network is modeled as an undirected network. Undirected networks have been assumed in previous warning dissemination studies

Values	Value Location	Communication Channel	Source
81.3%, 58.6% disregarded information	hazmat transportation accidents	N/A	[26]
2.74 trustworthy (1–5 Likert scale)	news in Singapore	social media	[30]
45%	disasters in Beijing	email	[38]
50%	disasters in Beijing	microblog	[38]
41.3%	disasters in Beijing; survey	SMS	[40]
43.3%	disasters in Beijing; survey	cell phone	[40]
38.91%	disasters in Beijing; survey	oral	[40]
48.3%	disasters in Beijing; survey	microblog	[40]

Table 17: w_l literature values.

[11, 27] and a reciprocal relationship can be assumed for all layers but social media. Although a form of social media might be designed such that "following" others might not be reciprocal in informal emergency warning networks, we assume that these cases are somewhat rare.

One important aspect of an undirected network is that a newly warned node could attempt to recontact their warning source. Indeed, warning recipients sometimes do recontact their original warning sources to seek or provide additional information about the threat and protective actions [36].

7.9.2 Phone Layer

We set the phone layer of the simulation as a network with the small-world property using the Watts-Strogatz (WS) model. Phone networks have been shown to have the small-world property [1, 20, 34]. Coverage is very high, with one study citing 97.2% for SMS and 99.0% for cell phone [40]. The same study also provided the average number of people forwarded to for different communication types: 11.8 on SMS and 9.7 on voice phone calls. [34] identified a phone network as a WS network with an average node degree of 6 and rewiring probability of 0.7. Nonetheless, [20] identified a network with an average node degree of 20. To account for these widely varying values, we set the phone layer to have a rewiring probability of 0.7 and an average node degree of 10, which splits 6 and 20 and is approximately the same as the average number of people warned.

The number of people warned by phone depends on previous warning success. If an individual decides to warn, they do so and check their probability again, repeating until they cease attempting. The expected number of people warned 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 that an individual will attempt to contact the same person twice. This feature is consistent with people monitoring a threatening situation (e.g., an approaching hurricane) by repeatedly exchanging information with trusted others—a process known as "milling" [36, 18].

7.9.3 Word-of-Mouth Layer

Previous studies have incorporated spatial features into social networks [1], so we set the simulation's word-of-mouth layer as a random geometric graph (RGG) based on real-world data. Coverage is essentially perfect, with one study citing 100% for oral communication [40]. Our real-world data is drawn from two sources: a possible population distribution of Seaside, Oregon [33] and household locations approximated by 2020 census data for Coos Bay, Oregon [31]. 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 because [40] found the distribution of oral communication was entirely within 90 meters, with the vast majority, 93.6%, within 60 meters. Based on this finding, we allow for connections between any individuals within 60 meters apart but no farther. Of course, this distance could be easily adjusted for future analysis.

The word-of-mouth layer is affected by 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 talk directly to neighbors but they can likely still communicate virtually via cell phone or social media, so those layers are unaffected by the evacuation. Otherwise, the probability of relaying a warning in the word-of-mouth layer follows the same process as the phone layer.

7.9.4 Social Media Layer

We set the social media layer of the simulation as a scale-free network using the Barabási–Albert (BA) model, consistent with the findings of [1, 3, 37]. Coverage is much lower than in phone and word-of-mouth networks: 66.5% [40], 63% [24], 47.7% [28], 24.7% [28], and 12.5% [23]. The average number of people contacted to relay a warning is much higher than that of the phone networks [39] because social media is a broadcast channel. 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. We choose values of $0.374n$ and 105 respectively, with n being the total number of nodes (26363 for Coos Bay or 4502 for Seaside). To select these values we 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 the coverage and forwarding numbers in the literature.

When an individual decides to warn people 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 channels. The broadcast that occurs in social media has similar properties to the broadcast process by which community officials issue a warning at the beginning of the simulation.

7.10 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 [5]. 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 packages which make the core simulation much simpler:

- Graphs [7]: mathematical graphs and utility functions
- MetaGraphs: functionality on top of Graphs to support node properties
- Distributions [4]: 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
- JLSO [8]: importing and exporting data to/from JLSO files (compressed data type)
- Makie: plotting
- Colors: colorschemes for plotting
- ProgressMeter: progress tracking on the terminal

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