Modeling and Analyzing the Traffic Flow during Evacuation in Hurricane Irma (2017)

Kairui Feng[1], Ning Lin[1]

[1] Department of Civil and Environmental Engineering, Princeton University

Abstract

Hurricane evacuation modeling is challenging due to a scarcity of evacuation data and the complexity of human decision-making and travel behavior. We build a system for rapidly predicting the hurricane evacuation traffic flow based on hurricane forecasting, evacuation orders, road network, and population information. The system integrates an evacuation demand model, an origin-destination model, and a route choice model into a link flow-based mean-field traffic model. We evaluate and calibrate the model with traffic observations from Hurricane Irma (2017), which induced a massive evacuation and traffic congestions throughout Florida State. The model skillfully captures the spatial and temporal evacuation features, including peak traffic flows and daily traffic fluctuations. The model can be applied to support evacuation management. Our analysis shows that a minor adjustment to the evacuation order could considerably alleviate the traffic congestion during Hurricane Irma.

1 Introduction

Communities along the Atlantic and Gulf coasts are vulnerable to hurricanes. As a hurricane approaches, many coastal dwellers may be forced to evacuate to avoid jeopardizing their lives (Xian et al. 2018). When a large number of people attempt to evacuate at the same time, however, the traffic flow may surpass the capacity of road networks. Hurricane Irma (2017) triggered possibly Florida's greatest evacuation in history, with 7 million people under mandatory evacuation orders and 4 million evacuation vehicles; traffic congestions began in mid-Florida and quickly spread throughout the state (Feng and Lin 2021). Fortunately, the evacuation process finished before Irma made landfall. However, Irma demonstrated once again the difficulty for local governments in issuing evacuation orders to strike a balance between waiting long enough to avoid the cost of an unnecessary evacuation and evacuating early enough to prevent a loss of life, as discussed for previous events (Czajkowski & Kennedy 2010). For example, during Hurricane Sandy (2012), New York City issued evacuation orders only about 8 hours before the subway system was shut down (Wall Street Journal October 28, 2012), and the NYU Medical Center was evacuated after the power failed. More than 2.5 million people evacuated from Florida when Hurricane Floyd (1999) approached, but the storm missed Florida and made landfall in North Carolina (Dow and Cutter, 2002). In the future, more residents along the United States' coastline may be forced to evacuate more frequently due to the effects of climate change (Marsooli et al. 2019). A better understanding of storm evacuation mechanisms and continuously improved evacuation prediction models are needed.

The evacuation process is referred as a feedback system with two stakeholders: households and the local government taking actions under exogenous information--probabilistic or ensemble hurricane prediction (Fig. 1; Sadri et al. 2014, Yi et al. 2017). As a hurricane approaches, the householders receive hurricane predictions and evacuation orders issued by the local government. They combine the information with their household situations (location, current traffic conditions, age, family composition, previous hurricane experience, property state, time of the day, personal interpretation of the hurricane prediction and governmental order, etc.; Huang et al. 2016) to determine whether to begin an evacuation and if so, when to leave, where to go, and by which route. Their actions can affect traffic conditions, which can be monitored in part by the local government. Next, based on the updated hurricane forecasts and observed human behavior, the local government re-evaluates the evacuation necessity among the areas under its jurisdiction and issues new orders. The householders receiving the updated hurricane predictions and governmental order may change their evacuation decisions. The loop goes on until the hurricane makes landfall or the evacuation is finished.

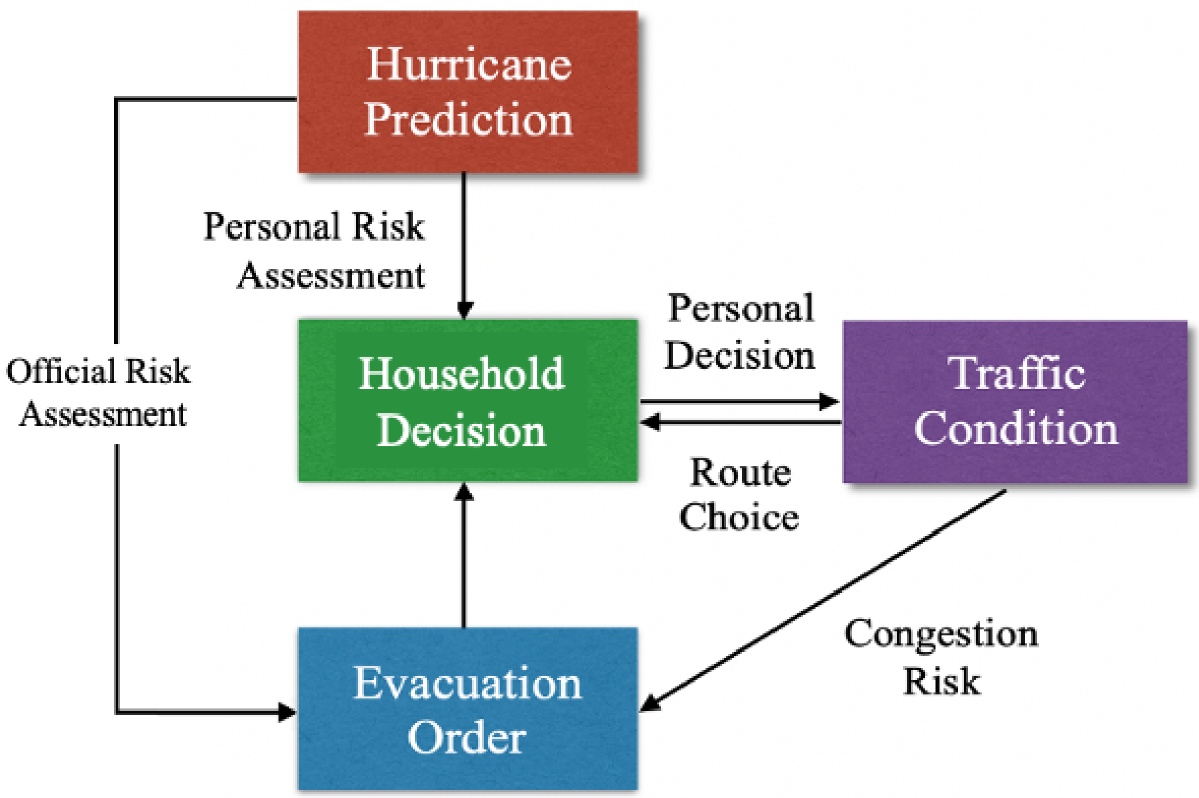

Fig. 1. Flowchart of hurricane evacuation process.

Modeling hurricane evacuation is challenging due to two constraints (Pel et al. 2012, Urbina & Wolshon 2003, Robinson et al. 2017, Wolshon et al. 2005): 1) complex human decision-making processes under evolving hurricane predictions and governmental evacuation orders and 2) data deficiency for time-varying traffic observations and household level decisions. Constraint 1) complicates predicting traffic conditions during evacuation and often require considerable computer resources for agent-based modeling of individual behaviors (Yin et al. 2014) or game-theory-based large-scale optimization (Brown et al. 2010). The increased demand for computational resources may constrain the size of the model parameter space and result in the model being under-fit. The traditional dynamic traffic simulators (Li et al. 2012; Chiu et al. 2008; Nava et al. 2012) estimate the daily traffic flow using synthetic origin-destination demands and thus cannot be directly used for predicting evacuation processes. Furthermore, data limitations (Constraint 2) complicate the process of testing and calibrating prediction models (Mesa-Arango et al. 2013). These two constraints lead to the shortage of prediction models verified with real-world traffic data at the global scale (Yin et al. 2014). Lindell et al. (2019) and Baker et al. (1991) summarized the modeling procedures and components of large-scale evacuation processes; however, only a few models have been validated, and they are validated mainly at regional scales (e.g., for Florida Keys area during Hurricane Georges of 1998, Yang et al. 2019; for New Orleans during Hurricane Katrina of 2005, Dixit et al. 2011; and for Southeastern Louisiana region during Hurricanes Katrina and Gustav, Montz and Zhang 2015).

Following the procedures of hurricane evacuation, we develop an algorithm for rapidly predicting the hurricane evacuation traffic flow through integrating a time-dependent sequential logit model (TDSLM) for individual evacuation demand (Gudishala and Wilmot 2012), a dynamic origin-destination (OD) model (Simini et al. 2012), and an en-route model for individual evacuation route choice (Dia 2002) into a link flow-based mean-field traffic model.

This model is capable of forecasting hourly traffic volume on each link section, capturing congestions, and tracking individuals' evacuation decision, route choices, and destination. The decision models are as flexible in this framework as it is in standard agent-based models, but the dynamic traffic simulation based on the mean-field theory resolves the computational challenge generated by the agent-based model's enormous agent population[1]. By solving the mean-field model with an efficient differential equation solver, we can search a large parameter space for the model's tunable parameters and calibrate the model to reproduce observed dynamic evacuation characteristics. Also, this model can achieve prediction accuracy in global congestion patterns by calibrating all model components collectively rather than individually in order to minimize accumulation of inaccuracies. To illustrate its application, in this study we evaluate and calibrate the model with traffic observations from Hurricane Irma for the Florida State.

We also apply the analysis results to investigate evacuation behavior during Hurricane Irma. Several recent studies have investigated evacuation behavior in the aftermath of Hurricane Irma. For example, Wong et al. (2020) analyzed the observed decision-making behavior of a sample of individuals impacted by Irma; the study identified two latent segments, distinguished by demographics and risk perception that tend to be either evacuation-keen or evacuation-reluctant, that responded differently to mandatory evacuation orders. Goodie et al. (2019) found that younger adults and those who lived with children were more likely to evacuate; they also found that perceived risk and previous trauma were associated with evacuation decisions while hurricane experience was not. Other studies employed social network data to reveal the origins

[1] This framework allows one to flexibly make assumptions on agent-level evacuation behaviors while solving the traffic model on a mean-field manner, although one could also directly apply the mean-field simulator to predict the global evacuation traffic with predefined OD information.

and destinations of the evacuees in Hurricane Irma. Long et al. 2020 showed that evacuators' decisions might be significantly affected by their political standpoint. Marasco et al. (2020) found a preference for evacuation during the daytime in Hurricane Irma, which confirmed the results from previous studies dating to Baker (1991). Hong and Frias-Martinez (2020) showed that distance is a dominant predictive factor, with counties geographically closer to the predicted hurricane track generally having more significant evacuation flows. These studies analyzed behavioral data directly in order to investigate specific characteristics of behavior. In this study, we compare the behavior characteristics derived inversely from traffic observations through our model with the evacuation behaviors reported in existing literatures.

To our knowledge, this is the first hurricane evacuation prediction model that can account for all stages of the evacuation process (i.e., evacuation demand estimation, OD estimation, and route choice) and be validated as a single system at the global level. Additionally, our model predicts the congestion patterns for the entire evacuation more accurately and efficiently compared to typical local evacuation models (Gudishala and Wilmot 2012, Long et al. 2020, Goodie et al. 2019). We also illustrate a direct application of this model in evacuation management by examining the effect of the issuance of evacuation orders on simulated traffic flow. Our analysis indicates that a small adjustment to the evacuation orders could considerably alleviate the traffic congestion during Hurricane Irma.

2 Model Formulation

As a hurricane approaches, potential evacuees will decide if and when they will evacuate and then choose their destinations and routes to the destinations. Therefore, their decision process can be described in three parts: 1) decide whether and when to leave, 2) find a destination where enough capacity remains for evacuators, and 3) take a route to the destination[2]. To reflect this decision process, the traffic prediction modeling in this paper consists of a traffic demand model (Section 2.1), dynamic OD model (2.2), and route choice model (2.3). These models are integrated into a mean-field differential equation set that solves the global dynamic traffic conditions and evacuation decisions over time (2.4). In Section 2.5, we incorporate real data from Hurricane Irma, including hurricane prediction, governmental order, and local population and road network, into the modeling process, and we fit/calibrate the model using sparse high-way observations, reconstructed local traffic data, and a genetic algorithm to minimize the difference between simulated and observed traffic conditions.

2.1 Traffic demand model

Evacuation decision-making is a sequential choice process. If time is discretized into time intervals, at time t a household has the binary choice to evacuate or not, provided that the decision to not evacuate was made in all earlier choices. If the choice at time t is not to evacuate, the household faces the same binary choice at time t+1, and so on, until either a decision to evacuate is made or the end of the analysis period is reached. At each time step, the evacuation

[2] These decisions are not necessarily made in sequence. For example, some evacuees who have repeated experience with hurricane evacuation have established a consistent destination and route that they have already chosen before they decide to evacuate. Some evacuees pick a route and travel inland until they arrive at a destination where accommodation is available.

decision of each householder can be estimated using the random utility theory (Fu and Wilmot 2004).

The probability that a household i will evacuate at time t, $P^e_{t,i}$, or stay, $P^s_{t,i}$, given that it did not evacuate earlier, can be expressed in the form of a regular binary logit model:

$$P^e_{t,i} = \frac{\exp(V^e_t)}{\exp(V^e_t) + \exp(V^s_t)}, P^s_{t,i} = 1 - P^e_{t,i};\ t = 1,2,\ldots,T \tag{1}$$

where V^e_t/V^s_t represents the utility of a household choosing to evacuate/stay at time t, and T is the total number of time steps. Then the evacuation probability $P_{t,i}$ at time t is

$$P_{t,i} = P^e_{t,i} \prod_{\tau=1}^{t-1} P^s_{\tau,i} \tag{2}$$

which is the probability that the household makes a time-independent evacuation decision to stay for time point *t-1* and leave at time point *t* (Fu et al. 2006). The probability that the household makes a time-independent evacuation decision to stay until time point *t* is $S_{t,i} = \prod_{\tau=1}^{t} P^s_{\tau,i}$.

In this paper, following Gudishala & Wilmot (2013), 5 factors are considered for the utility function (linear): evacuation order (Boolean factor for voluntary or mandatory evacuation), hurricane category (forecasted category when the hurricane makes landfall, 0~5), time of the day, current distance from the storm center, and storm surge risk (forecasted probability of experiencing 10-ft surge above the mean sea level). The time of day is reflected by 3 Boolean dummy variables: TOD1 (12:00 a.m.~5:59 a.m.), TOD2 (6:00 a.m. ~ 11:59 a.m.), and TOD3 (12:00 p.m.~5:59 p.m.), with nighttime (6:00 p.m. ~11:59 p.m.) used as the base. In the analysis, the coefficients for these factors in the utility function are considered model parameters to be fitted with real traffic data. Note that in this model, if there is no evacuation order being issued, evacuees may still evacuate following the binary logit model with the dummy variable of evacuation order set as zero. It should also be noted that in reality, many other factors are also involved; for example, consideration of economic cost for transportation, lodging, food, and lost wages (Lindell et al. 2019) and other demographic and political factors revealed by previous studies on Irma (as reviewed earlier). However, these detailed demographic data may not be available in general. Thus, following the evacuation decision making model of Gudishala & Wilmot (2013), we consider only the basic factors in evacuation demand, with the broader aim to illustrate the evacuation simulation framework developed in this paper.

2.2 Dynamic OD model

The classical gravity model is used to generate a destination for each origin depend on the distance between the OD pair and the traffic attraction of the destination (Simini et al. 2012). An adjusted gravity model is chosen to assign a destination for each evacuation-willing household dynamically, and the gravity weight $G_{t,i}(j)$ for a household at node i and time t while choosing node j as the destination is:

$$\mathrm{G}_{\mathrm{t,i}}(j) = \frac{m_{t,j}^{\alpha} S_{t,j}^{\beta}}{TT_{t,ij}^{\gamma}} \tag{3}$$

where α, β, and γ are adjustable exponents. $\mathrm{m}_{t,j}$ is the unoccupied shelter/hotels/householding volume at time t. The travel time of the estimated shortest route (starting at node i) $TT_{t,ij}$ is chosen to capture the time-based distance between nodes i and j. The probability that a household will stay at node j until time t, which is $S_{t,j}$ discussed above, is used to reflect the safety level of the location *j*. The population at node *i* would decide (probabilistically) the destination based on the gravity weight for each node *j* at every time step.

2.3 Route choice model

The traditional game-theory based model used in previous evacuation simulation research (Chen 2006, Yi et al. 2017) is limited in that they rely on pre-specified rules of behavior that are difficult to validate and capture in real evacuations. Lindell and Prater (2007) and Pel et al. (2012) criticized the use of user equilibrium for evacuation prediction, considering the inability of evacuees to learn traffic conditions by experience since evacuations are rare events. Thus, when applying equilibrium-driven models to evacuation problems, the application domain should be limited, and additional assumptions may be applied. For example, Feng and Lin (2021) used user equilibrium to reconstruct traffic flow for Florida during Hurricane Irma by separating the state into 15 time-analysis zones and assuming directional traffic flow. This treatment reduces the deviation of the real evacuation traffic from the equilibrium state.

Here, we employ an en-route model to capture the household driving behavior. The assumption of the game-theory based model that travelers cannot deviate from their (pre-trip) chosen route is relaxed in the case of en-route route choice. Here, travelers observe prevailing traffic conditions during their travel and make route choices accordingly. En-route choice models thus assume that travelers at each intersection determine the next downstream direction based on evacuation route guidance or available information on the prevailing (instantaneous or predicted) traffic conditions (Pel et al. 2012). A few evacuation studies use en-route choice models, including NETVAC (Network Emergency Evacuation Model), which allows myopic route improvisation (where evacuees focus on the traffic conditions directly ahead; Lindell and Prater, 2007). Dia (2002) allows evacuees to compare their usual route with the best alternative route, and Chiu et al. (2008) allows vehicles to take other routes if the current route is congested. Other studies use hybrid route choice models such as DYNASMART (Sbayti and Mahmassani 2006), DynusT (Pel et al., 2008), and EVAQ (Pel et al., 2010).

When we simulate en-route route choice, link flow fractions (also called split proportions or turn fractions) are computed at all intersection nodes, and travelers are propagated from one intersection node to the next along the downstream links. We assume the time cost of the following link section is generally available for evacuees as they have access to global congestion information at each time point through the GPS or mobile tools such as Google Map. Thus, as illustrated in Fig. 2, the probability for a person at node *i* with the destination at node *j* to choose a downstream link *k* ($f_{t,i,j,k}$) is computed based on the traffic time on this link ($TT_{t,k,pre}$) and the belief of the time cost in the shortest forthcoming route travel time ($TT_{t,k,post}$) at time *t*, using the random utility theory (Feng et al. 2020a and 2022):

$$\mathrm{f}_{\mathrm{t,i,j,k}} = \frac{\exp\left(-\theta \cdot \ (TT_{t,k,pre} + \ TT_{t,k,post})\right)}{\sum_{k\in\xi_i}\exp\left(-\theta \cdot \ (TT_{t,k,pre} + \ TT_{t,k,post})\ \right)} \tag{4}$$

where θ is the diversion intensity parameter (to be determined), which describes the capacity of drivers to predict the travel time of different routes in the model. If $\theta = +\infty$, the driver will select the route with the shortest time with probability 1; if $\theta = 0$, the driver will select the route randomly (Patriksson, 2015). ξ_i is the set of downstream links for node *i*. The traffic time on each link at a given time point , $TT_{t,k}$, is calculated using the Bureau of Public Roads (BPR) function : $TT_{t,k}(x_{t,k}) = \mathrm{tt}_0 \left(1 + \alpha \cdot \frac{x_{t,k}}{C_0 \cdot LN}\right)^{\beta}$, which reflects the monotonic relationship between traffic flow ($x_{t,k}$) and time cost on a given link, with tt_0 as the free-flow (unimpeded) travel time of the link, C_0 the traffic carrying capacity of one lane, LN the number of lanes of that given link, and α and β two parameters related to the link type (estimated by Feng & Lin (2021) based on camera observations along eight highways for Hurricane Irma). $TT_{t,k,post}$ is calculated based on the current traffic conditions on forthcoming travel links, using the shortest road algorithm on a sparse matrix (SPSM) (Johnson 1977).

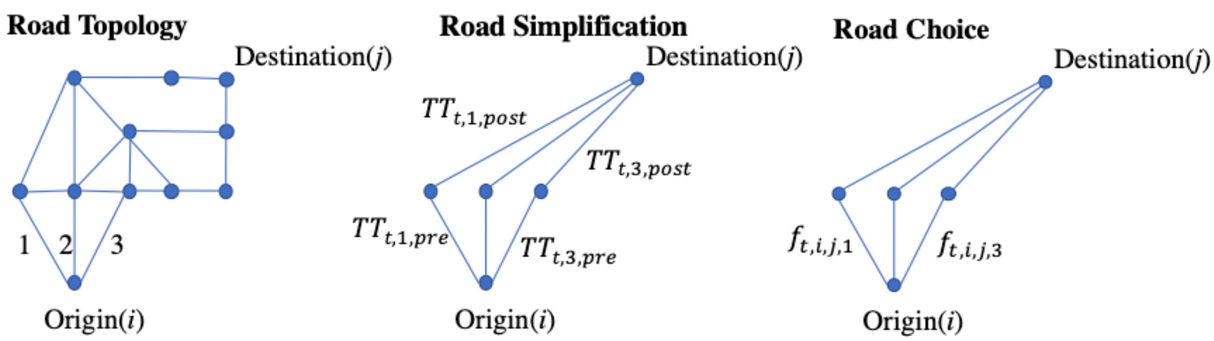

Fig 2. Illustration of link choice probability estimation for a household at origin (*i*) to travel to destination (*j*) based on the travel time on the next link ($TT_{t,k,pre}$) and the estimated least travel time for the forthcoming route ($TT_{t,k,post}$).

Further, the fractions of evacuees at node *i* travel through the downstream link *k* is:

$$\mathrm{f}_{\mathrm{t,i,k}} = \sum_{j \in \phi} \mathrm{f}_{\mathrm{t,i,j,k}} \cdot \mathrm{G}_{\mathrm{t,i}}(j) \, / \sum_{j \in \phi} \mathrm{G}_{\mathrm{t,i}}(j) \qquad (5)$$

where $\mathrm{G}_{\mathrm{t,i}}(j)$ is the gravity weight function in Eq. 3 and ϕ is the set of all the nodes (possible destinations) in the transportation system.

This route choice model assumes that evacuees are myopic, focusing on the traffic condition directly ahead, and optimistic about the forthcoming traffic (Lindell and Prater, 2007), avoiding the large computational cost caused by enumerating over all the possible routes between each OD pair. From a microscopic perspective, this model might be over-simplified given that many evacuees may make route choice based on route familiarity or concern about loss of GPS or cell phone access (Lindell et al. 2019). However, it needs to be noticed that, the route choice model applied here is statistical and aiming at predicting the macroscopic traffic flow of evacuation. The microscopic mechanism might be biased from the reality as many factors related to the decision making process are not involved, which should be addressed in future research. For research focusing on agent-level routing mechanisms, other en-route model could be used to substitute the model employed here with pre-defined parameters or unknown parameters that could be fitted with this framework. In addition, by assuming a BPR function for each link, we cannot explicitly model micro-traffic behaviors on onramps/interchanges/weaving areas, while Dixit et al. (2011) found that onramps and interchanges may significantly impede the traffic and propagate congestions upstream and downstream. Future work may further improve the predictive capability of this model by adopting micro-traffic behavior modular from existing models(Lindell et al. 2019).

2.4 Markov decision-based mean-field dynamic evacuation model

If we compose the link fractions of all the nodes together, we obtain a Markovian transition matrix ($\mathrm{M_t}$) for all the n nodes in ϕ and m links in ξ at time t:

$$\mathrm{M}_{\mathrm{t}}^{m\times n} = \begin{bmatrix} f_{t,1,1} & \cdots & f_{t,n,1} \\ \vdots & \ddots & \vdots \\ f_{t,n,1} & \cdots & f_{t,n,m} \end{bmatrix} \tag{6}$$

The evacuating population on all the nodes follows this matrix to flow into each link:

$$\delta\vec{\mathrm{x}}_{t,in}^{m\times 1} = \mathrm{M}_{\mathrm{t}}^{m\times n} \cdot (P_t^{n\times 1} \otimes \mathrm{N}_{\mathrm{t}}^{\mathrm{n}\times 1}) \tag{7}$$

where $\delta\vec{\mathrm{x}}_{t,in}^{m\times 1}$ is the inflow into road network at time t, estimated by coupling the population remained at each node ($\mathrm{N}_{\mathrm{t}}^{\mathrm{n}\times 1}$), the probability for them to go out for evacuation ($P_t^{n\times 1}$), and the probability for them to choose one specific link ($\mathrm{M}_{\mathrm{t}}^{m\times n}$). Operator $\otimes$ is the Hadamard product (referring to component-wise multiplication of the same dimension).

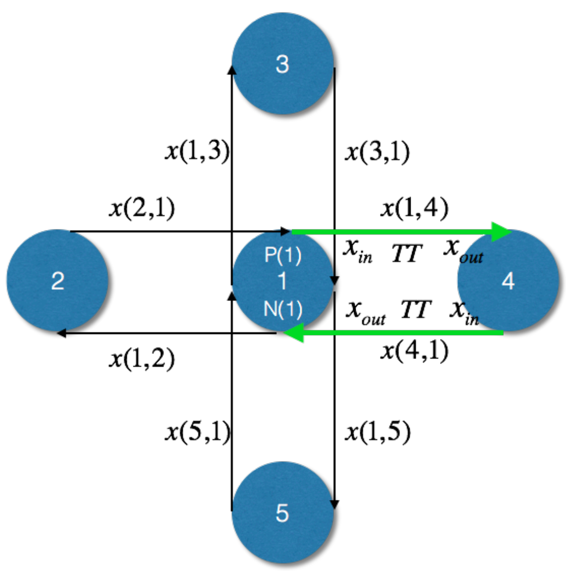

Fig. 3: The Link Transformation Schematic Diagram. The central node 1 has 4 links out and 4 links in, while each link is defined by a directed number set of two node numbers. At a given

time point, each node has two quantities: evacuation probability for each household P and node population N, while each link has an instantaneous traffic flow x, an out traffic x_{out} (flow into nodes), an inward traffic x_{in}, and a time cost TT based on traffic flow x.

The traffic flows on the road network, as illustrated in Fig 3, can be described by the dynamic traffic flow equation set:

$$\begin{cases} d\vec{\mathrm{x}}_{t,in}^{m\times 1} = \mathrm{M}_{\mathrm{t}}^{m\times n} \cdot \left(\vec{P}_{t}^{n\times 1} \otimes \vec{N}_{\mathrm{t,node}}^{\mathrm{n}\times 1}\right) dt & (8) \\ d\vec{x}_{t,out}^{m\times 1} = \left(1 - \frac{d}{dt}\overrightarrow{TT}^{m\times 1}(t)\right) \otimes \vec{x}_{t-\overrightarrow{TT},in}^{m\times 1} dt & (9) \\ \overrightarrow{TT}^{m\times 1}(t) = BPR\left(\vec{x}_{t-\overrightarrow{TT}}^{m\times 1}\right) & (10) \\ d\vec{\mathrm{x}}_{t}^{m\times 1} = -d\vec{\mathrm{x}}_{t,out}^{m\times 1} + d\vec{\mathrm{x}}_{t,in}^{m\times 1} & (11) \\ d\vec{N}_{\mathrm{t,i}}^{\mathrm{n}\times 1} = H_{out}^{n\times m} \cdot d\vec{\mathrm{x}}_{t,out}^{m\times 1} - H_{in}^{n\times m} \cdot d\vec{\mathrm{x}}_{t,in}^{m\times 1} & (12) \end{cases}$$

where *t* is the time point under discussion, $\vec{x}$ is the vector of the traffic flow on each link, and $\vec{x}_{in}/\vec{x}_{out}$ is the traffic inflow/outflow vector. $\overrightarrow{TT}$ is the traffic time cost vector calculated by the BPR function. Eq. 8 describes the outgoing population from one node into the road network as discussed in Eq. 7. Eq. 9 describes the outgoing population from a link section into a node considering the changing vehicle density. Eq. 10 calculates the travel time of each link based on the traffic information. The travel time of the link is determined by the traffic flow at the beginning of the travel period on the link. Eq. 11 is the continuity law for a link section: the current number of vehicles on this link section is decided by the vehicles flowing in/out at this time moment. Eq. 12 describes the relationship between nodes and links: the vehicles flowing out of a link should be absorbed into a node and then assigned to another link or stay in that node. However, if the population of each node exceeds its capacity during the calculation process, the over-capacity population will be directly assigned to the following links by the Markovian transition matrix (Eq. 6). This model can trace the proportion of vehicles at a given intermediate node that began their evacuation from a specific origin node by multiplying the Markovian transition matrix of link choice with the distribution of local population at each time step. The ability to trace the distribution of the origin of vehicles is critical for calibrating traffic assignment models (Ma & Qian 2018) or optimizing transportation policies (Yi et al. 2017).

Eqs. 8-12 is a Lipchitz full-rank ordinary differential equation set and can be solved with the Euler method efficiently. At each time step, $M_t^{m \times n}$ is calculated using the SPSM method, and $\overrightarrow{TT}$ is calculated using a one-dimension search. Each step of this simulation model is computational efficient because of the matrix structure of the datasets and operators. The simulation time for each time step is in $O(n \vee m)$ because both sparse matrix multiplication and SPSM are $O(n \vee m)$ algorithms. The link number (n) is larger, and almost certainly much larger, than the node number (m) in any evacuation route system. Hence, the algorithm usually takes computational time in O(n). For a temporal resolution $\delta t,$ the entire simulation would take computational time in $O\left(n \cdot \left[\frac{T}{\delta t}\right]\right)$. This time cost is much smaller than that for the traditional dynamic traffic analysis methods, which use piece-wise linearization methods and take the computational time in $O\left(n^{3.5} \cdot \left[\frac{T}{\delta t}\right]^2\right)$ on average (Ma & Qian 2018). Taking advantage of the high-efficiency packages built for matrix calculation, the full 5-day simulation for Florida can be finished in 10 seconds on one core of a single PC. This computational efficiency brings the convenience to search over a very wide parameter space for fitting/calibrating the model. All the simulations in this paper are conducted on a desktop with an Intel Core i9-9900 K CPU 4.30 GHz ×8,4400 MHz 4 ×16 GB RAM, 4 TB SSD.

2.5 Datasets and model calibration

To accomplish the hurricane evacuation simulation, we first need to obtain data about the transportation network. Overviews of Florida and the major highways on the transportation network are shown in Figure 4a. Florida has an area of around 170,000 km^2 and a population of ~ 20 million in 2017 (Fig. 4b). (As a reference, ~6 million people were involved in Irma's evacuation process, with a mean travel distance of ~200 miles; Feng and Lin 2021.) The transportation network abstracted from the GIS data provided by the Federal Highway Administration (FHWA) is modeled as consisting of 1520 nodes and 5767 links (Federal Lands Highway 2018). The speed limit of each highway can be found in the FHWA data set (Florida Traffic Information 2018). Typically, a major interstate highway or turnpike has design speeds of 70 miles/h. A state road has a design speed of 45 or 55 miles/h. The parameters for calculating travel time in the BPR function come from the highway criterion and the over-normal-capacity (i.e., ratio of traffic flow to link capacity larger than 2.5) speed is assumed to be 10 miles/h (BPR; Li et al. 2010; Feng & Lin 2021). Under hurricane evacuation, roadway shoulders were open for evacuation traffic on four corridors: I-75 Alligator Alley; I-75 from Wildwood to the Georgia state line; I-10 from Jacksonville to I-75; and I-4 from Tampa to Orlando. This operation requires fewer resources than contraflow plans, which reverse lanes to make highways one-way only. This operation is also considered in the evacuation simulation.

The hurricane prediction comes from the National Oceanographic and Atmospheric Administration (NOAA; Irma Prediction and Record 2017), providing the hurricane observation at each time point and also the changing hurricane prediction over time (the projected trajectory and hurricane intensity). The storm surge prediction is also included (the probability of surge to be 10 ft above mean sea level; USGS 2017). The time series of spatial governmental evacuation orders come from the Florida Traffic Administration (Florida Traffic Information 2018). Here we estimate the capacity of each city with governmental reported shelter numbers (TCpalm 2017) and hotel room numbers (STR 2017). Notice that the city capacity contains not only the shelters and hotels opening but also the friends' or relatives' houses, which are difficult to estimate and not modeled in this paper. The impact is small for high-risk areas, where the evacuation rate is high and those evacuated can not accommodate others. However, the under-estimation of housing resources may lead to an over-estimation of evacuation flow at low-risk regions, where many evacuees may be accommodated in their friends' or relatives' houses (Lindell et al. 2019).

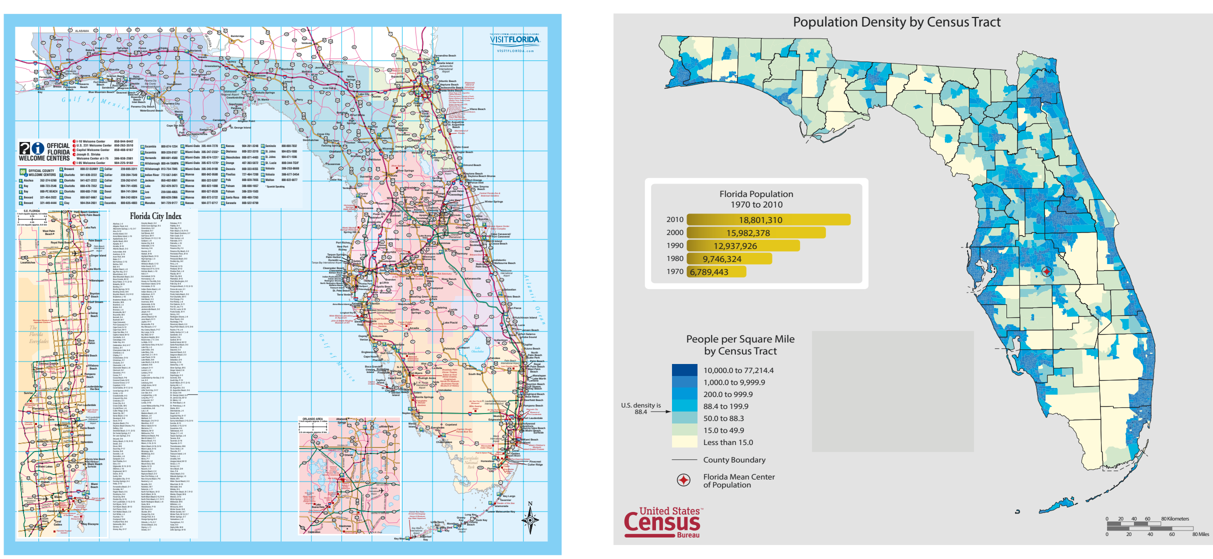

Fig. 4. Road network and population distribution of the State of Florida. (a) Road map (FBT 2017). (b) Population distribution census data (Census Bureau 2010).

To carry out the evacuation simulation, the parameters of the human behavior models, including the traffic demand model (Eq.1-2), the dynamic OD model (Eq.3), and the route choice model (Eq.4), must be known. The discrete choice model in the traffic demand model has six parameters in total, the dynamic OD model has three parameters, and the route choice model has one parameter. These parameters can be derived from earlier research, for example, Gudishala and Wilmot (2013) for the traffic demand model, Erlander and Stewart (1990) for the OD model, Bekhor et al. (2012) (with Highway Capacity Manual (1985) for the BPR function) for the route choice model. By including these parameters, our model could forecast evacuation traffic. However, in this study, we obtain these parameters through fit/calibrate the model using available observations. The data on traffic flow and traffic speed on the major highways (including portions of Routes 1 and 27 and I-75, I-95, I-4, and I-10) come from the Florida Department of Transportation (FDOT, 2017). The traffic data indicates the number of vehicles that passed the camera every three hours. Feng and Lin (2021) used these FDOT traffic camera data from major highways to reconstruct the traffic flow (every three hours) for all links in Florida with a speed restriction greater than 35 mph during Hurricane Irma using game theory. Here we make use of this reconstructed dataset to fit the model, as it contains estimated evacuation rate out of each node at each time point for both main highways and local links. We use the original camera data from FDOT for highways to evaluate the fitted model.

Among the calibration parameters, those in the traffic demand model have the most impact on simulation outcomes. Thus, a two-stage calibration framework is used. First, Feng & Lin's (2021) reconstructed dataset gives the evacuation rate for each area every three hours. We fitted the binary logit model for evacuation (Eq. 1-2) using the reconstructed traffic demand and predictors (i.e., hurricane and storm surge projections, evacuation order, hurricane category, time of day, and evacuation rate at each time point for each location; Table 1). We additionally extract data on the destination distributions from the reconstructed dataset using the agent-based model presented in Feng et al. (2020b), and we use the reconstructed OD matrix to fit the gravity model parameters using log-linear regression [Eq.3; $\alpha = 1.35(1.21 - 1.49), \beta = 0.73(0.67 - 0.79)$ and $\gamma = 1.74(1.69 - 1.79)$]. Then, only one parameter (diversion intensity) in the Route Choice Model (Eq. 4) remains to be calibrated, and hence we employ one-dimension search to minimize the mean square error between the observed highway traffic and the simulated data (θ = 0.021 (0.019~0.023) per minute). The confidence interval for this parameter is determined using bootstrapping (sampling a 90% subset from the observation to fit the model).

3 Simulation Results and Implications

3.1 Simulation Results

The simulation provides a relatively close match to the real global traffic conditions, including at two peak evacuation periods: the evening of 9/06/17 & 9/07/17 (Fig. 5). The model captures the spatial-varying traffic peaks. In lower Florida, where the hurricane risk was high, including Key West, Miami, and Tampa, the model matches well with real data. Our model shows a larger amount of traffic on the upper east coast of Florida compared to the real data, possibly because the model overestimated the number of people leaving Florida while many stayed on the upper east coast (in homes of relatives or friends; not modeled). In remote downstream areas without much hurricane risk (Pensacola, Tallahassee), the model shows some distortion. This is partly because of the cumulative error diffused from the upstream evacuation simulation. Also, as these areas had low hurricane risk, the daily traffic might be still functioning, which our hurricane evacuation model does not consider.

The observed traffic volume time series of main highways are also compared with simulated traffic conditions in Fig. 6. Generally, the simulation matches the temporal patterns in camera records. The model underestimates the night traffic volume for some cameras and dates (e.g., cameras 322 and 428). This underestimation may be induced by an overestimation of the capacity for the upstream cities, as we assume all the hotels are available when the hurricane comes, and Orlando, which is upstream of cameras 322 and 428, has a large hotel volume. The simulation also overestimates the traffic at camera 322 for 9/5; this uncertainty may be induced by the fact that Orlando residents had lower evacuation willingness than predicted, given its relatively greater distance from the coast, a parameter not directly included in the model.

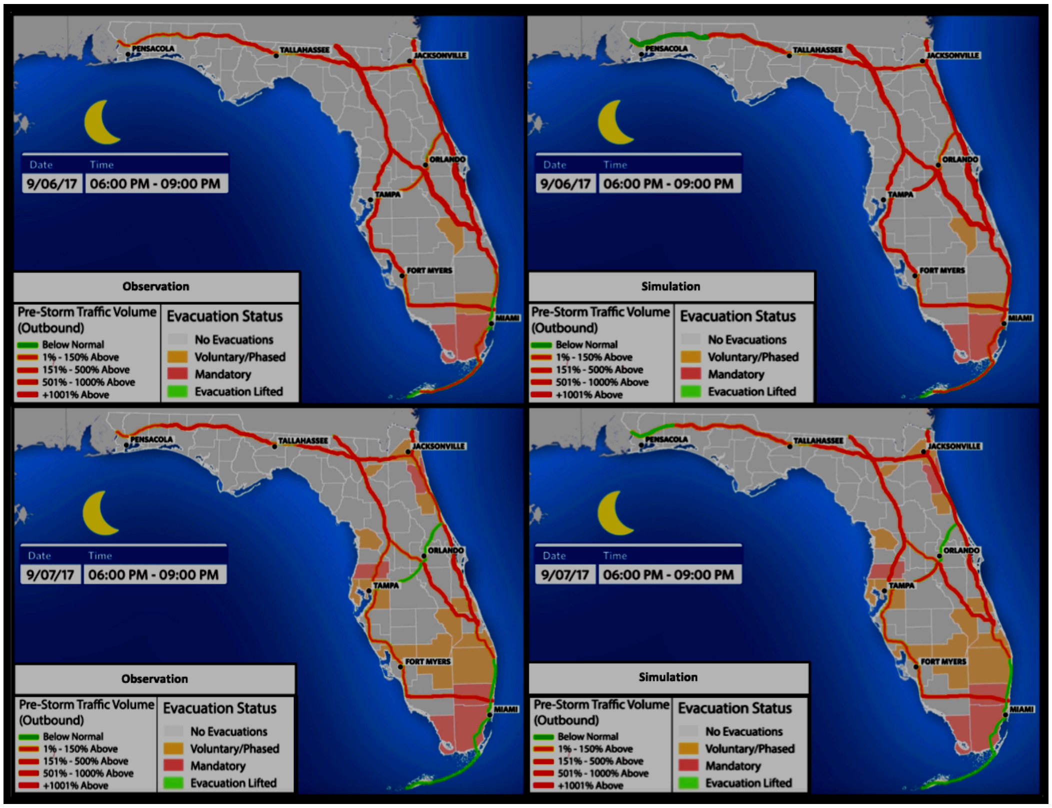

Fig. 5. Simulation results of global traffic conditions compared with observations on 9/6 and 9/7 evenings (color indicates traffic volume relative to normal traffic; shadows show the evacuation order status).

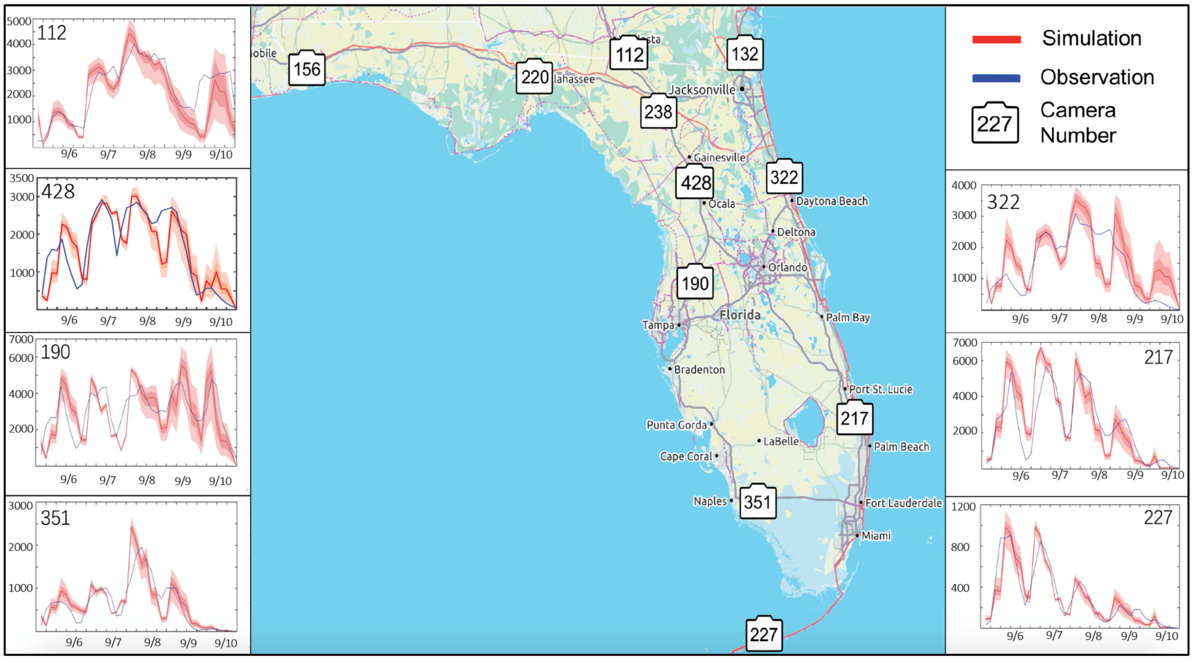

Fig. 6. Simulation results of local traffic conditions compared with observations from 7 cameras (blue lines show the observed traffic volume; red lines show simulations of the traffic volume; the unit for the traffic volume is veh/h).

3.2 Implications of the analysis results

Many empirical studies have evaluated the OD model and link choice model. However, whether the traffic demand model derived from experiments conducted in lab contexts accurately predicts global traffic flow warrants more examination. Thus, it is intriguing to analyze the parameters in the fitted traffic demand model (Table 1). Comparing the fitted parameters and those estimated by a social questionnaire survey for Louisiana residents in Gudishala & Wilmot (2013) enables an examination of various factors involved in Florida residents' evacuation decision-making process during Hurricane Irma. We follow the variable definitions in Gudishala & Wilmot (2013), except that they considered the storm surge risk as whether the storm surge was greater than 10 ft (0 or 1) while we use the forecasted probability (0-1) of experiencing 10-ft surge above the mean sea level, as in real cases the hurricane information is forecasted and uncertain.

Table 1. Fitted parameters in the traffic demand model compared with the survey-based estimates in Gudishala & Wilmot (2013). The corresponding variables are evacuation order (Boolean factor for voluntary or mandatory evacuation), hurricane category (forecasted category when hurricane makes landfall, 0~5), time of the day (reflected by 3 Boolean dummy variables: TOD1 (12:00 a.m.~6:00 a.m.); TOD2 (6:00 a.m. ~ 12:00 p.m.); TOD3 (12:00 p.m.~18:00 p.m.)), Time-dependent distance (log-normed distance from the storm), and storm surge risk (forecasted probability of experiencing 10-ft surge above the mean sea level).

VARIABLE	EVACUATION ORDER	HURRICANE CATEGORY	TOD1	TOD2	TOD3	DISTANCE	STORM SURGE
ESTIMATE	0.110 (0.100~0.120)	0.145 (0.140~0.150)	-0.032 (-0.037~-0.027)	0.040 (0.034~0.046)	0.037 (0.032~0.043)	148.2 (138.4~158.0)	0.015 (0.011~0.019)
G&W 2013	0.112 (0.039~0.185)	0.080 (0.056~0.103)	0.208 (-0.075~0.117)	0.325 (0.229~0.421)	0.140 (0.041~0.240)	128.6 (69.0~188.3)	0.154 (0.029~0.279)

The comparison of the model parameters (coefficients) shows that people were concerned about the hurricane category more in the case of Irma, possibly because the notifications given by the government made people trust that hurricane Irma was the "worst hurricane in 50 years" and would "harm their life" (CNN 2017). Also, the impact of hurricane category on human reaction is nonlinear. The questionnaire survey covered category-2~4 hurricanes, but Irma was a much stronger (category-5) hurricane. The TOD1 (nighttime) effect is dramatically different between the Irma analysis and the survey result. Residents seemed unwilling to evacuate at nighttime during Irma, which is quite natural, as in real life, people tend to be less likely to evacuate at nighttime than in the evening. The positive coefficient for TOD1 in the questionnaire survey result may reflect the bias of the questionnaire result based on a single experiment (Gudishala & Wilmot 2013). On the questionnaire survey, people may choose evacuation at night, considering benefits of traveling in light traffic. However, in real decision-making scenarios, the difficulty of driving at night (darkness, fatigue, cold, etc.) may outweigh the benefit of light traffic conditions (Huang et al. 2012 and Huang et al. 2017). This difficulty-ignoring-advantage-enlarging (or opposite) effect of participants often appears in survey investigations and is difficult to correct (Shrout et al. 2018). We also find that the evacuation rate did not change tremendously during the day as shown in the Gudishala and Wilmot (2013) survey. The storm surge risk was found to have a much smaller influence on evacuation probability than that in the survey. This limited influence might have occurred because before Irma, the storm surge projection was not highlighted, and people might have focused more on the hurricane track and category projection, relative to the survey estimates. Storm surge threat has been found to be an important motivator for people to evacuate in many events (Huang et al., 2016), but not in some other events (Wei et al., 2014). It may be important for the government to emphasize more on possible surge risk for surge-prone areas. We also observe that people weighed distance to the storm slightly more when making evacuation decisions compared to the results from the survey (Gudishala and Wilmot, 2013).

It is natural to compare the model's performance under Irma's specific parameters with the general parameters given in Gudishala & Wilmot (2013). Here we perform a numerical experiment by varying the input behavioral parameters. We set the routing and destination choice parameters to be the same as in Section 3.1, but we set the evacuation parameters of the demand model as in Gudishala & Wilmot (2013). We show the corresponding results in Fig. 7 for highways 217, 351, and 428. The root mean square error (averaged over the time window of the simulation) of the modeled results with the parameters in this paper are 146 veh/hr, 43 veh/hr and 85 veh/hr, for highways 217, 351, and 428, respectively. The root mean square error of the modeled results with the Gudishala & Wilmot (2013) parameters are 194 veh/hr, 61 veh/hr and 173 veh/hr. The error of the simulation results with the parameters obtained in this paper is correspondingly 25%, 30%, 51% smaller than the error of the simulation results with the Gudishala & Wilmot (2013) parameters. The Gudishala and Wilmot (2013) parameters generally underestimate the peak traffic volume and largely underestimate the total evacuation volume (Fig. 7). The results indicate that, under different hurricanes, evacuation behavior may change significantly. Thus, it is important to adjust evacuation parameters for difference locations and situations when possible.

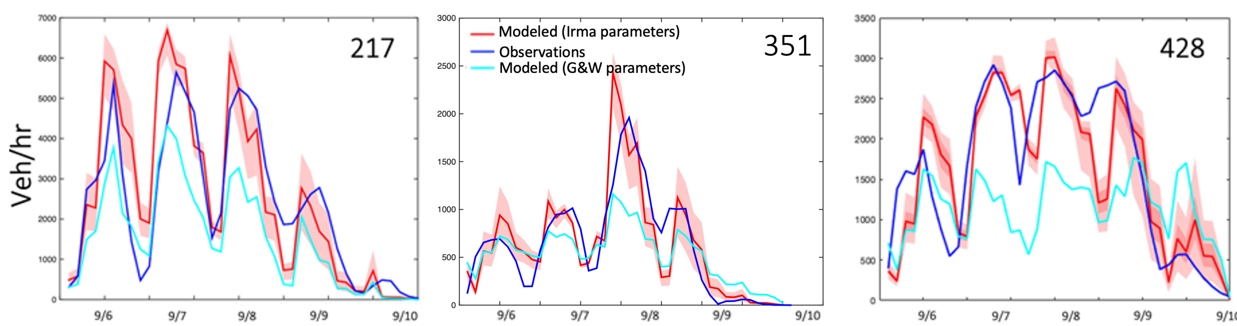

Fig. 7 The evacuation model performance under different demand parameters. Red lines show the fitted parameters results in Section 3.1, dark blue lines show the observations, and light blue lines show the traffic modelling with previous demand model parameters from Gudishala & Wilmot (2013).

4. Applications in Evacuation Management

The analysis of the evacuation process of Hurricane Irma reveals some potential to improve evacuation management. One possible solution for reducing traffic is to reserve lanes (contraflow plans) for evacuation traffic flow (Urbina and Wolshon 2003); however, this strategy was not applied in Florida during Hurricane Irma because of logistical concerns. In this section, we discuss the potential improvement on the traffic that coordinated evacuation orders may lead to. The implementation of coordinated evacuation orders is difficult in reality, as it should be noticed that every city in Florida has the authority to issue evacuation orders. However, these orders sometimes created interference. For example, Miami ordered its residents to evacuate the morning of 9/6, and it took the evacuees about a day (estimated with a large standard deviation using reconstructed traffic time in Feng and Lin 2021) to reach Orlando. Those Miami residents kept going northward on 9/7 in the morning and merged with those evacuating from Tampa, who evacuated the morning of 9/7. Therefore, the two traffic peaks from Miami and Tampa merged and blocked I-75 (No. 428 camera).

Here we employ a simple illustrative analysis using the developed model to show its application for improving evacuation management. Considering that the Miami evacuees happened to converge with Tampa evacuees during the evacuation, we slightly adjust the evacuation order to separate their evacuation peaks. The evacuation order in Miami is set to be earlier for 1 day in our model, and the traffic flow time series output of I-75 (No. 428 camera; the most crowded link section during the evacuation process, with traffic flow ~2 times its normal volume) is monitored. In this case, the traffic simulation result (Fig 8, purple curve) shows that the evacuation peak for I-75 decreases significantly, by 10% (from 3064 to 2770 veh/h). The total evacuation process (i.e., 95% vehicles have reached their destinations or left Florida) is half a day longer, but it still finishes half a day before the predicted hurricane landfall (predicted as 9/10 morning on 9/6 afternoon). To further test the sensitivity of the traffic to the evacuation order, we also perform experiments that set Tampa's evacuation earlier by 1 day (orange curve) and Tampa's evacuation later by 1 day (green curve). Setting Tampa's evacuation earlier by 1 day will enlarge the traffic peak by 10%, while setting it later by 1 day will not affect the traffic peak. These results show that a slight change in evacuation orders may greatly change the evacuation traffic, and thus the local government holds the power to better manage the hurricane evacuation. We argue that it is beneficial for the government to establish coordinated evacuation management to make evacuation decisions more temporally and spatially consistent, based on simulations using an efficient global traffic prediction model such as the one developed here.

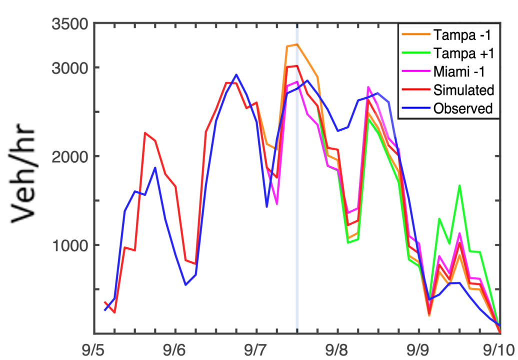

Fig. 8. Comparison of traffic simulation results for the original and hypothetical evacuation orders on Route 428. Blue curve shows the observed traffic flow. Red curve shows the simulation result with the original evacuation order. Orange/green curve shows the simulation result with the evacuation order in Tampa set one day earlier/later. Magenta curve shows the

simulation results with the evacuation order in Miami set one day earlier. The light blue line marks the time of peak evacuation traffic.

Another observed challenge of the evacuation management is associated with the uncertainty of hurricane projection. For 9/5~9/7, the predicted track of Hurricane Irma swayed across Florida from east coast to west coast. When it was predicted to head towards Miami, residents on the Atlantic Coast feared the worst, and many on the west side of the state felt safer. By 9/9, however, the storm track shifted to the west, putting Gulf Coast cities like Naples, Fort Myers, and Tampa at risk of the most punishing winds and storm surge. Floridians who had traveled from east coast cities to the west in search of safety felt confused, as did those living in the west. Collier County (between Tampa and Miami) did not order its evacuation until 9/8; Collier County experienced a wind gust of 142 mph, 65 homes were demolished (1,008 homes had major damage), and two deaths occurred. Thus, hurricane forecasting modeling with high precision is critical for hurricane evacuation management, especially for Florida, which may be affected by hurricanes from different directions and in need of long-distance evacuation routes due to its long and narrow geophysical shape. The efficient evacuation simulation model we developed here can be used for ensemble forecasting of the traffic flow to account for the uncertainties in hurricane projection. In addition, the efficient model can be applied in real time and updated as hurricane prediction progresses.

Finally, the evacuation prediction model can be used to study evacuation decision-making. For example, the findings in the behavioral analysis in this paper suggest that it is better for local governments and media to highlight the surge risk. Better risk communication may help people make better evacuation decisions based on their real risks. In turn, with better risk communication, people might have more confidence in local evacuation orders and behave more as predicted, which could also help in the design of more rational evacuation policy.

4 Conclusion

Hurricane evacuation management is extremely difficult due to a paucity of data on extreme events, the complexity of human decision-making and travel behavior, and the high degree of uncertainty associated with storm predictions. To address some of these challenges, we built a framework for fast hurricane evacuation prediction that is based on storm forecasts, evacuation orders, and road network and population data. The system integrates a traffic demand model, an origin-destination model, and a route choice model into a link flow-based mean-field traffic model, simplifying the agent-based simulation to a road-level simulation while still keeping the agent-level information. In comparison to existing evacuation models, ours does not require an artificial or case-specific OD input to match the peak traffic observations; our model uses only hurricane predictions and evacuation orders as input for each time point. With its outstanding computational efficiency and simple modeling structure, the model may be used to investigate the effect of many factors on the evacuation process, such as hurricane projection and evacuation orders.

We employ the case of Hurricane Irma (2017), the largest evacuation that has happened in Florida, to test the efficiency, predictive capability, and interpretability of the proposed framework. Given the high computational efficiency of the framework, we can simulate a large-scale evacuation such as in Hurricane Irma, which involved ~6000 links and ~4 million vehicles, in 10 seconds on a personal computer. This computational efficiency enables the model to be calibrated by searching through a large parameter space. The model is found to accurately capture the temporal and spatial evacuation characteristics of Irma, including traffic peaks. The model fits well with observations in lower Florida, including Key West, Miami, and Tampa, where the anticipated hurricane risk was high. The incorrect prediction occurs solely in upper Florida, where the storm risk was lower and daily traffic might have continued to operate normally, which our hurricane prediction model did not consider. In future work, we will compare this model with other evacuation models which may potentially be used for state-scale evacuation modeling as listed in Hardy and Wunderlich (2007) on their prediction accuracy and computational efficiency.

As an application, the model can be used to investigate evacuation behavior through fitting behavioral parameters in the model with the traffic observations. Compared to parameters derived from a previous survey-based study by Gudishala and Wilmot (2013), the behavioral characteristics revealed by this model are within reasonable ranges. However, our fitted parameters indicate that coastal residents were more concerned with the hurricane category scenario and were significantly less willing to evacuate at nighttime during Hurricane Irma. As a result, the evacuation traffic predicted using fitted behavioral parameters and using the Gudishala and Wilmot (2013) parameters differ significantly in terms of peak evacuation flow and night evacuation rate, and the Gudishala and Wilmot (2013) prediction significantly underestimates the evacuation traffic in terms of traffic congestion and total evacuation amount. The multi-stage parameter fitting strategy utilized in this paper could be viewed as a data/model-driven approach complimentary to survey-based models.

Moreover, the model can be used to assist government decision making during the evacuation process. Our analysis indicates that releasing the evacuation order one day earlier in the Miami region might result in a 10% reduction in peak traffic flow on the most congested route without delaying the evacuation. Beyond optimizing evacuation orders, a variety of different evacuation tactics can assist in mitigating link congestion and ensuring a safe evacuation. Due to the model's computational efficiency, these diverse strategies, including opening road shoulders and reserving lanes (counter side), may also be easily examined in our model by modifying the input road network data.

Individual behaviors are likely to have a significant impact on the global evacuation (as also shown in this paper). The behavioral parameters in this paper were estimated from one single event (Irma) for a specific region (Florida). Future studies should assess the degree to which these parameters can predict the evacuation flows in other regions affected by hurricanes with various features. Our simulation is based on an estimation of the volume of unoccupied shelters and hotels for destination selection, assuming that the majority of households in high-risk areas will evacuate (Feng and Lin 2021) and so will be unable to accommodate evacuees/peers/friends from other regions. Because the majority of people in upper Florida would stay home and could accommodate their friends, and previous research indicates that 62 percent of evacuating households may stay in peers' homes (Lindell et al., 2019), our modeling may be biased for low-risk areas. As a result, our simulation results are consistent with observations for lower Florida, while our model overestimates the traffic flow for upper Florida (also due to the fact that local commuting traffic is not included in the current model for those less impacted areas). To more accurately predict the evacuation process for low-risk areas, the model needs to account for the proportion of households in the evacuating city that have peers in other cities ready to accommodate them during an evacuation (Lindell et al. 2019); this model extension is left for future study. Additionally, thanks to our model's computational efficiency, it can be updated in real time in response to changing traffic conditions. In a subsequent study, we will construct a temporally evolving framework for updating the traffic model with real-time observations as the event evolves, enabling the model to adapt flexibly to a variety of events and human behaviors.

ACKNOWLEDGMENTS:

This material is based upon work supported by the National Science Foundation (grant 1652448). We also thank the Florida Department of Transportation for providing the camera data during Hurricane Irma.

Declarations of interest: none

Reference:

Ahmed, Md Ashraf, Arif Mohaimin Sadri, and Mohammed Hadi. "Modeling social network influence on hurricane evacuation decision consistency and sharing capacity." Transportation research interdisciplinary perspectives 7 (2020): 100180.

Bekhor, S., Chorus, C. and Toledo, T., 2012. Stochastic user equilibrium for route choice model based on random regret minimization. Transportation research record, 2284(1), pp.100-108.

Bergstra, J., Yamins, D., & Cox, D. (2013). Making a science of model search: Hyperparameter optimization in hundreds of dimensions for vision architectures. In International Conference on Machine Learning (pp. 115-123).

Branston D.Link capacity functions: A review. Transportation Research, 1976, 10(4): 223-236.

Brodar, Kaitlyn E., et al. ""My Kids Are My Priority": Mothers' Decisions to Evacuate for Hurricane Irma and Evacuation Intentions for Future Hurricanes." Journal of Family Issues41.12 (2020): 2251-2274.

Brown, C., White, W., van Slyke, C., & Benson, J. D. (2010). Development of a Strategic Hurricane Evacuation-Dynamic Traffic Assignment Model for the Houston, Texas, Region. Transportation Research Record: Journal of the Transportation Research Board, 2137(1), 46–53. https://doi.org/10.3141/2137-06

Bureau of Public Roads 1964, "Traffic assignment manual," Office of Plan- ning, Urban Planning Division.

Census Bureau 2010 https://www2.census.gov/geo/maps/dc10_thematic/2010_Profile/ Last Visited 03-02-2018

Chen, X., Meaker, J. W., & Zhan, F. B. (2006). Agent-based modeling and analysis of hurricane evacuation procedures for the Florida Keys. Natural Hazards, 38(3), 321.

Chiu, Y.-C., Zheng, H., Villalobos, J. A., Peacock, W., & Henk, R. (2008). Evaluating Regional Contra-Flow and Phased Evacuation Strategies for Texas Using a Large-Scale Dynamic

Traffic Simulation and Assignment Approach. Journal of Homeland Security and Emergency Management, 5(1). https://doi.org/10.2202/1547-7355.1409

CNN 2017 https://edition.cnn.com/2017/09/06/americas/hurricane-irma-caribbean-islands/index.html last visited: 03-18-2018

Collins, Jennifer, et al. "The effects of social connections on evacuation decision making during Hurricane Irma." Weather, climate, and society 10.3 (2018): 459-469.

Czajkowski, J., & Kennedy, E. (2010). Fatal tradeoff? Toward a better understanding of the costs of not evacuating from a hurricane in landfall counties. Population and Environment,31(1/3), 121-149.

Deo, N. (2017). Graph theory with applications to engineering and computer science. Courier Dover Publications.

Dia, H. (2002). An agent-based approach to modelling driver route choice behavior under the influence of real-time information. Transportation Research: Part C, 10, 331. https://doi.org/10.1016/S0968-090X(02)00025-6

Dow, K., Cutter, S.L., 2002. Emerging hurricane evacuation issues: hurricane Floyd and South Carolina. Natu. Hazards Rev. 3, 12–18. doi: 10.1061/(ASCE) 1527-6988(2002)3:1(12) .

Erlander, Sven, and Neil F. Stewart. The gravity model in transportation analysis: theory and extensions. Vol. 3. Vsp, 1990.

Evacuation Guide 2017 http://www.sun-sentinel.com/news/weather/hurricane/guide/fl-hurricane-fleeing-20170419-story.html Last Visited 03-02-2018

Federal Lands Highway 2018 https://flh.fhwa.dot.gov/about/ Last Visited 03-02-2018

Feng, K. and Lin, N., 2021. Reconstructing and analyzing the traffic flow during evacuation in Hurricane Irma (2017). Transportation Research Part D: Transport and Environment, 94, p.102788.

Feng, K., Li, Q. and Ellingwood, B.R., 2020a. Post-earthquake modelling of transportation networks using an agent-based model. Structure and Infrastructure Engineering, 16(11), pp.1578-1592.

Feng, K., Lin, N., Xian, S. and Chester, M.V., 2020b. Can we evacuate from hurricanes with electric vehicles?. Transportation research part D: transport and environment, 86, p.102458.

Feng, K., Wang, C., Li, Q. , 2022. Fast Post-earthquake modelling of transportation system. Submitted to Structural Safety

Florida Backroads Travel(FBT 2017) https://www.florida-backroads-travel.com/florida-road-map.html Last Visited 03-02-2018

Florida Traffic information 2018 https://fdotwp1.dot.state.fl.us/TrafficInformation/ Last Visited 03-02-2018

Fu, H., Wilmot, C., 2004. Sequential logit dynamic travel demand model for hurricane evacuation. Transp. Res. Rec. 1882, 19–26. doi:10.3141/1882-03.

Fu, H., Wilmot, C.G., Baker, E.J., 2006. Sequential logit dynamic travel demand model and its transferability. Transp. Res. Rec. 1977, 17–26. doi:10.3141/1977- 05.

Ghorbanzadeh, Mahyar, et al. "Spatiotemporal analysis of Highway traffic patterns in Hurricane Irma evacuation." Transportation Research Record (2021): 03611981211001870.

Goodie, Adam S., Adithya Raam Sankar, and Prashant Doshi. "Experience, risk, warnings, and demographics: Predictors of evacuation decisions in Hurricanes Harvey and Irma." International Journal of Disaster Risk Reduction 41 (2019): 101320.

Gudishala, R., & Wilmot, C. (2012). Comparison of Time-Dependent Sequential Logit and Nested Logit for Modeling Hurricane Evacuation Demand. Transportation Research Record: Journal of the Transportation Research Board, 2312, 134–140. https://doi.org/10.3141/2312-14

Gudishala, R., & Wilmot, C. (2013). Predictive Quality of a Time-Dependent Sequential Logit Evacuation Demand Model. Transportation Research Board of the National Academies, Washington, D.C., 2013, pp. 38–44. DOI: 10.3141/2376-05

Hong, Lingzi, and Vanessa Frias-Martinez. "Modeling and predicting evacuation flows during hurricane Irma." EPJ Data Science 9.1 (2020): 29.

IRMA Prediction and Record 2017 https://www.nhc.noaa.gov/archive/2017/IRMA.shtml Last Visited 03-04-2018

Johnson, D.B. (1977). Efficient algorithms for shortest paths in sparse networks. Journal of the ACM 24(1), 1-13.

Li, A. C., Nozick, L., Davidson, R., Brown, N., Jones, D. A., & Wolshon, B. (2012). Approximate solution procedure for dynamic traffic assignment. Journal of Transportation Engineering, 139(8), 822-832.

Long, Elisa F., M. Keith Chen, and Ryne Rohla. "Political storms: Emergent partisan skepticism of hurricane risks." Science advances 6.37 (2020): eabb7906.

Ma, W. and Qian, Z.S., 2018. Estimating multi-year 24/7 origin-destination demand using high-granular multi-source traffic data. Transportation Research Part C: Emerging Technologies, 96, pp.96-121.

Marasco, David, et al. "Time to leave: an analysis of travel times during the approach and landfall of Hurricane Irma." Natural Hazards 103 (2020): 2459-2487.

Marsooli, R., Lin, N., Emanuel, K. and Feng, K., 2019. Climate change exacerbates hurricane flood hazards along US Atlantic and Gulf Coasts in spatially varying patterns. Nature communications, 10(1), pp.1-9.

Martín, Yago, Susan L. Cutter, and Zhenlong Li. "Bridging twitter and survey data for evacuation assessment of Hurricane Matthew and Hurricane Irma." Natural hazards review 21.2 (2020): 04020003.

Mesa-Arango, R., Hasan, S., Ukkusuri, S. V., & Murray-Tuite, P. (2013). Household-Level Model for Hurricane Evacuation Destination Type Choice Using Hurricane Ivan Data. Natural Hazards Review, 14(1), 11–20. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000083

Sadri, A.M., Ukkusuri, S.V., Murray-Tuite, P. and Gladwin, H., 2014. How to evacuate: model for understanding the routing strategies during hurricane evacuation. Journal of transportation engineering, 140(1), pp.61-69.

Nava, E., Shelton, J., and Chiu, Y.-C. (2012). "Analyzing impacts of dynamic reversible lane systems using a multi-resolution modeling approach." 91st Transportation Research Board Annual Meeting, Transportation Research Board, Washington, DC.

Patriksson M.. The traffic assignment problem: models and methods. Courier Dover Publications, 2015.

Pel, A. J., Bliemer, M. C. J., & Hoogendoorn, S. P. (2012). A review on travel behaviour modelling in dynamic traffic simulation models for evacuations. Transportation, 39(1), 97–123. https://doi.org/10.1007/s11116-011-9320-6

Pel, A. J., Bliemer, M. C., & Hoogendoorn, S. P. (2008). Analytical macroscopic modeling of voluntary and mandatory emergency evacuation strategies. In TRAIL in Perspective. Proceedings 2008, 10th International TRAIL Congress Netherlands TRAIL Research School.

Pel, A.J., Hoogendoorn, S.P., Bliemer, M.C.J., 2010. Impact of variations in travel demand and network supply factors for evacuation studies. Transportation Research Record: Journal of the Transportation Research Board 2196, 45–55.

Rahman, Rezaur, et al. "Assessing the crash risks of evacuation: A matched case-control approach applied over data collected during Hurricane Irma." Accident Analysis & Prevention 159 (2021): 106260.

Robinson, R. M., Foytik, P., & Jordan, C. (2017). Review and Analysis of User Inputs to Online Evacuation Modeling Tool. Transportation Research Board, 23435(17–06460), 9.

Shrout, P. E., Stadler, G., Lane, S. P., McClure, M. J., Jackson, G. L., Clavél, F. D., … Bolger, N. (2018). Initial elevation bias in subjective reports. Proceedings of the National Academy of Sciences, 115(1), E15–E23. https://doi.org/10.1073/pnas.1712277115

Simini, F., González, M. C., Maritan, A., & Barabási, A. L. (2012). A universal model for mobility and migration patterns. Nature, 484(7392), 96-100.

Skyrms, B., & Pemantle, R. (2009). A dynamic model of social network formation. In Adaptive networks (pp. 231-251). Springer, Berlin, Heidelberg.

Staes, Brian, Nikhil Menon, and Robert L. Bertini. "Analyzing transportation network performance during emergency evacuations: Evidence from Hurricane Irma." Transportation Research Part D: Transport and Environment 95 (2021): 102841.

STR2017, https://www.strglobal.com

Tampa Bay Journal http://www.tampabay.com/news/weather/hurricanes/just-imagine-15-million-in-evacuation-gridlock-as-a-hurricane-aims-at/2323818 Last Visited 03-02-2018

TCPalm 2017, http://data.tcpalm.com/storm-shelters/

Urbina, E., & Wolshon, B. (2003). National review of hurricane evacuation plans and policies: A comparison and contrast of state practices. Transportation Research Part A: Policy and Practice, 37(3), 257–275. https://doi.org/10.1016/S0965-8564(02)00015-0

Wall Street Journal https://www.wsj.com/articles/SB10001424052970203880704578084701930663668 Last Visited 03-02-2018

Wang, S., and Toumi, R. 2016 "On the relationship between hurricane cost and the integrated wind profile." Environmental Research Letters 11.11: 114005.

Whitley, D. (1994). A genetic algorithm tutorial. Statistics and computing, 4(2), 65-85.

Wolshon, B., Urbina Hamilton, E., Levitan, M., & Wilmot, C. (2005). Review of Policies and Practices for Hurricane Evacuation. II: Traffic Operations, Management, and Control. Natural Hazards Review, 6(3), 143–161. https://doi.org/10.1061/(ASCE)1527-6988(2005)6:3(143)

Wong, Stephen D., et al. "Fleeing from hurricane Irma: Empirical analysis of evacuation behavior using discrete choice theory." Transportation Research Part D: Transport and Environment 79 (2020): 102227.

Xian, S., Feng, K., Lin, N., Marsooli, R., Chavas, D., Chen, J. and Hatzikyriakou, A., 2018. Brief communication: Rapid assessment of damaged residential buildings in the Florida Keys after Hurricane Irma. Natural Hazards and Earth System Sciences, 18(7), pp.2041-2045.

Yabe, Takahiro, and Satish V. Ukkusuri. "Effects of income inequality on evacuation, reentry and segregation after disasters." Transportation research part D: transport and environment 82 (2020): 102260.

Yi, W., Nozick, L., Davidson, R., Blanton, B. and Colle, B., 2017. Optimization of the issuance of evacuation orders under evolving hurricane conditions. Transportation Research Part B: Methodological, 95, pp.285-304.

Yin, W., Murray-Tuite, P., Ukkusuri, S. V., & Gladwin, H. (2014). An agent-based modeling system for travel demand simulation for hurricane evacuation. Transportation Research Part C: Emerging Technologies, 42, 44–59. https://doi.org/10.1016/j.trc.2014.02.015

Zhu, Yi-Jie, Yujie Hu, and Jennifer M. Collins. Estimating road network accessibility during a hurricane evacuation: A case study of hurricane Irma in Florida. Transportation research part D: transport and environment 83 (2020): 102334.

Baker, E. J. (1991). Hurricane evacuation behavior. *International Journal of Mass Emergencies and Disasters, 9*, 287-310.

Huang, S-K., Lindell, M.K. & Prater, C.S. (2016). Who leaves and who stays? A review and statistical meta-analysis of hurricane evacuation studies. *Environment and Behavior, 48,* 991-1029. DOI: 10.1177/0013916515578485.

Huang, S.K., Lindell, M.K., Prater, C.S., Wu, H.C. and Siebeneck, L.K., 2012. Household evacuation decision making in response to Hurricane Ike. Natural Hazards Review, 13(4), pp.283-296.

Huang, S.K., Lindell, M.K. and Prater, C.S., 2017. Multistage model of hurricane evacuation decision: Empirical study of Hurricanes Katrina and Rita. Natural Hazards Review, 18(3), p.05016008.

Lindell, M.K., Murray-Tuite, P., Wolshon, B. & Baker, E.J. (2019). *Large-Scale Evacuation: The Analysis, Modeling, and Management of Emergency Relocation from Hazardous Areas.* New York: Routledge.

Lindell, M.K. & Prater, C.S. (2007). Critical behavioral assumptions in evacuation analysis for private vehicles: Examples from hurricane research and planning. Journal of Urban Planning and Development, 133, 18-29.

Maghelal, P., Peacock, W.G., & Li, X. (2017). Evacuating together or separately: Factors influencing split evacuations prior to Hurricane Rita. *Natural Hazards Review*, *18*(2), 04016008.

Wei, H-L., Lindell, M.K., & Prater, C.S. (2014). "Certain death" from storm surge: A comparative study of household responses to warnings about Hurricanes Rita and Ike. *Weather, Climate & Society, 6,* 425-433.

Dixit, V., T. Montz, and B. Wolshon. Validation techniques for region-level microscopic mass evacuation traffic simulations, Transportation Research Board, Washington, D.C.,2011,

Montz, T. and Zhang, Z., 2015. Modeling regional hurricane evacuation events: calibration and validation. Natural Hazards Review, 16(4), p.04015007.

Yang, Y., Mao, L. and Metcalf, S.S., 2019. Diffusion of hurricane evacuation behavior through a home-workplace social network: A spatially explicit agent-based simulation model. Computers, environment and urban systems, 74, pp.13-22.

Sbayti, H. and Mahmassani, H.S., 2006. Optimal scheduling of evacuation operations. Transportation Research Record, 1964(1), pp.238-246.

Hardy, M., Wuderlich, K. (2007). Evacuation Management Operations (EMO) Modeling Assessment: Transportation Modeling Inventory, Report No. DTFH61-05-D-00002. Washington DC: United States Department of Transportation, Research and Innovative Technology Administration.