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Exploring the Role of Social Media and Individual Behaviors in Flood Evacuation Processes: An Agent-Based Modeling Approach

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Key Points:

- Social media is integrated with global broadcast and neighbor observations in a consistent model to simulate agents' opinion dynamics
- Our model simulates lower evacuation rates when social media are more influential and individuals have less trust in global flood warnings
- Evacuation rates respond to the percentage of stubborn agents in a nonlinear manner

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Abstract Flood warnings from various information sources are important for individuals to make evacuation decisions during a flood event. In this study, we develop a general opinion dynamics model to simulate how individuals update their flood hazard awareness when exposed to multiple information sources, including global broadcast, social media, and observations of neighbors' actions. The opinion dynamics model is coupled with a traffic model to simulate the evacuation processes of a residential community with a given transportation network. Through various scenarios, we investigate how social media affect the opinion dynamics and evacuation processes. We find that stronger social media can make evacuation processes more sensitive to the change of global broadcast and neighbor observations, and thus, impose larger uncertainty on evacuation rates (i.e., a large range of evacuation rates corresponding to sources of information). For instance, evacuation rates are lower when social media become more influential and individuals have less trust in global broadcast. Stubborn individuals can significantly affect the opinion dynamics and reduce evacuation rates. In addition, evacuation rates respond to the percentage of stubborn agents in a nonlinear manner, i.e., above a threshold, the impact of stubborn agents will be intensified by stronger social media. These results highlight the role of social media in flood evacuation processes and the need to monitor social media so that misinformation can be corrected in a timely manner. The joint impacts of social media, quality of flood warnings, and transportation capacity on evacuation rates are also discussed.

1. Introduction

With the rapid development of computer-mediated technologies and more universal internet accessibility, social media, such as Twitter, Facebook, MySpace, WeChat, Flickr, and other information sharing platforms, have become important tools for individuals to obtain and share information with each other (Asur & Huberman, 2010; Gil de Zúñiga & Diehl, 2017; Kwak et al., 2010). Unlike conventional media such as radio and television that are typically developed for one-to-many information dissemination, social media allow both one-to-many and many-to-many information dissemination and message exchange (Bassett et al., 2012; Houston et al., 2015). Individuals can easily share their daily activities, news, opinions, ideas, etc., with their neighbors, families and friends, interest groups, and the public through social networks that transcend territorial boundaries, which makes communication between individuals faster and more efficient (Zhu, 2017). Due to the many advantages in information dissemination and social networking, social media have been used in a variety of domains. These include political activities (e.g., presidential elections, Gil de Zúñiga et al., 2012, protests such as Arab Spring, Hussain & Howard, 2013), economic behaviors such as business and marketing (Asur & Huberman, 2010; Marshall et al., 2012), and coordination and management during natural disasters (Alexander, 2014; Houston et al., 2015; Kongthon et al., 2012; Palen et al., 2010; Smith et al., 2015). This study focuses on the role of social media in evacuation processes during flood events.

Floods are common natural disasters in the U.S. and many other countries and have caused significant economic damage and loss of life (Heaney et al., 2000; Smith & Matthews, 2015). Flood warning systems have been recognized as efficient tools for flood damage mitigation and crisis management (Cloke & Pappenberger, 2009; Pappenberger et al., 2015; Parker, 2017; Parker et al., 2009). However, studies have shown that the benefits of flood warnings can be significantly affected by (1) the delivery of flood warnings that determines if communities in flood zones can receive accurate and timely flood warnings, and (2) some socioeconomic factors (e.g., education and income of the members in household, economic value of the home) that could affect households' responses and reactions to flood warnings (Kongsomsaksakul et al., 2005; Parker et al., 2007, 2009; Parker & Handmer, 1998). Therefore, it is important to evaluate the benefits of flood warnings in the context of a coupled social, economic, and hydrologic framework (Di Baldassarre et al., 2013, 2014; Girons Lopez et al., 2017; Sivapalan et al., 2012), with consideration of the heterogeneity in households' responses to flood warnings.

In recent years, social media have been used to spread warnings of natural disasters, including floods, to increase awareness of the danger and to provide efficient communications between affected individuals, emergency managers, and first responders (Alexander, 2014; Houston et al., 2015; Kongthon et al., 2012; Palen et al., 2010). For example, during the 2009 Red River flood, over four million Tweets were posted that are related to sandbagging, evacuation, damage reports, and other flood-related subjects (Palen et al., 2010; Vieweg et al., 2010). Similarly, significant numbers of Twitter messages were generated and shared by citizens in flood zones during the 2011 Thai flood. These messages provided up-to-the-minute information about location-based flood conditions, available resources, and needed rescues. Emergency responders can use the information to create instant flood situation maps and to better coordinate available resources for rescues and evacuations (Kongthon et al., 2012; Russell, 2011).

Despite these advantages, social media could also pose potential threats to crisis management when outdated, false, or misleading information is spread through social media (Acemoglu et al., 2010; Alexander, 2014; Del Vicarioa et al., 2016; Nguyen et al., 2012). This concern is partially the result of individuals having limited time to verify the accuracy of information on social media during emergencies. For example, during Japan's Fukushima nuclear crisis in 2011, rumors claiming that iodized salt can prevent radiation-related illness and that all importing of sea salt would be exposed to nuclear pollution after the nuclear meltdown were rapidly and widely spread on China's social media. Many people rushed into supermarkets and grocery stores to buy and hoard salt, which resulted in market swarms and unprecedented salt shortage in many regions of China (Brenhouse, 2011). In the case of Hurricane Sandy in 2012, altered images and false news were spread and shared by many social media users, and were even picked up by mainstream media in New York City until they were corrected by field checking (Alexander, 2014). The impact of such misinformation from social media in natural disaster management requires timely attention.

Motivated by this need, this study examines how social media affects individuals' flood risk awareness and consequent evacuation processes. We consider a residential area with an impending flood event, where emergency managers obtain and broadcast flood warnings to the residents. The residents receive the flood warnings from emergency managers and communicate with each other through social media (e.g., Twitter, Facebook, MySpace, WeChat, Flickr, and other social media platforms) to share their opinions about their perceived flood risk. A resident will choose to evacuate to a safe area if he thinks that the flood is sufficiently likely to occur.

Some studies have modeled individuals' evacuation behaviors as responses to flood warnings (Chen & Zhan, 2008; Dawson et al., 2011; Du et al., 2016; Zhang et al., 2009). For example, Dawson et al. (2011) integrated a hydrodynamic model and a traffic model to estimate the number of people exposed to floods under varying storm surge conditions. Furthermore, Du et al. (2016) investigated how individuals' evacuation behaviors are affected by their heterogeneous responses to flood warnings, as well as flood prediction accuracy and lead time. The results show that residents' evacuation behaviors can be significantly affected by various individuals' flood risk-tolerance thresholds.

Studies have also modeled how individuals form their opinions through social interactions. Among them, Hegselmann and Krause (2002) proposed various models for simulating individuals' opinion formation within interacting groups. Watts (2002) developed a binary-decision model in which individuals' decisions are explicitly dependent on the actions of their neighbors. The model was shown to be capable of capturing some important features of global cascades in social and economic systems. Bassett et al. (2012) developed an opinion dynamics model to simulate individual's opinion formation when exposed to multiple information sources (e.g., communication on social media and observations of the neighbors' actions) in natural disasters. Similarly, McCullen et al. (2013) developed an innovation diffusion model in which households form

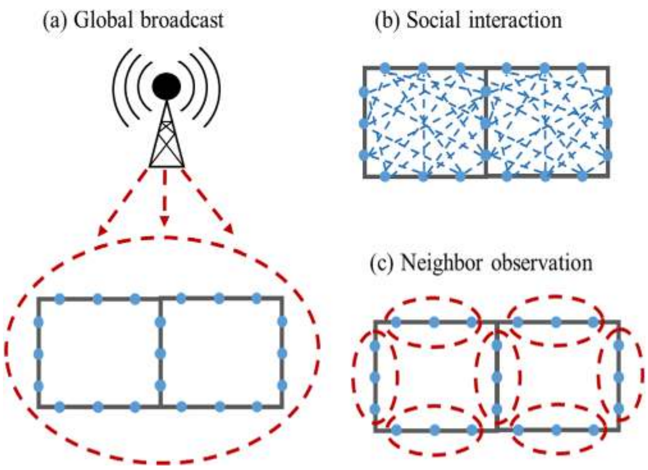

Figure 1. Illustration of three types of information sources related to flood warning dissemination: (a) global broadcast that spreads flood warnings from the global source to all of the individuals, (b) social media that allow pairwise information exchange (illustrated by the blue dashed lines), and (c) neighbor observations that consider the influence of each individual's neighbors (illustrated by the red circles).

opinions through pairwise social interactions and choose to adopt innovations when their motivations exceed a certain threshold. Moreover, Yildiz et al. (2013) investigated the role of stubborn individuals, who can influence others but do not change their own opinions, in a group's opinion dynamics.

Although existing studies have shown how individuals' opinions can be shaped by social networking, few studies have taken into account information from multiple sources in a consistent framework to analyze the impact of social media on opinion dynamics. Real-world information sources includue global broadcast, social media, and observations of other individuals' actions (Acemoglu & Ozdaglar, 2011; Crokidakis & Anteneodo, 2012; Ghaderi & Srikant, 2013; Jia et al., 2015), as illustrated in Figure 1. Global broadcast is information that emergency managers spread to all of the agents in the system (Bassett et al., 2012). Examples of global broadcast include radio and television emergency alerts, as well as some other public notices. Social media (e.g., Twitter and Facebook) allow for pairwise information transmission between the agents in a group. When two agents interact on social media, they will exchange each other's opinion on flood risk (Acemoglu & Ozdaglar, 2011). Neighbor observation takes account of how an agent's opinion is affected by the actions of other agents in a group (Watts, 2002). In this study, we integrate social media with global broadcast and neighbor observations into a general quantitative framework with consideration of individual heterogeneity in beliefs about different sources of information and learning attitudes (i.e., the extent to which individuals adopt new information).

Moreover, according to our knowledge, there is still a need to bridge the gap between opinion dynamics and evacuation processes that are influenced by individuals' opinions on flood risk, evacuation decisions, and transportation networks. Thus, we propose a modeling tool to couple the simulation of opinion dynamics and the evacuation processes. An agent-based model (ABM) is developed to simulate opinion dynamics. A traffic model is used to simulate the evacuation process. The coupled ABM and traffic model simulates how individuals update their awareness of flood risk and how individuals' opinion dynamics affect their evacuation processes in the transportation network. Using the modeling tool, we address the following research questions: (1) Will social media increase the level of people's flood risk awareness in an impending flood event? (2) Do social media help increase the evacuation rate of a community? (3) How do stubborn individuals (i.e., those who do not change their opinions on flood risk even when new information is available to them) affect the opinion dynamics and evacuation processes of the community?

The remainder of this paper is structured as follows: Section 2 introduces the methodology, focusing on modeling individuals' opinion dynamics when exposed to multiple information sources and their evacuation processes in a transportation network. Section 3 presents an example of a hypothetical residential area, the modeling results, and discussions. Section 4 discusses the empirical data that are needed to implement the model in a real-world case study and how to collect the data from multiple sources. Finally, conclusions are presented in section 5.

2. Methodology

We consider a residential area consisting of households and a transportation network. Following the approach of our prior work (Du et al., 2016), the transportation network in this paper is represented by a directed graph consisting of a number of links (i.e., roads) and nodes (i.e., road intersections). Each household is represented by an agent with a set of attributes and rules that describe the agent's geographical location, risk-tolerance threshold for flooding, priorities to the various information sources, and learning attitudes, etc.

2.1. Modeling Opinion Dynamics

In this study, an agent's opinion (denoted by a continuous variable S, $S \in [0, 1]$) refers to his perception of how likely there will be a flood in the residential area (Lorenz, 2005). Following previous studies (Schelling, 1973; Watts, 2002), we assume that each agent has a flood risk-tolerance threshold (denoted by a continuous variable τ, $\tau \in [0, 1]$). At each time step, the agent will make a binary decision (denoted by a binary variable X, $X \in \{0, 1\}$) to evacuate ($X=1$) or not ($X=0$) in the face of the flood risk. In this study, we use a simple decision rule to describe agents' evacuation decisions: at any time step t, an agent j will choose to evacuate if his opinion of flood risk exceeds his risk-tolerance threshold:

$$X_{j,t}=\begin{cases} 0 & \text{if} \quad S_{j,t} < \tau_{j,t} \\ 1 & \text{if} \quad S_{j,t} \geq \tau_{j,t} \ \text{ or } \ X_{j,t-1}=1 \end{cases} \tag{1}$$

Opinion dynamics refers to the process in which agents form and update their opinions over time. Given that agents might not always collect information to update their opinions at each time step, we simulate agents' opinion dynamics as a stochastic process: At each time step, an agent will either choose to collect new information and update his opinion or not. Let a binary variable $\mu_{j,t}$ ($\mu_{j,t} \in \{0, 1\}$) denote whether agent j updates his opinion at time t. When choosing not to update his opinion ($\mu_{j,t}=0$), the agent will keep his opinion of time step $t-1$ (i.e., $S_{j,t}=S_{j,t-1}$). Otherwise, the agent will use new information on flood risk to update his opinion.

For agent j at time step t, we use $I^G_{j,t}$, $I^S_{j,t}$, *and* $I^N_{j,t}$ to denote the information about flood risk obtained from global forecast, social media, and neighbor observations, respectively. Each of these information sources is described in turn below.

Let G_t denote the value of flood risk broadcast from a global source at time t (i.e., $G_t \in [0, 1]$, a higher value of G_t indicates a higher flood risk). Since global broadcast is a one-to-many information broadcast process, we assume that all of the agents will obtain the same global information at each time step (i.e., $I^G_{j,t}=G_t$).

Following previous studies, an agent's information obtained from social networking is modeled as a linear combination of the opinions of all of the agents that are connected to the agent (DeGroot, 1974; Ghaderi & Srikant, 2014; Hegselmann & Krause, 2002). Some studies have shown that the opinions of some agents (e.g., opinion leaders, experts, etc.) are more influential than those from others (Dubois & Gaffney, 2014; Zhang et al., 2016). Denoting $\omega_{ij,t}$ as the weighting factor that measures how much agent j weights agent i's opinion at time t, agent j's information obtained from social networking ($I^S_{j,t}$) can be modeled as a weighted average of information from all agents with whom agent j communicates, as shown in equation (2):

$$I^S_{j,t}=\sum_{i=1}^{n} \omega_{ij,t} S_{i,t-1} \tag{2}$$

We assume agents' social networking is a binary stochastic process: at each time step t, agent j either exchanges information with agent i (i.e., agent j reads agent i's post on social media at time t, denoted by $a_{ij,t}=1$) or not (i.e., $a_{ij,t}=0$). Taking account of all of the n agents that could be socially connected with agent j, weighting factor $\omega_{ij,t}$ can be represented by equation (3).

$$\omega_{ij,t}=\frac{a_{ij,t}}{\sum_{i=1}^{n} a_{ij,t}} \tag{3}$$

In a social network with n agents, agents with stronger social connections have larger probabilities to read each other's posts. In this study, we assume that agents who are physically closer to each other have stronger social connections and thus have larger probabilities to share their opinions (Bassett et al., 2012). Denoting the distance between agents i and j as d_{ij} and the maximum distance between any of the two agents in the system as $d_{\max}$, we use a simple model to represent the relationship between the probability that they exchange information at time t and their distance: $p(a_{ij,t}=1)=1-d_{ij}/(d_{\max}+1)$.

The assumption of agents' social interaction (i.e., the likelihood of social interaction decreases with proximity) employed in this study is based on intuitive reasoning that individuals living closer to each other will have more chance to meet each other to exchange information on social media. However, we admit that this assumption does not necessarily hold true in some real-world case studies, but the validation of the assumption goes beyond the scope of this work. Future work can validate or refine this assumption by mapping individuals' social connections using data mining tools when detailed social communication data become available (Gil de Zúñiga & Diehl, 2017; Sobkowicz et al., 2012; Zhu, 2017).

Combining equations (2) and (3), agent *j*'s information obtained from social media can be represented by equation (4):

$$I_{j,t}^{S}=\sum_{i=1}^{n}\frac{a_{ij,t}}{\sum_{i=1}^{n}a_{ij,t}}S_{i,t-1} \tag{4}$$

In contrast to sharing opinions over social media, neighbor observations are observed *actions*. Many studies have shown that an agent's opinion is often affected by the actions of other agents in the group, due to the fact that individuals might not have sufficient information to make decisions, or their ability to process information is limited during emergency situations (Centola, 2010; Kearns et al., 2009; Schelling, 1973; Watts, 2002). We use the weighted average of the actions of an agent's neighbors to represent the information obtained from neighbor observations. Agent *j*'s neighbors can be defined by a group of agents that are close to *j* in their residential area. In this study, we define agent *j*'s neighbors as the set of agents that live on the same road as *j* (e.g., the red circles in Figure 1c) based on the assumption that agents who live on the same street can directly observe the actions of each other. Let b_{ij} denote if agents *i* and *j* are neighbors ($b_{ij}=1$) or not ($b_{ij}=0$), agent *j*'s information obtained from neighbor observations can be represented by equation (5):

$$I_{j,t}^{N}=\sum_{i=1}^{n}\frac{b_{ij,t}}{\sum_{i=1}^{n}b_{ij,t}}X_{i,t-1} \tag{5}$$

So far, we have modeled how agents obtain information from multiple separate sources. When all of these information sources are available, agents might have different degrees of trust in, and are influenced differently by, these information sources, depending on a variety of factors. For example, if global broadcast information has proven to be unreliable in the past, people might rely less on global broadcast. Similarly, rumors and misleading information on social media might reduce the influence of social media on agents' opinion formation. McCullen et al. (2013) proposed using a set of weighting factors to formulate agents' opinion dynamics driven by multiple information sources. In this study, we follow this approach and introduce three information influence parameters, α_j, β_j, and γ_j to represent the influence of global broadcast, social media, and neighbor observation on agent *j*'s opinion adoption, respectively, and $\alpha_j+\beta_j+\gamma_j=1$. Thus, the information obtained from multiple sources can be represented by equation (6).

$$I_{j,t}=\alpha_j I_{j,t}^{G}+\beta_j I_{j,t}^{S}+\gamma_j I_{j,t}^{N} \tag{6}$$

When new information on flood risk is obtained, the agent *j* will update his opinion on flood risk. We adopt the Widrow-Hoff learning rule to simulate the agent's opinion dynamics (Sutton, 1988; Widrow & Hoff, 1988; Widrow & Lehr, 1993), as shown in equation (7).

$$S_{j,t}=S_{j,t-1}+\theta_j\times\Delta I_{j,t} \tag{7}$$

where $\Delta I_{j,t}$ is the difference between the flood risk obtained from multiple sources at time *t* and the agent's original opinion on flood risk at time $t-1$ ($\Delta I_{j,t}=I_{j,t}-S_{j,t-1}$). θ_j is the agent's learning rate, which is a behavioral parameter measuring how much the agent adheres to his past opinion when new information is available. This parameter considers that an agent might not completely abandon his past opinion to accept new information ($\theta_j=1$), nor completely disregard new information to keep his past opinion ($\theta_j=0$) (Friedkin & Johnsen, 1999). The concept of opinion adherences is based on observations that individuals' beliefs typically display some amount of inertia (Dash & Gladwin, 2007; Watts, 2002). Combining equations (6) and (7), agent *j*'s opinion dynamics can be represented by equation (8).

$$S_{j,t}=(1-\theta_j)S_{j,t-1}+\theta_j(\alpha_j I_{j,t}^{G}+\beta_j I_{j,t}^{S}+\gamma_j I_{j,t}^{N}) \tag{8}$$

The opinion dynamics model (i.e., equation (8)) presented in this study is a more general form compared with those used in previous models (e.g., Bassett et al., 2012; McCullen et al., 2013). For example, by setting

Table 1
The Values of Model Parameters

Scenario	α_j	β_j	γ_j	θ_j	$p_{j,t}$ [a]	τ_j	G_t
Case 1	1 (0)[b]	0	0				
Case 2	0.5 (0.1)	0.5 (0.1)	0	0.5 (0.1)	0.1 (0.1)	U (0.1, 0.9)[c]	1
Case 3	0.5 (0.1)	0	0.5 (0.1)				

[a] $p_{j,t}$ is the probability that agent j receives information from multiple sources to update his opinion at time step t.
[b] $x_1(x_2)$ indicates the value of the parameter is sampled from a Gaussian distribution in which the mean and the coefficient of variation of the variable is set as x_1 and x_2, respectively.
[c] $U(x_1, x_2)$ means the value of the parameter is sampled from a uniform distribution in which the lower and upper bound of sample space is set as x_1 and x_2, respectively.

$(\alpha_j, \beta_j, \gamma_j, \theta_j)=(1, 0, 0, 0.5)$ (i.e., the agent only uses global information and treats prior opinion and new information equally), equation (8) becomes equivalent to the opinion dynamics model driven by global information proposed by Bassett et al. (2012). Similarly, the model is made equivalent to that given by McCullen et al. (2013) by setting $\theta_j=1$ (i.e., the agent only uses new information to update his opinion).

In addition, equation (8) considers differences in people's behaviors through the agents' behavioral parameters $\alpha_j, \beta_j, \gamma_j$, and θ_j. This takes advantage of the strength of agent-based models in representing the heterogeneity in agents' behaviors (Huang et al., 2013), and relaxes the assumption that all agents in a community behave in the same manner (e.g., as handled in the opinion dynamics model by Bassett et al., 2012). In this hypothetical study without behavioral data, we use a coefficient of variation (C_v) for each of the behavioral parameters (α, β, γ, and θ) to measure the level of agents' behavioral heterogeneity. Following previous studies (Bertella et al., 2014; Marino et al., 2008), we use a normal distribution to sample the behavioral parameters for each agent. Table 1 provides an example of assigning agents' behavioral parameters under three specific scenarios.

2.2. Modeling the Evacuation Process

Agents that decide to evacuate will move from their current location to the evacuation destination in the transportation network. We assume all agents have good knowledge of the transportation network and will choose the shortest route to evacuate. We use a categorical parameter K_j to represent agent j's evacuation status. $K_j=0$ denotes that agent j decides not to evacuate; $K_j=1$ when agent j decides to evacuate but does not arrive at the destination; $K_j=2$ when the agent arrives at the destination, which represents a successful evacuation case.

In this study, we adopt the Nagel-Schreckenberg traffic model (N-S model) to simulate agents' evacuation behaviors via a transportation network (Nagel & Schreckenberg, 1992). The N-S model is an individual-oriented cellular automation model for traffic flow simulation and is capable for simulating complex and dynamic traffic flow in large-scale transportation systems. Recently, the N-S model has been used for emergency evacuation simulation (Lee et al., 2014; Nagel & Rickert, 2001; Naghawi & Wolshon, 2010). In the N-S model, space and time are both discrete variables and each traffic road in the transportation network is divided into cells, each of which can be occupied by one vehicle. At each time step, the moving speed and the location of a vehicle is constrained by: (1) the previous moving speed of the vehicle, (2) the acceleration and deceleration rate, (3) the number of empty cells in front of the vehicle required to avoid collision, and (4) maximum moving speed allowed in the transportation network. We apply the all-way stop rule in road intersections: Vehicles must stop when arriving at road intersections and proceed only when the way ahead is clear. When multiple vehicles approach at the same road intersection, vehicles' right-of-way proceeds following the order of their arrival times. For details of the N-S model and how it is implemented to simulate agents' evacuation process, see Nagel and Schreckenberg (1992), Nagel and Rickert (2001), and Du et al. (2016).

2.3. Model Outputs at the System Level

We use multiple indicators to measure behaviors at the system level (i.e., a community), which result from the evacuation of individual agents, including: (1) agents' opinion trajectory S ($S=[S_{t=1}, S_{t=2}, \ldots, S_{t=T}]$, where $S_{t=k}$ is the average opinion over all agents at time step k), (2) agents' decision trajectory X ($X=[X_{t=1}, X_{t=2}, \ldots, X_{t=T}]$, where $X_{t=k}$ is the average decision over all agents at time step k), and (3) agents' evacuation rate Φ (i.e., $\Phi=[\Phi_{t=1}, \Phi_{t=2}, \ldots, \Phi_{t=T}]$, where $\Phi_{t=k}$ is the percentage of agents that successfully evacuate to the destination at time step k).

Given the fact that not everyone opens social media channels at all times for social interaction, information transmission, and social communication are assumed to occur in a stochastic manner. In addition, coupling the opinion dynamics and evacuation behaviors can make the system highly nonlinear, noncontinuous and stochastic. It is very difficult, if not impossible, to obtain closed-form analytical solutions for such a system. Therefore, we conduct the analysis using a numerical simulation approach, which is similar to other opinion dynamics or social information network models (Bassett et al., 2012; Martins, 2008; Martins & Galam, 2013; Rodriguez et al., 2016). The Monte Carlo method (i.e., execution of the model multiple times with model inputs that are randomly and repeatedly sampled from the sampling space) is applied in this study to obtain numerical results for the problem under various scenarios (Decker, 1991). We execute the model 1,000 times (the number of simulations that ensures output stabilization for this study) to obtain the ensemble opinion trajectory $\langle S \rangle$, ensemble decision trajectory $\langle X \rangle$, and ensemble evacuation rate $\langle \Phi \rangle$.

3. A Demonstration Example

We apply the model described above in a synthetic residential area, which consists of a transportation network and a group of agents (Figure 2). Following previous studies, we use L and T to represent the units of length and time, respectively (Du et al., 2016; Zhang et al., 2009). In this transportation network, all of the roads are assumed to have length of 100 L, indicating that each road can be divided into 100 cells. Among the 16 nodes in the transportation network, the one on the bottom right is set as the evacuation destination.

We assume that agents are uniformly distributed along the roads in the transportation network. Residential density (denoted by d) is represented by the number of agents on a road in the transportation network, and is set as 10 in this study (i.e., corresponding to 240 agents in the transportation network). The sensitivity of residential density is examined in section 3.5.

The following sections present the modeling results. Sections 3.1 and 3.2 present scenario-based analysis and sensitivity analysis, respectively. Next, sections 3.3 and 3.4 evaluate the impacts of social media and stubborn agents on evacuation processes, respectively. Finally, section 3.5 shows how evacuation rates are jointly affected by sources of information, transportation capacity, and flood warnings with various forecast capabilities.

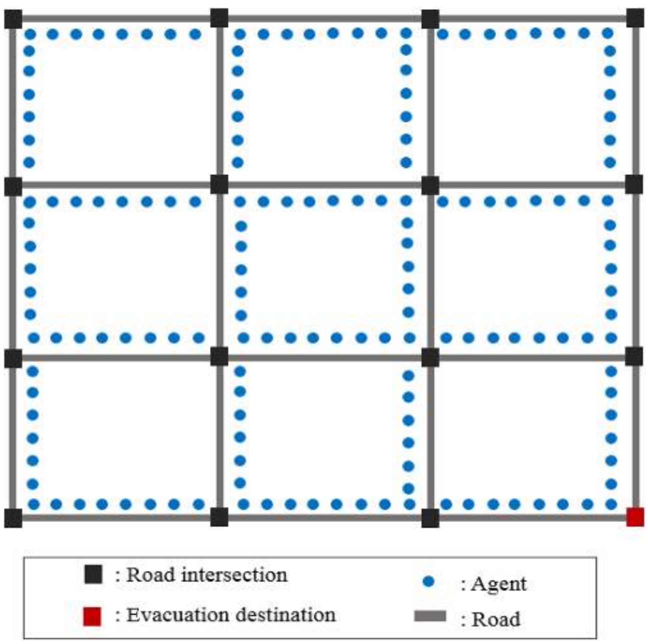

Figure 2. Illustration of the synthetic case study area that consists of a transportation network and a number of agents. The transportation network is a regular lattice network with 24 roads and 16 nodes (the node on the bottom right is set as the designated evacuation destination for all of the agents). The agents are uniformly distributed along the roads.

3.1. Scenario-Based Analysis

To assess the impact of model parameters on the results, a scenario-based analysis is conducted. We design three scenarios, each of which represents a special combination of information sources. The first scenario considers the case in which only global broadcast information is available. The second case considers the case with only global broadcast and social media, without neighbor observations. The third case considers the scenario with only global broadcast and neighbor observations, without social media. Table 1 lists the values of the key parameters in the model.

Figure 3 provides an overview of a randomly selected agent's opinion trajectory S under the three model parameter cases, as well as overall statistics on all agents. By comparing cases 1 and 2, it can be noticed that, with the presence of social media, agents' opinions update in a smoother manner as a function of time (comparing Figure 3a and Figure 3d). There is also less variance among agents' opinions in case 2, which results in a cascade-like pattern for opinion update (Figure 3e). However, the speed of agents' opinion update is slower in case 2 compared with case 1, implying that social media could slow down the speed of agents' opinion update. This result is consistent with the findings by Bassett et al. (2012).

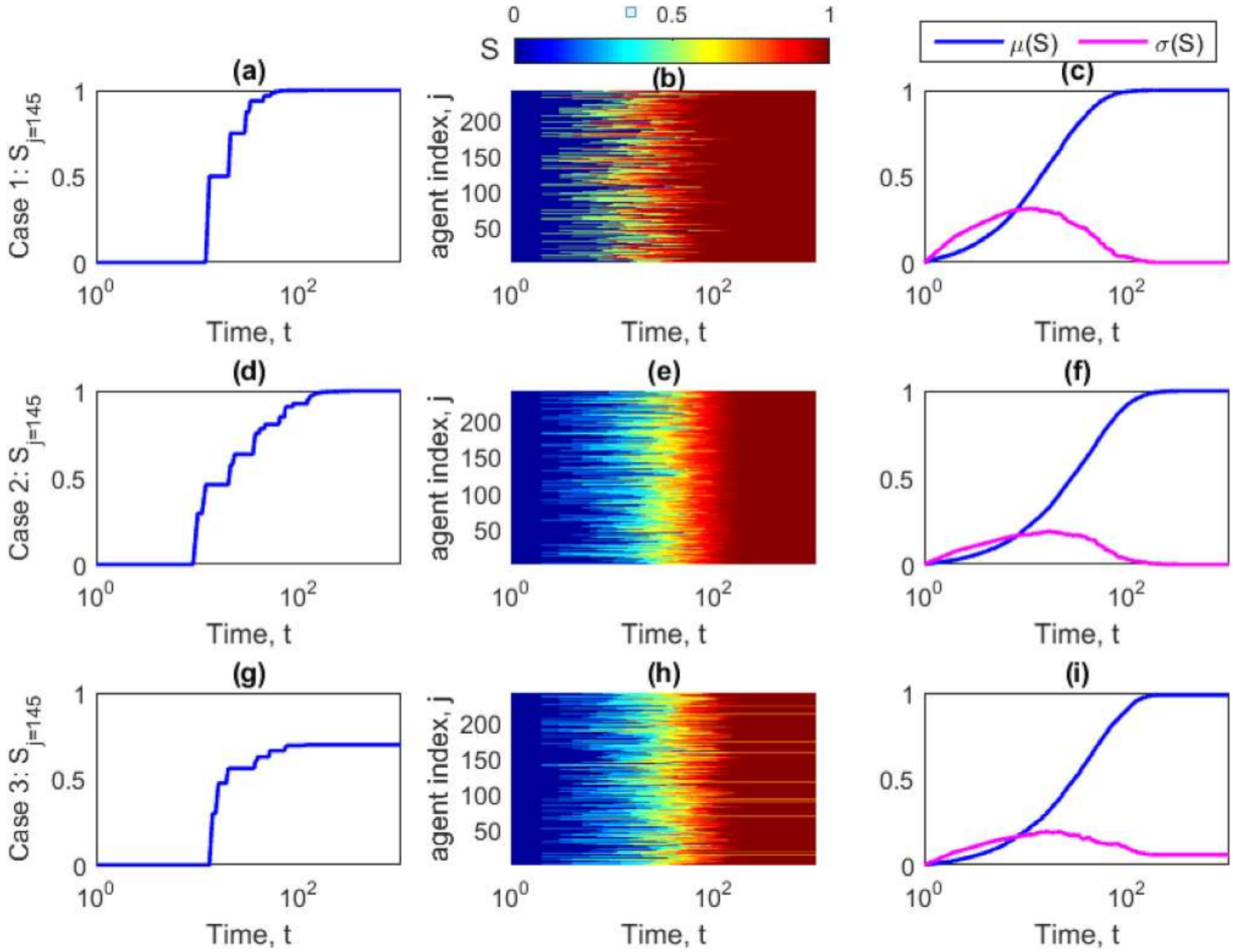

Figure 3. (a) The opinion trajectory for a randomly selected agent in case 1. (b) The opinion trajectory for all of the agents in case 1. (c) The mean (blue line) and standard deviation (red line) of all the agents' opinions in case 1. Figures 3d–3f and 3g–3i present the corresponding results for cases 2 and 3, respectively.

In case 3, when agents' opinion exchange only occurs through neighbor observation, the individual agent's opinion trajectory is smoother than that in case 1. This indicates that information exchange, either by social media or by neighbor observation, can make agents' opinion trajectory smoother and reduce the variance in agents' opinions (red lines in Figures 3f and 3i). However, agents do not reach opinion consensus in case 3. A few agents' opinions are less than 1 at the end of the simulation (e.g., agent 145 in Figure 3g). As illustrated by the blue line in Figure 3i, agents' average opinion is less than, although very close to, 1 in the end.

We further investigate how the agents' opinion dynamics affect their evacuation processes under these three cases (Figure 4). Notice that the agents in case 1 start to take evacuation actions earlier than cases 2 or 3 (the green lines in Figures 4c, 4f, and 4i). This is consistent with the results presented in Figure 3, which shows that information exchange through either social media or neighbor observations will slow down the speed of agents' opinion update. However, there is no noticeable difference in the percentage of agents at status 2 over time (i.e., agents that successfully evacuate to the destination, corresponding to the red lines in Figures 4c, 4f, and 4i). We also notice that all the agents in cases 1 and 2 eventually choose to evacuate. In comparison, some agents in case 3 do not evacuate (e.g., Figures 4g and 4h). This suggests that the decision-making rule based on neighbors' actions sometimes will keep some agents from updating their opinions, especially when no one takes initial evacuation actions.

3.2. Sensitivity Analysis

Next, a sensitivity analysis is conducted to understand the influence of agents' opinion adherence parameter (θ) and weighting parameters (α, β, γ) on agents' ensemble opinion trajectory $\langle S \rangle$, decision trajectory $\langle X \rangle$, and evacuation rate $\langle \Phi \rangle$.

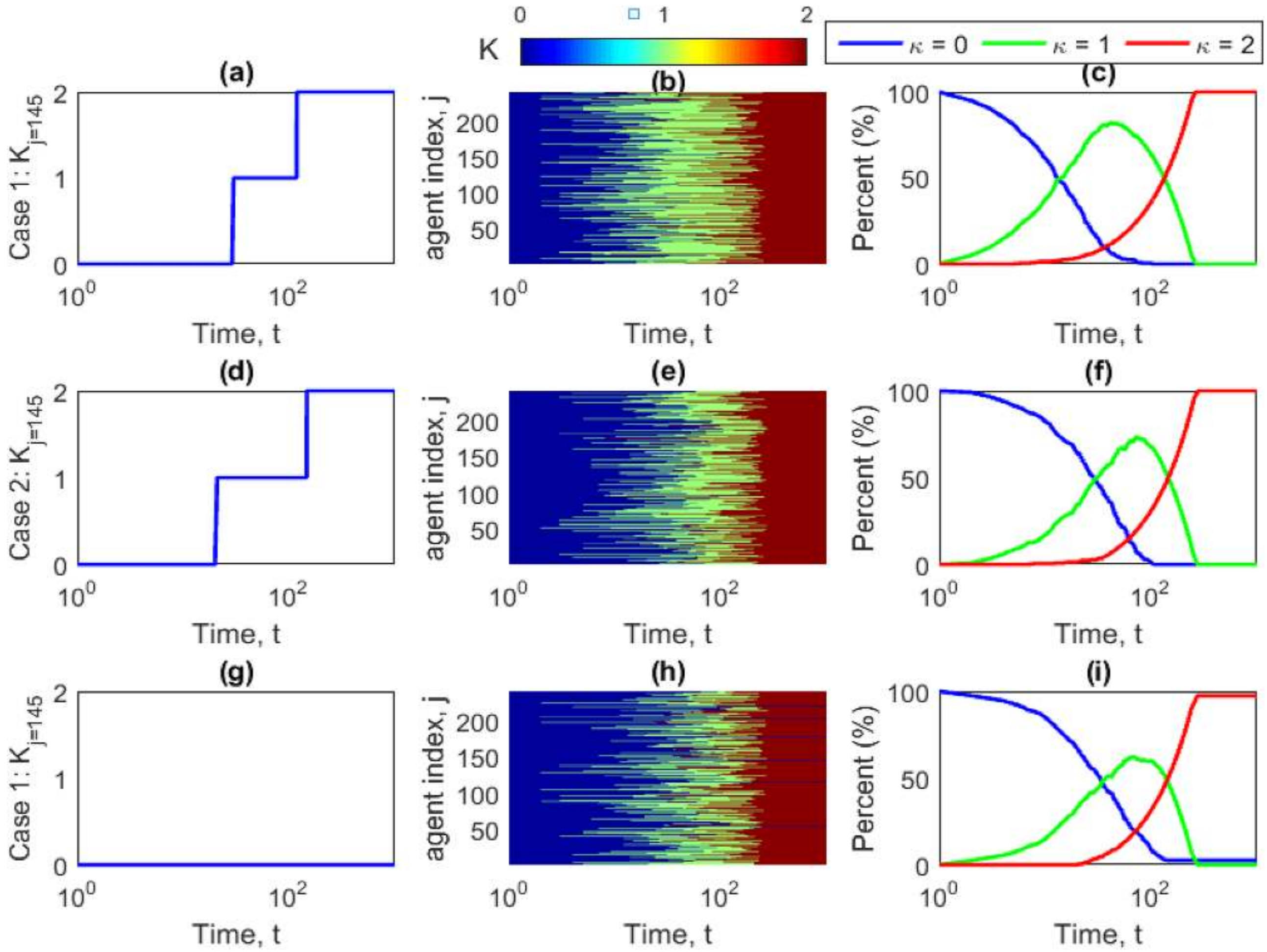

Figure 4. (a) The evacuation status of a randomly selected agent in case 1. (b) All agents' evacuation status in case 1. (c) The percentage of each type of agents as a function of time in case 1. Figures 4d–4f and 4g–4i present the corresponding results for cases 2 and 3, respectively.

Figures 5a–5c show the impacts of opinion adherence parameter θ on the model results. The figures indicate that a smaller θ (i.e., agents adhere more to their past opinions) will slow down the speed of the agents' opinion update $\langle S \rangle$, evacuation actions $\langle X \rangle$, and evacuation rates $\langle \Phi \rangle$. However, the influence of θ on agents' evacuation rate $\langle \Phi \rangle$ is not as significant compared with opinion update $\langle S \rangle$ and evacuation actions $\langle X \rangle$. This is due to the constraint of traffic capacity as implied by Figure 4. We expect that θ will have a stronger impact on $\langle \Phi \rangle$ with less traffic bottlenecking.

Figures 5d–5i show the influences of α, β, and γ on the modeling results. It is observed that, in both cases 2 and 3, a decrease in α (i.e., the global broadcast has less impact on agents' opinion update) will slow down the speed of agents' opinion update $\langle S \rangle$, evacuation actions $\langle X \rangle$ and evacuation rates $\langle \Phi \rangle$. There are no opinion updates and evacuation actions when α is small enough (e.g., $\alpha \leq 0.1$ in Figures 5g–5i) in case 3. Under these conditions, agents' opinions remain unchanged because their opinions are mainly affected by their neighbors' actions. For each member in the group, an agent will not update his opinion if his neighbors do not take evacuation actions. This in turn results in no opinion updates and no agent will evacuate in the end.

3.3. Impacts of Social Media on Agents' Evacuation Processes

The sensitivity analysis of the previous section considers at most two information sources simultaneously. In this section, we consider all three information sources (i.e., global broadcast, social media, and neighbor observation as illustrated in Figure 6a) and evaluate how they jointly affect agents' opinion dynamics and evacuation processes. In particular, we analyze the impacts of social media on the modeling results.

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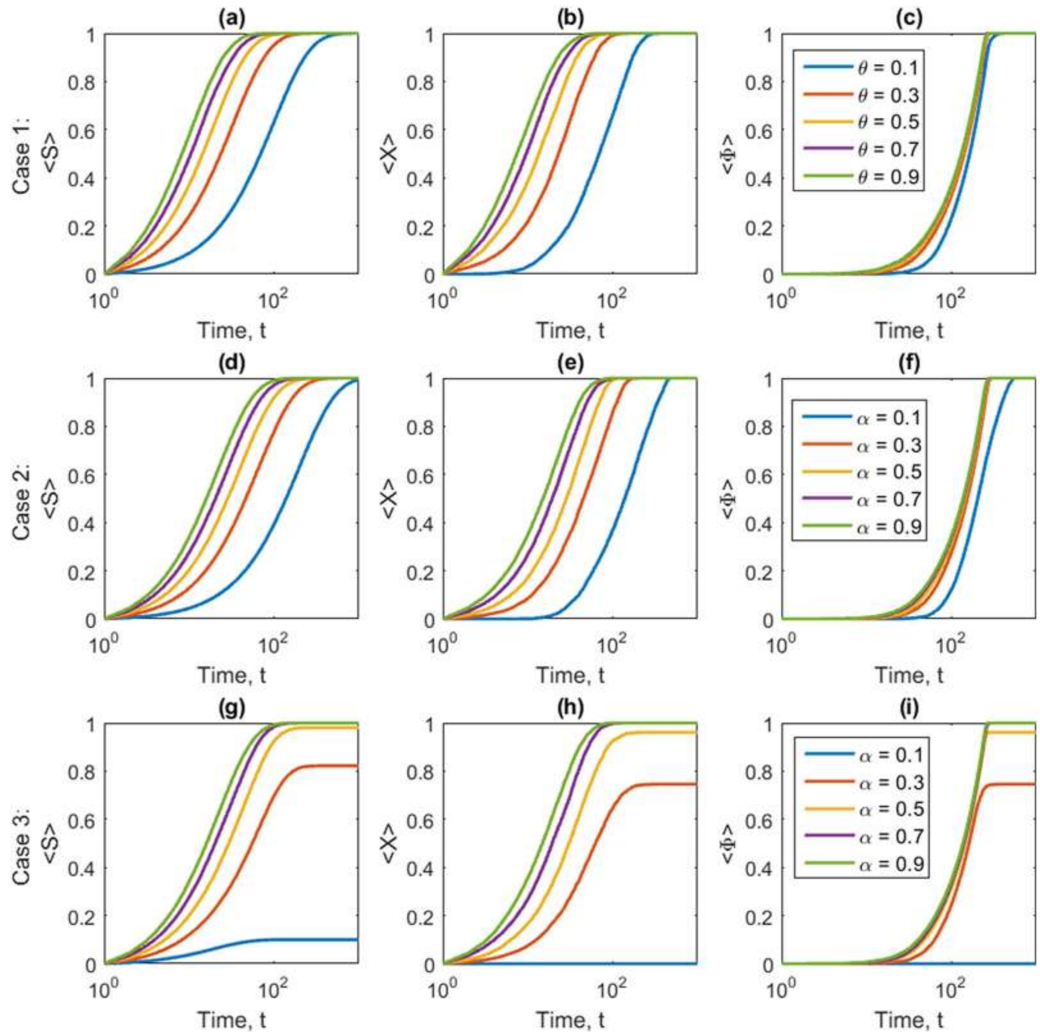

Figure 5. The impact of the opinion adherence parameter θ on (a) agents' opinion trajectory $<S>$, (b) decision trajectory $\langle X \rangle$, and (c) evacuation rate $\langle \Phi \rangle$ for case 1. The impact of α on agents' (d) opinion trajectory $<S>$, (e) decision trajectory $<X>$, and (f) evacuation rate $<\Phi>$ for case 2. The corresponding results for case 3 are presented in Figures 5g–5i. Note that θ=0.5 for the analysis in cases 2 and 3.

Figure 6b shows the agents' evacuation rates under different settings of influence parameters α, β, and γ. The modeling results provide several implications. First, we observe that the system can achieve a high evacuation rate when global broadcast has a large influence on agents' opinion dynamics (i.e., α is large, corresponding to zone B in Figure 6b). In contrast, agents' evacuation rate is low when neighbor observation has large influence (i.e., γ is large, corresponding to zone A in Figure 6b).

Second, increasing influence of social media will make the system more sensitive to the influence of other information sources (i.e., from zone C to D and E in Figure 6b). For example, a small change in α or γ leads to a significant change in agents' evacuation rates in zone E. Social media result in lower evacuation rates when the influence of global information decreases (indicated by the solid arrow in Figure 6b). On the other hand, social media will increase evacuation rates when the influence of global broadcast increases (indicated by the dashed arrow in Figure 6b).

The results suggest that the influence of the global forecast α is crucially important to agents' evacuation behaviors. No agents will evacuate if the influence of global information is very weak. This is similar to a real-world case of a 2016 flash flood in Xingtai, a city in China. The local government's flood warning was not on time, many local residents did not take evacuation actions, and more than 150 people lost their lives in the flood (Makinen, 2016).

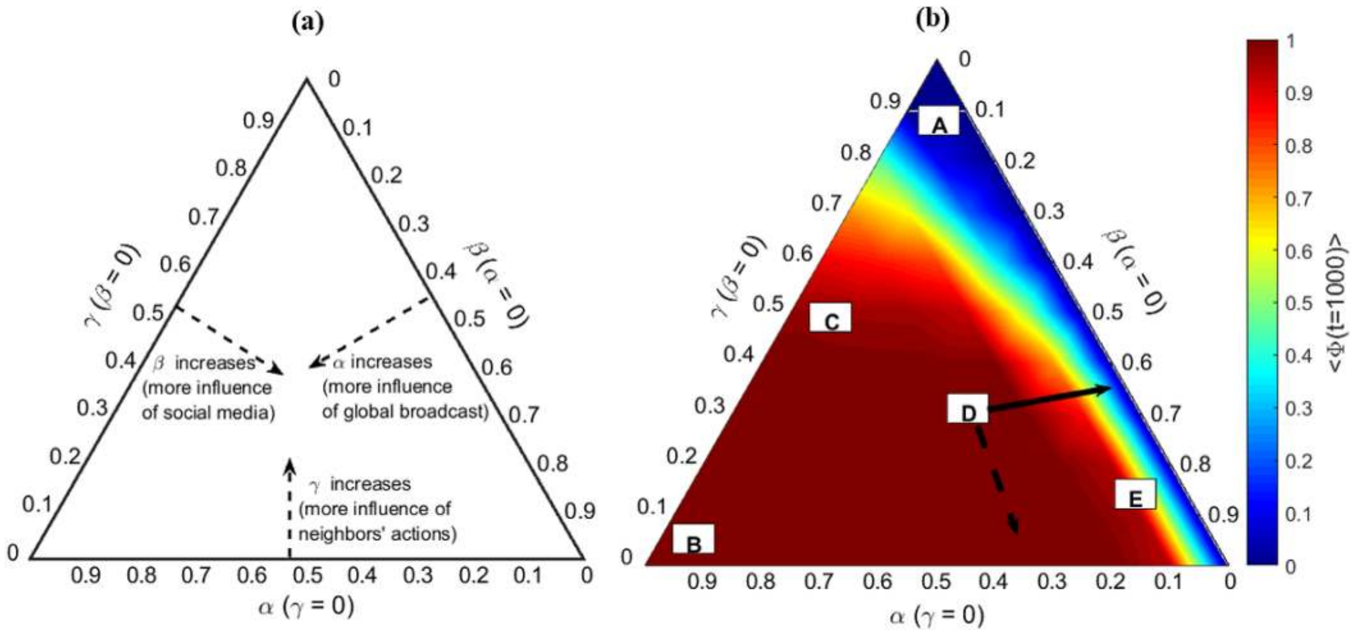

Figure 6. (a) Illustration of the scenarios that consider influences of the three information sources. (b) Ternary plot of agents' evacuation rates $<\Phi>$ $(t=1,000)$ under different settings of influence parameters α, β, and γ.

The results here also show that communication through social media decreases the variation among individuals' opinions and causes them to take actions at a similar pace. This is in line with empirical observations of herd-like behaviors during emergency situations, in which some people simply follow others' actions (Haque, 1995; Schelling, 1973; Watts, 2002). Social media ease sharing of individual opinions and enhance influence on others' decision making, and thus could cause unexpected collective behaviors or even chaos (e.g., the "salt-rush" in China after the 2011 Japan nuclear crisis, Brenhouse, 2011).

3.4. Impacts of Stubborn Agents Escalated by Social Media

Many previous studies have indicated that some agents insist on their own opinions and ignore any new information (Galam & Jacobs, 2007; Yildiz et al., 2013). These agents are typically referred to as *stubborn agents* in the study of opinion dynamics (Ghaderi & Srikant, 2014). For example, in the case of the 2007 Cyclone Sidr in Bangladesh, thousands of individuals remained in their homes despite receiving early warnings and evacuation orders from emergency managers (Paul & Dutt, 2010). This section investigates how the behaviors of stubborn agents affect the opinion dynamics and evacuation processes of the entire community.

In this study, stubborn agents' opinions are set as 0 over the entire simulation time. Figure 7 presents the entire population's average opinions and evacuation rates corresponding with various percentages of stubborn agents in the group. The stubborn agents in the current hypothetical study are randomly chosen from the group of agents. In a real-world application of the proposed modeling framework, empirical approaches, such as surveys and interviews, can be conducted to identify stubborn agents (Hasan et al., 2011; Lindell et al., 2005; Parker et al., 2009). The results show that stubborn agents can prevent the entire group from updating their opinions to high levels and therefore reduce agents' evacuation rates, especially when there are many stubborn agents or social media weighting is higher (β is larger). For example, the agents' evacuation rates decrease from 80% to 58% when the percentage of stubborn agents increases from 10% to 20% (the red line in Figure 7b). With a fixed 5% of stubborn agents in the group, the agents' evacuation rates are reduced to 94%, 91%, and 73% when β is 0.3, 0.5, and 0.7, respectively (Figure 7b). In particular, as can be seen, evacuation rates respond to the percentage of stubborn agents in a nonlinear manner when social media become more influential. When the percentage of stubborn agents exceeds a threshold (e.g., 5% in Figure 7b for the red line), the impact of stubborn agents on evacuation rates will be intensified by sources of information. Stronger social media can significantly reduce evacuation rates (e.g.,

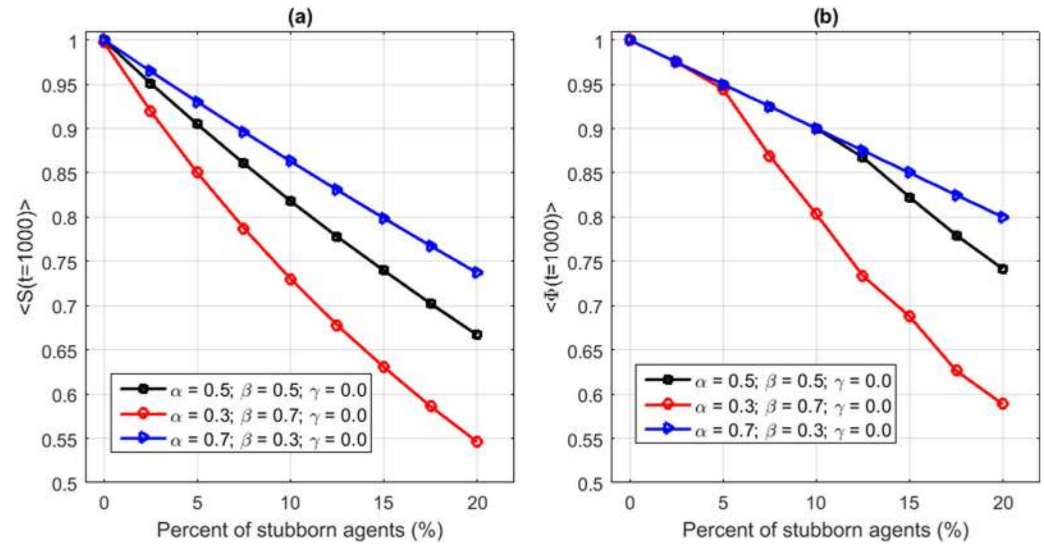

Figure 7. The impacts of stubborn agents on agents' (a) average opinion $<S>$ $(t=1,000)$ and (b) evacuation rates $<\Phi>$ $(t=1,000)$.

in the case of 10% stubborn agents, evacuation rates decrease from 90% to 80% when β increases from 0.5 to 0.7).

Figure 8 illustrates how the impacts of stubborn agents on the evacuation rate are affected by the weights of multiple information sources. Figure 8a displays agents' evacuation rates with 5% stubborn agents in the group. It is noticed that the patterns of the agents' evacuation rates are consistent with those shown in Figure 6b (e.g., zone A has a low evacuation rate due to limited influence of global flood warnings). However, the evacuation rate in Figure 8a changes in a smoother manner. Figure 8b compares the differences between the cases with (Figure 8a, 5% stubborn agents) and without stubborn agents (Figure 6b). It is noticed that the impact of stubborn agents increases from regions C to D and E. This implies that social media, as they become more influential, make the evacuation process more vulnerable to stubborn agents. This is shown in some real-world incidences of inaccurate and misleading information from social media, e.g., altered images and false news about the flood conditions during the days of Hurricane Sandy in 2012

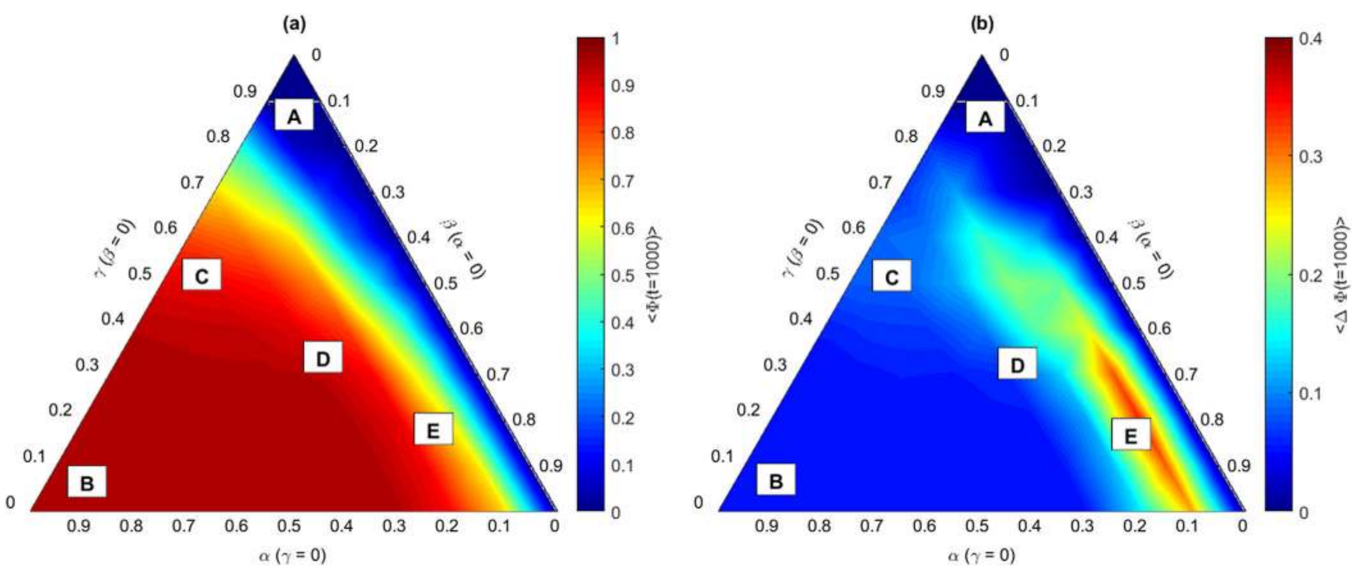

Figure 8. (a) Ternary plot of agents' evacuation rates $<\Phi>$ $(t=1,000)$ with 5% of stubborn agents in the group, and (b) the differences in $<\Phi>$ $(t=1,000)$ between the scenario with 5% of stubborn agents (Figure 8a) and the scenario without stubborn agents (Figure 6b).

(Alexander, 2014). Thus, it is important for emergency managers to identify stubborn agents in the community and correct the misinformation that they broadcast through social media in a timely manner during a crisis.

3.5. Impacts of Flood Forecast Quality and Transportation Capacity

Lastly, we investigate the impacts of two other key factors on agents' opinion dynamics and evacuation processes: flood forecast quality and transportation capacity. In an impending flood event, the predicted flood probability will increase over time before the flood. Furthermore, forecast with better prediction capability will give a higher flood probability with a longer lead time. Considering these two factors, we modify the methods described previously by adding a simple model, for illustrative purpose, to represent the predicted flood risk as a function of time t during the flood forecast horizon (FH) ($t=1, 2, \ldots, FH$), shown in equation (9):

$$G(t)=\frac{1}{FH}t+\delta;\ G(t)\in[0,\ 1] \tag{9}$$

where $\delta\in[-1,\ 1]$ is a parameter that measures the quality of flood warnings. A larger δ is associated with flood warnings that can predict higher flood risk in flood events. As illustrated in the results given in Figure 9a, predicted flood risk $G(t)$ is closer to 1 (actual flood risk) when δ is larger.

Figures 9a–9c show that the quality of the flood forecast can significantly affect agents' opinions on flood risk and evacuation rates. Poor quality of flood warnings (i.e., with smaller δ) results in slower update of flood risk awareness (Figure 9b) and fewer agents choosing to evacuate (Figure 9c). This concurs with the need for improving the reliability of flood warnings for crisis management, as evidenced by the case of 2016 Xingtai flood in China (Makinen, 2016).

Furthermore, we assess the joint impacts of multiple modeling parameters, i.e., flood forecast uncertainty, residential density (a substitute for network capacity), and weights of information sources, on agents'

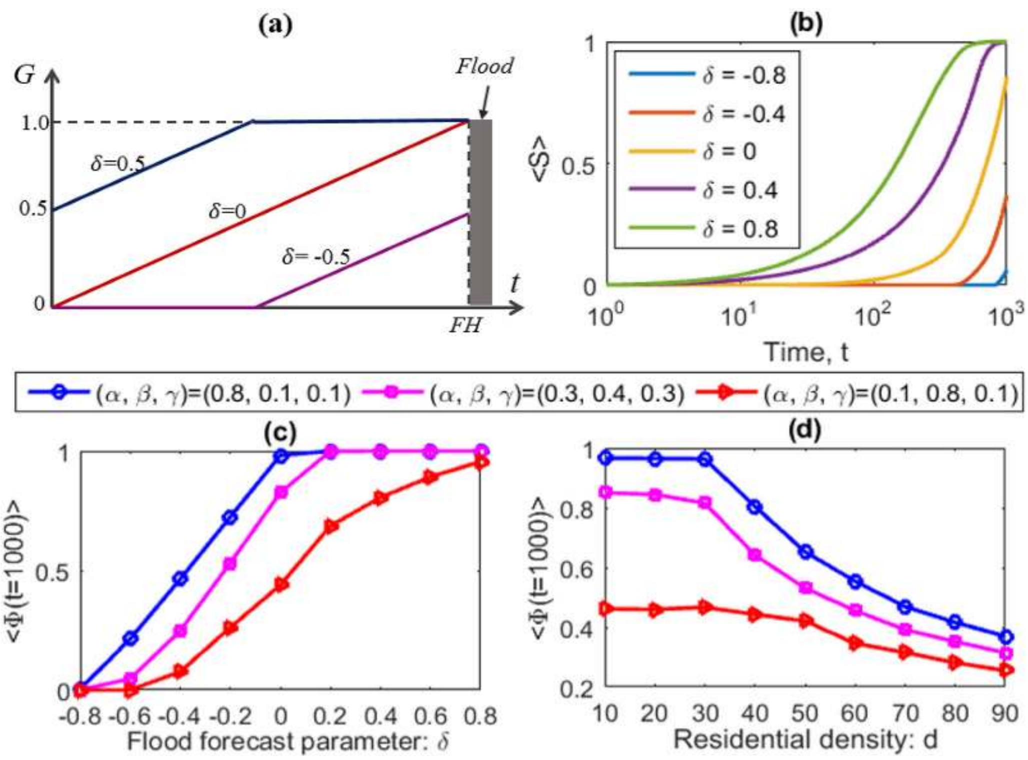

Figure 9. (a) A simple model of flood forecast quality with smaller δ for poorer forecast. (b) Agents' opinion trajectories under scenarios of different flood risk forecast qualities when $(\alpha,\beta,\gamma)=(0.3,0.4,0.3)$. (c) The joint impacts of weighting parameters for information sources (α, β, and γ) and forecast quality (δ) on agents' evacuation rate (when the residential density is set as $d=20$). (d) The joint impacts of weighting parameters and residential density on agents' evacuation rate (when $\delta=0$).

evacuation rates (Figures 9c–9d). In general, the figures show that evacuation rates are higher when global flood warnings are more influential (α is larger), flood forecast quality is higher (δ is larger), and residential density is lower (d is smaller). However, the impacts of each individual parameter on the modeling results also depend on other parameters. The complex interplay of these parameters is summarized as follows.

First, under a poor flood forecast scenario (e.g., $\delta < 0$), the quality of flood warnings becomes a dominant factor that affects the modeling results. When flood forecast improves (δ becomes larger), the weighting parameters for information sources (α, β, and γ) become more important factors. It is also noticed that more influential social media can slow down the increase of agents' evacuation rates with improved flood forecast (Figure 9c). Second, when the residential density is low (e.g., $d=10$), the weighting parameters for information sources are the dominant factors on agents' evacuation rates. In contrast, when residential density is high (e.g., $d=90$), the weighting parameters have little impact on the modeling results (Figure 9d). These findings suggest that the quality of flood warnings and residential density determine the range of agents' evacuation rates. In comparison, the weighting parameters of the information sources determine the actual evacuation rates based on the influence of the various information sources. When flood warning and residential density are not hard constraints (e.g., $\delta \geq 0; d \leq 30$ in Figures 9c and 9d), the weighting parameters of the information sources become the dominant factors that affect agents' evacuation processes. This highlights that crisis management in flood events requires (1) satisfactory flood forecasts, (2) efficient flood warning dissemination systems, and (3) well-planned evacuation procedures in a community with low residential density and high transportation capacity (Litman, 2006; Murray-Tuite & Wolshon, 2013).

4. Discussion

Opinion dynamics and flood evacuation are complex social phenomena. This study presents a theoretical modeling framework that couples an opinion dynamics model and a traffic model to simulate how individuals update their flood risk awareness and how they behave under the influence of social media. Due to the lack of empirical data, the modeling results of this study are derived from a representative, although hypothetical, residential area. To apply the modeling framework to a real-world flooding evacuation case study, one needs to collect a variety of data from multiple sources, as listed in the following.

The first set of data is on weather forecast and flood warnings in the neighborhood. These data can be acquired from local and regional weather forecast services (e.g., National Weather Service) (Bedient et al., 2003; Sorensen, 2000). The second set of data is about the traffic network and the transportation infrastructure in the community, as inputs for the traffic model. This set of data is available from local and regional transportation departments and/or web mapping services (e.g., satellite imagery and street view from Google and Bing map) (Farkas et al., 2014; Wu et al., 2007). The third set of data is on demography and residents' behaviors on the usage of social media during flood events. These data include, but are not limited to, the population and the geographical distribution of the residents, the individuals who use social media during flood events, the number of social friends on their social networks and the influences from their social friends, the weights on multiple flood warning sources, and the identification of stubborn individuals in the community. These data can be acquired from census bureaus and by conducting interviews and surveys in the neighborhood community (Huang et al., 2012; Lindell et al., 2005; Paul & Dutt, 2010). In addition, with advanced data retrieval tools, such as Application Programming Interface (API), considerable amount of data can be collected from social media websites for real-time analysis (Li et al., 2012; Rieder, 2013).

The current study focuses on developing a theoretical modeling framework. Based on a hypothetical case study, we conduct a sensitivity analysis for multiple modeling parameters to understand the role of social media and individual behaviors in flood evacuation under the various scenarios. Future work can implement the model with a real-world case study by collecting the various data as listed above. Implementing the model with empirical data can lead to more insights and a more realistic estimation of the influence of social media in a particular residential community. However, it is not expected that such applications will qualitatively alter the findings and implications obtained from the hypothetical study as presented in this paper.

5. Conclusions

In this study, we develop an agent-based modeling framework that couples a general opinion dynamics model and a traffic model to investigate the influence of opinion dynamics on flood evacuation processes.

The coupled model simulates agents' opinion dynamics and evacuation processes under the influence of multiple information sources, flood forecast quality, and transportation systems. The results show that stronger social media can make evacuation processes more sensitive to the change of global flood warnings and/or neighbor observations, and thus, impose larger uncertainty on evacuation processes (i.e., a large range of evacuation rates corresponding to the change of global information and/or neighbor observation). We also find that evacuation rates respond to the percentage of stubborn agents in a nonlinear manner. After the percentage of stubborn agents exceeds a threshold, the impact of stubborn agents on evacuation rates will be intensified by sources of information, and stronger social media can significantly reduce evacuation rates under this condition. Therefore, social media impose uncertainties to the flood evacuation processes and complicate evacuation planning and coordination during flood events.

Our results highlight the importance of mapping inaccurate or misleading information in social media and identifying stubborn individuals to allow first responders and emergency managers to mitigate any undesirable influences. In addition, flood warnings with low quality and high residential density can result in low evacuation rates, which highlight the need for improving the quality flood warnings and transportation infrastructure during flooding events.

Opinion formation, flood risk perception, and evacuation decision are complex processes that need both empirical and theoretical investigation from interdisciplinary fields (Gladwin et al., 2009; Haque, 1995; Parker et al., 2007). Social media not only provide efficient communication platforms for individuals to exchange information, but also create large amounts of data that describe people's behaviors. These data can be collected and analyzed by advanced data query and machine learning technologies (Bellomo et al., 2016; Gil de Zúñiga & Diehl, 2017; Granell et al., 2016). Synthetic models, such as the one presented in this study, can benefit from these data and technologies for model verification and calibration. Recommended future studies include the use of empirical data to measure the various behavioral parameters, validating or modifying assumptions in the opinion dynamics simulation, extending the model to more realistic and complex transportation networks, investigating the differences in social media platforms, and incorporating uncertainties in spatial and temporal variability in flood warnings.

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References

Acemoglu, D., & Ozdaglar, A. (2011). Opinion dynamics and learning in social networks. *Dynamic Games and Applications*, *1*, 3–49. https://doi.org/10.1007/s13235-010-0004-1

Acemoglu, D., Ozdaglar, A., & ParandehGheibi, A. (2010). Spread of (mis)information in social networks. *Games and Economic Behavior*, *70*(2), 194–227. https://doi.org/10.1016/j.geb.2010.01.005

Alexander, D. E. (2014). Social media in disaster risk reduction and crisis management. *Science and Engineering Ethics*, *20*(3), 717–733. https://doi.org/10.1007/s11948-013-9502-z

Asur, S., & Huberman, B. A. (2010). Predicting the future with social media. In *Proceedings of the international conference on web intelligence and intelligent agent technology* (pp. 492–499). Institute of Electrical and Electronics Engineers: Toronto, ON.

Bassett, D. S., Alderson, D. L., & Carlson, J. M. (2012). Collective decision dynamics in the presence of external drivers. *Physical Review E*, *86*(3), Article 36105. https://doi.org/10.1103/PhysRevE.86.036105

Bedient, P., Holder, A., Benavides, J., & Vieux, B. (2003). Radar-based flood warning system applied to tropical storm Allison. *Journal of Hydrologic Engineering*, *8*(6), 308–318. https://doi.org/10.1061/(ASCE)1084-0699(2003)8:6(308)

Bellomo, N., Clarke, D., Gibelli, L., Townsend, P., & Vreugdenhil, B. J. (2016). Human behaviours in evacuation crowd dynamics: From modelling to "big data" toward crisis management. *Physical of Life Reviews*, *18*, 1–21. https://doi.org/10.1016/j.plrev.2016.05.014

Bertella, M. A., Pires, F. R., Feng, L., & Stanley, H. E. (2014). Confidence and the stock market: An agent-based approach. *PLoS One*, *9*(1), e83488. https://doi.org/10.1371/journal.pone.0083488

Brenhouse, H. (2011). China's great salt rush: Nuke fears cause supermarket swarms, *Time*. Retrieved from http://newsfeed.time.com/2011/03/17/the-great-salt-rush-nuke-fears-have-chinese-swarming-supermarkets, accessed 23 September 2016

Centola, D. (2010). The spread of behavior in an online social network experiment. *Science*, *329*(5996), 1194–1197. https://doi.org/10.1126/science.1185231

Chen, X., & Zhan, F. B. (2008). Agent-based modelling and simulation of urban evacuation: Relative effectiveness of simultaneous and staged evacuation strategies. *Journal of Operational Research Society*, *59*(1), 25–33. https://doi.org/10.1057/palgrave.jors.2602321

Cloke, H., & Pappenberger, F. (2009). Ensemble flood forecasting: A review. *Journal of Hydrology*, *375*(3–4), 613–626. https://doi.org/10.1016/j.jhydrol.2009.06.005

Crokidakis, N., & Anteneodo, C. (2012). Role of conviction in nonequilibrium models of opinion formation. *Physical Review E*, *86*, Article 61127. https://doi.org/10.1103/PhysRevE.86.061127

Dash, N., & Gladwin, H. (2007). Evacuation decision making and behavioral responses: Individual and household. *Natural Hazards Review*, *8*(3), 69–77. https://doi.org/10.1061/(ASCE)1527-6988(2007)8:3(69)

Dawson, R. J., Peppe, R., & Wang, M. (2011). An agent-based model for risk-based flood incident management. *Natural Hazards*, *59*(1), 167–189. https://doi.org/10.1007/s11069-011-9745-4

Decker, K. M. (1991). The Monte Carlo method in science and engineering: Theory and application. *Computer Methods in Applied Mechanics and Engineering*, *89*(1–3), 463–483. https://doi.org/10.1016/0045-7825(91)90054-A

DeGroot, M. (1974). Reaching a consensus. *Journal of American Statistical Association*, *69*(345), 118–121.

Del Vicarioa, M., Bessi, A., Zollo, F., Petroni, F., Scala, A., Caldarelli, G., . . . Quattrociocchi, W. (2016). The spreading of misinformation online. *Proceedings of the National Academy of Science of the United States of America*, *113*(3), 554–559. https://doi.org/10.1073/pnas.1517441113

Di Baldassarre, G., Kemerink, J. S., Kooy, M., & Brandimarte, L. (2014). Floods and societies: The spatial distribution of water-related disaster risk and its dynamics. *WIREs Water*, *1*, 133–139. https://doi.org/10.1002/wat2.1015

Di Baldassarre, G., Viglione, A., Carr, G., Kuil, L., Salinas, J. L., & Bloschl, G. (2013). Socio-hydrology: Conceptualising human-flood interactions. *Hydrology and Earth System Sciences*, *17*(8), 3295–3303. https://doi.org/10.5194/hess-17-3295-2013

Du, E., Rivera, S., Cai, X., Myers, L., Ernest, A., & Minsker, B. (2016). Impacts of human behavioral heterogeneity on the benefits of probabilistic flood warnings: An agent-based modeling framework. *Journal of American Water Resources Association*, *53*(2), 316–332. https://doi.org/10.1111/1752-1688.12475

Dubois, E., & Gaffney, D. (2014). The multiple facets of influence: Identifying political influentials and opinion leaders on Twitter. *American Behavioral Scientist*, *58*(10), 1260–1277. https://doi.org/10.1177/0002764214527088

Farkas, K., Nagy, A., Tomas, T., & Szabo, R. (2014). Participatory sensing based real-time public transport information service. In *IEEE international conference on pervasive computing and communication workshops* (pp. 141–144). Budapest, Hungary: Institute of Electrical and Electronics Engineers (IEEE).

Friedkin, N., & Johnsen, E. (1999). Social influence networks and opinion change. *Advances in Group Processes*, *16*, 1–29.

Galam, S., & Jacobs, F. (2007). The role of inflexible minorities in the breaking of democratic opinion dynamics. *Physica A*, *381*, 366–376. https://doi.org/10.1016/j.physa.2007.03.034

Ghaderi, J., & Srikant, R. (2013). Opinion dynamics in social networks: A local interaction game with stubborn agents. In *American control conference* (pp. 1982–1987). Washington, DC: Institute of Electrical and Electronics Engineers (IEEE).

Ghaderi, J., & Srikant, R. (2014). Opinion dynamics in social networks with stubborn agents: Equilibrium and convergence rate. *Automatica*, *50*(12), 3209–3215. https://doi.org/10.1016/j.automatica.2014.10.034

Gil de Zúñiga, H., & Diehl, T. (2017). Citizenship, social media, and big data: Current and future research in the social sciences. *Social Science Computer Review*, *35*(1), 3–9. https://doi.org/10.1177/0894439315619589

Gil de Zúñiga, H., Jung, N., & Valenzuela, S. (2012). Social media use for news and individuals' social capital, civic engagement and political participation. *Journal of Computer and Communication*, *17*(3), 319–336. https://doi.org/10.1111/j.1083-6101.2012.01574.x

Girons Lopez, M., Di Baldassarre, G., & Seibert, J. (2017). Impact of social preparedness on flood early warning systems. *Water Resources Research*, *53*, 522–534. https://doi.org/10.1002/2016WR019387

Gladwin, H., Willoughby, H. E., Lazo, J. K., Morrow, B. H., & Peacock, W. G. (2009). Social science research needs for the hurricane forecast and warning system. *Bulletin of the American Meteorological Society*, *90*, 25–29. https://doi.org/10.1175/2008BAMS2606.1

Granell, C., Havlik, D., Schade, S., Sabeur, Z., Delaney, C., Pielorz, J., . . . Mon, J. L. (2016). Future Internet technologies for environmental applications. *Environmental Modelling and Software*, *78*, 1–15. https://doi.org/10.1016/j.envsoft.2015.12.015

Hasan, S., Ukkusuri, S., Gladwin, H., & Murray-Tuite, P. (2011). Behavioral model to understand household-level hurricane evacuation decision making. *Journal of Transportation Engineering*, *137*(5), 341–348. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000223

Haque, E. C. (1995). Climatic hazards warning process in Bangladesh: Experience of, and lessons from, the 1991 April cyclone. *Environmental Management*, *19*(5), 719–734. https://doi.org/10.1007/BF02471954

Heaney, J. P., Peterka, J., & Twight, L. T. (2000). Research needs for engineering aspects of natural disasters. *Journal of Infrastructure System*, *6*(1), 4–14. https://doi.org/10.1061/(ASCE)1076-0342(2000)6:1(4)

Hegselmann, R., & Krause, U. (2002). Opinion dynamics and bounded confidence: Models, analysis and simulation. *Journal of Artificial Societies and Social Simulation*, *5*(3), 1–33. https://doi.org/citeulike-article-id:613092

Houston, J. B., Hawthorne, J., Perreault, M. F., Park, E. H., Hode, M. G., Halliwell, M. R., . . . Griffith, S. A. (2015). Social media and disasters: A functional framework for social media use in disaster planning, response, and research. *Disasters*, *39*(1), 1–22. https://doi.org/10.1111/disa.12092

Huang, Q., Parker, D. C., Sun, S., & Filatova, T. (2013). Effects of agent heterogeneity in the presence of a land-market: A systematic test in an agent-based laboratory. *Computers, Environment and Urban Systems*, *41*, 188–203. https://doi.org/10.1016/j.compenvurbsys.2013.06.004

Huang, S., Lindell, M. K., Prater, C. S., Wu, H., & Siebeneck, L. K. (2012). Household evacuation decision making in response to Hurricane Ike. *Natural Hazards Review*, *13*(4), 283–296. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000074

Hussain, M. M., & Howard, P. N. (2013). What best explains successful protest cascades? ICTs and the fuzzy causes of the Arab Spring. *International Studies Review*, *15*, 48–66. https://doi.org/10.1111/misr.12020

Jia, P., Mirtabatabaei, A., Friedkin, N. E., & Bullo, F. (2015). Opinion dynamics and the evolution of social power in influence networks. *Society for Industrial and Applied Mathematics*, *57*(3), 367–397. https://doi.org/10.1137/130913250

Kearns, M., Judd, S., Tan, J., & Wortman, J. (2009). Behavioral experiments on biased voting in networks. *Proceedings of the National Academy of Science of the United States of America*, *106*(5), 1347–1352. https://doi.org/10.1073/pnas.0808147106

Kongsomsaksakul, S., Yang, C., & Chen, A. (2005). Shelter location-allocation model for flood evacuation planning. *Journal of the Eastern Asia Society for Transportation Studies*, *6*, 4237–4252.

Kongthon, A., Haruechaiyasak, C., Pailai, J., & Kongyoung, S. (2012). The role of Twitter during a natural disaster: Case study of 2011 Thai flood. *Technology Management for Emerging Technologies*, 2227–2232. https://doi.org/10.1142/S0219877014400124

Kwak, H., Lee, C., Park, H., & Moon, S. (2010). What is Twitter, a social network or a news media?. In *The international world wide web conference* (pp. 591–600). Raleigh, NC: Association for Computing Machinery (ACM).

Lee, K. S., Eom, J. K., & Moon, D. (2014). Applications of TRANSIMS in transportation: A literature review. *Procedia Computer Science*, *32*, 769–773. https://doi.org/10.1016/j.procs.2014.05.489

Li, R., Ravi, K., & Chang, K. C.-C. (2012). TEDAS: A Twitter-based event detection and analysis system. In *IEEE 28th international conference on data engineering* (pp. 1273–1276). Washington, DC: Institute of Electrical and Electronics Engineers (IEEE).

Lindell, M. K., Lu, J.-C., & Prater, C. S. (2005). Household decision making and evacuation in response to hurricane Lili. *Natutal Hazards Review*, *6*(4), 171–179. https://doi.org/10.1061/(ASCE)1527-6988(2005)6:4(171)

Litman, T. (2006). Lessons from Katrina and Rita: What major disasters can teach transportation planners. *Journal of Transportation Engineering*, *132*(1), 11–18. https://doi.org/10.1061/(ASCE)0733-947X(2006)132:1(11)

Lorenz, J. (2005). A stabilization theorem for dynamics of continuous opinions. *Physica A*, *355*, 217–223. https://doi.org/10.1016/j.physa.2005.02.086

Makinen, J. (2016). Government flood warning in China was too little, too late, survivors say, *Los Angeles Times*. Retrieved from http://www.latimes.com/world/asia/la-fg-china-floods-xingtai-20160724-snap-story.html, accessed 5 January 2017

Marino, S., Hogue, I. B., Ray, C. J., & Kirschner, D. E. (2008). A methodology for performing global uncertainty and sensitivity analysis in systems biology. *Journal of Theoretical Biology*, *254*(1), 178–196. https://doi.org/10.1016/j.jtbi.2008.04.011

Marshall, G. W., Moncrief, W. C., Rudd, J. M., & Lee, N. (2012). Revolution in sales: The impact of social media and related technology on the selling environment. *Journal of Personal Selling & Sales Management*, *32*(3), 349–363. https://doi.org/10.2753/PSS0885-3134320305

Martins, A. (2008). Mobility and social network effects on extremist opinions. *Physical Review E*, *78*(3), Article 36104. https://doi.org/10.1103/PhysRevE.78.036104

Martins, A., & Galam, S. (2013). Building up of individual inflexibility in opinion dynamics. *Physical Review E*, *87*(4), Article 42807. https://doi.org/10.1103/PhysRevE.87.042807

McCullen, N. J., Rucklidge, A. M., Bale, C. S. E., Foxon, T. J., & Gale, W. F. (2013). Multiparameter models of innovation diffusion on complex networks. *SIAM Journal on Applied Dynamical Systems*, *12*(1), 515–532. https://doi.org/10.1137/120885371

Murray-Tuite, P., & Wolshon, B. (2013). Evacuation transportation modeling: An overview of research, development, and practice. *Transportation Research Part C: Emerging Technologies*, *27*, 25–45. https://doi.org/10.1016/j.trc.2012.11.005

Nagel, K., & Rickert, M. (2001). Parallel implementation of the TRANSIMS micro-simulation. *Parallel Computing*, *27*(12), 1611–1639. https://doi.org/10.1016/S0167-8191(01)00106-5

Nagel, K., & Schreckenberg, M. (1992). A cellular automaton model for freeway traffic. *Journal de Physique I*, *2*(12), 2221–2229. https://doi.org/10.1051/jp1:1992277

Naghawi, H., & Wolshon, B. (2010). Transit-based emergency evacuation simulation modeling. *Journal of Transportation Safety & Security*, *2*(2), 184–201. https://doi.org/10.1080/19439962.2010.488316

Nguyen, D. T., Nguyen, N. P., & Thai, M. T. (2012). Sources of misinformation in online social networks: Who to suspect? In *IEEE military communications conference* (pp. 1–6). Orlando, FL: Institute of Electrical and Electronics Engineers (IEEE).

Palen, L., Starbird, K., Vieweg, S., & Hughes, A. (2010). Twitter-based information distribution during the 2009 Red River Valley flood threat. *Bulletin of the American Society for Information Science*, *36*(5), 13–17. https://doi.org/10.1002/bult.2010.1720360505

Pappenberger, F., Cloke, H. L., Parker, D. J., Wetterhall, F., Richardson, D. S., & Thielen, J. (2015). The monetary benefit of early flood warnings in Europe. *Environmental Science & Policy*, *51*, 278–291. https://doi.org/10.1016/j.envsci.2015.04.016

Parker, D., Priest, S., & Tapsell, S. (2009). Understanding and enhancing the public's behavioural response to flood warning information. *Meteorological Applications*, *16*, 103–114. https://doi.org/10.1002/met

Parker, D., Tunstall, S., & McCarthy, S. (2007). New insights into the benefits of flood warnings: Results from a household survey in England and Wales. *Environmental Hazards*, *7*(3), 193–210. https://doi.org/10.1016/j.envhaz.2007.08.005

Parker, D. J. (2017). Flood warning systems and their performance. *Oxford Research Encyclopedias: Natural Hazard Science*, Retrieved from http://naturalhazardscience.oxfordre.com/view/10.1093/acrefore/9780199389407.001.0001/acrefore-9780199389407-e-84; https://doi.org/10.1093/acrefore/9780199389407.013.84

Parker, D. J., & Handmer, J. W. (1998). The role of unofficial flood warning systems. *Journal of Contingencies and Crisis Management*, *6*(1), 45–60. https://doi.org/10.1111/1468-5973.00067

Paul, B. K., & Dutt, S. (2010). Hazard warnings and responses to evacuation orders: The case of Bangladesh's cyclone Sidr. *Geographical Review*, *100*(3), 336–355. https://doi.org/10.1111/j.1931-0846.2010.00040.x

Rieder, B. (2013). Studying Facebook via data extraction: The Netvizz application. In *Proceedings of the 5th annual ACM web science conference* (pp. 346–355). Paris, France: Association for Computing Machinery (ACM).

Rodriguez, N., Bollen, J., & Ahn, Y. Y. (2016). Collective dynamics of belief evolution under cognitive coherence and social conformity. *PLoS One*, *11*(11), e0165910. https://doi.org/10.1371/journal.pone.0165910

Russell, J. (2011). As floods batter Thailand, its citizens turn to the Internet for help, *Next Web*. Retrieved from https://thenextweb.com/asia/2011/10/14/as-floods-batter-thailand-its-citizens-turn-to-the-internet-for-help/#.tnw_A14oHRrL, accessed 17 January 2015

Schelling, T. C. (1973). Hockey helmets, concealed weapons, and daylight saving: A study of binary choices with externalities. *Journal of Conflict Resolution*, *17*(3), 381–428.

Sivapalan, M., Savenije, H., & Blöschl, G. (2012). Socio-hydrology: A new science of people and water. *Hydrological Process*, *26*(8), 1270–1276. https://doi.org/10.1002/hyp.8426

Smith, A. B., & Matthews, J. L. (2015). Quantifying uncertainty and variable sensitivity within the US billion-dollar weather and climate disaster cost estimates. *Natural Hazards*, *77*(3), 1829–1851. https://doi.org/10.1007/s11069-015-1678-x

Smith, L., Liang, Q., James, P., & Lin, W. (2015). Assessing the utility of social media as a data source for flood risk management using a real-time modeling framework. *Journal of Flood Risk Management*, *10*(3), 370–380. https://doi.org/10.1111/jfr3.12154

Sobkowicz, P., Kaschesky, M., & Bouchard, G. (2012). Opinion mining in social media: Modeling, simulating, and forecasting political opinions in the web. *Government Information Quarterly*, *29*(4), 470–479. https://doi.org/10.1016/j.giq.2012.06.005

Sorensen, J. H. (2000). Hazard warning systems: Review of 20 years of progress. *Natural Hazards Review*, *1*(2), 119–125. https://doi.org/10.1061/(ASCE)1527-6988(2000)1:2(119)

Sutton, R. S. (1988). Learning to predict by the methods of temporal differences. *Machine Learning*, *3*(1), 9–44. https://doi.org/10.1007/BF00115009

Vieweg, S., Hughes, A. L., Starbird, K., & Palen, L. (2010). Microblogging during two natural hazards events: What twitter may contribute to situational awareness. In *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 1079–1088). Atlanta, GA: Association for Computing Machinery (ACM).

Watts, D. J. (2002). A simple model of global cascades on random networks. *Proceedings of the National Academy of Science of the United States of America*, *99*(9), 5766–5771. https://doi.org/10.1073/pnas.082090499

Widrow, B., & Hoff, M. E. (1988). Adaptive switching circuits. In J. A. Anderson & E. Rosenfeld (Eds.), *Neurocomputing: Foundations of research* (pp. 123–134). Cambridge, MA: MIT Press.

Widrow, B., & Lehr, M. A. (1993). Artificial neural networks of the perceptron, madaline and backpropagation family. In H.-W. Bothe, M. Samii, & R. Eckmiller (Eds.), *Neurobionics: An interdisciplinary approach to substitute impaired functions of the human nervous system* (pp. 133–205). Amsterdam, the Netherlands: Elservier.

Wu, Y.-J., Wang, Y., & Qian, D. (2007). A Google-map-based arterial traffic information system. In *IEEE intelligent transportation systems conference* (pp. 968–973). Seattle, WA: Institute of Electrical and Electronics Engineers (IEEE).

Yildiz, E., Ozdaglar, A., Acemoglu, D., Saberi, A., & Scaglione, A. (2013). Binary opinion dynamics with stubborn agents. *ACM Transactions on Economics and Computation*, *1*(4), 1–30. https://doi.org/10.1145/2538508

Zhang, B., Chan, W. K., & Ukkusuri, S. V. (2009). Agent-based modeling for household level hurricane evacuation. In *Proceedings of the 2009 winter simulation conference* (pp. 2778–2784). Austin, TX: Institute of Electrical and Electronics Engineers (IEEE).

Zhang, L., Zhao, J., & Xu, K. (2016). Who creates trends in online social media: The crowd or opinion leaders? *Journal of Computer and Communications*, *21*(1), 1–16. https://doi.org/10.1111/jcc4.12145

Zhu, Q. (2017). Citizen-driven international networks and globalization of social movements on Twitter. *Social Science Computer Review*, *35*(1), 68–83. https://doi.org/10.1177/0894439315617263