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Dynamic-data-driven agent-based modeling for the prediction of evacuation behavior during hurricanes

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ABSTRACT

Establishing an efficient disaster management strategy against severe natural disasters is essential to mitigate and relieve their catastrophic consequences. In order to understand the situation during such devastating events, it is crucial to incorporate individuals' behaviors and their decision-making processes, which requires an amalgamation of information from various sources such as survey data, information regarding location and intensity of disasters, government's policies, and supplies in the affected region. This work proposes a dynamic-data-driven model for individual decision-making processes capable of tracking people's preference value over time, incorporating dynamic environmental changes using Bayesian updates. An agent-based simulation was used to model each of the components vital to devise an effective disaster management strategy. Moreover, the proposed model allows deriving quantitative relationships among people's evacuations, their demographic information, and risk perception based on environmental changes, including traffic status, gas outage, and government notice. For this study, the authors considered Florida's situations during hurricanes Irma, Michael, and Dorian in 2017, 2018, and 2019. What-if analyses were also conducted to find the best disaster management policy for government agencies to minimize the hurricane's effect, which will help prepare for future disaster situations.

1. Introduction

Throughout the world, people face various types of natural disasters, such as hurricanes, wildfire, floods, or earthquakes. Careful pre-planning of procedures is vital to efficient evacuation in these situations, but as the lack thereof leads to higher evacuation times and an increase in casualties. Broadcasts through social media, television, and other sources further complicate critical situations and lead to people's deviations from the plans provided by government agencies. One example of a difficulty that can arise is a shortage of resources: an individual deciding to evacuate may influence others' desire to fill their inventory, triggering a mass surge in demand for daily supplies including food, water, fuel, and road space. The cost of resources escalates as a result of the unpredictable increase in demand and shortage in markets, and government agencies are unable to regulate the supply [28]. As human behavior differs from person to person, broadcasted information from government agencies profoundly influences people's decisions to evacuate as well as their buying behavior under disaster circumstances [21]. Typically, these agencies provide different levels of alerts based on a careful assessment of the disaster impact and effects. To provide timely warnings and to optimize the allocation and organization of

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Table 1
List of recent category 5 Hurricanes (NHC Data Archive [79]).

	Nominal Damage (Billions $)	Year	Storm Classification	Casualties
Matthew	$15.1	2016	Category 5	> 600
Irma	$64.5	2017	Category 5	> 134
Maria	$91.6	2017	Category 5	> 3054
Michael	$25.1	2018	Category 5	> 74
Dorian	$8.28	2019	Category 5	> 68

resources, disaster management strategies are essential. The digital age has provided a useful medium for broadcasting messages in real-time through social media, and taking into account the behavioral aspects of the individual's decision-making process can significantly increase the efficacy of these transmissions. Thus, for the development of an efficient disaster management strategy, it becomes necessary to consider the disaster characteristics from various information sources as well as human behaviors during the disaster situation.

Among different natural disasters, a hurricane is one of the most devastating disasters, especially in the southern part of the United States. Every year approximately four to five hurricanes hit the Florida region, forcing people to evacuate. Among recent hurricanes to hit Florida, Hurricane Irma was the most intense hurricane to strike the continental US [78]. Table 1 summarizes the damage and causalities caused by Category 5 hurricanes in the last four years. Strong hurricanes have been observed every year, which necessities an efficient management strategy to relieve any damages from them. According to Table 1, the direct damage was always appraised more than a billion dollars whenever Category 5 hurricane landed in the US. Thus, it necessities to devices effective disaster management policies to relieve the consequences by hurricanes.

Due to the involvement of a variety of agent types (hurricanes, people, counties, etc.) in a disaster situation, a comprehensive simulation model to represent the behavior of these agents is of paramount importance. Over the years, agent-based simulation (ABS) has become a powerful tool in predicting the behavior of individual agents as well as representing the collective behavior of a specific group of people, representing human behavior in a disaster situation. By considering different states of people in the environment, ABS facilitates a high-fidelity representation of the people's decision situations under different scenarios. Since ABS can provide independent reasoning and analysis capabilities to each agent, higher levels of accuracy can be achieved in mimicking the behavior of agents (e.g., individuals, groups of people, and government agencies). Moreover, ABS offers added value by imparting autonomous behaviors to different environmental factors raised by natural disasters, especially hurricanes.

This paper aims to propose a highly comprehensive and scalable simulation, enabling the prediction of evacuation behaviors in disaster management applications, especially hurricanes. The significant contributions of this work can be summarized as follows: first, a generalized simulation model is developed, addressing heterogeneity and stochasticity of evacuation decisions using the cognitive decision-making framework. The framework enables the simulation model to consider the effects of people's demographic factors on their evacuation decisions. Second, a data-driven simulation approach has been incorporated by considering the dynamic changes in the environmental factors, including gas shortage, hurricane movement, and evacuation orders, while integrating them into human decision-making. Finally, case studies from Hurricanes Irma, Michael, and Dorian validated the outcome of the performed analysis, which would greatly assist in devising an efficient strategy for government agencies under various "what-if" scenarios.

The remaining four sections of this paper are organized as follows: Section 2 provides a comprehensive literature review summarizing research works in the domain of evacuation decision making, simulation modeling, and analysis on disaster management applications. The individual decision-making framework, simulation modeling, and implementation using the ODD protocol has been illustrated in great detail in Section 3. Section 4 demonstrates the analysis based on different “what-if” experiments to devise new strategies for the effective delivery of the best disaster response. In conclusion, the authors summarize the novel aspects and key findings of the proposed works and possible future extensions in this domain.

2. Literature review

A major challenge faced by local and federal government agencies during a disaster situation is devising an efficient disaster management strategy that would minimize supply shortages and traffic congestion on the roads. Solving such problems requires in-depth understanding and reasoning behind people's decisions related to evacuation during such situations. Hurricanes, in particular, have gained significant research attention for evacuation procedures due to their severity and impact, especially considering geographical areas and different combinations of population types. After the Federal Emergency Management Agency (FEMA) started analyzing people's behavior during hurricanes in 1991 [2], evacuation behavior modeling has been studied by many researchers over the last decades. Major subjects in hurricane situations include three primary questions: evacuation decision (whether one evacuates or not), evacuation time (when to evacuate), and route choice (what kinds of routes chosen during the hurricane). The authors have summarized this behavior research in Table 2.

In the research regarding evacuation decision, Fu and Wilmot [19] used the sequential logit model to tackle evacuation decisions based on the demographic information. Hasan et al. [26] analyzed evacuation decisions accounting for people's previous hurricane experiences and conducted an extensive case study of Hurricanes Andrew, Ivan, and Katrina. The local or state authorities' evacuation notices and information from news media were also analyzed by Huang et al. [30], while Huang et al. [30] considered the number and type of vehicles on evacuation decisions. Gudishala and Wilmot [23] proposed a time-dependent logit model to estimate people's

Table 2
Summary of literature on evacuation behaviors.

Types of Behaviors	Authors	Major Findings
Evacuation Decisions	Gudishala and Wilmot [23]	Prediction using time-dependent logit model
	Hasan et al. [25,26]	Modeling of heterogenous evacuation behavior based on household information
	Huang et al. [30]	Effects of demographics on evacuation decisions
	Murray-Tuite and Wolshon [51]	Summary and classification of all relevant literatures on evacuation decision
	Yin et al. [69]	Estimation of travel demand using probability distribution
Departure Time	Elliott and Pais [18]	Departure time prediction in hurricane Katrina
	Hasan et al. [24]	Effects of demographics on departure time in Katrina
	Liang et al. [38]	Traffic estimation using multi-level simulations (micro vs. macro)
	Lindell and Prater [39]	Determination of behavioral variables for departure time estimation
	Mesa-Arango et al. [46]	Discrete choice model for time estimation
	Wang et al. [65]	Evacuation time and speed in the simulation model
Route Choice	Akbarzadeh and Wilmot [1]	Time-dependent route choice model
	Chen et al. [9]	Optimal route management policy using zone-based approach
	Sadri et al. [60]	Effects of demographic information on route choice
	Sadri et al. [72]	Effects of destination and agent interactions on route choice
	Wu et al. [67]	Derivation of the factors for route choice

evacuation decisions over time. Murray-Tuite and Wolshon [51] studied traffic demand modeling considering gas supplies and social cues. Dixon et al. [16] derived the relationship between household information and evacuation decisions, while Cimellaro et al. [71] considered the level of people's anxiety for the determination of input parameters based on experimental data. Goodie et al. [22] conducted a detailed survey after the catastrophic hurricanes such as Harvey and Irma using logistic regression. Yang et al. [68] performed the analysis to evaluate the evacuation threshold, which measures people's initial tendency for evacuation. Pham et al. [53] also studied previous hurricane experiences, proving the effect of "unnecessary evacuation."

The critical aspect of behaviors under hurricane is to incorporate time and location factors in decisions. Notably, there is a significant relationship between evacuation time and the choice of evacuation routes, a vital consideration for the development of effective disaster management policy. Chen et al. [9] used a zone-based analysis approach to provide the optimal route management policy under hurricanes, while Elliott and Pais [18] analyzed survey data to examine the relationship between evacuation time and demographic information. Lindell and Prater [39] performed an analysis of evacuation time, providing the empirical probability distribution to demonstrate evacuation time behaviors. Wu et al. [67] analyzed the factors which determine the evacuation time and found that personal experiences, traffic conditions, and cost are the essential elements. Akbarzadeh and Wilmot [1] developed a time-dependent route choice model considering accessibility, distance, level of service in each highway, and road type. In a related study on tsunamis, Wang et al. [65] analyzed the evacuation time and speed of humans using an agent-based approach. Urbina and Wolshon [64] considered all possible evacuation roads in Florida, including I-10, I-75, and SR 528, while Sadri et al. [59] used the logit model to illustrate the routing decisions under a hurricane.

There are many possible approaches to modeling human behaviors, but the authors chose the agent-based modeling (ABM) approach. The main advantage of using ABS is that it allows human-behavior models as well as variant environmental settings to be combined into a unified model. Furthermore, agents' behaviors, including their actions and reactions, can be modeled using straightforward rules or logics such as state diagrams or dynamic equations. From the literature, the authors found much relevant research using ABS for behavior modeling in a disaster situation. Since the natural disaster is a complicated situation involving many factors in one event, Kullu et al. [34] deployed a communication model using autonomous agents in crowd simulation, while Karbovskii et al. [32] proposed a multimodal ABS for mass gathering during the evacuation. These approaches are often called macroscopic simulations, which consider several macro-level factors, including socioeconomic factors, the intensity of events, and uncertainties.

Table 3 summarizes agent-based modeling (ABM) approaches used in the different evacuation situations under hurricanes, earthquakes, and tsunamis. Under the hurricane situation, the primary modeling object regards traffic modeling. For example, Chen et al. [9] used ABM for predicting evacuation time and resource management policy, while Liang et al. [38] used a hierarchical modeling approach for traffic estimation. Feng and Lin [73] focused on the effects on the evacuation order, whereas Gehlot et al. [20] combined ABM with network optimization for dynamic load balancing. Yang et al. [68] used zone-based spatial modeling to estimate people's evacuation threshold. For earthquakes, the spatial and temporal data modeling are often combined with ABM. GIS data was utilized for crowd evacuation modeling [13], while D'Orazio et al. [14] considered different phases for policy generation. In terms of policy generation, Hashemi and Alesheikh [27] evaluated different scenarios to find the optimal management policy, while Liu et al. [42] incorporated the interaction among people. ABM is also an effective tool for studying tsunamis due to its large-scale and catastrophic consequences. Sahal et al. [74] offer micro and macro modeling approaches for people's shelter selection and their accessibility over time. Development of disaster management policy is also a significant research topic for tsunamis, including studies such as those by Mas et al. [45] and Mostafizi et al. [49]. The latter one especially considered social vulnerability to access the community's resilience.

One of the significantly related research themes that have emerged is the application of social networks data analytics to demonstrate interaction among people in disasters. Sadri et al. [59] focused on the role of social networks as an information source to estimate evacuation behaviors, whereas Kryvasheyeu et al. [33] employed the sensor network approach to analyze the dynamics of

Table 3
Summary of literature on agent-based modeling in different disasters.

Types of Disaster	Authors	Modeling Objects
Hurricane	Chen et al. [9]	Evacuation time and route management policy
	Yin et al. [69]	Estimation of travel demand using probability distribution
	Liang et al. [38]	Traffic estimation using hierarchical modeling
	Feng and Lin [73]	Analysis of the effects of the evacuation order
	Gehlot et al. [20]	Dynamic load balancing for network optimization
	Yang et al. [68]	Personal evacuation threshold using a zone-based approach
Earthquake	Crooks and Wise [13]	Crowd evacuation modeling with GIS data
	Hashemi and Alesheikh [27]	Different scenarios for policy generation
	D'Orazio et al. [14]	Evacuation phases, motions, and time
	Liu et al. [42]	Agent interaction and the effect of environmental change
Tsunami	Sahal et al. [74]	Multi-level simulations for the prediction of the selection of shelters and measurement of the accessibility
	Mas et al. [45]	Evaluation of evacuation plans and mitigation efforts
	Wang et al. [65]	Assessment of the mortality rate with milling time, interaction, and walking speeds
	Mostafizi et al. [49]	Vulnerability assessment to network resilience, Evaluation of resource allocation policy

social networks during hurricane Sandy. Many researchers have followed suit, examining the effects of social connections by studying the structure and dynamics of social networks [11,54]. The emerging use of social media complicates the problem, as people now experience physical and social stimuli via different forms of information sources and messaging systems (Morss et al. [48]). More recently, due to the advance of the usage of mobile equipment, Stowe et al. [62] applied classification methods using twitter data while Long et al. [43] recorded smartphone data to keep track of evacuation behavior patterns during hurricanes.

Validation of such models has been rigorously discussed by many researchers to check the quality of input data and the reasonable assumptions of scenarios. Zhu et al. [70] have studied the effects of typical assumptions, including the time of the day and the evacuation rate, by introducing different possible scenarios during the hurricane. Bukvic and Owen [5] have listed significant constraints considered for the development of such models, including demands in evacuation, personal risks, and hurricane intensity factors, among others. The Monte Carlo technique, along with ABM for parameter estimation was used, [3], especially Zhu et al. [70] incorporated Markov Chain Monte Carlo (MCMC) simulation into ABM to address the randomness of the agents.

Evacuation behaviors have been studied using different methodologies, such as advanced statistics, decision analysis, and optimization. Huang et al. [29] conducted a statistical analysis on official warnings, vulnerable residential areas, storm conditions, social interactions, and other factors influencing the evacuation decisions of the people living in affected regions. Sarwar et al. [61] used a binary logit model to evaluate a household's evacuation decisions, while Dosa et al. [17] used an instrumental variable analysis. In terms of decision analysis, Kailiponi [31] applied a multi-attribute utility theory to analyze evacuation decisions, and Liu et al. [41] implemented the cumulative prospect theory to study emergency response decisions. From the optimization viewpoint, Saadatseresht et al. [58] used an evolutionary optimization algorithm the find the optimal allocation strategies, while a spatial optimization model was used to derive the evacuation risk of the transportation network in the emergency [10]. Even heuristic algorithms were used to derive the level of overall flow in the network during the evacuation [63], and a robust optimization approach was used to derive an optimal evacuation plan under uncertainties during evacuation [52].

From the literature, the authors found that it is crucial to incorporate variations in the individual/behavioral rules ("heterogeneity") and interaction/random factors ("stochasticity"). Moreover, many researchers have pointed out ABM's limited reproducibility and expressiveness. Thus, this work adopted the ODD (Overview, Design Concepts, and Details) framework to demonstrate these issues. The ODD framework was introduced within Ecology society to demonstrate the behavior of agents and their relationship to the environment (Grimm et al. [75]). ODD has three primary contents: overview, design concepts, and details; each containing has sub-modules which have been updated to complement ABM's lack of reproducibility. (Grimm et al. [76]). The overview module demonstrates the purpose of the model, while the design concepts module supports underlying methodologies and overall framework. The Details module illustrates the setting and initialization of the simulation system, which can improve the simulation's reproducibility. The extended model is called ODD + D (Decision) [50] to incorporate individual decision-making frameworks in ABS. The significant contribution of their work is an incorporation of the decision-making, adaption, and learning of the framework. [50]. In this work, the authors have followed the ODD + D framework by incorporating decision-making and learning.

3. Simulation modeling

This section focuses on the simulation modeling of the agent-based approach following the ODD (Overview, Design, and Details) framework. Section 3.1 describes the overview of the simulation model, including the purpose, primary composition of the agents with parameters, and variables. The methodological details of the individual decision-making framework in terms of perception, sensing, and learning are explained in Section 3.2. Section 3.3 conveys the simulation implementation details in terms of initializations, parameter evolution, and model execution. This section will help ensure the extensibility and scalability of the proposed work for different disaster management applications.

Table 4
Agents, parameters, and variables.

Entities	Parameters	Variables
People	Age, Income, Locations, Properties in the area, Work duty	Weight values, Evaluation of alternatives, Status of evacuation
County	Population	Distance from the hurricane landfalls, Station of evacuation orders
Gas Station	Capacity, Location	Fuel status, Status of closure
Hurricane	NA	Hurricane path, Hurricane strength
Shelter	Capacity, Location	Status of occupancy

3.1. Overview

3.1.1. Purpose

The purpose of the simulation model is to generalize the decision-making model while incorporating dynamic changes of preference value over time. The proposed model can be used in various decision support tools for different applications but is particularly suited for disaster management. Two key features of the proposed approaches are the representation of heterogeneous human behavior and the dynamic evolution of behaviors under uncertain situations while combing both static and dynamic aspects of the environment to keep track of human decisions. As the perception of risk differs among people, we used a descriptive modeling approach named Extended Decision Field Theory (EDFT), which is explained in Section 3.2. EDFT interprets the evolution of peoples' preference values over time as a stochastic process, which helps to understand time-dependent human behavior. The authors also provided the rationale to convert people's demographic information to determine the parameters of EDFT, better representing heterogeneous behaviors of people under the disaster. Also, a data-driven feature is also implemented using the Bayesian parameter updates during the simulation run within the EDFT framework. Therefore, the proposed framework encompasses evacuation behaviors concerning two perspectives, i.e., heterogeneity and stochasticity.

3.1.2. Agents, parameters, and variables

Table 4 illustrates all types of agents and their parameters and variables. The person agent represents the residents living in the affected area under the disaster. In the simulation model, they are all the residents living in Florida during Hurricane Irma. From the literature review, it is evident that heterogeneous agents are used to representing evacuation behaviors in order to increase the fidelity of the simulation under hurricanes [55,56]. All the demographic information is incorporated into the parameter values, which do not change over time during the simulation runs. The authors assume that agents make evacuation decisions based on their decision criteria to reflect realistic situations during the hurricane. Variables of people agents are related to their decision-making model DFT, as people's decisions are affected by weight values and their subjective evaluation of the alternatives concerning each criterion. The authors modeled those values as variables to incorporate agents' heterogeneous behavior and dynamic data-driven updates of human decisions under the disaster.

In addition to the person agent, the simulation model considers three agents: gas station, county, and hurricane. The first two agents represent the gas station owner/manager and the local government. The county agent focuses on replicating the release of the evacuation order based on the population size, proximity, and strength of hurricanes, and evacuation orders to minimize economic loss and fatalities. Though the authors used the data in the case study, it could be used as an independent variable in the what-if analysis. Since irregular buying patterns are regularly observed during the disaster situation, the authors decided to incorporate the behavior of one of the essential commodities for the evacuation, the gas station. The parameters of the gas station agent are their capacity and location, and the simulation model tracks the gas stock level of gas station agents and determines the status of closure since our interest is to predict the number of gas stations that face a gas shortage. For the study, the authors considered all evacuation notifications released by all counties in Florida. Finally, the work uses GIS-based location information embedded within AnyLogic software, and all the spatial information governed the agent-movement.

3.1.3. Process overview (flowchart and state diagram)

Fig. 1(a) shows the flowchart of evacuation decision-making. Once the simulation starts, the initialization parameters are assigned based on the demographic and environmental factors. The next major step is to decide whether or not to evacuate, determined based on the EDFT (Section 3.2) and dynamic parameter evolution (Section 3.3). After the decision has been made, subsequent decisions pertaining to a suitable time and route selection are required for an effective disaster management plan. The chosen combination of the aforementioned decision points (governed by EDFT) provides an estimate of the population choosing shelters or state-level evacuation, while another population is comprised of people choosing not to evacuate due to a variety of reasons and staying at their initial location. The significant outcomes of the process would classify people based on their evacuation decision, and subsequently, their final location and deliberation until the determination of the final location. This work focuses more on evacuation decisions under the EDFT framework.

Fig. 1(b) shows a state chart as an ABS implementation tool for a flowchart of human evacuation decision-making behavior. A state diagram is a common representation of different states of behavior for any decision-makers in the agent-based modeling paradigm. The human evacuation decision is governed by different states and their state transitions within the state-chart. Once a people agent decides on evacuation, it also decides for a final location (e.g., shelter or state-level evacuation) and evacuation time.

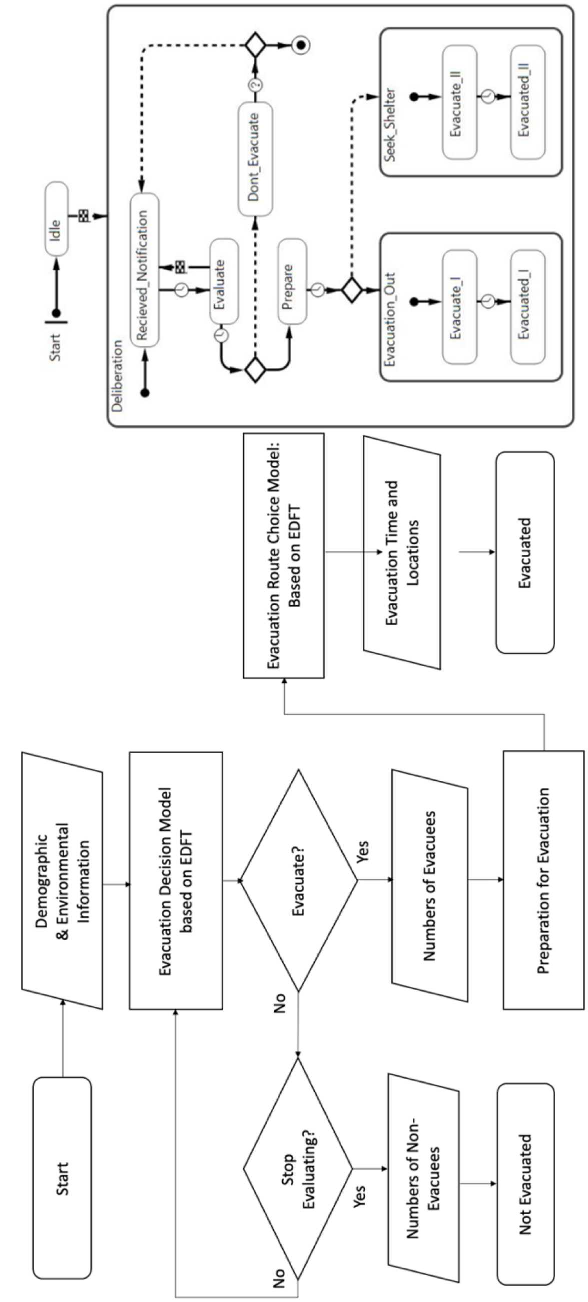


Fig. 1. (a) Flowchart of evacuation decision-making (b) State-chart representation.

The composite states within the state chart demonstrate these sequential decision-making procedures, while each decision point is recorded during the model execution. The detailed methodology behind each of the composites is explained in Section 3.2.

3.2. Design concepts

This section describes the individual decision-making model Decision Field Theory (DFT) used for the proposed simulation model. Consequent sub-sections detail how DFT conveys the important factors for decision-making processes, including learning, sensing, and interaction within the Extended DFT (EDFT). The theoretical development of EDFT is briefly described for the demonstration of heterogeneity and stochasticity. These findings provide the rationale to assign realistic parameter values in the simulation, which will be discussed in Section 3.3.

3.2.1. Individual decision-making framework: DFT

A realistic evacuation decision-making model is an essential component of the proposed simulation model. Since different attributes affect people's decisions, a multi-attribute decision-making model will facilitate the estimation of people's behavior. This paper used Decision Field Theory (DFT) to model people's behavior under the hurricane situation. After Decision Field Theory (DFT) was introduced by Busemeyer and Townsend [7], this cognition-based decision-making framework has been widely adopted for human behavior modeling in different applications [6].

DFT keep tracks of the individual's preference values $\boldsymbol{P} = [p_1, \cdots, p_n]$ of the possible options (n number of options given) at each decision point. In the evacuation application, before a person selects whether or not to evacuate at every decision point, DFT is used to measure preference values based on their quantified values of decision criteria ($\boldsymbol{M}$) (m number of attributes are considered by persons) and their weights ($\boldsymbol{W}$). The dimension of matrix $\boldsymbol{M}$ is n by m. Eq. (1) shows the formula of DFT, and (2) is a vector representation.

$$\boldsymbol{P}(t+h) = \boldsymbol{SP}(t) + \boldsymbol{CMW}(t+h) \tag{1}$$

$$\begin{bmatrix} P_1(t+h) \\ P_2(t+h) \\ \vdots \\ P_{n-1}(t+h) \\ P_n(t) \end{bmatrix} = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1,\,n-1} & s_{n,n} \\ s_{21} & s_{22} & \cdots & s_{2,n-1} & s_{2,n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ s_{n-1,\,1} & s_{n-1,2} & \cdots & s_{n-1,n-1} & s_{n-1,n} \\ s_{n,1} & s_{n,2} & \cdots & s_{n,\,n-1} & s_{n,n} \end{bmatrix} \begin{bmatrix} P_1(t) \\ P_2(t) \\ \vdots \\ P_{n-1}(t) \\ P_n(t) \end{bmatrix}$$
$$+ \begin{bmatrix} 1 & -\frac{1}{n-1} & \cdots & -\frac{1}{n-1} & -\frac{1}{n-1} \\ -\frac{1}{n-1} & 1 & \cdots & -\frac{1}{n-1} & -\frac{1}{n-1} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ -\frac{1}{n-1} & -\frac{1}{n-1} & \cdots & 1 & -\frac{1}{n-1} \\ -\frac{1}{n-1} & -\frac{1}{n-1} & \cdots & -\frac{1}{n-1} & 1 \end{bmatrix} \begin{bmatrix} m_{11} & m_{12} & \cdots & m_{1,\,m-1} & m_{1,m} \\ m_{21} & m_{22} & \cdots & m_{2,\,m-1} & m_{2,m} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ m_{n-1,\,1} & m_{n-1,2} & \cdots & m_{n-1,m-1} & m_{n-1,m} \\ m_{n,1} & m_{n,2} & \cdots & m_{n,\,m-1} & m_{n,m} \end{bmatrix} \begin{bmatrix} w_1(t+h) \\ w_2(t+h) \\ \vdots \\ w_{m-1}(t+h) \\ w_m(t+h) \end{bmatrix} \tag{2}$$

$\boldsymbol{S}$ is the stability matrix considering the effect of the preference at the previous preference state, which can be regarded as a memory effect. In the stability matrix $\mathbf{S}$, the diagonal element s_{ii} represents the forgetting process from the previous preference state and the off-diagonal element s_{ij} for $i \neq j$ denotes the inhibitory competitions to be selected between alternatives. Diagonal elements (s_{ii}) are set to 0.9, meaning that the previous preference value is highly influential to the current value. On the other hand, non-diagonal values s_{ij} is set to -0.01, implying that they slightly have a negative influence on the opposing option, according to literature [6]. $\boldsymbol{M}$ is the value matrix representing the subjective evaluation of people on each attribute at each decision time, $\boldsymbol{W}$ is the weight vector regarding the importance weight of each attribute, and $\boldsymbol{C}$ is the contrast matrix regarding the competition to be selected as a final decision between options [6, 8]. In the contrast matrix, $c_{ii} = 1 \textit{ and } c_{ij} = -1/(n-1) \ \forall \ i \neq j$, where n is the number of options so that increasing preference for one option will decrease the preference for the alternative options. This configuration results in the preference value summing up to zero [6]. Thus, if the decision-maker has two options for choice, the preference value to one option increases while the other decreases.

Fig. 2(a) illustrates sample paths of two competing alternatives' preference values. Under the evacuation situation, P_1 and P_2 represent the options 1) to evacuate and 2) not to evacuate, respectively. According to the construction of the $\mathbf{C}$ matrix in Equations (2), the increase in one of the preference values leads to a decline in the other's preference value, while satisfying the sum of two preference values become zero. Therefore, if there are two options in the evacuation decision (for example, either to evacuate or not), only one of the preference values needs to be checked. Within the DFT framework, people's decisions are invoked by setting either threshold value or decision time, as shown in Figure 2(b). If the preference value exceeds some predetermined value (colored in purple), then the person chooses the option whose preference value is larger. On the other hand, people choose the alternative with higher preference value at a specific given time.

3.2.2. Sensing and learning by EDFT

During a disaster situation, the environmental status may be highly variable, causing decision-makers under the situation to continually update their subjective evaluation of options with respect to decision criteria. Thus, it is necessary to incorporate dynamic

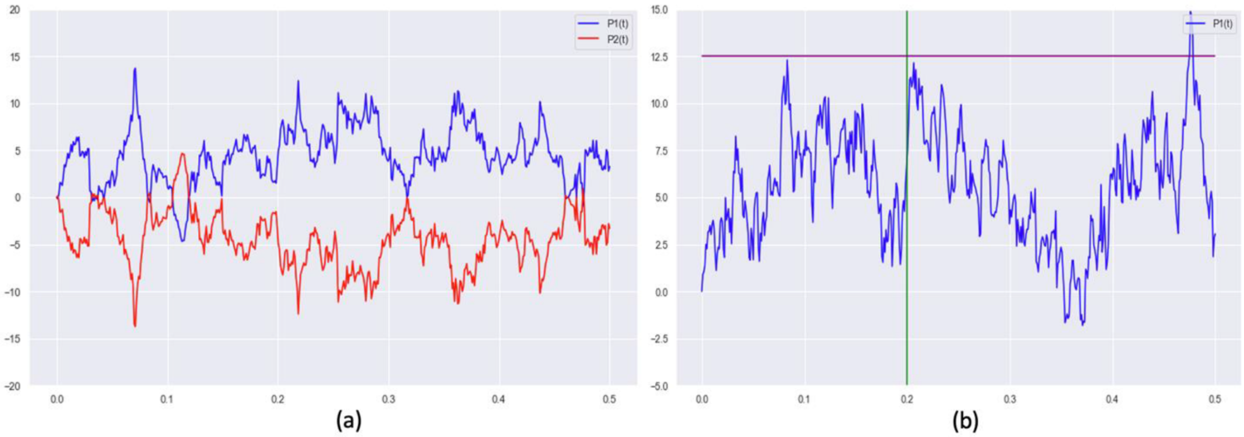


Fig. 2. Illustration of preference evolution within DFT: (a) Evolution of preference values with two alternatives (b) Decisions by threshold (purple line) or time (green line).

changes in perception over time. Among the variant models of DFT, Extended Decision Field Theory (EDFT) [35] allows consideration of the dynamic change of the environmental setting. The main difference between the original DFT and EDFT models is the evaluation matrix $\boldsymbol{M}$: $\boldsymbol{M}$ in the DFT model remains the same over time, while $\boldsymbol{M}(t+h)$ in the EDFT model changes over time. Based on the research on DFT, the expected preference value can be derived theoretically (Busemeyer and Diederich [6]), while the expectation of EDFT can only be derived under rigorous assumptions, including independence of $\boldsymbol{M}$ and $\boldsymbol{W}$ [36]. Fig. 3 demonstrates the preference evolution over time in DFT (colored in Red) and in EDFT (colored in Blue) using the same random seed. The evolution of EDFT shows a high level of variability compared to that of DFT because EDFT considers dynamic changes of both weight values and subjective evaluation over time, as shown in Fig. 3. In this way, the EDFT is able to thoroughly represent people's perception of environmental changes using sensing and learning capabilities. Eq. (3) and (4) show the formula and the vector representation of EDFT, respectively.

$$\boldsymbol{P}(t+h) = \boldsymbol{SP}(t) + \boldsymbol{CM}(t+h)\boldsymbol{W}(t+h) \tag{3}$$

$$\begin{bmatrix} P_1(t+h) \\ P_2(t+h) \\ \vdots \\ P_{n-1}(t+h) \\ P_n(t) \end{bmatrix} = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1,\,n-1} & s_{n,n} \\ s_{21} & s_{22} & \cdots & s_{2,n-1} & s_{2,n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ s_{n-1,\,1} & s_{n-1,2} & \cdots & s_{n-1,n-1} & s_{n-1,n} \\ s_{n,1} & s_{n,2} & \cdots & s_{n,\,n-1} & s_{n,n} \end{bmatrix} \begin{bmatrix} P_1(t) \\ P_2(t) \\ \vdots \\ P_{n-1}(t) \\ P_n(t) \end{bmatrix}$$
$$+ \begin{bmatrix} 1 & -\frac{1}{n-1} & \cdots & -\frac{1}{n-1} & -\frac{1}{n-1} \\ -\frac{1}{n-1} & 1 & \cdots & -\frac{1}{n-1} & -\frac{1}{n-1} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ -\frac{1}{n-1} & -\frac{1}{n-1} & \cdots & 1 & -\frac{1}{n-1} \\ -\frac{1}{n-1} & -\frac{1}{n-1} & \cdots & -\frac{1}{n-1} & 1 \end{bmatrix} \begin{bmatrix} m_{11}(t+h) & m_{12}(t+h) & \cdots & m_{1,\,m-1}(t+h) & m_{1,m}(t+h) \\ m_{21}(t+h) & m_{22}(t+h) & \cdots & m_{2,\,m-1}(t+h) & m_{2,m}(t+h) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ m_{n-1,\,1}(t+h) & m_{n-1,2}(t+h) & \cdots & m_{n-1,m-1}(t+h) & m_{n-1,m}(t+h) \\ m_{n,1}(t+h) & m_{n,2}(t+h) & \cdots & m_{n,\,m-1}(t+h) & m_{n,m}(t+h) \end{bmatrix} \begin{bmatrix} w_1(t+h) \\ w_2(t+h) \\ \vdots \\ w_{m-1}(t+h) \\ w_m(t+h) \end{bmatrix} \tag{4}$$

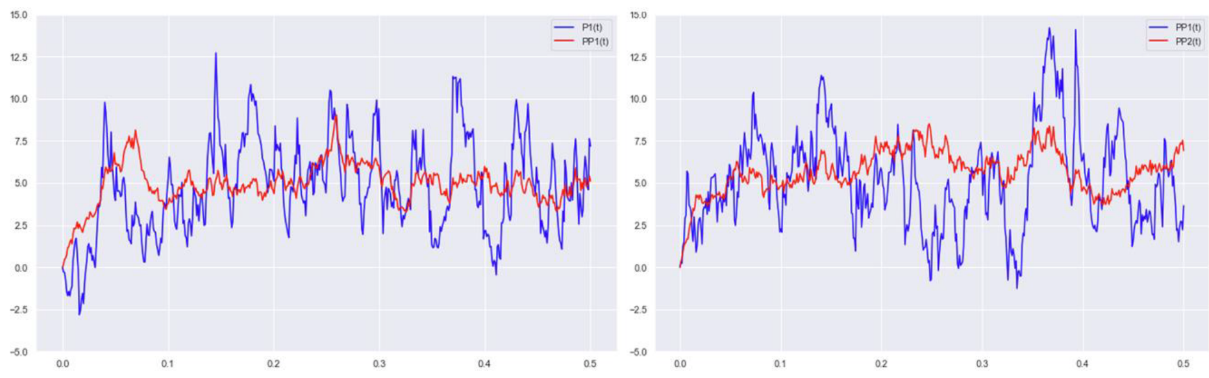


Fig. 3. Two exemplary sample paths showing evolution differences of DFT (red line) and EDFT (blue line).

3.2.3. Interaction by EDFT

As research shows that social interaction among people significantly affects evacuation decisions under hurricanes [4,40,59], the authors examined the incorporation of social interaction within the EDFT framework by applying the DeGroot's model [37], as shown in Eqs. (5) and (6). Consider that there are k number of agents with two alternatives within the network, assuming that all agents interact based on the adjacency matrix. Then, the matrix $\bar{\boldsymbol{P}}$ can be constructed with a dimension of $2k \times 1$, enlisting all the preference values of all agents. Once people update preference values, their subjective sensing, and learning from EDFT (in Section 3.2.3) updates the values again by incorporating social interaction. These procedures will keep iterating until either of two termination criteria - time or threshold - is satisfied. Eq. (5) and (6) shows the formula and the interaction process within the EDFT framework.

$$\bar{\boldsymbol{P}}(t+2h) = \boldsymbol{A}\bar{\boldsymbol{P}}(t+h) \tag{5}$$

$$\begin{bmatrix} P_{11}(t+2h) \\ P_{12}(t+2h) \\ \vdots \\ P_{k-1,1}(t+2h) \\ P_{k-1,2}(t+2h) \\ P_{k,1}(t+2h) \\ P_{k,2}(t+2h) \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & a_{12} & 0 & \cdots & a_{k,k} & 0 \\ 0 & a_{11} & 0 & a_{12} & \cdots & 0 & a_{k,k} \\ \vdots & \vdots & \vdots & \vdots & \cdots & \vdots & \vdots \\ a_{k-1,1} & 0 & a_{k-1,2} & 0 & \cdots & a_{k-1,k-1} & 0 \\ 0 & a_{k-1,1} & 0 & a_{k-1,2} & \cdots & 0 & a_{k-1,k-1} \\ a_{k,1} & 0 & a_{k,2} & 0 & \cdots & a_{k,k} & 0 \\ 0 & a_{k,1} & 0 & a_{k,2} & \cdots & 0 & a_{k,k} \end{bmatrix} \begin{bmatrix} P_{11}(t+h) \\ P_{12}(t+h) \\ \vdots \\ P_{k-1,1}(t+h) \\ P_{k-1,2}(t+h) \\ P_{k,1}(t+h) \\ P_{k,2}(t+h) \end{bmatrix} \tag{6}$$

Collins et al. [11] demonstrated the effects of social connections on evacuation decisions under Hurricane Irma. Two important findings from work are that people's evacuation decisions are significantly affected if they have more social connections or if they have dense social connections ([12,47]). The authors examined these findings within the EDFT framework under the three different network structures shown in Fig. 4(a), (b), and (c).

Fig. 5 shows the evolution of five agents' preference values over time. If there is no interaction among the five agents, no strong correlation among the agents' preference value is observed (Fig. 5(a)). However, as the level of interaction increases from Fig. 5(b) to 5(c), their preference values show an increasing correlation pattern among, illustrating the validity of the EDFT framework for the incorporation of social interaction under the disaster situation.

3.2.4. Prediction and stochasticity under EDFT

One merit of using EDFT is its capability of predicting people's preference value. If W and M are independent and stationary, the limiting expectation of preference values can be shown as Eqn 6a. [36]. Moreover, if W is assumed to follow iid Gaussian Distribution [57], the choice probability under the two alternatives decision scenario can be analytically derived as Eq. (7) [36].

$$\lim_{t\to\infty} E[\boldsymbol{P}(t)] = (\boldsymbol{I} - \boldsymbol{S})^{-1}\boldsymbol{C}E[\boldsymbol{M}]E[\boldsymbol{W}] \tag{6a}$$

$$Pr[X|X, Y] = \int_{p_x} \int_{p_y:\{p_x - p_y \geq 0\}} \frac{\exp\left[\frac{-((p_x - p_y) - (\xi_x - \xi_y))^2}{2\lambda}\right]}{\sqrt{2\pi\lambda}} dp_y\, dp_x \tag{7}$$

where ζ_x and ζ_y are limiting expected preference values of options X and Y in Eqn 6a, and λ is the sum of two diagonal values of the limiting covariance matrix while subtracting two times of its non-diagonal element. Using them, the simulation model can predict the people's decision and their expected value at the end, enabling the prediction of human behaviors. In Section 3.3.2, the authors demonstrate the relationship between the expectation of weight vectors and the demographic datasets using the choice probability to assign the appropriate values to the weight vectors in EDFT.

3.3. Details

This section demonstrates the details of the proposed simulation model with subsections, including initiation, input data and parametrization, parameter evolution, and model execution. Section 3.3.1 describes the simulation model's initial setting with particular attention to the implementation logic of the EDFT model. The next section shows the reasoning of the updates of EDFT

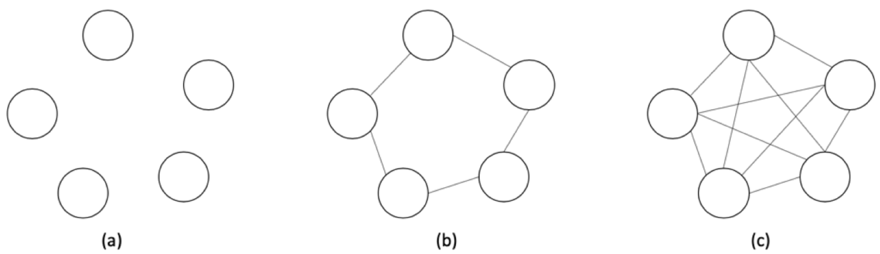


Fig. 4. Three types of networks: (a) No interaction (b) Ring structure (c) Clique.

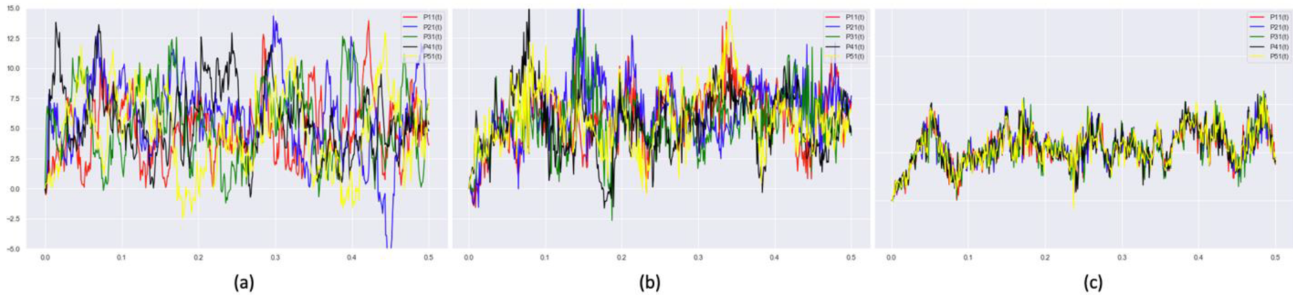


Fig. 5. Evolution of five agents' evacuation preference values (a) Evolution under no interaction (b) Evolution under the ring structure (c) Evolution under the clique.

Table 5
Survey data used from literature for model development.

Authors	Studied Hurricanes	Authors	Studied Hurricanes
Pham et al., [53]	Hurricane Matthew	Sarwar et al., [61]	Hurricane Ivan
Martin et al., [44]	Hurricane Matthew and Irma	Collins et al., [11]	Hurricane Irma
Goodie et al., [22]	Hurricane Harvey	Zhu et al., [70]	Hurricane Irene and Sandy
Yang et al., [68]	Hurricane Georges	Wong et al., [66]	Hurricane Irma
Bian et al., [4]	Hurricane Katrina	Dixon et al., [16]	Hurricane Ike

parameters, especially the weight vector. Data-driven parameter updates from environmental changes are explained in Section 3.3.2, and the four model execution phases of mitigation, preparedness, response, and recovery are explained in Section 3.3.4.

3.3.1. Initialization

Determination of alternatives and their decision criteria precede the implementation of EDFT. The two options for people under the hurricane period are whether to evacuate or not. First, the decision criteria for evaluations of alternatives must be determined. The authors collected recent survey data regarding evacuation decisions from the literature review, enlisting all the literature whose survey data is used for the model development in Table 5. All the reasons for evacuation or non-evacuation from the survey are listed in the last column of Table 6. These are then classified into four categories: “Safety,” “Information,” "Efforts," and “Protection” to derive direct attributes based on their common characteristics. For example, from the survey and corresponding analysis, people are more likely to evacuate when they receive orders from authorities or news media. Those two factors are correlated and can be classified as an "Information" attribute. The direct attributes of safety and information increase the likelihood of people's evacuation. On the other hand, the other attributes, “Efforts” and “Protection,” decrease the possibility of evacuation. Thus, these four decision criteria are defined and represented as w_i, where $i \in \{1, 2, 3, 4\}$, respectively. The weight values are assumed to follow an independent Gaussian distribution to characterize the heterogeneity of a person agent, by setting that all w_i' follow $N(0.25, 0.025)$ before normalizing the values, as shown in Eqs. (8) and (9). This setting assures that one decision criterion has no precedence over the others at the simulation model start-up.

$$\boldsymbol{W}' = [w'_1 \sim N(0.25, 0.025), w'_2 \sim N(0.25, 0.025), w'_3 \sim N(0.25, 0.025), w'_4 \sim N(0.25, 0.025)] \quad (8)$$

$$\boldsymbol{W} = [w_1, w_2, w_3, w_4] = \left[\frac{w'_1}{w'_1 + w'_2 + w'_3 + w'_4}, \frac{w'_2}{w'_1 + w'_2 + w'_3 + w'_4}, \frac{w'_3}{w'_1 + w'_2 + w'_3 + w'_4}, \frac{w'_4}{w'_1 + w'_2 + w'_3 + w'_4}\right] \quad (9)$$

The initialization of $\boldsymbol{M}$ requires an understanding of the attributes’ effects on two options. For example, those who own pets or businesses where they live are less likely to evacuate than others, making them not evacuating option better according to the “Protection” criteria. This illustrates how the evacuating option can be positively rated for “Safety” and “Information” criteria, while it is negatively rated with respect to “Efforts” and “Protection” criteria. The sign of m_{ij} values of $\boldsymbol{M}$ are determined based on this observation, while their scales are set to between 0 and 1. The initial values of $\boldsymbol{M}$ elements are given to follow a Beta distribution with $\alpha = \beta = 1$, which indeed is Uniform (0, 1) distribution. The assigned values of the matrix $\boldsymbol{M}$ are summarized in Table 7.

Note that these initial values of $\boldsymbol{W}$ and $\boldsymbol{M}$ force the expected value of $\boldsymbol{CMW}$ to be zero vectors under the independence assumption of $\boldsymbol{W}$ and $\boldsymbol{M}$, as shown in Eq. (8).

$$E[\boldsymbol{CMW}] = CE[\boldsymbol{M}]E[\boldsymbol{W}] = \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} 0.5 & 0.5 & -0.5 & -0.5 \\ -0.5 & -0.5 & 0.5 & 0.5 \end{bmatrix} \begin{bmatrix} 0.25 \\ 0.25 \\ 0.25 \\ 0.25 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad (8)$$

As seen in Eq. (8), the expected preference values of both options remain zero under the initial setup. The next two sections show how

Table 6
Development of alternatives and decision criteria from the survey.

Positive Effects on the Choice of	Notation in EDFT	Direct Attributes	Reasons considered from the survey
Evacuating	w_1	Safety based on the perception of risks (Safety)	Did not think the home was safe Hurricane was severe and its landfall was close
	w_2	Beliefs on evacuation orders and forecasting (Information)	Received mandatory or voluntary Orders Watched news and media's updates
Not evacuating	w_3	Costs or efforts for evacuation (Efforts)	Evacuation costs were high/Did not have enough money Did not want to sit in traffics/Did not want to leave
	w_4	Desire to save personal properties (Protection)	Had personal properties (houses, business, and pets) Had a requirement to go to work

Table 7
Initial values of $\boldsymbol{M}$.

Attr. Options	Safety	Information	Efforts	Protection
Evacuating	$m_{11} \sim Beta(1, 1)$	$m_{12} \sim Beta(1, 1)$	$m_{13} \sim -Beta(1, 1)$	$m_{14} \sim -Beta(1, 1)$
Not evacuating	$m_{21} \sim -Beta(1, 1)$	$m_{22} \sim -Beta(1, 1)$	$m_{23} \sim Beta(1, 1)$	$m_{24} \sim Beta(1, 1)$

these $\boldsymbol{W}$ and $\boldsymbol{M}$ values update once the data is imported during the simulation run to represent heterogeneity and stochasticity over time.

3.3.2. Incorporation of demographics

The proposed simulation model uses the demographic datasets of individuals in the hurricane-affected area. People's heterogeneity is achieved by incorporating demographic information into the EDFT framework in the proposed simulation. This incorporation requires an understanding of the relationship between demographic variables and their affecting attributes; thus, the authors assume that demographic variables affect the determination of weight values ($\boldsymbol{W}$) within the EDFT framework, as shown in Table 8. For example, people living close to the shore have a higher priority on the "Safety" criterion than the others, while people with lower income will have a higher priority on the "Evacuation" criterion. Table 8 lists all demographic variables and their affecting attributes in the simulation.

Based on the surveyed data regarding evacuation decisions in the literature listed in Table 5, it has been noted that logistic regression was often used to find the marginal effect of a demographic factor on the evacuation decision. This section demonstrates the reasoning to determine the input parameters of EDFT based on the demographic information, and the logistic regression model results from the literature. Consider the logistic regression model regarding evacuation decision, as shown in Eq. (9):

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_l x_l \tag{9}$$

where p represents the evacuation probability, $x_{i\in\{1,2,\cdots l\}}$ the independent variable of demographic information, $\beta_{j\in\{0,\cdots,l\}}$ effects of odds ratio per each independent variable, and l number of all demographic factors considered in the survey. As explained in Section 3.2.4, the limiting choice probability can be analytically traceable of an evacuation option within the EDFT framework. Recall Eq. (7) to demonstrate the choice probability under the evacuation scenario, as shown in Eq. (10):

$$\Pr[Evac|Evac,\ NEvac] = \lim_{t\to\infty} \Pr[P_1(t) - P_2(t) > 0] = \int_0^\infty \frac{\exp\left(-\frac{(x-([\xi_1(t)-\xi_2(t)])^2}{2\lambda}\right)}{\sqrt{2\pi\lambda}} dx \tag{10}$$

where $[\xi_1, \xi_2]^T = (\boldsymbol{I} - \boldsymbol{S})^{-1}\boldsymbol{C}E[\boldsymbol{M}]E[\boldsymbol{W}]$, $\lambda = \Omega_{11} + \Omega_{22} - 2\Omega_{12}$, and $\boldsymbol{\Omega}$ represents the limiting covariance matrix of preference values [37,77] Thus, one can relate the logistic regression model to the limiting choice probability, as shown in Eq. (11).

$$\ln\left(\frac{\int_0^\infty \frac{\exp\left(-\frac{(x-[\xi_1(t)-\xi_2(t)])^2}{2\lambda}\right)}{\sqrt{2\pi\lambda}} dx}{1 - \int_0^\infty \frac{\exp\left(-\frac{(x-[\xi_1(t)-\xi_2(t)])^2}{2\lambda}\right)}{\sqrt{2\pi\lambda}} dx}\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n \tag{11}$$

If initial values of $\boldsymbol{W}$ and $\boldsymbol{M}$ discussed in Section 3.3.1 are plugged into the left part of Eq. (11), the odd-ratio becomes 1, and consequently, the logit value becomes 0 as shown in Eq. (12). Eq. (12) supports the initial setting of the proposed simulation, confining that any option is not preferred over the other.

Table 8
Major demographic variable and its corresponding direct attributes.

Direct Attributes	Safety (w_1)	Information (w_2)	Efforts (w_3)	Property (w_4)
Demographic Variables	Location, Children	Education	Income, Vehicle ownership, Age (over 65)	House/Business ownership, Job duty, Pets, Years of residence

Table 9
Examples of the determination of **W** vector using logistic models.

Logit Model [44]		EDFT Model	
Predictor Variable (binary)	Odds ratio	Corresponding Direct Attributes	Assigned expected weight value
Resident status Monroe	4.6	Safety (w_1)	$E[w_1'] = 0.25 + 0.411$
Resident status Broward	0.6		$E[w_1'] = 0.25 - 0.092$
Resident status Lee	1.9		$E[w_1'] = 0.25 + 0.143$
Logic Model [61]		EDFT Model	
Predictor Variable (binary)	Coefficient	Corresponding Direct Attributes	Assigned expected weight value
Mandatory evacuation order	0.307	Information (w_2)	$E[w'_2] = 0.25 + 0.0647$
Voluntary evacuation order	0.181		$E[w'_2] = 0.25 + 0.0372$

$$\ln\left(\frac{\int_0^{\infty}\frac{\exp\left(-\frac{(x-[\xi_1(t)-\xi_2(t)])^2}{2\lambda}\right)}{\sqrt{2\pi\lambda}}dx}{1-\int_0^{\infty}\frac{\exp\left(-\frac{(x_A-[\xi_1(t)-\xi_2(t)])^2}{2\lambda}\right)}{\sqrt{2\pi\lambda}}dx}\right)=\ln\left(\frac{\int_0^{\infty}\frac{\exp\left(-\frac{x^2}{2\cdot\lambda}\right)}{\sqrt{2\pi\cdot\lambda}}dx}{1-\int_0^{\infty}\frac{\exp\left(-\frac{x^2}{2\cdot\lambda}\right)}{\sqrt{2\pi\cdot\lambda}}dx}\right)=\ln\left(\frac{0.5}{1-0.5}\right)=0 \tag{12}$$

Eq. (11) delivers the reasoning to change any result from the logistic regression to the input parameter $\boldsymbol{W}$ values in the proposed simulation model. The limiting choice probability within EDFT depends on the expected values of $\boldsymbol{W}$. If an odds ratio or estimated coefficient of a particular demographic variable is given from survey data, the increase or decrease of the expectation of weight vectors can be set by equalizing the left and right-hand sides of Eq. (11). Table 9 shows examples of applying the odds ratio or

Table 10
Changes in weight values based on odds-ratios or coefficients from the logit model.

EDFT Increases in E[w_i']	Evacuation Choice Probability	Logit Model Odd-ratio	Coefficient	EDFT Increases in E[w_i']	Evacuation Choice Probability	Logit Model Odd-ratio	Coefficient
0.01	0.512	1.051	0.050	0.26	0.743	2.891	1.061
0.02	0.525	1.104	0.099	0.27	0.749	2.989	1.095
0.03	0.537	1.158	0.147	0.28	0.755	3.089	1.128
0.04	0.548	1.214	0.194	0.29	0.761	3.192	1.161
0.05	0.560	1.272	0.241	0.30	0.767	3.296	1.193
0.06	0.571	1.331	0.286	0.31	0.773	3.403	1.225
0.07	0.582	1.392	0.331	0.32	0.778	3.511	1.256
0.08	0.593	1.455	0.375	0.33	0.784	3.622	1.287
0.09	0.603	1.519	0.418	0.34	0.789	3.736	1.318
0.10	0.613	1.585	0.460	0.35	0.794	3.851	1.348
0.11	0.623	1.653	0.502	0.36	0.799	3.968	1.378
0.12	0.633	1.722	0.543	0.37	0.803	4.088	1.408
0.13	0.642	1.793	0.584	0.38	0.808	4.210	1.437
0.14	0.651	1.866	0.624	0.39	0.813	4.334	1.467
0.15	0.660	1.941	0.663	0.40	0.817	4.461	1.495
0.16	0.669	2.018	0.702	0.41	0.821	4.589	1.524
0.17	0.677	2.096	0.740	0.42	0.825	4.720	1.552
0.18	0.685	2.177	0.778	0.43	0.829	4.854	1.580
0.19	0.693	2.259	0.815	0.44	0.833	4.989	1.607
0.20	0.701	2.344	0.852	0.45	0.837	5.127	1.635
0.21	0.708	2.430	0.888	0.46	0.840	5.268	1.662
0.22	0.716	2.518	0.923	0.47	0.844	5.411	1.688
0.23	0.723	2.608	0.959	0.48	0.847	5.556	1.715
0.24	0.730	2.700	0.993	0.49	0.851	5.703	1.741
0.25	0.736	2.794	1.028	0.50	0.854	5.853	1.767

Table 11
Demographic information of Florida (Census.gov/quickfacts).

Age	Percentage (%)	Education	Percentage (%)	Income	Percentage (%)
Under 19	25.3	No diploma	20.1	< $15,000	16.3
20 to 34	18.8	Highschool	28.7	$15,000~$35,000	28.7
35 to 54	28.4	College	43.1	$35,000~$50,000	35.9
55 to 64	9.7	Post-graduate	8.1	> $50,000	21.1
Over 65	17.6				
Affecting Criteria: Safety		Affecting Criteria: Information		Affecting Criteria: Efforts (Cost)	

coefficient values of predictor variables from the survey to determine the $\boldsymbol{W}$ vector. Since all the weight values are normalized at every deliberation point, Table 10 focuses on the determination of $\boldsymbol{W'}$ vector (before normalization) along with the corresponding odd-ratios or coefficient values of logistic regression. The proposed approach, therefore, generalizes the incorporation of odd ratios or coefficient values within logistic regression into the EDFT framework by setting the weight vector for different survey datasets.

Table 11 shows three important demographic information of Florida, which were shown to be significant for evacuation decisions. The odds-ratios or coefficients of those significant demographic variables were converted to corresponding the expected weight values for the EDFT model. As explained previously, the three weights, safety, information, and efforts, are derived from demographic information such as age, education level, and income, respectively. The heterogeneity of agents was implemented by incorporating these values. In terms of demographic information for age groups, the region comprises 25.3% of people under the age of 19, whereas 17.6% of people belong to the age group of greater than 65. Around 48.8% of the population have studied high school, whereas 8.1% of the people have studied post-college. A significant population belongs to the middle class with income between $15,000 to $50,000. Age group distribution in the region significantly affects individual safety during a disaster. In contrast, the belief in the information from different sources (e.g., social media and news) can be estimated by their education level. Also, the monetary efforts towards the evacuation are significantly impacted by the income level of the people.

Since this study's focus is on people's decisions and their effect on evacuation patterns in Florida, it was also important to accurately represent the distribution of Florida residents. Census data is only taken once a decade, so other sources for population data were necessary. The demographic information for the simulation model was taken from the office of Economic and Demographic Research (FLOEDR), a Florida Legislature that creates a yearly estimate of the total population at the state and county level. Another essential part of the simulation model was determining how many people needed to be represented in the model, and estimates were also used to establish the ratio of residents in each county to the overall population in Florida. These values would influence the distribution of agents within each county of the model. Table 12 offers an example of how the information from FLOEDR was used for the model. The list is sorted from the highest populated counties to the least; Miami-Dade County held the largest proportion of the state's population at 12.97%, while Liberty County had the least at 0.03%. The relative population ratio of each county has been recorded and used to demonstrate the population distribution in the Florida area.

3.3.3. *Incorporation of environmental changes*

Under the disaster situation, dynamic environmental changes can be the critical factors affecting evacuation decisions. These environmental factors include evacuation notices from local or federal authorities, gas shortage status around an agent's region, and changes in the hurricane's strength and/or path. Incorporation of such a change is crucial in developing a data-driven model for efficient disaster management. This section describes how dynamic changes of hurricane landfalls and strength, evacuation notice

Table 12
Top 20 Counties with the largest population in Florida (retrieved from FLODER).

County	Population	Percentage (%)	County	Population	Percentage (%)
Miami-Dade County	2761,581	12.97	Brevard County	596,849	2.80
Broward County	1951,260	9.16	Volusia County	547,538	2.57
Palm Beach County	1485,941	6.98	Pasco County	539,630	2.53
Hillsborough County	1436,888	6.75	Seminole County	467,832	2.20
Orange County	1380,645	6.48	Sarasota County	426,718	2.00
Pinellas County	975,280	4.58	Manatee County	394,855	1.85
Duval County	950,181	4.46	Collier County	378,488	1.78
Lee County	754,610	3.54	Osceola County	367,990	1.72
Polk County	708,009	3.32	Marion County	359,977	1.69

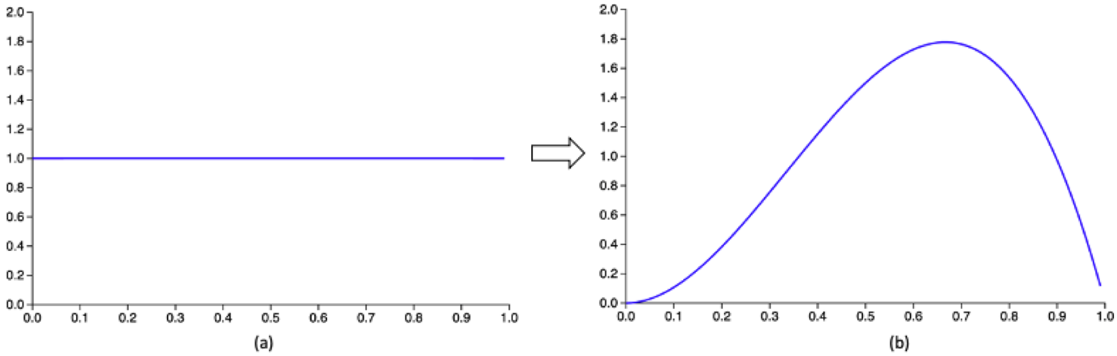
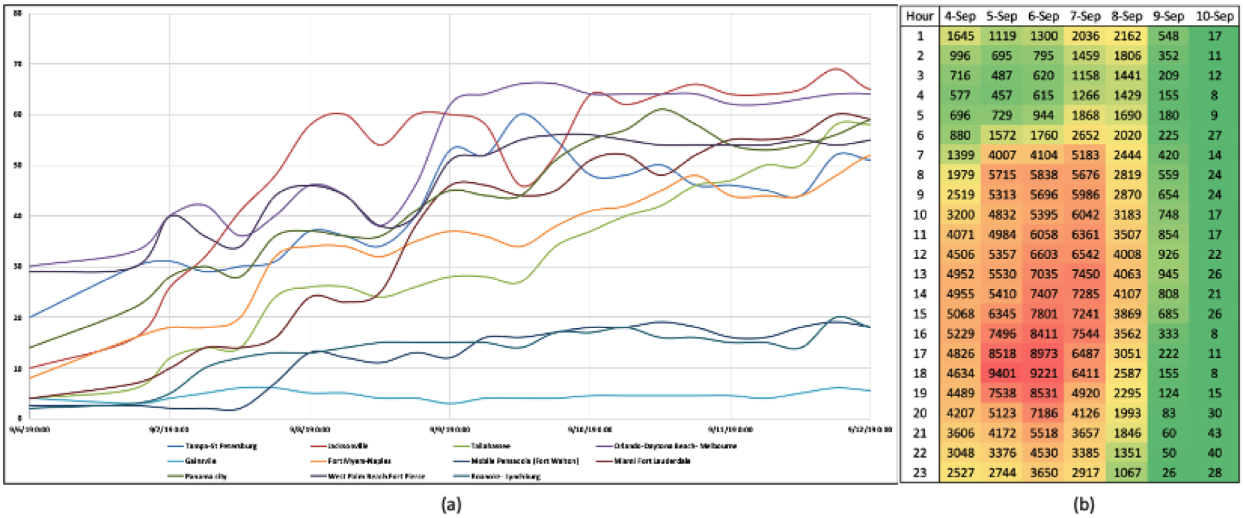


Fig. 6. Prior-posterior distribution for elements of ***M*** (a) PDF of prior Beta (1, 1) (b) PDF of posterior Beta (5,3).

Table 13
Environmental factors dynamic changes of ***M*** elements.

Criterion	Safety	Information	Efforts	Property
Environmental factors	Hurricane strength and landfalls	Evacuation notice	Gas shortage data Traffic data	Off duty status
Corresponding changes in *M*	First column (m_{11}, m_{21})	Second column (m_{12}, m_{22})	Third column (m_{13}, m_{23})	Fourth column (m_{14}, m_{24})



Hour	4-Sep	5-Sep	6-Sep	7-Sep	8-Sep	9-Sep	10-Sep
1	1645	1119	1300	2036	2162	548	17
2	996	695	795	1459	1806	352	11
3	716	487	620	1158	1441	209	12
4	577	457	615	1266	1429	155	8
5	696	729	944	1868	1690	180	9
6	880	1572	1760	2652	2020	225	27
7	1399	4007	4104	5183	2444	420	14
8	1979	5715	5838	5676	2819	559	24
9	2519	5313	5696	5986	2870	654	24
10	3200	4832	5395	6042	3183	748	17
11	4071	4984	6058	6361	3507	854	17
12	4506	5357	6603	6542	4008	926	22
13	4952	5530	7035	7450	4063	945	26
14	4955	5410	7407	7285	4107	808	21
15	5068	6345	7801	7241	3869	685	26
16	5229	7496	8411	7544	3562	333	8
17	4826	8518	8973	6487	3051	222	11
18	4634	9401	9221	6411	2587	155	8
19	4489	7538	8531	4920	2295	124	15
20	4207	5123	7186	4126	1993	83	30
21	3606	4172	5518	3657	1846	60	43
22	3048	3376	4530	3385	1351	50	40
23	2527	2744	3650	2917	1067	26	28

Fig. 7. (a) Gas shortage in each county (b) Traffic flow in I-95 at the intersection with State Rd 824.

Table 14
Hazard based on proximity and intensity.

Proximity Intensity	Closest (<100 miles)	Closer (100 miles to 300 miles)	Moderate (300 miles to 500 miles)
Category 4 and 5 (> 58 m/s)	**Catastrophic**	**Critical**	Major
Category 2 and 3 (> 43 m/s)	**Critical**	Major	Minor
Category 1 (> 33 m/s)	Major	Minor	Negligible
Tropical Strom (18 m/s)	Negligible	< Negligible	< Negligible

status, gas shortage status, and off-duty status are embodied in the EDFT framework. The authors used the Bayesian approach to update the distribution of M elements using real-time data.

As explained in Section 3.3.1, elements of $\boldsymbol{M}(t+h)$ matrix are initially assumed to follow a Beta distribution with $\alpha_{prior} = \beta_{prior} = 1$ (Fig. 6(a)). These elements are updated based on the real-time hourly data sets during the simulation run, which are modeled as Bernoulli random variables ($\boldsymbol{X}_{i \in \{1,2,\cdots h\}} \in \{0, 1\}$). Then, the posterior distribution of $\boldsymbol{M}$ elements will follow a Beta distribution with $\alpha_{posterior} = \alpha_{prior} + \sum_i X_i$ and $\beta_{posterior} = \beta_{prior} + (h - \sum_i X_i)$ by the Bayesian approach, where h means the time duration under EDFT. By modeling environmental changes as a Bernoulli random variable, the update of distribution parameters of elements in $\boldsymbol{M}(t+h)$ can capture the environmental change. For example, assume that the time duration of EDFT is set to six hours, and the simulation model keeps track of the hourly traffic level to see whether it increases or not. The increase in the hourly gas outage level can be modeled as a binary variable ($X_i \in \{0, 1\}$), and there exist six binary variables ($X_1, X_2, X_3, X_4, X_5, X_6$) within one deliberation time. Suppose that the hourly gas outage increases for the last four hours, then $\sum_{i=1}^{6} X_i = 4$. Then, the evaluation results of evacuation and no-evacuation options with respect to the "Effort" criterion will be updated as $m_{13} = -Beta(5, 3),\ \ m_{23} = Beta(5, 3)$ as shown in Fig. 6(b). This real-time update of $\boldsymbol{M}$ enables the incorporation of a data-driven feature into EDFT while allowing the proposed model to represent the dynamic effect of environmental changes on the evacuation decision.

Table 13 summarizes the possible factors of environmental changes and their corresponding changes of $\boldsymbol{M}$. For example, as the distance between a hurricane and people changes over time, people's evaluation results of both options (evacuation vs. non-evacuation) with respect to the "Safety" criterion also shift over time, resulting in changes of the first column of $\boldsymbol{M}$ matrix. Repetitive adequate evacuation notice leads to a higher rate of the evacuation option concerning the "Information" criterion. However, if many gas stations face a shortage, higher efforts will be required for individuals to leave their area, leading to a decreased evaluation of the evacuation decision with respect to the "Efforts" criterion. Lastly, the percentage of businesses forced to close due to the safety reason can affect the rate of options for the "Property" criterion.

Fig. 7(a) shows the percentage of gas stations facing outages in Florida during Hurricane Irma. The number of gas stations that faced shortages during the period was checked using a data set from GasBuddy (GasBuddy.com), which offers the percentage of gas stations without fuel at the county level rather than levels related to individual gas stations' shortages. Every 6 or 12 h, the website posted the status of gas shortage in each county. According to Fig. 7(a), eight counties in Florida faced the gas outage problem of more than 40 percent of gas stations running out of gas. Fig. 7(b) shows the traffic volume in I-95 at the intersection with State Rd 824 on an hourly basis from September 4 to 10. Green represents light traffic while red indicates heavy traffic; this graph illustrates that the traffic level peaked in the afternoon on September 5 and 6. Since both datasets show an increase or a decrease every hour, these hourly changes can be modeled as a Bernoulli random variable (increase: $X_i = 1$, decrease: $X_i = 0$), therefore, the posterior distribution of $\boldsymbol{M}$ is as explained previously.

Table 14 describes the hazard assessment based on the quantification of risk perception. The idea is borrowed from the US military system safety framework, demonstrating system safety in terms of occurrence and severity (Defense, D. D. MIL-STD-882E [15]). This matrix is widely used to appraise hazards in the evaluation of system safety. The authors tailored the matrix to fit the hazard assessment of hurricanes by evaluating risk perception with respect to hurricane strengths and landfalls. This table is used for the evolution of parameter **M** especially m_{11} and m_{12}, representing the evaluation of evacuating and non-evacuating options with respect to safety criteria.

For example, the model updates the m_{11} and m_{12} every hour if the hazard level changes. If the perception of risk moves from Minor threat to Major threat, then the corresponding Bernoulli random variable $\boldsymbol{X}_i$ and n become 1. Then the evaluation results of evacuating and non-evacuating options with respect to safety criteria are updated by assigning $Beta(\alpha + 1,\ \beta + 1 - 1)$and $-\ Beta(\alpha + 1, \beta + 1 - 1)$ to m_{11} and m_{21}, respectively. These updates allow the simulation model to consider the dynamic changes in people's risk perception during the simulation run.

3.3.4. Model execution

The timeline for the simulation model was set up according to the NSC report during hurricanes Irma, Michael, and Dorian. For example, the timeline for the Irma, Michael, and Dorian models are from August 31 to September 12, from October 7 to October 16, and from August 24 to September 10, respectively. Since the report published the locational information, we were able to represent the hurricane's movement over time, along with other agents. As a hurricane draws closer to Florida, counties issue voluntary and/or mandatory hurricane evacuation statutes indicating how important it is for people to leave that area. Some states issue voluntary notices which transition to mandatory, mandatory first, or do not issue any evacuation notice. Once the hurricane passes, evacuation notices are gradually changed then lifted, signifying that it is safe to return to certain counties. The simulation model reflects the accompanying changes in behavior: person agents gradually evacuate throughout the simulation model, and the evacuation peaks as the hurricane approaches Florida. The determination to evacuate or not runs through a state chart by incorporating EDFT. As groups of persons leave, some need gas before leaving and travel to a nearby gas station agent. Fuel levels of gas stations are tracked throughout the simulation using the state diagram. The amount of gas bought by people is assigned based on different levels of car possession, for which we used triangular distribution from 13 gallons to 40 gallons. If a gas station runs out of gas, it enters an "empty" state in which it must wait to be potentially refueled during the simulation run.

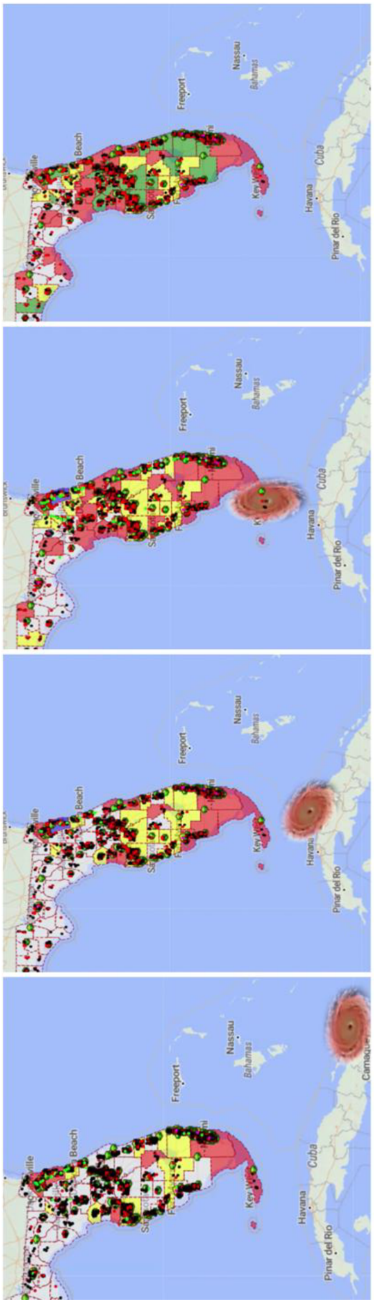


Fig. 8. Different phases of hurricane Irma in simulation.

An evacuating person can choose to go to one of the evacuation points outside of Florida or a shelter agent. Simulation logic favors going to an evacuation point as space is limited in shelters, and shelters have restrictions. We have selected four evacuation points based on survey data. Using the AnyLogic Software feature, these points are mapped to the real GIS points, letting agents reach one of the points using the real road. The GIS search function was also used to create the initial population of gas stations for the model, with a total of 2791 gas stations found, each able to hold between 30,000 and 40,000 gallons. For people evacuating Florida, exit points at the edge of the state along significant interstates highway were determined using FDOT information and Google Maps data in 2017. Evacuation points were placed in large cities likely to be chosen by Florida residents during the hurricane along with state exit points along major interstates.

Counties were used to show evacuation policy change over time. During hurricanes, each county is responsible for declaring voluntary or mandatory evacuation states. Each county agent in the simulation model represents the behavior of counties represented by GIS regions. At the start of the simulation, all counties are colored in transparent, indicating that there is no current evacuation notice to any county. During the simulation, if a county announces a voluntary evacuation, it turns yellow. Mandatory evacuations cause a county to turn red. After the hurricane, counties turn green as evacuation notices are removed (Fig. 8). The number of gas stations needed to be scaled down as well to match the estimated gas bought by 4074 people by considering the relative ratio to gas stations and the total population. The density of gas stations is related to the density of people; thus, the scaled-down population of gas stations shows a comparatively large number of gas stations in Miami-Dade County to the rest of the state, which is logical as the county houses the largest proportion of people, 13%. Hurricane movement was implemented in the simulation model using historical data and GPS locations during hurricane Irma to show the progress of the hurricane relative to agent decision-making in Florida. Information was gathered from a government hurricane report with other relevant information such as wind speed and air pressure, as shown in the NHC report (NHC report 2018 [78]), depicting the hurricane's motion toward its historical point, given in longitude and latitude, updated every 6 h. Using AnyLogic, the agent-based simulation model was developed to represent the evacuation behaviors during the hurricane. Fig. 8 depicts different agents and their status in the simulation model.

In Fig. 8, the left figure provides an overview of the simulation setting, while the right figures show the changes in the evacuation order issued by each county in Florida (red: mandatory, yellow: voluntary, green: orders are officially removed). During the simulation execution, the total number of people who evacuated the city was tracked, then compared for accuracy against the actual number of people who evacuated Florida. The four phases of execution of the simulation model (initiation, evacuations start, evacuation peak, the hurricane passed by Florida) correspond to the four stages of disaster management: mitigation, preparedness, response, and recovery. In the first phase (initiation and mitigation), hurricane Irma forms in the Atlantic Ocean and approaches islands in the Caribbean, when people began to recognize the impending threat to Florida. This phase lasts from September 4–6, where most people have not started to consider evacuation with the exception of some counties beginning to issue both voluntary and mandatory evacuation notices. In the next phase, actual evacuation starts, which corresponds to the emergency preparedness stage, September 6 to the morning of September 7, where more counties recommend evacuation, and people begin to consider leaving Florida or going to the shelter. Some people may start evacuating during this time, but Hurricane Irma is still in the Caribbean area and not close enough for most people to consider leaving their homes. During the third phase from September 7–8, people begin evacuating in large volumes; this peak evacuation time corresponds to the response phase in disaster management. At this point, Hurricane Irma is approaching and passing over Cuba. More counties are declaring voluntary and mandatory evacuation notices, which leads to a significant increase in traffic followed later by the county's mandatory evacuation declaration based on updated hurricane path predictions. In the last phase, from September 9 to 15, hurricane Irma reaches and passes through Florida. Those who have not yet left evacuate to a shelter or attempt to stay in their homes. Traffic levels normalize after hurricane Irma moves through Florida. By this time, 49 of Florida's 67 counties have issued evacuation notices: 35 mandatories and 14 voluntaries. In Section 4, what-if analysis has been adopted to achieve higher accuracy of the developed simulation model for validation.

4. Validation

For the development of the proposed simulation, the construction of the environment is key in the precise estimation of people's

Fig. 9. Paths and strengths of three Hurricanes (from the left: Irma, Michael, Dorian) [Images: In Wikipedia, retrieved November 15, 2019].

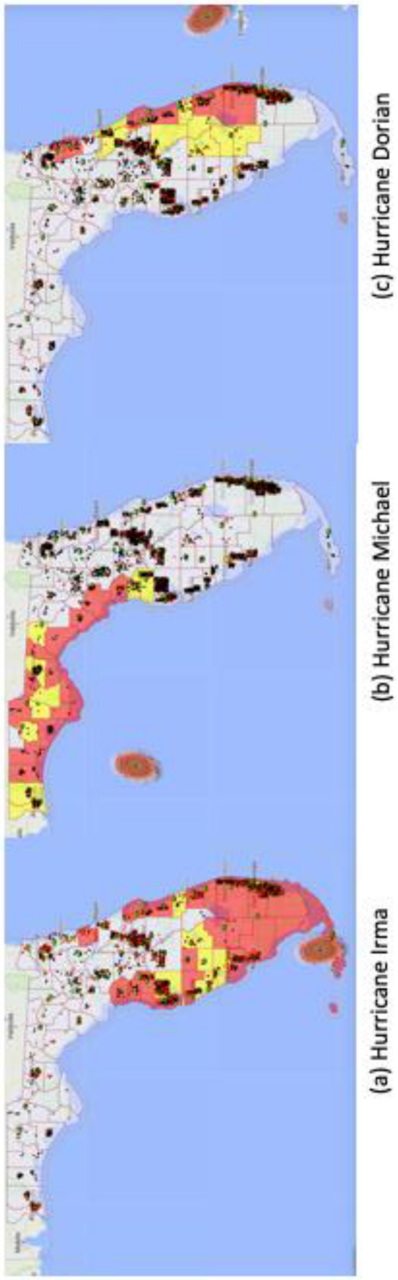


Fig. 10. Status of Evacuation Orders: (a) Irma (b) Michael (c) Dorian.

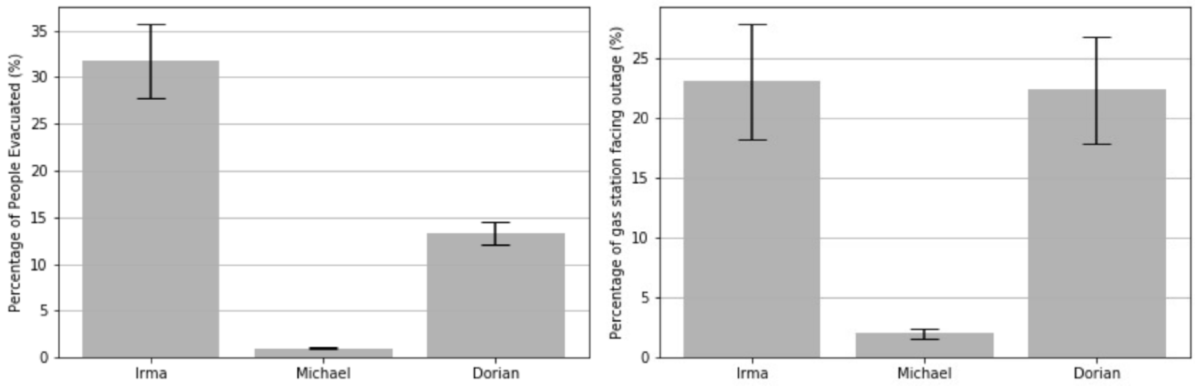


Fig. 11. Percentage of people evacuated (left) and of gas outage (right).

behavior. The first step was to collect all different types of data, including geographical regions, human behavior distributions, hurricane movements, gas shortages, and government notification information in order to develop and validate a model that can accurately reflect the series of events hurricane Irma, Michael, Dorian. These data sets came from research papers, government reports, news outlets, reputable survey companies, and government resource sites like the Federal Emergency Management Agency (FEMA: http://fema.gov). To correctly estimate the number of people that evacuated out of Florida during hurricane Irma, multiple survey data has been used [4,22,68]. Under the hurricane situation, people had four decision alternatives: 1) evacuate outside of Florida, 2) evacuate to another city within Florida, 3) not evacuate but stay in the shelter, and 4) stay at home. The survey revealed that only 31% of people evacuated outside of Florida. In Section 4, we compare the number of people evacuating outside of Florida in the simulation model to the real data for validation.

Fig. 9 shows the path of three hurricanes (Irma, Michael, and Dorian) that hit Florida. The color of the dots along the hurricane path represents the intensity based on the Saffir-Simpson scale, which classifies hurricanes into five categories based on wind speed. Hurricanes classified as Category 5 have wind speeds of at least 70 m/s, whereas Category 4 hurricanes entail a wind speed of at least 56 m/s. In Fig. 9, the red dots indicate that the maximum wind speed exceeds 70 m/s, signifying that all three hurricanes were classified as Category 5. On top of the strength, it is evident that hurricane Irma passed right over Florida while the other two hurricanes veered off to the left or the right from Florida.

Fig. 10 shows three snapshots of evacuation behaviors in hurricanes Irma, Michael, and Dorian. Each county released different evacuation orders, either mandatory (red) or voluntary (yellow). For example, hurricane Irma was supposed to pass through the mid of Florida area. All the counties in the southern part of Florida and coastal counties were released mandatory orders at the initial phase of the hurricane. Since the southern part of Florida has a higher population density, hurricane Irma led to a higher number of evacuations compared to other hurricanes. According to the survey, articles, and government reports, around 31 percent of the total population in Florida evacuated during hurricane Irma [22]. In the case of hurricane Michael, the hurricane hit the northwestern part of Florida, where population density is lower compared to other parts (Fig. 10). Thus, around 22 counties released evacuation orders (mandatory or voluntary); the number of people living in those counties is less than 1 percent of the total population in Florida. Only 12 counties released evacuation orders (mandatory in 5 counties, voluntary in 7 counties) during hurricane Dorian, but the relative population in these counties were quite large. This led to a higher evacuation rate during Dorian than Michael, so it is known that around 14 percent of the total population evacuated during Dorian. For validation, the authors incorporated the real data providing the number of hurricane-related evacuations that were simulated based on EDFT. Also, it was checked that the number of people evacuating during three hurricanes is significantly close to the actual number of people evacuated in three different hurricanes.

In order to perform the validation, 50 runs of simulation under each hurricane situation was executed, and the percentage of people evacuating outside of Florida was compared with actual numbers. Since 4074 agents are used to represent the entire population in the simulation model, results were compared with the real evacuation results obtained. Thus, a null hypothesis was established to check whether the average number of people evacuating Florida in the simulation model is close to 1302, 41, 530 (i.e., 31, 1, and 14 percent of the total people in the simulation) in the periods of hurricane Irma, Michael, and Dorian, respectively. Simultaneously, as shown in Fig. 11 (left), it is evident that people evacuated during Hurricane Irma is higher than hurricane Dorian, but the percentage of evacuation during Dorian is higher than that of hurricane Michael. Therefore, we conclude that the proposed simulation model can appropriately represent the actual evacuation behaviors in Florida during the hurricane periods of Irma, Michael, and Dorian.

At the same time, we also checked the percentage of gas stations facing outages during these hurricanes, spreading the demand out over time based on the available information. Since the gas shortages were reported over time, the shortages in the model were validated at various time points during the simulation. Gas shortages were compared based on averages over all runs. Based on the

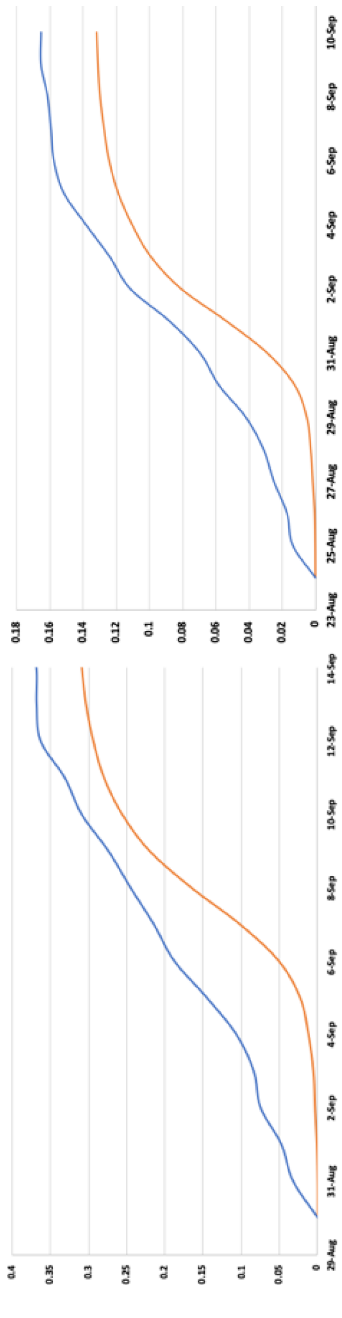


Fig. 12. The proportion of people evacuated over time during Irma (left), during Dorian (right).

Table 15
ANOVA results (left) and confidence intervals (right) based on three different policies.

	Degree of Freedom	Sum of Square	Mean Square	F-value	P-value		Lower Bound	Estimates	Upper Bound
Policy	2	3685.2	1842.6	995.03	$<0.001^{****}$	Policy 1 & 2	6.9238	8.1417	9.3596
Residual	28	51.9	1.853			Policy 1	17.7988	18.6803	19.5618
Total	30	3737.1	1844.45			No policy	25.2160	26.4626	27.7092

survey and the data from Gasbuddy.com, the percentages of gas stations with outages were 25.11, 0.7, 24.77 in Irma, Michael, and Dorian, respectively. Even though the number of people that evacuated during Dorian is less than Irma, the gas outage is very similar (Fig. 11 (right)) for two reasons: 1) the path of Dorian was on track for Miami, which has a larger population; 2) despite not evacuating, people purchased more gas than necessary based on their hurricane experiences in 2017 and 2018. Thus, we conclude that in order to reduce gas outages, the government could place a restriction on gas purchases during the disaster.

Since one of the goals of this study is to minimize the number of gas stations facing shortages during hurricanes, it is important to spread out the number of people evacuating over the hurricane time period. As the results above revealed that the number of evacuees during hurricane Michael was too small, only two cases are considered (Irma and Dorian) for the simulation. We considered two different scenarios based on the actions of the government. One possible action that the government could take to alleviate shortages would be releasing the evacuation order in waves so that the number of people leaving and purchasing gas is more evenly distributed. In practice, hurricane watch or warning order is released first before the mandatory order, but most of the evacuation decisions are made only after the mandatory evacuation order.

Fig. 12 represents evacuation patterns under two different scenarios in hurricanes Irma (left) and hurricanes Dorian (right), respectively. The blue line in the left figure represents what might have happened if the government had released the mandatory orders as a series (August 30, September 2, and 5), allowing for demand to spread out and congestion to be reduced. The orange line shows the proportion to the people evacuating under the scenario that the government notification was released on September 5 in Irma. This increases the congestion level, as the orange-colored graph becomes sharp. Indeed, the orange line shows a sharp rise on September 5, indicating the time at which the government issued a single evacuation order and a correlating spike in congestion. The observed spike due to the evacuation order was also observed in evacuation literature [53], demonstrating that the proposed model is consistent with the literature and the real phenomenon. Though the series of mandatory evacuation orders increases the total number of people evacuating, the congestion level will be reduced.

Similarly, this pattern remains the same in hurricane Dorian: observing the blue line, it is assumed that there are three orders given in a series on August 24, 27, and 30 (Fig. 12, right). However, with the single mandatory evacuation on Aug 30, the evacuation pattern increases sharply, leading to severe congestion. According to Pham et al. [53], hurricanes including Matthew shows a similar spike after the release of evacuation order, thus signifying the applicability of the proposed model to other hurricanes. The study supports reducing congestion by spacing out evacuation notices. As shown in the blue line, the evacuation spread out, and the congestion level will be decreased, whereas a one-time mandatory evacuation order will affect severe congestion. Therefore, the study strongly supports reducing congestion by spacing out mandatory orders.

While issuing evacuation orders in waves is one clear step the government can take to minimize congestion during hurricanes, we have enriched our study by evaluating different policies for effectiveness: 1) do nothing 2) release an evacuation order several times (policy 1) 3) release evacuation orders in series (policy 1) and provide training (policy 2) together. In this context, training means increasing the proportion of “responsive” people. The null hypothesis is that the percentage of gas outages under different policies remains the same. Thus, the response variable (Y) is the percentage of gas stations facing outage, and the independent variable has three levels. As P-value is small enough according to the ANOVA results in Table 15, we reject the null hypothesis concluding that different policies will change the percentage of gas station outages. By imposing both polices 1 and 2 to the public, it decreases 18% of gas station outage on average compared to the scenario where no policy is released (Table 15, right). Thus, we can conclude that it is evident that enacting both policies will reduce the level of gas outages, as the government adopts two policies together.

Finally, the authors checked the assumptions of residuals in the ANOVA. As in Fig. 13, the constant variance assumption is shown to be satisfied. From Levene's Homogeneity of Variance test, the P-value is 0.7867, which means there is not significant evidence to reject the null hypothesis. Also, according to the Q-Q plot, most residual points lie close to a 45 line, so it satisfies the normality assumption. From Shaprio's Normality test, it is found that the P-value is 0.66998, meaning we do not have significant evidence to reject the null hypothesis. Thus, we conclude that both stability and normality assumptions have been satisfied.

Another critical factor for effective planning and managing disaster situations is connectedness among individuals in society. As mentioned earlier, a series of evacuation notices by the government significantly affect the number of evacuations. Along with a series of evacuation notice, the authors hypothesized that individuals within the society are well connected, which increases the rate of evacuations. The combination of a repeated evacuation notice and the well-connectedness of the society would help increase the evacuation rate while helping people make evacuation decisions at the early stage. To test this hypothesis, the authors considered two factors: the repeated evacuation notice and connectedness within society. The repeated evacuation notice was implemented by the repeated announcement of the same evacuation order three times. Connectedness within society was incorporated by changing the average number of degrees within the society from 0 to 3. ANOVA (Table 16) was performed to observe the main effects and interaction effects of the factors mentioned above, providing the effectiveness of the simulation model for better disaster management and broader managerial implications.

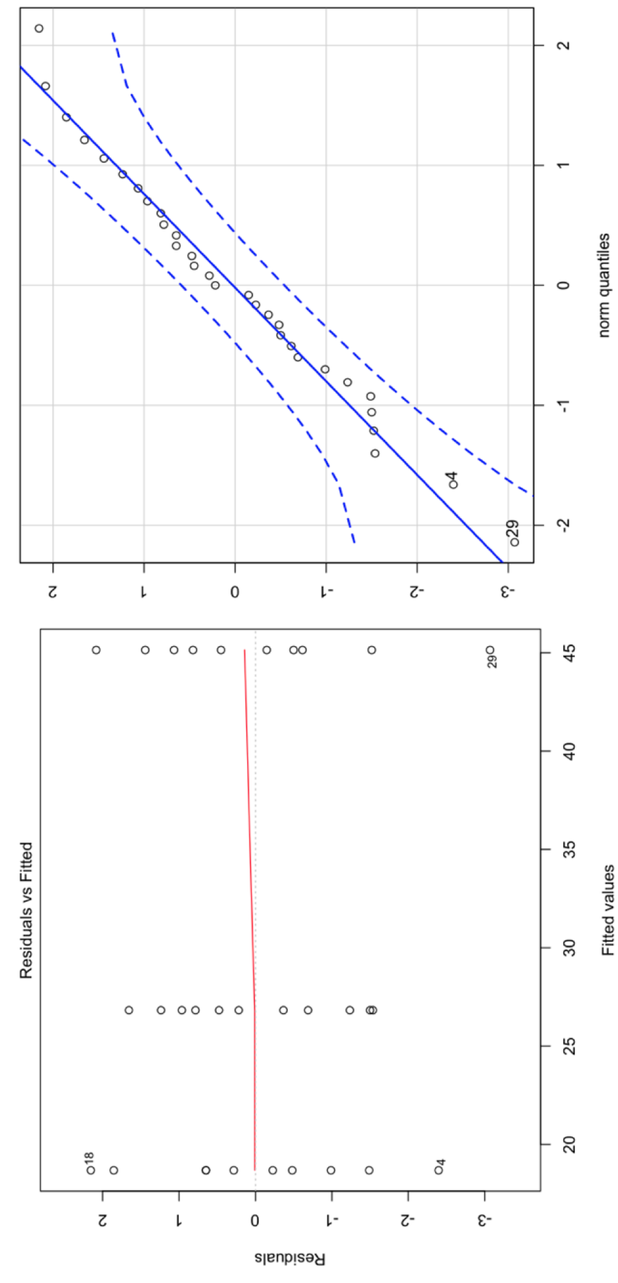


Fig. 13. Residual tests: Equality of variance (left), Normality (right).

Table 16
Two factors (evacuation notice and connectedness) ANOVA results.

Sources of Variation	DF	Sum Sq	Mean Sq	F value	Pr(>*F*)
Repeated Evacuation Notice (RN)	1	6907	6907	256.00	<0.001****
Connectedness in Society (CS)	1	5851	5851	216.84	<0.001****
Interaction effects (EF*CS)	1	603	603	22.35	<0.001****
Residuals	391	10,550	27		

As shown in Table 16, the p-values corresponding to both factors are lower than any significance level ($\alpha = 0.1, 0.05, 0.01$); they significantly affect the evacuation numbers within the region. Also, since the interaction factor is shown to be significant, one can find that if two different policies were released together, it could lead to better disaster management. Thus, it is evident that the well-connected and evacuation notice frequency can help the stakeholders make informed decisions about evacuation planning and efficiently manage the traffic conditions during the evacuation.

5. Conclusion

This paper presents a dynamic data-driven simulation for modeling and analysis of a disaster situation for devising an efficient disaster management policy. The situations during different hurricanes in Florida were modeled by the amalgamation of data sets such as evacuations, gas outage, hurricane characteristics, and geographic regions, providing a high-fidelity simulation model to study and analyze hurricanes as well as other types of disaster situations. The static as well dynamic data were incorporated into individual decision-making framework to analyze and observe the dynamic evolution of preference values over time for different types of unforeseen events. To endorse the robustness and validity of the proposed approach, case studies of three major hurricanes – Irma, Dorian, and Michael - have been incorporated to perform a risk assessment for catastrophic, critical, and major threat disaster situations, respectively. Moreover, the disaster-affected regions were evaluated for the implementation of different policies to reduce casualties and asset loss. Based on the conducted what-if analysis, training and well-organized disaster evacuation strategy would significantly contribute to smooth evacuations. Thus, the proposed simulation paradigm will facilitate stakeholders in government, homeland security, and the population to make informed decisions about disaster management and evacuation policies.

This work establishes a high degree of correspondence between the real evacuation patterns and the simulation patterns during hurricane Irma. Due to the incorporation of spatial and temporal analysis, the proposed approach expedites the evaluation of alternative governmental strategies to reduce the congestion on the roads and to devise effective resource allocation during disasters. There can be many ways of extending the proposed work to gain deeper insights for effective disaster management. Firstly, the proposed approach can be enlarged by incorporating the numerical weather prediction framework such as Weather Research and Forecasting (WRF), which can perform the operational forecasting of the disasters' meteorological aspects. This extension will help perform rich experimentation by considering different scenarios for hurricane parameters such as paths and speed. Secondly, the utilization of locally distributed multi-level simulations (at the city-level, county-level, and state-level) will facilitate a hierarchical modeling approach to maintain each module's coherence and increase the interplay among those modules. Finally, the proposed simulation model can be extended for different types of disasters as well as locations. For instance, one can examine the model within other hurricane vulnerable states such as Texas and Louisiana. Moreover, policies dedicated to a specific type of disaster can be derived by testing the model within wildfires, earthquakes, or tsunamis. These examinations will bring a generalization of the proposed simulation model.

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