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Understanding the influence of multiple information sources on risk perception dynamics and evacuation decisions: An agent-based modeling approach

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ABSTRACT

Evacuation is one of the most effective strategies to reduce risk during natural disasters. Although many studies have investigated factors affecting evacuation decisions (e.g., socio-economic, risk forecast, demographic, environmental cues, etc.), how all these factors interplay in forming the overall risk perception and evacuation decision is underexplored. Here, we present an agent-based model that leverages empirical evidence from post-disaster surveys to create evacuation tendencies of the agents (households) and integrates flood-related hazard risk, household socio-demographic factors, social network characteristics and decisions, and neighbors' decisions to dynamically evolve complex decision-making pattern during hurricane evacuation. We simulate the effect of multiple information sources and their perceived credibility on evacuation participation by separately determining evacuation compliance (defined as evacuation from places where official mandatory evacuation order is issued) and shadow evacuation (defined as spontaneous evacuation from places where a mandatory order is not issued). We use socio-demographic data from U. S. Census Bureau, building footprint data from County Website, run off data from Stormwater Management Model (SWMM) of U.S. Environmental Protection Agency, and all other data were synthetically generated within the model. Our case study based on a community of Miami-Dade County indicates that higher perceived credibility of hazard risk leads to higher evacuation compliance. We have also found that while social networks increase overall evacuation participation, they also increase shadow evacuation and higher trust on neighbor actions reduces evacuation rates. This study gives insights for emergency management to design appropriate strategies for providing hazard forecasts or communicating overall risk during disasters.

1. Introduction

Hurricanes are one of the most destructive and costliest natural disasters in the United States. Emergency officials often declare evacuation orders to save human lives during an approaching hurricane. Such evacuation orders are expected to propagate through multiple sources (traditional news media, social networks, social media, etc.) to inform people living in the risk zone. In response to evacuation orders and forecasted risk, households take evacuation decisions, which depend on a complex and dynamic process [1–3].

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The delivery of accurate and timely information is crucial to improve situational awareness of the affected communities. But the effectiveness of such information depends on the perceived credibility of the information sources and household response to such information, which further depend on the socio-economic and demographic characteristics of a household and their prior hazard experiences [4–6]. Natural disasters like flooding/hurricanes are likely to increase in severity and frequency for a variety of reasons including (but not limited to): climate change, increases in population, increasing land-use development in high-risk areas. Thus, understanding the evacuation decision making process is increasingly important in the context of new digital era where information can be received from many different sources.

The desired outcome of an evacuation scenario is high evacuation compliance (received a mandatory evacuation order and evacuated) and low shadow evacuation (defined as evacuation without any mandatory order).[1] Because of the heterogeneities in household risk perceptions and the differences in credibility of information sources, the outcome of an evacuation scenario may become different than expected. For example, during Hurricane Irma the state of Florida had an overall 31% non-compliance and 46% shadow evacuation rates [7,8]. Hence, evacuation response to warnings should be evaluated considering multiple information sources and their perceived credibility among households from different socio-demographic groups. Previous studies, including statistical and agent-based models, have considered multiple information sources [4,9,10]. Among these models, the statistical models [4,11] could not capture the dynamics of these information sources and the agent-based models are mostly based on synthetic data without considering household socio-economic and demographic characteristics.

The most relevant studies [12–15] that used agent-based models to understand evacuation behavior and risk perceptions have at least one of the following gaps – 1) have created agents in a synthetic space or an aggregated space (census tract, blocks, etc.) that limits the understanding of spatial effects among neighbors, 2) have not integrated flood risk and corresponding risk perception considering a spatially aware model, 3) have not considered the credibility of information sources and how it affects risk perception, 4) have not considered shadow evacuation separately.

In this study, we develop an agent-based model that combines hydrologic characteristics, socio-demographic characteristics, and multiple information sources to understand risk perception and evacuation behavior of the households of an area. Previous studies suggested that people from Miami-Dade area are more concerned about inland flooding from heavy rainfall than storm surge despite living in a coastal area [16]. We use simulated runoff depth prediction as an indicator of potential flooding considering the climatic, land uses/cover, and hydrological aspects of a region. Then we use the predicted runoff depth to generate the initial risk perception of a household, which solves the requirement of initial seed generation. The novelty of our study is that we integrate detailed runoff depth information, actual neighborhood (with the spatial distribution of households), and social network to model risk perception and evacuation decision of a household. We also model how multiple information sources (runoff predictions, neighbor observation, and opinion in social network) and household's trust in these information sources are linked to evacuation compliance and shadow evacuation. This study contributes to the literature by answering the following research questions:

- How to develop an agent-based model (ABM) considering how a household perceives flood risk and makes evacuation decisions.

In the ABM model, we integrate runoff predictions from a process-based hydrologic model, parcel level land use characteristics, household socio-demographic characteristics, and information sources to model risk perception dynamics and evacuation decisions.

- What is the effect of a household's trust on forecasts on evacuation participation?

We use a locally relevant, block level ($1\ km \times 1\ km$) rainfall-induced runoff predictions to model the perception of potential flood risk and corresponding evacuation decision of a household.

- What is the effect of social networks on a household's evacuation decision, and how does a household's trust on opinion dynamics of social networks affect the overall evacuation participation?

We construct social networks among the households and model the influence of opinion dynamics (circulating over the social networks) on household evacuation decisions.

- How does observing neighbor activities affect a household's evacuation decision in an actual neighborhood setting, and how a household's trust on neighbors' observation affect the overall evacuation dynamics?

Past studies have created agents in a synthetic space or an aggregated space (census tract, blocks, etc.) that limits the understanding of spatial effects among the neighbors. We capture the influence of an actual neighborhood and household locations on evacuation decisions by assigning household agents at a building footprint level.

2. Literature review

Evacuation behavior models can be divided into two broad categories: (i) statistical models [17–19] that use empirical data collected by a survey to understand contributing factors of evacuation behavior; (ii) computational models [12,15,20] that use behavioral theories to simulate evacuation behavior. The statistical modeling approach includes different types of logit models, most frequently a binary logit model where evacuation is modeled as a binary decision process (evacuate or not) [8,21]. These studies have found that socioeconomic, demographic factors, social ties, etc., play an important role on evacuation decisions [19,21]. The statisti-

[1] Shadow evacuations: did not receive a mandatory evacuation order but evacuated (it should be noted that shadow evacuations typically refer only to mandatory evacuation orders, not voluntary evacuation orders).

cal modeling approach, however, cannot capture the dynamics of the collective evacuation behavior that evolves from the social interactions among households; because it is very challenging to collect such empirical data [10,22]. A computational model such as an agent-based model allows incorporating the findings from the statistical models and other phenomena (risk propagation, dynamic forecast, social interaction) where heterogeneous agents (households) interact with each other and take decisions, and hereby affect the collective evacuation behavior [23]. Studies have found that the households reliability on weather forecast increases the likelihood to evacuate [4]; but the forecast might be less reliable and overblown for some households depending on the conveyed message [6,16], and they might look for other information sources/channels such as community, peers, internet, etc. [24,25].

Many studies have used agent-based models to understand evacuation behavior under the influence of social networks [12–15]. Widener et al. [14] found that social influence increases evacuation participation using a random subset of the population on a case study of Bay County, Florida. Yang et al. [12] proposed a home-workspace based social network for Florida-key regions to simulate the effect of social networks on evacuation decisions. This study has the following limitations: it considered neighbors as a part of social networks and did not consider that households can observe their spatially close neighbors' activity (evacuating or not) without having a social link between them; Florida Key is a unique geographic location that might not be representative to other location. Moreover, all of these ABMs have simulated the social network influence as a factor of evacuation decision without considering other information sources and did not consider the credibility/trust of peer pressure (or information from their connections). Thus, it is unknown what is the relative effect of social network, neighbor observation, and forecast accuracy for varying degree of trust on the information sources in the risk perception dynamics and evacuation decisions.

Du et al. [9] used an agent-based model to simulate the effect of online social networks and neighbor observations separately on flood evacuation behavior considering the trust on multiple information sources. However, this study is based on a hypothetical space and hazards; thus, representativeness of the results on actual social and neighbor effect is unknown.

In this study, we develop an agent-based model by incorporating flood risk and household's trust on multiple sources of influence (forecast, social networks, and neighbors' influence) to understand the dynamics of risk perception and evacuation behavior. We generate realistic runoff data of Miami-Dade County and create households using the most recent census data. We present our results on a case study created for the households located in a zip code of Miami-Dade County.

3. Data description

To simulate evacuation behavior in a geographical area, we collect data from multiple sources such as runoff predictions, sociodemographic distributions, building footprint, and property data.

The building dataset contains total 12,982 properties/buildings and 80.4% of them are residential buildings. The residential buildings have total 10,583 floors and 15,291 units. We generate synthetic runoff depth data using a process-based hydrologic model at the 1 km × 1 km block resolution (details on the hydrologic model and runoff depth predictions are given in the supporting information). We collect building footprint and property type from Miami-Dade County website [26]. The building data provide the location of a building and the type of its use (e.g., residential, commercial, unit count, floor count, etc.). We collect the 2018 5-year American Community Survey (ACS 5) [27] data for Miami-Dade County. We combine the data at a block group level, which is the smallest geographical unit for which census bureau publishes sample data [28]. We include data for the following table ids: B01001 (population), B19001 (household), B09019 (sex), B09020 (age), B19001 (income), B02001 (race), and B15002 (education).

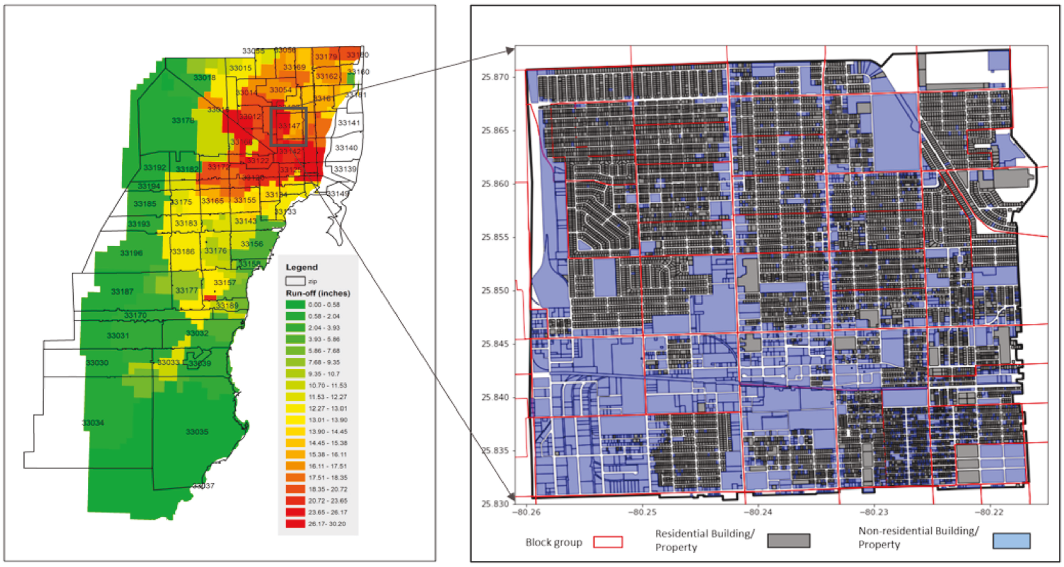
3.1. Study area

We focus on zip code 33147 of Miami-Dade County as the area of interest for our simulation (see Fig. 1). We choose this zip code because the predicted runoff depth varies over the block-groups present in it and the area has socio-demographic diversity (see section 4.2.1). In our study area, the runoff depth varies from approximately 16 inch–25 inch. Hence, this study area will capture evacuation behavior on different level of flood risk and heterogeneity in household risk perceptions. The study area has 46,933 population, 7.25 sq. Mile of land area, 49% male population, and 34.4% white people. The centroid of our study area is about 4.5 miles from the coast. Although the study area has relatively low to moderate risk of coastal flooding and hurricane, it has relatively moderate to high risk of riverine flood [29]. According to FEMA [29], the community resilience score of the study area is around 53.4 indicating that it has relatively moderate ability to prepare for anticipated natural hazards, adapt to changing conditions, and withstand and recover rapidly from disruptions when compared to the rest of the U.S. Furthermore, the community has a relatively high susceptibility to the adverse impacts of natural hazards when compared to the rest of the U.S [29].

Fig. 1(a) shows the runoff depth over Miami-Dade County – the runoff depth of zip code 33147 ranges from 13 to 26 inches. Fig. 1 (b) shows the spatial distribution of the building/property inventory of zip 33147. It has 40 block groups where 32 are completely inside and 8 are partially inside the boundary of the zip code. Some block groups have a high density of residential buildings and some have a low density of residential buildings among these 40 block groups. The lowest density is 1 residential building per block group, highest is 538 residential buildings per block group and the mean density value is 254.4. Hence, the selected study area is well-suited to capture the effects of flood risk and socio-demographic and neighborhood density on evacuation behavior.

4. Methodology

Our study has three main methodological parts: (i) creating synthetic households, (ii) creating social network among households, and (iii) modeling risk perception dynamics and evacuation behavior. Grimm et al. [30] proposed a standard protocol, also known as ODD (Overview, Design concepts, and Details) protocol, for describing agent-based models to make model descriptions more understandable and reproducible. Given below is the description of the model following the seven elements – purpose, state variables and



(a) (b)

Fig. 1. Study Area. (a) Run-off depth distribution on Zip codes (or block group) over Miami-Dade County (b) Residential and non-residential property/building distribution over the block-group of Zip 33147.

scale, process overview and scheduling, design concepts, initialization, input data, and submodels – of ODD protocol for individual and agent-based model [30,31]:

4.1. Purpose

The purpose of the model is to analyze risk perception dynamics and evacuation decisions influenced by multiple information sources, opinion dynamics among households, and neighbor observations.

4.2. State variables and scales

The entities of the model are households within the geographic area of zip code 33147 of Miami Dade county shown in section 3.1. All the households are characterized by socio-demographic characteristics and evacuation intent/risk tolerance threshold. Based on the perceived risk and the risk tolerance threshold a household decides whether to evacuate or not. The simulation follows a discrete time step: we updated the states of the simulation at the end of an hour. That means that one step of the model corresponds to 1 h and we run the simulation for 120 h. We tested different time durations as step sizes and chose an hour as optimum to keep the simulation run-time short without losing many details about the dynamics in evacuation decisions. A smaller step size would increase simulation run-time without giving any additional insights on evacuation dynamics. The next two subsections describe the process of household creation and characterization process.

4.2.1. Creating synthetic households

We create 15,291 synthetic households in our study area. The United States Census Bureau defines household as following – “A household consists of all the people who occupy a housing unit. A house, an apartment or other group of rooms, or a single room is regarded as a housing unit when it is occupied or intended for occupancy as separate living quarters; that is, when the occupants do not live with any other persons in the structure and there is direct access from the outside or through a common hall” [32]. We assign the household characteristics (gender, employment, education, income, and race) only for the main (or head) [32]. Householder according to block group level distribution of 2018 5-year American Community Survey data. We assign a single household to each unit of a building according to the residential property data. Fig. 2 shows the joint and marginal distributions of the characteristic of the synthetic households for our study area (zip 33147) based on data collected from 2018 5-year American Community Survey data.

Previous studies suggested that a household's evacuation behavior depends on its demographic and socio-economic attributes. Existing literatures found that hurricane evacuation models are transferable to some extent across populations [33], time and geography [34]. We estimate a household's evacuation tendency/willingness based on household characteristics of the main householders (as shown in Fig. 2) using a binary logit model adopted from this study [35]. The binary logit model is given in equation (1).

$$\textit{Evacuation tendency}, \pi_i = \frac{e^{\beta x_i}}{1 + e^{\beta x_i}} \tag{1}$$

where, π_i is the evacuation tendency of household i, x_i are the characteristics variables of household i, β are the coefficients of the binary logit model adopted from Ref. [35]. Please find the explanatory variables and model co-efficient in Table 1. The model is based

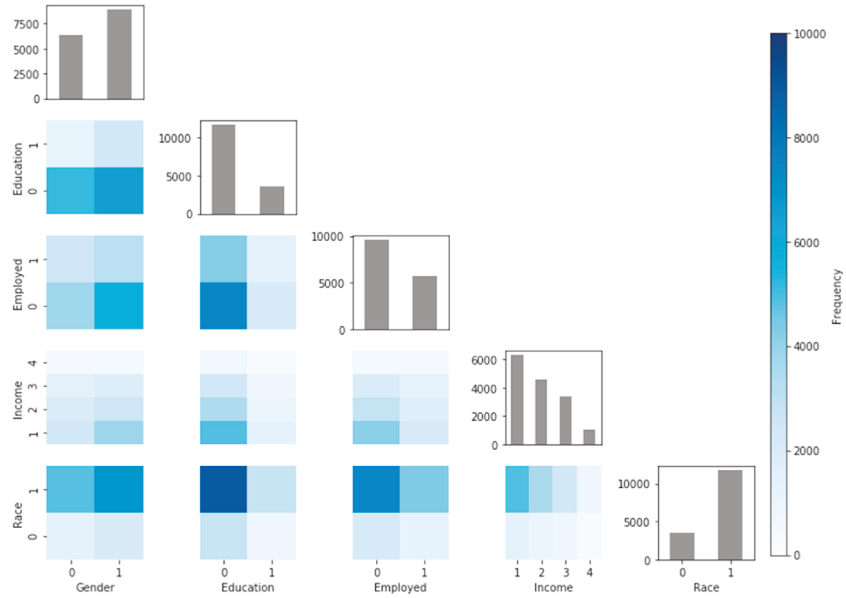


Fig. 2. Joint and Marginal Distribution of the Synthetic Households. Here the variables are gender (0 = male, 1 = female); Education (1 = some college or higher, 0 = less than college), Employed (0 = unemployed, 1 = employed), Income (1 = less than 25 k, 2 = between 25 k to 50 k, 3 = 50 k to 100 k, 4 = greater than 100 k), Race (0 = white, 1 = other).

Table 1
Model parameters of the adopted evacuation decision (binary logit) model [35].

Parameter	Estimate	Standard Error
Intercept	−0.480	0.267
Gender (0 = male, 1 = female)	−0.294	0.143
Employed (0 = unemployed, 1 = employed)	−0.323	0.174
Age over 65 (0 = age less than 65, 1 = age over 65)	0.678	0.202
Education (1 = some college or higher, 0 = less than college)	0.221	0.185
Income Level ($)		
<25,000	0.000	–
25,000–50,000	0.067	0.247
50,000–100,000	0.438	0.244
>100,000	0.480	0.152
Married (0 = unmarried, 1 = married)	0.432	0.162
Race (0 = white, 1 = other)	0.520	0.170

on seven explanatory variables – gender, education, employed, age over 65, income level, married, and race. A positive sign of a parameter indicates that households with the corresponding factor are more likely to evacuate (or have higher evacuation tendencies), and a negative sign of a parameter indicates that households with the corresponding factor are less likely to evacuate (or have lower evacuation tendencies). So, a household with an educated member is more likely to evacuate compared to a household without any educated member; households of income level 25 k to 50 k, 50 k to 100 k, and >100 k are more likely to evacuate compared to households with income level <25 k; households with married main householders are more likely to evacuate compared to households with unmarried main householders; households with main householders aged over 65 are more likely to evacuate compared to households with main householders age <65; households with race 'other' are more likely to evacuate compared to household with race white. On the other hand, households with female main householders are less likely to evacuate compared to households with male main householders and employed households are less likely to evacuate compared to unemployed households.

The risk tolerance threshold of a household is assigned based on the evacuation tendency computed from the socio-economic characteristics of a household. We assign the risk tolerance assuming that a household with a lower evacuation tendency has a higher threshold of risk tolerance and vice versa [12]. We used an "equal interval assignment' approach similar to this study [12] to assign a 'risk tolerance threshold'. We divided the evacuation tendencies (0–1) into ten equal intervals. If a household's evacuation tendency falls within a specified interval, risk tolerance threshold is assigned as difference between 1 and the lower limits of the interval. For a household j, the risk tolerance τ_j can be calculated using the following equation:

$$\tau_j = 1 - \pi^{l_i}\ , if\ \pi^{l_i} < \pi_j < \pi^{u_i} \tag{2}$$

where, $i = 1,2,3, - - - ,n$ equal interval and π^{u_i},π^{l_i} are the upper limit and lower limit of the interval i, respectively, and $\pi^{u_i} - \pi^{l_i}$ *is constant*. In our study, we have used ten ($n = 10$) equal intervals. We predicted the evacuation tendencies for the 15,291 synthetic households in our study area and later assigned the risk tolerance threshold based on equation (2). Table 2 shows equal interval values of evacuation tendencies and the corresponding risk tolerance threshold. Third column of Table 2 shows the percentage of households (total 15,291) that falls within the specified risk tolerance threshold.

4.2.2. Creating social network and neighborhood

The evacuation decision of a household does not only depend on its characteristics but also on the surrounding neighborhood and social network [36]. Studies suggest that the connections among households are most likely to work as a small world network [12], proposed by Watts and Strogatz [37]. We create small world network between the synthetic households generated in the previous step. A household is more likely to connect with its nearby connections during an emergency. As our study area is a zip code with diagonal distance of around 6.4 km, all households are equally likely to be connected with each other. For each household, we create a small world undirected (i.e., communication can happen both ways) network with average degree, k_a of n. Here, average degree, n means on average each household will be connected with n different households in the network. Where value of n can be 2 to 15 based on previous studies [12,14]. While creating the social network we assumed that there exists some sort of friendship (relatives, family members, or social media friends, etc.) between the households. However, we assigned neighbors only based on spatial proximity and no friendship is required. We assign neighbors based on the spatial proximity of the households ranging from 300 m to 1 km for different simulation setup.

4.3. Process overview and scheduling

At every time step, the risk perceptions of the households are updated based on their previous risk perceptions and the following information sources: risk perception from social network, neighbor's evacuation activity and hazard forecasts. If the updated risk perception is greater than its risk tolerance threshold, the evacuation status is set as evacuated for the rest of the simulation. The frequency of risk perception updating decision of a household is decided based on a random probability distribution. However, the updating is synchronous for the households who decide to update their risk perceptions.

4.4. Design concepts

Risk perception dynamics and evacuation decision at a community level evolves from household's own perception about information reliability and interaction among social networks and neighbors. Fig. 3 shows the overall design concept of the model. Each household form its own risk perception of hazard and then update the risk perception over time after communicating with the social network and neighbors. If the social connections have high risk perception, household risk perception will be higher. Similarly, if a household observe that most of its neighbor is evacuating its risk perception will increase. However, households put different weight (α,β,γ) to these information sources with stochastic weights (to capture the heterogeneity among households). At each time step, a household evaluates the updated risk with its risk tolerance and decides whether to evacuate or not. The details are discussed in the Submodels section.

4.5. Initialization

We implemented the simulation in Java programming-based Repast Simphony agent-based modeling framework [38]. In Repast Simphony, an ABM consists of three main components: agents, projections, and context. Context works as a container of agents and projections and defines the behavior of agents, interactions between agent and projection. Projection on the other hand imposes structure of the agents. More details about Repast Simphony can be found here [39]. In our simulation, synthetic households are the agents; social network and location of the households are two different projections. We implemented a Repast Simphony context that performs the following main tasks: a) assigns household agents to the residential buildings (or location projection), b) assigns household agents to the social network and sets neighbors, c) defines rules for risk perception dynamics and evacuation decision. Simulations are initialized with 15,291 synthetic households with the following attributes: a) risk tolerance thresholds based on socio-demographic characteristics, b) information credibility sampled from a normal distribution ranging from 0 to 1, where 1 means completely trust the information source, 0 means no trust, c) initial risk perception value (ratio of forecasted runoff depth at household's

Table 2
Assignment of Risk Tolerance Thresholds based on Evacuation Tendency.

Evacuation Tendency, (π)	Risk Tolerance Threshold (τ)	Percentage of Households
0–0.1	1.0	–
0.1–0.2	0.9	44.11
0.2–0.3	0.8	23.76
0.3–0.4	0.7	18.80
0.4–0.5	0.6	8.91
0.5–0.6	0.5	3.52
0.6–0.7	0.4	0.83
0.7–0.8	0.3	0.065
0.8–0.9	0.2	–
0.9–1.0	0.1	–

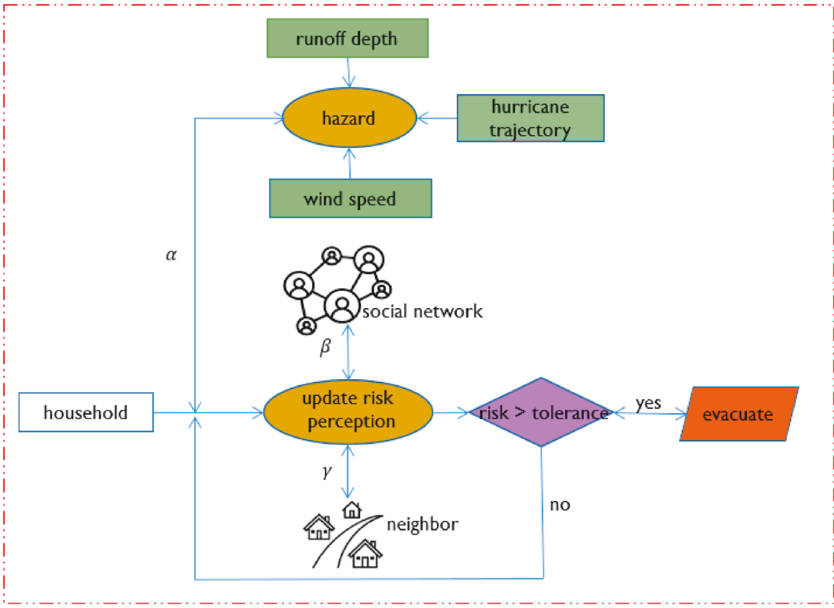


Fig. 3. Design concept of the ABM for risk perception dynamics and evacuation decisions.

home location and maximum permissible runoff depth) induced by hazard forecast. We used a Markov Chain Monte Carlo based sampling method based on the distribution shown in Fig. 2 to generate socio-demographic characteristics of each agent (i.e., household). Census block group level aggregated data was used to estimate the number of agents/households and conditional probability distribution (e.g., given a main householder is male what is the probability of that householder to be employed?). Pseudo-code of similar approach can be found in this study [35].

4.6. Input data

This element of the ODD protocol describes the following question- "does the model use input from external sources such as data files or other models to represent processes that change over time?" [30]. In our simulation, the dynamics of the model does not depend on external input. We assumed that the hazard forecast does not change over time.

4.7. Submodels

This section describes the mathematical equations and parameters that are used to model the dynamics of risk perceptions and evacuation behavior. The list of the parameters can be found in Table 3. We develop a threshold-based model to simulate evacuation decisions of the households, where each household (agent), j has a set of attributes: risk tolerance threshold, sensitivity towards landfall time, trust on different information sources, information search behavior, and learning attitude.

Following previous studies [9,40], we represent the perceived risk of a household as a continuous variable. Each household will update its perceived risk over time and will decide whether to evacuate or not. A household will evacuate if the perceived risk is

Table 3
Parameters of the ABM. Here $N(\mu,\sigma)$ represents that the corresponding value of the parameter is drawn from a normal distribution with mean μ and standard deviation σ.

Parameters		Scenario 1	Scenario 2	Scenario 3
Hazard Risk	Runoff depth, τ_{rd}(inch)	22		
	Trust in hazard forecast, α_j	1	N(0.5,0.1)	N(0.5,0.1)
Social Network Influence	Trust in social network, β_j	0	N(0.5,0.1)	0
	Maximum permissible distance, d_{max}(kilometer)	3		
	Average no. Of social connections, K_{avg}	6		
Neighbor Observation	Trust in neighbor observation, γ_j	0	0	N(0.5,0.1)
	Threshold distance, τ_N (meter)	300		
Landfall Time	Mean of time difference from landfall, C_j	N(45,10)		
	Standard deviation of time difference from landfall, σ_j	N(20,10)		
Opinion Update Probability	p_j	N(0.3,0.1)		
Learning Rate	θ_j	N(0.5,0.1)		

greater than its risk tolerance threshold. Let, $R_{j,t}$, τ_j are the perceived risk of a household and the risk tolerance threshold of household j at time t, respectively. If $R_{j,t} > \tau_j$ household j will evacuate ($E_{j,t} = 1$), otherwise the household will stay ($E_{j,t} = 0$) at time t.

$$E_{j,t} = \begin{cases} 1 & \text{if } R_{j,t} > \tau_j \text{ or } E_{j,t-1} = 1 \\ 0 & \text{if } R_{j,t} \le \tau_j \end{cases} \tag{3}$$

At any given time t, a household forms its risk perception based on the influence I_t received from multiple sources of information and the perceived time difference from landfall (see Equation (4)). Hurricane landfall time plays a crucial role in shaping household risk perception and each household perceives the risk differently with respect to the time difference from landfall [10] as follows:

$$R_{j,t} = I_{j,t} \times e^{-\frac{(t-C)^2}{2\sigma^2}} \tag{4}$$

where, C is the mean and σ is the standard deviation of the time difference from landfall when the risk perception is maximum. A household may not collect new information at every time step. Thus, we model the risk perception dynamics as a stochastic process where the parameter $p_{j,t}\ (update = 1)$ determines whether a household j will search for new information or not. If a household chooses not to collect any new information, then $I_{j,t} = I_{j,t-1}$. At time t, if a household j chooses to collect new information it will look for 3 information sources: (i) hazard risk forecast $(I^H_{j,t})$, (ii) social network/media $(I^S_{j,t})$, (iii) neighborhood activity $(I^N_{j,t})$.

$$I^{New}_{j,t} = \alpha_j I^H_{j,t} + \beta_j I^S_{j,t} + \gamma_j I^N_{j,t} \tag{5}$$

where, α_j, β_j, and γ_j are the trust (or weight) parameters on building household $j's$ influence on new information and $\alpha_j + \beta_j + \gamma_j = 1$.

We also consider that a household is likely to be skeptic about the new influence and may only partially accept the new influence. Because of this opinion adherence tendency, households do not completely abandon their past information influence [9,41]. The parameter θ_j dictates what percentage of newly formed influence will be added to form the latest information influence I_t. Here, θ_j also serves as the learning rate of a household j in a Widrow-Hoff learning rule [9,42].

$$I_{j,t} = I_{j,t-1} + \theta_j \Delta I_{j,t} = I_{j,t-1} + \theta_j \left(I^{New}_{j,t} - I_{j,t-1} \right) = (1-\theta_j)\, I_{j,t-1} + \theta_j I^{New}_{j,t} \tag{6}$$

We represent the hazard risk primarily in terms of flood risk due to heavy rainfall during a hurricane. Since our study area is less likely to face storm surge (not within the storm surge zone) and significant wind gust variation (because of small geographical area), we assume that a household will consider only the inland flooding to form its hazard related influence on risk perception. Here, we introduce a threshold runoff depth τ_{rd} that will dictate whether emergency officials will declare evacuation or not. At time t, a household will form a hazard related risk by the amount of the ratio of the forecasted runoff depth at the home location at household j and τ_{rd}.

$$I^H_{j,t} = \frac{runoff\ depth\ at\ j's\ home\ location}{maximum\ permissible\ runoff\ depth\ (\tau_{rd})} \tag{7}$$

A household is also likely to collect information from its social network. At time t, the collected information is modeled as a linear combination of the information obtained from its connected households following the setting of previous studies [9,43]. A household may not collect information from all the connected households of its social network. Here, we assume that a household is more likely to collect information from the connected households who live closer to that household.

$$I^S_{j,t} = \sum_{i=1}^{n} w_{i,j} I_{i,t-1} = \sum_{i=1}^{n} \frac{a_{ij,t}}{\sum_{i=1}^{n} a_{ij,t}} I_{i,t-1} \tag{8}$$

where $a_{ij,t}$ represents whether household j has read or collected the opinion of household i ($a_{ij,t} = 1$) or not ($a_{ij,t} = 0$) and the probability of $a_{ij,t} = 1$ depends on the distance, d_{ij} between household $i$and household j and the maximum considerable distance d_{max}. The probability of exchanging opinion between two households reduces with increasing distance ($d_{i,j}$) between them. Here, d_{max} controls the upper bound of the distance $d_{i,j}$ and $p(a_{ij,t} = 1) = 0$, for $d_{i,j} \ge d_{max} + 1$.

$$p\left(a_{ij,t} = 1\right) = 1 - \frac{d_{ij}}{d_{\max} + 1} \tag{9}$$

We simulate the information obtained from the neighbors as the observed action of the neighbors (whether a neighbor has evacuated or not) [9,44]. We assume that households living in proximity may not necessarily know each other – thus cannot share opinion – but the households can easily observe their neighbors whether they have evacuated or not. The obtained information of a household is the weighted average of the observed action of the neighbors (see Equation (10)).

$$I_{j,t}^{N} = \sum_{i=1}^{n} \frac{b_{ij,t}}{\sum_{i=1}^{n} b_{ij,t}} E_{i,t-1} \tag{10}$$

where, $b_{ij,t}$ represents if household i is a neighbor of household j ($b_{ij,t} = 1$) or not ($b_{ij,t} = 0$) based on a threshold distance τ_N.

$$b_{ij,t} = \begin{cases} 0 \ \ if \ d_{ij} > \tau_N \\ 1 \ \ if \ d_{ij} \le \tau_N \end{cases} \tag{11}$$

5. Results

In our experiment of risk perception dynamics and evacuation behavior, we run all the simulation for 120 h. The simulation follows discrete time-steps, where at each step, time is increased by 1 h. We implemented the simulation in Repast Simphony agent-based modeling framework [38]. In our simulation, we create an agent's (household's) risk tolerance threshold based on the socio-economic and demographic heterogeneity. To represent heterogeneity in behavior, we assign household parameters (learning rate, trust on information source, information seeking behavior, etc.) sampled from a distribution. We represent the influence of information sources through three separate scenarios as presented in Table 3.

In scenario 1, we assume that a household relies on hazard forecast only, without considering any influence from social network and neighbor observation ($\alpha = 1, \beta = 0, \gamma = 0$). In scenario 2, a household relies on hazard forecast [$\alpha \in N(0.5,0.1)$] and information from social network [$\beta \in N(0.5,0.1)$], without any neighbor observation ($\gamma = 0$). Similarly, in scenario 3, a household considers hazard forecast [$\alpha \in N(0.5,0.1)$] and neighbor observation [$\gamma \in N(0.5,0.1)$], without considering any information from social network ($\beta = 0$).

Fig. 4(a) and (b) and 4(c) show the results of the scenarios in terms of spatial distribution of evacuation compliance and shadow evacuation. Fig. 4(d) shows the temporal variation of evacuation participation in the simulated scenarios. The temporal dynamics shows that the evacuation started early, and the participation rate is higher for scenario 1 followed by scenario 2. In scenario 3, evacuation participation is significantly low, and evacuation started late compared to scenarios 1 and 2. Among the three scenarios, scenario 1 has the highest evacuation participation rate (40.29%) including evacuation compliances and shadow evacuation (see Fig. 4(a)). However, reliance on hazard information also increases shadow evacuation which is less desirable for managing evacuation traffic [45]. Shadow evacuation is likely to increase if households with less risk tolerance (or high evacuation tendency) evacuate despite living in a low-risk zone. The influence of social network information decreases overall evacuation participation (both compliance and shadow evacuation) compared to scenario 1 (see Fig. 4(b)). We also observe in scenario 3 that relying on neighbor behavior significantly lowers evacuation participation (see Fig. 4(c)). Compared to scenarios 1 and 2, evacuation participation significantly decreases for all threshold distances, τ_N (parameter that controls whether a household is neighbor or not) between 300 m and 1000 m. Similar findings have also been observed in a previous study [9]. In summary, we found scenario 1 (residents making evacuation decisions based on hazard forecast only) has the highest evacuation and other influences create confusion about evacuation decisions. Mathematically, we assumed the trust value upper bounded to 1. For scenario 1, because residents have full trust on hazard forecast only, residents will have the right amount of risk perceptions. For the other influences (neighbor or social network), there are mixed (some residents will evacuate and other will not) risk perceptions and the net risk perception can be considered as confused (if there is large difference between the resulted risk perception and expected risk perception based on hazard forecast).

The scenarios shown in Fig. 4 combines influences of two information sources where the trust is equally divided between those sources. Next, we run the simulation for different combinations of trust values of the three information sources (hazard risk + social network + neighbor observation) and the results are shown in Fig. 5. We run simulation for trust values with a 0.1 interval and plot the contour map over the resulted evacuation rate by linearly interpolating the intermediate evacuation rate. Fig. 5(a) shows how to interpret the trust values with respect to the three axes showing trust values for hazard forecast, social network, and neighbor observation. We find similar trends in the effects of information sources on overall evacuation participation (Fig. 5(b)), evacuation compliance (Fig. 5(c)), and shadow evacuation (Fig. 5(d)). We divided each contour map in three zones: A, B, and C, representing high, medium, and low evacuation rates, respectively.

Simulation result shows that evacuation participation is likely to be higher when a household has higher trust on hazard forecast. It also shows that when evacuation participation increases, it increases in both evacuation compliance and shadow evacuation rates (see Fig. 5(c) and d). Evacuation participation is almost zero when households have very low (≤ 0.1) trust on hazard forecasts. The influences of neighbor observation or social network depend on the trust values of the remaining two information sources (sum of trust values is 1 at any point in the contour, $\alpha_j + \beta_j + \gamma_j = 1$). For example, for a given trust value of hazard forecast, as the influence of neighbor observation (γ) increases, the overall evacuation, compliance, and shadow evacuation rates decrease (zone A to B to C in Fig. 5). Similarly, for a given trust value of social network, as the influence of neighbor observation (γ) increases, the overall evacuation, compliance, and shadow evacuation rates decrease. Higher trust in neighbor's observation is likely to lower evacuation participation (e.g., for $\gamma \ge 0.4$ see zone C in Fig. 5). In zone C, a lower trust in hazard forecast reduces the perceived risk for some neighbors which further influences other households not to evacuate. On the other hand, for a given trust value of hazard forecast, as the influence of social network (β) increases, the overall evacuation, compliance, and shadow evacuation rates increase (see Fig. 5 from right to left). However, for a given trust value of neighbor's observation, evacuation rate is not same for all zones (zone A, B, and C in Fig. 5). For example, at zone A and above for a given trust value of neighbor's observation, the trust value of social network has no effect (or same)

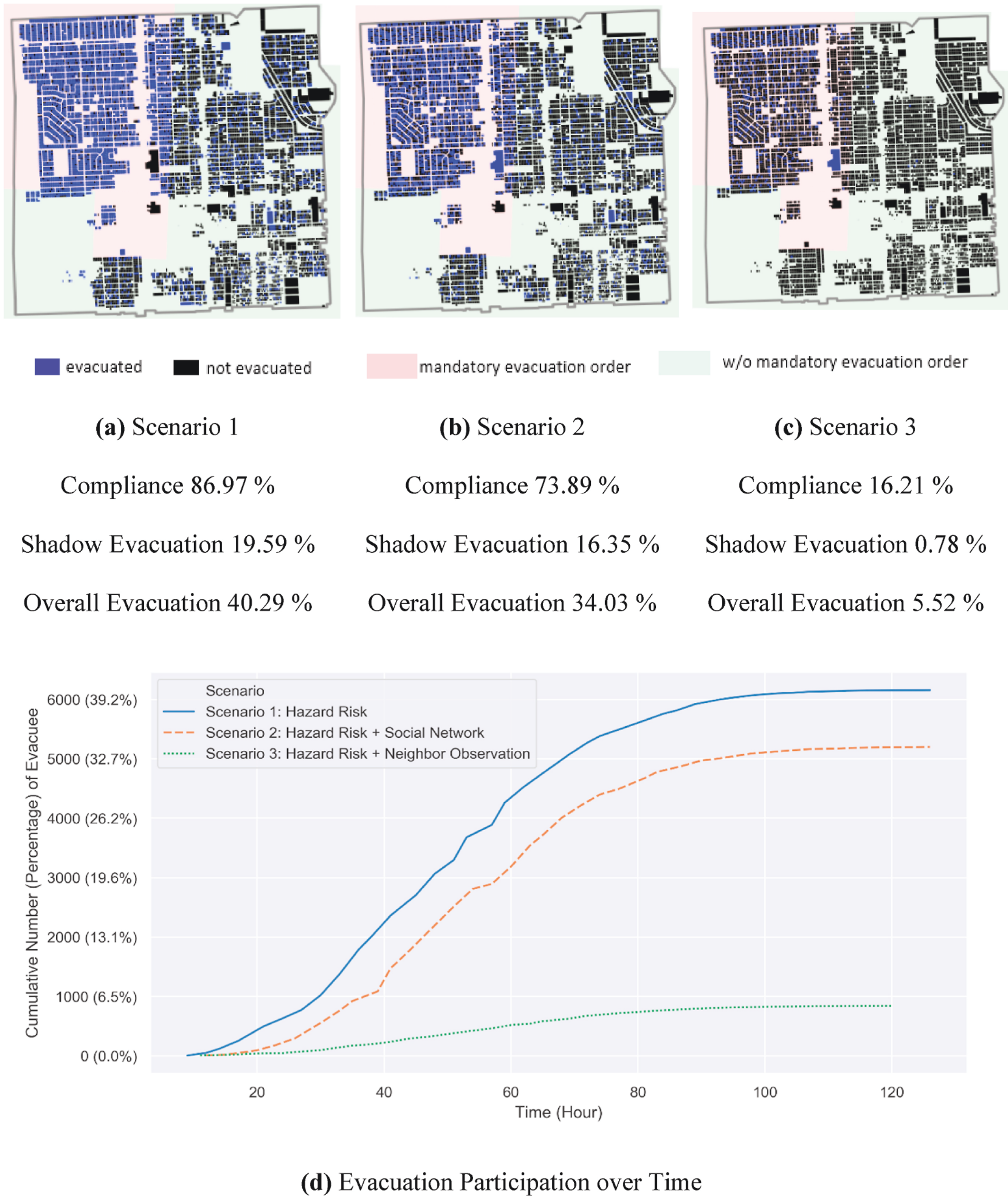
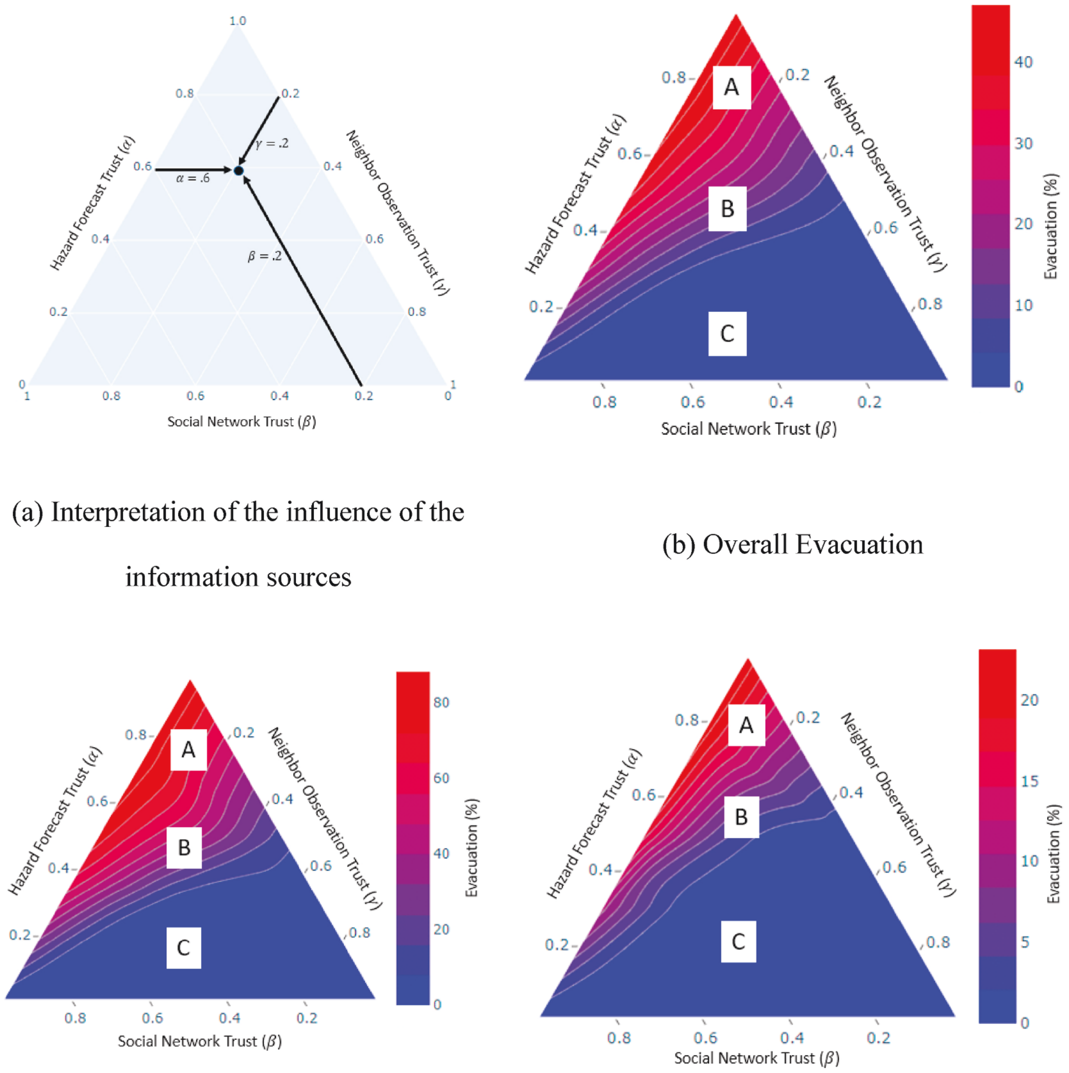


Fig. 4. Effect of Information Sources on Evacuation Participation. (a) Indicates the results of scenario 1, (b) indicates the results of scenario 2, (c) indicates the results of scenario 3, (d) shows evacuation participation over time.

in evacuation participation. But, around zone B, for a given trust value of neighbor's observation, increasing trust in social network increases evacuation participation up to a certain trust value ($\beta \leq 0.5$), beyond that increasing social network trust decreases evacuation participation. This is because increasing trust value on social network beyond 0.5 downplays the trust on hazard forecast (since $\alpha_j + \beta_j + \gamma_j = 1$) to such an extent that evacuation participation is reduced under the combined effects of the information sources.

However, the influence of social network also depends on the network size of a household [4,14]. From the sensitivity analysis of network size (see Fig. 6(b)) we find that evacuation participation rate increases with the increase in network size of a household up to a certain size (34%–37.2% for an increase in average degree from 6 to 10); after that, increase in network size does not affect evacuation participation (almost same result for network size 10 and 15, see Fig. 6(b)). Another effect of network size is that the increase in overall evacuation rate (with increase in network size) mainly happens for shadow evacuation (16.35%–21.86% for an increase in network size from 6 to 10). Evacuation participation also depends on how a household updates its risk perception when they obtain new information (see Fig. 6(a)). The quicker a household updates its belief based on new information, the higher evacuation participation is.



(a) Interpretation of the influence of the information sources

(b) Overall Evacuation

(c) Evacuation Compliance

(d) Shadow Evacuation

Fig. 5. Combined Effects of three Information Sources on Evacuation Participation. (a) Interpretation of the axes, (b) overall evacuation (c) evacuation compliance or percentage of evacuee from mandatory evacuation zone (d) shadow evacuation, percentage of evacuee from w/o mandatory evacuation zone.

6. Discussion

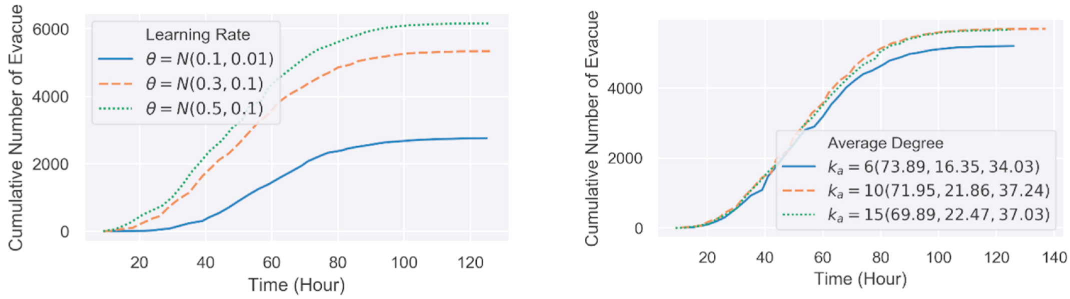
This section describes results and interpretation of the of simulation under each research question mentioned in the introduction of this study. We divided the discussion into 4 subsections following the research questions of the study.

6.1. *How to develop an agent-based model (ABM) considering how a household perceives flood risk and makes evacuation decisions?*

In our study, we have used socio-demographic characteristics from census and building/property dataset to assign a household's realistic neighbor and social network, and integrated run-off depth to simulate flood risk. Later we define rule for risk perception dynamics and evacuation decision. We provided the details of the simulation in the methodology section following the ODD protocol. We implemented the simulation on Repast Simphony (Java) framework.

6.2. *What is the effect of a household's trust on forecasts on evacuation participation?*

The results of this study, based on the generated households living in a zip code (33147) with a hypothetical hazard risk, imply that information sources greatly affect household evacuation participation. Provided hazard risk is forecasted accurately (higher trust on the forecast), the most desirable evacuation scenario is expected if households make their decisions based on the forecasted risk



(a) Learning Rate (b) Average Degree

Fig. 6. Evacuation Participation Rate for different Parameters. (a) Shows the cumulative number of evacuees over time for different distribution of learning rate (b) shows the cumulative evacuation participation for different values of average degree of the social networks. The values within the braces shows the evacuation compliance, shadow evacuation, and overall evacuation participation rates, respectively.

only. This result is consistent with previous studies that reliance on weather/forecast related information increases the likelihood of evacuation [4,11].

6.3. What is the effect of social networks on a household's evacuation decision, and how does a household's trust on opinion dynamics of social networks affect the overall evacuation participation?

We construct social networks among the households and model the influence of opinion dynamics (circulating over the social networks) on household evacuation decisions. If households make their evacuation decisions using information from social networks, overall evacuation and shadow evacuation are likely to increase with the increase in network size up to a certain network size. This finding is consistent with the results from previous studies [12,14]. These studies considered only friends, family, and close relative with a network size of up to 8 and found a constant positive effect of network size on evacuation participation. However, these studies did not consider the influence of trust on information from household social network or online social media. We capture the effect of social media by increasing the network size and find that the influence of social network is not consistently positive. This finding also confirms previous result that the influence of social media imposes uncertainties to evacuation rates [9]. A survey-based study also found insignificant effects of social media on evacuation decisions [11].

6.4. How does observing neighbor activities affect a household's evacuation decision in an actual neighborhood setting, and how a household's trust on neighbors' observation affect the overall evacuation dynamics?

We model the influence of neighbor observation as a conformity effect: a household is more likely to evacuate if majority of its neighbors are evacuated. However, studies suggest that this conformity effect might be insignificant or other factors can convolute such effects [4]. In our study, we find that if households take evacuation decisions by observing their neighbors (or put higher trust on neighbor observation), evacuation participations are likely to decrease significantly.

In all simulation setup, we find that more households have evacuated from the mandatory evacuation zones (evacuation compliance) which is consistent with previous studies [4,21]. Overall, the influence of the information sources follows similar trend for both evacuation compliance and shadow evacuation: if evacuation compliance increases shadow evacuation increases too. This finding is in line with the findings of a study on Jacksonville, Florida that in general, trust on information might increase shadow evacuation if households are not sure about their local risks [11].

6.5. Implications for research and practice

This study makes important contributions to evacuation and emergency management literature. Greater level of perceived risk increases the likelihood to evacuate [46] and households have different level of risk tolerance because of socio-demographic heterogeneity. Existing agent-based models in the evacuation context are mostly based on synthetic data and do not consider the reliability of information source in modeling evacuation decision. Our study combines the dynamics of risk perception and how this risk perception translates to evacuation decision based on the perceived reliability of those information sources. Most of the data used in the ABM is publicly available, hence the model can be implemented for other regions to estimate the expected evacuation compliance and shadow evacuation rate for an upcoming hurricane.

Based on the findings of our study, emergency managers may adopt several strategies to increase evacuation compliance and reduce shadow evacuation. Please find the recommendations based on the findings of our study in Table 4.

Emergency managers should ensure quality information about the hazards so that households may have high trust on the information because accurate information is likely to increase evacuation compliance. Hazard forecast should be provided with enough location details, otherwise higher trust on hazard forecast in general can induce shadow evacuation. Local news channels may be used for providing localized hazard forecast in this case [11].

The households seek information in their social networks and such communications affect their risk perceptions. Our study finds that it is better if households consider only the close friends (network size ≤ 8) in collecting information about evacuation decision;

Table 4
Summary of Key Findings and Recommendations based on the research questions of the study.

Research Question	Findings	Recommendations
How to develop an agent-based model (ABM) considering how a household perceives flood risk and makes evacuation decisions?	We developed an ABM integrating forecasted run-off depth to simulate flood risk and considering information credibility to model the risk perception dynamics and household evacuation decisions. We run the model and presented results for a zip code in Miami-Dade County.	The proposed framework can be used for any region to understand the complex dynamics of risk perception of households considering hazard risk forecast and other factors. However, we recommend collecting region specific survey data or established existing evacuation behavior models for that region to feed into the ABM.
What is the effect of a household's trust on forecasts on evacuation participation?	Higher trust in hazard forecast increases evacuation participation- both in evacuation compliance and shadow evacuation.	Emergency management agencies should ensure the reliability of hazard forecast and quality of warning information so that the warning messages are clearly understood. They should also provide hazard forecast with enough location details so that households can differentiate between a mandatory and a voluntary evacuation order.
What is the effect of social networks on a household's evacuation decision, and how does a household's trust on opinion dynamics of social networks affect the overall evacuation participation?	Size (number of online or offline friends or relatives) of social network increases evacuation up to certain point and after that bigger social network tends to decrease evacuation compliance or increases shadow evacuation.	Emergency management agencies should increase their presence in online social media so that households can get official hazard forecast from social media in addition to collecting information from their peers.
How does observing neighbor activities affect a household's evacuation decision in an actual neighborhood setting, and how a household's trust on neighbors' observation affect the overall evacuation dynamics?	Higher trust on neighbor's evacuation decision generates low evacuation participations.	Emergency management agencies should provide accurate information about the risk and should recommend residents to take decisions based on the official orders.

bigger network will not necessarily increase compliance and rather might increase shadow evacuation. Now-a-days people are increasingly using online social media platforms to collect information during emergencies. Thus, emergency management agencies should increase their presence in online social media so that households can get official hazard forecast from social media in addition to collecting information from their peers.

In a neighborhood, not all households will comply with an evacuation order. Although it is suggested that households watch out for neighbors who need help to evacuate or taking protective measures [47], we find that if households rely more (put higher trust) on neighbor's behavior, evacuation compliance is likely to be lower. Thus, emergency managers should emphasize on providing accurate information about the risk and should recommend residents to take decisions based on the official news.

6.6. Limitations and future research directions

Our study has some limitations. We have not considered all aspects of a hurricane hazard scenario such as wind speed, storm surge, etc. We assume that agents take evacuation decisions based on the perceived risks; however, practical constraints may affect evacuation decision despite having higher risk perception. For instance, despite perceiving the storm as a high risk, a household that has no car and nobody to help may downplay the effect of a hurricane. Future studies may consider this aspect given the data availability of such households. Although we have created households with socio-demographic heterogeneity, some characteristics such as information search behavior and learning rates are randomly assigned. Our primary concern in selecting the study area (Zip code 33147) is the variation in runoff depths to examine their effects in evacuation decision making. However, the decision-making process may not be generalizable to other regions because of the less generalizable characteristics of the households of zip code 33147 such as high poverty, lower than average social class membership, and low education and income. We have not considered household density or multiple families and heterogeneity in their makeup since in poor neighborhoods such as our study area household density is very high and multiple families, including singles and divorced persons, tend to congregate in single units of a building.

Future studies may collect survey data focusing on these aspects that will allow assigning information search and track evolution of risk perception with more granularity. We have used the parameters of a binary logit model developed for Northern Jersey, which might not be representative of our study area. Because of lack of data, we could not use some factors present in the evacuation related literature such as previous experience, mobility options, residential ownership, family sizes, pets, medical conditions, etc. Because of unavailability of ground truth data for our study region we could not validate the risk tolerance values. We used a simulated static total runoff depth to represent the hazard risk of a household. But hazard forecasts are dynamic and sometimes uncertain. Moreover, credibility of hazard forecast may vary based on the source of the forecast. Future studies may consider the dynamics of hazard forecast with the associated uncertainty and sources to model the reliability/trust of the information sources.

In our study area and experiment setup, we found scenario 1 (residents making evacuation decisions based on hazard forecast only) has the highest evacuation and other influences create confusion about evacuation decision. However, theoretically, it is possible to have highest evacuation rate for scenario 2 (social network) and scenario 3 (neighbor observation) if a resident collects risk perception selectively (we assumed a resident collect information from everyone in his/her social network and neighbor) from social network or a resident is surrounded by neighbors with very low risk tolerance.

We simulated the information collection from social networks based on small-world type random graphs. But the communication pattern in social networks, especially in an online social network, is still not well understood. Designing appropriate surveys to collect this information from the affected regions can help find more appropriate network structure and properties. We considered that more neighbors evacuating will always add to the information favoring an evacuation decision. But some studies had shown that the fear of looting can decrease the evacuation intention [36]. We did not consider the effect of likely infrastructure disruptions (e.g., power outage) on evacuation decisions. Studies suggested that evacuation is likely to happen even after landfall if the critical infrastructure is damaged due to a hurricane. Future studies can simulate these effects in a more complicated agent-based system.

7. Conclusions

The focus of the study is to simulate the influence of multiple information sources on households' risk perception dynamics and evacuation behavior. While focusing the mentioned objective, this study answers four research questions:

The first research question asks how to develop an agent-based model (ABM) considering how a household perceives flood risk and makes evacuation decisions. We create household features using the findings from existing literature and census data. We also use rainfall-induced runoff predictions to create the perception of potential flood risk and model the dynamics of risk perception transmission and evacuation decision through social and neighbor network.

The second research question is about the effect of a household's trust on forecasts on its evacuation participation. We find that information sources influence similarly to evacuation compliance and shadow evacuation – when evacuation compliance increases shadow evacuation also increases. Our study shows that increased trust on hazard forecast increases evacuation participation.

The third research question is about the effect of social networks on a household's evacuation decision, and how a household's trust on opinion dynamics of social networks affect the overall evacuation participation. We find that for a given trust on the hazard forecast increasing trust on social network is likely to increase evacuation rate. However, for a given trust in neighbor observation, increasing trust in social network creates uncertainty-evacuation increases up to some level of trust on social network then it decreases. Moreover, we find that a bigger network may increase the overall evacuation, but it may only increase shadow evacuation (i.e., from areas that are not under mandatory evacuation order).

The fourth research question asks how does observing neighbor activities affect a household's evacuation decision in an actual neighborhood setting, and how a household's trust on neighbors' observation affect the overall evacuation dynamics. We find that if the influence of neighbor observation is high, evacuation participation is likely to be lower. The influence of social networks however depends on the trusts in other information sources and the size of a household's social network.

This study has implications for emergency management practices. Although past studies suggested that the effect of social networks increases the likelihood to evacuate, our study finds that the increase may happen in shadow evacuation. Thus, it is important to increase the flow of accurate forecast information available to a large extent. Now-a-days social media play an important role in propagating information. Emergency management organizations should increase their presence in social media with accurate and reliable information on hazard risk.

Author contribution

The authors confirm contribution to the paper as follows: study conception and design: Kamol Chandra Roy and Samiul Hasan; data collection: Kamol Chandra Roy, Samiul Hasan, Omar I. Abdul-Aziz, Pallab Mozumder; data analysis and interpretation of results: Kamol Chandra Roy, Samiul Hasan; manuscript preparation and editing: Kamol Chandra Roy, Samiul Hasan, Omar I. Abdul-Aziz. All authors reviewed the results and approved the final version of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All data are publicly available. Inundation depths are available upon request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2022.103328.

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