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Reconstructing and analyzing the traffic flow during evacuation in Hurricane Irma (2017)

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ABSTRACT

Hurricane evacuation has long been a difficult problem perplexing local government. Hurricane Irma in 2017 created the most extensive scale of evacuation in Florida's history, involving about 6.5 million people in a mandatory evacuation order and an estimated 4 million evacuation vehicles. Traffic jams emerged in mid-Florida and rapidly spread to involve the entire state. To understand the hurricane evacuation process, the spatial and temporal evolution of the traffic flow is a critical piece of information, but it is usually not fully observed. Based on game theory, this paper employs the available traffic observation of main highways to reconstruct the traffic flow on all highways in Florida during Irma. The reconstructed traffic conditions compare well with those simulated by dynamic models while the reconstruction model is computationally much cheaper to use. Validation with smartphone data further confirms that the reconstruction model captures the traffic conditions for real evacuation processes. The reconstructed data show that the evacuation rates for 5 representative cities – Key West, Miami, Tampa, Orlando, and Jacksonville– in Florida were about 90.1%, 38.7%, 52.6%, 22.1%, and 7%, respectively. The peak evacuation traffic flows from Tampa and Miami arrived in the Orlando region at almost the same time, triggering the catastrophic congestion through the entire state. Also, the evacuation for Hurricane Irma was greater than that predicted by an evacuation demand model developed based on previous event and survey data. The detailed evacuation traffic flow reanalysis accomplished in this article lays a foundation for studying evacuation demand as well as developing evacuation management policies.

1. Introduction

The steady increase of the coastal population, coupled with a lack of adequate land use and building construction practices, has made evacuation before hurricane landfall an increasingly important protective action. During recent hurricane seasons, several intense hurricanes, including Hurricanes Harvey, Irma, and Maria in 2017, induced serious impacts and again raised the question of whether and how to evacuate. In particularly, Hurricane Irma (2017) created the largest scale of evacuation in U.S. history (Florida Department of Emergency Management, 2018). More than 6.5 million Floridians were ordered to leave their homes. As the storm approached, emergency managers in nearly every coastal county followed suit to issue evacuation orders (FDOT, 2017). As millions were evacuating, heavy traffic clogged major Florida highways for five days (Ellis et al., 2017).

Understanding the hurricane evacuation process requires complete and accurate datasets showing when and how many people left

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a given place through which road. For example, such traffic demand data can be used to validate sociological models for evacuation decision-making by providing revealed preference data as a complement to stated preference data (e.g., Hasan et al. 2010, Gudishala and Wilmot 2013, Urbina and Wolshon, 2003). Traffic demand data can also provide input for modeling evacuation traffic (e.g., Yi et al. 2017; Murray-Tuite and Wolshon, 2013). Such studies can in turn help the government to better manage hurricane evacuation.

However, evacuation traffic datasets are usually not fully available, possibly because monitoring and recording the traffic flow on the entire traffic network remain difficult for the government. The limitation in evacuation traffic data thus impedes evacuation studies. In this paper, we develop a game-theory-based approach to reconstruct traffic flows for hurricane evacuation on all highways based on partial observations of main highways. This method regards the traffic flow during evacuation as in an equilibrium state in which local traffic is in balance with the main highway traffic. We apply the reconstruction analysis to Florida during Hurricane Irma. The reconstructed traffic pattern is validated using smartphone data, news reports, and Twitter records. We further evaluate the reconstruction model by comparing it with two existing dynamic traffic assignment models. The computationally efficient method developed here can be applied to reconstruct traffic demand and flow in other large-scale hurricane evacuations.

Based on the reconstructed data, we analyze the evacuation process for five representative cities in Florida–Key West, Miami, Tampa, Orlando, and Jacksonville–that showed different evacuation patterns during Hurricane Irma. Hurricane Irma's predicted track varied from affecting Florida's east coast to its west coast, showing the potential to affect coastal cities on the east, west, and south, given the state's long and narrow geophysical shape. Key West is a tourist destination in the south tip (which is at the margin of Florida), with only one way out for evacuation. Miami has a large population and was on the predicted track of Hurricane Irma. Tampa, located on the west coast, was also predicted to be possibly hit hard. Orlando is located in mid-Florida. Although Orlando was predicted to have a relatively small hurricane risk, it served as a bottleneck region of this evacuation: most outgoing vehicles from Miami and Tampa had to pass through Orlando. Jacksonville had a low predicted risk but a large population. The main evacuation population there was passing-by evacuators coming from lower Florida. We analyze the traffic conditions including evacuation rates in these cities in detail. We also calculate the shadow evacuation rates and analyze the shelter capacity for the remaining populations for these cities. In addition, we compare the reconstructed traffic dataset with the predicted evacuation from an established evacuation demand model

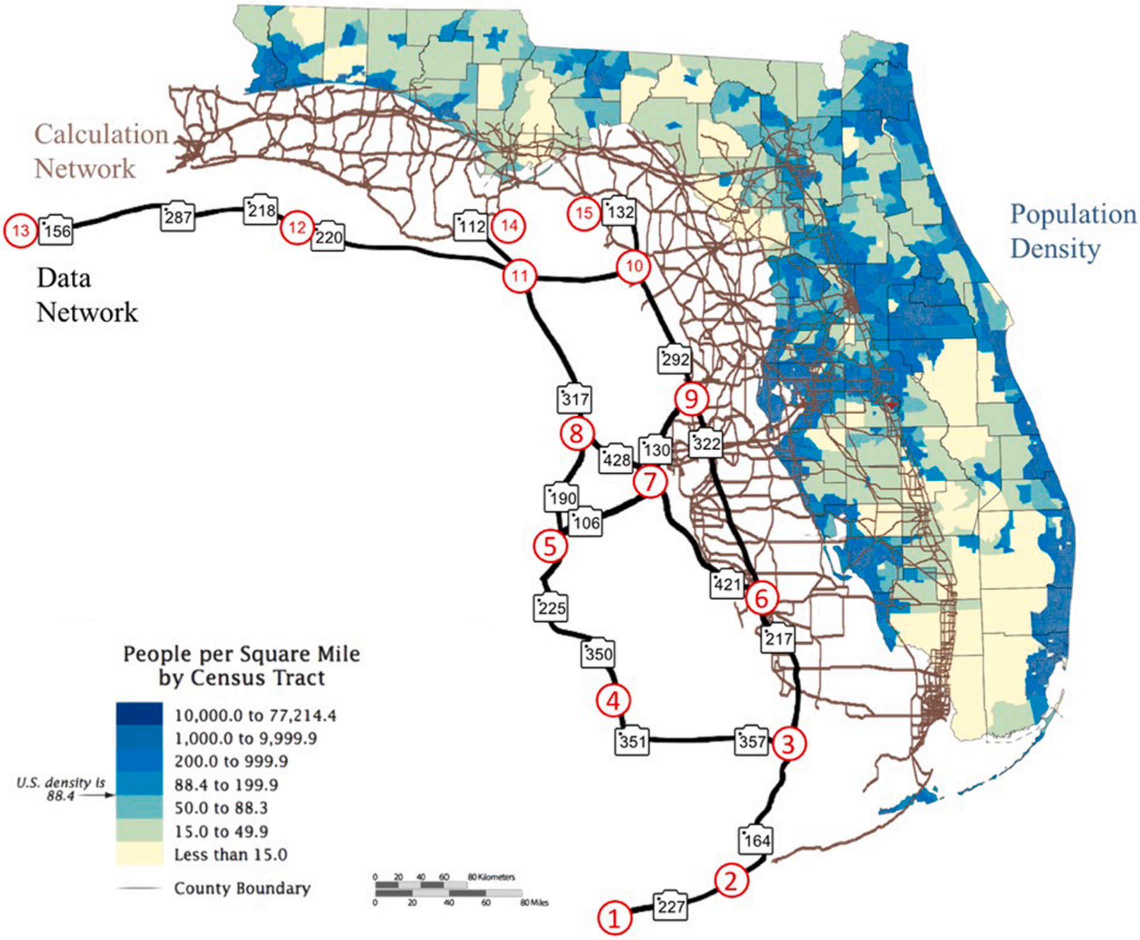

Fig. 1. Overlaid maps showing data-available sparse traffic network (upper layer; red circles indicate traffic analysis zones), calculation based detailed highway network (middle level), and population density distribution (bottom layer).

(Gudishala and Wilmot 2013) to test whether the previous-event-and-survey-based preference could explain the real evacuation process during Hurricane Irma. The evacuation data reconstructed in our study could be an empirical benchmark for further studies, e.g., Feng et al. (2020b), of the evacuation process during Hurricane Irma.

2. Data and traffic reconstruction model

2.1. Data

The data needed for the traffic reconstruction include observations of the main highway traffic, the detailed transportation network, the population distribution, and the shelter/hotel distribution for the entire evacuation region, which in this case is the state of Florida. The traffic-flow data for the main highways (including parts of Routes 1 and 27 and I-75, −95, −4, and −10) are obtained from the Florida Department of Transportation spatial analysis for Hurricane Irma (FDOT, 2017). The traffic data show the number of vehicles that passed by the camera for every 3-hour period. The transportation network data used are a GIS database released by the Florida Department of Transportation (FDOT, 2017); here we consider only the roads with a speed limit over 35 mph to reduce the computational cost and increase the precision of the model. The population distribution is obtained from the Census Population data (Census, 2010). The overlying maps in Fig. 1 visualize the data. Since the data-available main highway network (the upper layer) is very sparse, our goal is to downscale the traffic data to the detailed traffic network (the middle layer, with over 10,000 links and 4,000 nodes), based on the population density distribution (the bottom layer). In the analysis, the population for each square mile of the bottom layer is allocated to the nearest node on the middle layer traffic network. The shelter data come from the Florida Division of Emergency Management.

2.2. Reconstruction model

2.2.1. Background

Our traffic reconstruction model is built on the classical traffic assignment model (which predicts traffic flow based on traffic demand)—the (static) user equilibrium (UE) assignment model—which has been widely used (Fisk 1980). The UE model is based on Wardrop's first principle, which states that no driver can unilaterally reduce his/her travel cost by shifting to another route (Wardrop & Whitehead 1952). The UE model is usually used to estimate the traffic flow on each road given traffic demand (e.g., Friesz et al. 1993), through solving the following optimization problem (LeBlanc et al. 1975):

$$\min_{\overrightarrow{x}} Z(\overrightarrow{x}) = \sum_a \int_0^{x_a} t_a(w)dw \tag{1}$$

with the following constraint:

$$\sum_{k\in\psi_{rs}} f_k^{rs} = D_{rs}, \forall r \in R, \forall s \in S \tag{2}$$

$$f_k^{rs} \geq 0, \forall k \in \psi_{rs}, r \in R, \forall s \in S \tag{3}$$

$$x_a = \sum_r \sum_s \sum_k f_k^{rs} \delta_{a,k}^{rs}, \forall k \in \psi_{rs}, r \in R, \forall s \in S \tag{4}$$

where x_a is the traffic flow volume on road a; $\overrightarrow{x}$ is the set of the traffic flow volume on all roads on the network; t_a is the travel time on road a, which is a road traffic impendence function (i.e., a relationship between road traffic time and traffic amount); D_{rs} is the traffic demand between the origin node r and destination node s; f_k^{rs} is the traffic flow volume of the k^{th} route between r and s; ψ_{rs} is the set of all the routes between r and s; R and S are the sets of all the origins and destinations in the traffic network, respectively; and $\delta_{a,k}^{rs}$ is a Boolean function showing whether the k^{th} route between r and s passes road a. The objective function defined by Eq. (1) minimizes the sum over all roads of the integral of the time cost of travel subjected to the flow conservation conditions (Eqs. (2) and (4)), which requires that all the traffic demands (given in this case) are assigned within the traffic network. The constraint in Eq. (3) ensures that the traffic flow on each route is non-negative.

The UE model has also been widely used to reconstruct the traffic demand given the traffic flow (Van Zuylen and Willumsen, 1980). The basic idea of traffic reconstruction is that different traffic demands (represented by an origin–destination or OD matrix) correspond to different traffic flow simulation results in the UE model; minimizing the difference between the simulated results and the observed traffic flow makes finding the OD matrix with the maximum likelihood possible. Thus, traffic reconstruction is usually raised as an inverse problem of traffic assignment. Traffic reconstruction solves the static OD estimation in a bi-level framework: in the upper level it validates traffic conditions with optimization (under a certain metric, e.g., mean square error), while in the lower level it estimates the traffic condition from the UE model. Lam and Lo (1990) solved this inverse problem of the static UE and carefully tested the accuracy of the reconstruction approach. The bi-level formulations for the static OD estimation problem were also discussed by Nguyen (1977), LeBlanc and Farhangian (1982), Fisk (1989), Yang et al. (1992), Florian and Chen (1995), and Jha et al. (2004).

Beyond static OD demand estimation, dynamic methods have been developed to deduct OD estimation when the traffic demand is changing over time. Dynamic OD estimation (DODE) is usually formulated as either a least square problem or a state-space model.

Cascetta et al. (1993) extended the concepts of static OD estimation problem and formulated a generalized least square (GLS) based framework for estimating dynamic OD demands. Tavana (2001) proposed a bi-level optimization framework that solves a GLS problem in the upper level and a dynamic traffic assignment (DTA) problem in the lower level. Dixon and Rilett (2002) tested one approach to solve the bi-level optimization framework, but the computational cost was significantly higher than that for reconstructing the static OD matrix. Zhou et al. (2003) extended the bi-level formulation to incorporate multi-day traffic data. To implement efficient estimation algorithms on real-time traffic management systems, Bierlaire and Crittin (2004) proposed a least-square-based real-time OD prediction framework for large-scale networks, but the framework cannot reanalyze individual events where the initial OD is unknown. Zhou and Mahmassani (2007) and Ashok and Ben-Akiva (2000) established state-space models for real-time OD estimation based on on-line traffic data feeds. Balakrishna et al. (2008) proposed using simultaneous perturbation stochastic approximation (SPSA) to approximate the gradient of the GLS formulation. Ma et al. (2020) explicitly calculated the loss gradient of the bi-level model to make solving the GLS problem for a long time period possible on city-level networks.

Although theoretically straightforward, the OD reconstruction problem is usually difficult to solve due to the curse of dimensionality, the large conditional number when applying gradient-based-optimization methods to find the optimal OD estimation, and the undirected graphical nature of the transportation network. However, these complexities can be reduced for the evacuation problem, where the OD matrix is simplified to be directional because evacuation is often directional (i.e., people head in similar directions) and involving only long-distance demands (e.g., people will not evacuate just from Miami South to Miami North). With a reduced directional OD matrix, the number of iterations required for solving the two-way traffic flow is relaxed, allowing one to separate the evacuation traffic network into pieces and solve the problem locally. We utilize these special properties to develop a new model for reconstructing evacuation traffic demand and flow based on sparse transportation data, and we apply the model to the entire state of Florida during Hurricane Irma. To the best of our knowledge, this is the first global-scale (for all of the evacuation traffic rather than the regional evacuation traffic within, e.g., a city) reconstruction of hurricane evacuation data, although some work has been done on regional scales (e.g., for New Orleans during Hurricane Katrina of 2005; Dixit et al. 2011). Our reconstruction model can capture the dynamic feature of the evacuation process, but it is essentially a static model. To ensure the quality of our results, we compare our model with the dynamic models of Balakrishna et al. (2008) and Ma et al. (2020). We show that our model results generally match their results; however, the computational cost of our model is one order lower than the dynamic models.

2.2.2. Method

Our evacuation traffic reconstruction is based on two assumptions: 1) the Wardrop Equilibrium, which states that travelers strive to find the shortest (least resistant) path from origin to destination and network equilibrium occurs when no traveler can decrease the travel cost by shifting to a new route (Wardrop & Whitehead 1952), and 2) evacuators arriving in any node on the traffic network have the same possibility to continue evacuating as the local people. The second assumption is needed since, based only on the traffic flow count, one cannot separate the incoming flow from local vehicles in the outgoing traffic flow. Unlike traditional static traffic reconstruction models, which are computationally expansive (Dixon and Rilett 2002) and thus often applied to reconstruct the traffic demand for only a given time period (Wang et al. 2016), here, given the computational efficiency of the new model, we calculate the traffic demand for each time period (i.e., every 3 h) and account for the existing evacuation demand in estimating the later demand. Thus, although a static model, the reconstruction method can partially capture the dynamic pattern of the evacuation process.

In constructing the model, we define traffic analysis zones (TAZs) and merge all traffic nodes into their nearest TAZ. We consider 15 TAZs for Florida, as shown with red circles in Fig. 1; these TAZs are defined to focus on population centers and also make sure that between any two TAZs, there is at least one available traffic counter. These TAZs are the units of origins and destinations. For each time step in the simulation, the traffic flow into and out of each TAZ is recorded, the evacuation rate for each TAZ is estimated, and the updated population at each TAZ is calculated as the sum of the remaining local population and incoming evacuators. We use the main highway traffic data as benchmarks to adjust the simulated traffic amount on each highway while neglecting the effect of traffic dynamics. In this case, the dynamic effect is largely negligible because the data comes in every 3 h, which is usually longer than the clearance time between two TAZs, consistent with the static equilibrium assumption of the UE model. Thus, for every 3-h time step of the evacuation process, we generally apply a 3-h window to perform the static UE analysis to obtain the estimated traffic demand. For the limited cases where the clearance time is longer than 3 h, the time window is extended to be larger than the clearance time between the TAZs.

Given the defined TAZs, the origin TAZs and destination TAZs (OD pairs) can be identified. The number of OD pairs is smaller in evacuation cases than normal traffic cases because under evacuation, the mainstream traffic may go in one direction (e.g., northwards from south Florida during Hurricane Irma). Also, the OD pairs can be classified into two groups: ODs between nearby TZAs on the top layer main highway network ("nearby") and ODs between TZAs on the second layer highway network ("long distance"). For the defined TAZs in Florida, these OD pairs are

Nearby: ①→②, ②→③, ③→④, ④→⑤, ③→⑥, ⑥→⑦, ⑥→⑨, ⑦→⑨, ⑤→⑦, ⑤→⑧, ⑦→⑧, ⑨→⑩,⑧→⑪, ⑪→⑭, ⑩→⑮, ⑪→⑫, and ⑫→⑬;

Long Distance: ③→⑤, ③→⑦, ⑦→⑪, ⑦→⑩, ⑦→⑭, and ⑦→⑮.

To analyze the entire traffic flow, one needs to consider only the direct traffic demand between TAZs (i.e., for all the OD pairs listed above). The indirect demand is always a combination of direct nearby and long-distance demands. For example, if a person goes from Miami ③ to Gainesville ⑧, the traffic demand will be calculated indirectly as from ③→⑦→⑧ or ③→④→⑤→⑧ or ③→⑥→⑦→⑧ instead of directly from ③ to ⑧, because no direct path exists from ③ to ⑧.

The reconstruction process follows three procedures at each time step: a) nearby traffic analysis for the traffic flow between nearby TAZs; b) "conflict" analysis, which eliminates the traffic flow "conflict" when merging the nearby analysis results; and c) long-distance analysis. These steps are discussed in the following three subsections. At the end of every time step, the traffic demands estimated in the last step will be added to the population of the destinations. In this way, the model captures the migration of possibly large populations. Without this dynamic feature, traditional static UE models cannot capture the possibly large evacuation demand from incoming evacuating people (e.g., ~300,000 vehicles heading from Miami to Orlando in Hurricane Irma), which could create significant inaccuracy in the estimated traffic demand.

a) Nearby Traffic Analysis

We adapt the UE model to reconstruct the hurricane evacuation traffic demand and flow between nearby TAZs (Fig. 2a). To do this, we need to establish the relationship between the traffic demand between nearby nodes in nearby TAZs and the main highway traffic flow. Given the UE model, for nearby TAZs, if the evacuation demand was given, then a traffic flow would be calculated for the main highway for every time step. If the evacuation demand given here was too small (large), then the main highway traffic flow calculated would naturally be lower (higher) than observed. Here we assume that only one possible evacuation demand between two nearby TAZs would match the observed main highway traffic flow, and thus we can find the traffic demand given the main highway traffic flow.

One necessary function in the UE model is the relationship between the resistance and the volume of traffic. Here we follow the classical Bureau of Public Roads (BPR 1964) function to model that effect. The travel time on every road can be calculated based on the BPR (1964) congestion function,

$$\mathrm{t_a}(x_a) = t_{a0}\left(1+\alpha\left(\frac{x_a}{c_a}\right)^{\beta}\right) \tag{5}$$

where t_{a0} is the free flow travel time on road a; x_a is the volume of traffic on road a (number of vehicles per hour, vph); c_a is the capacity of road a (vph); and$\mathrm{t_a}(x_a)$ is the predicted travel time on road a. The government takes various approaches to increase the effectiveness of highway usage when needed (Theodoulou and Wolshon, 1865). In this paper, the highway capacities are chosen following the Highway Capacity Manual (1985), and the road shoulder usage during the evacuation (after Sep. 8) is also considered following the FDOT (2017) instructions. The parameters α and β in the BPR function have large uncertainties. Zhao and Kockelman (2002), using empirical data, suggested setting α = 0.85 with a 90% confidence region (0.15~4.0) and β = 5.5 (1.4 ~ 11). In our analysis, making use of the traffic volume and traffic speed sensors data released for 8 outbound highways (FDOT, 2017), the α and β are fitted as 0.9 and 9.5, respectively, for typical 6-lane (3 lanes/direction), 70-mph-speed-limit interstate highways (I-75 and I-95), which match the parameters suggested in a government manual (Highway Capacity Manual 1985). Thus, we follow the manual, which recommends these parameters to be set as in Table 1.

The traffic demand is directional in evacuation. We assume the traffic demand between a traffic node (r) in an origin TAZ, O, and a traffic node (s) in a destination TAZ, D, as being

$$D_{rs}(\tau) = \begin{cases} P^{OD}(\tau)H_r(\tau)H_s(0)/\sum\limits_{\mathscr{S}\in \mathrm{TAZ_D}} H_{\mathscr{S}}(0) & \forall r\in TAZ_O \& s\in TAZ_D \\ 0 & if\ \ not \end{cases} \tag{6}$$

where TAZ_O represents the set of nodes in the origin TAZ and TAZ_Drepresents the set of nodes in the destination TAZ. The $P^{OD}(\tau)$ (%/hour) is the evacuation rate at time τ for the origin TAZ, O, and the destination TAZ, D. The$H_i(\tau)$ is the total number of vehicles at node i at time τ, which is estimated as the population at each node multiplied by the vehicle ownership rate for each county. We account for the tourist population for Key West ① and Big Pine Key ② because the tourism there is comparable to the local population, and we add half of the tourist population to the total number of vehicles, assuming two people share one rental car (Census, 2010); tourism for other TAZs is not accounted for since travelers there could leave Florida directly from the airports. Meanwhile, if all the hotels and shelters at the destination are occupied, then all the incoming vehicles are supposed to move on to the next destination. In

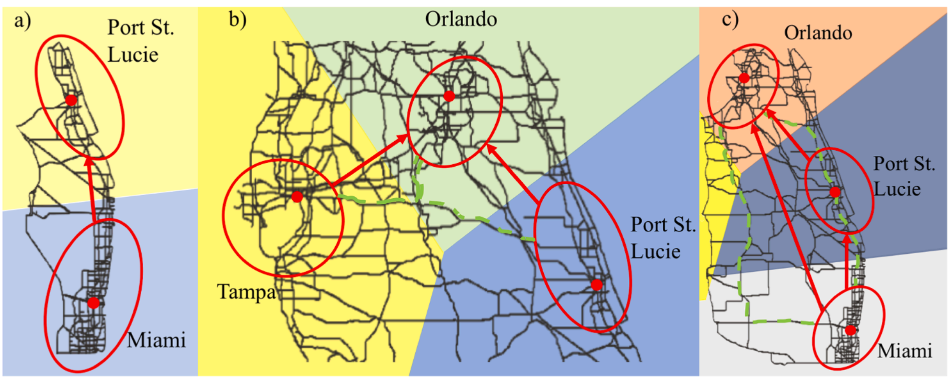

Fig. 2. Examples illustrating the three procedures of traffic reconstruction: a) analyzing the traffic between two nearby TAZs; b) analyzing the traffic conflict among three traffic zones; and c) analyzing long-distance traffic demand. Red circles highlight the TAZs with the red dots showing the centers; the red arrows show the main evacuation direction; the green dash curves show the potential "conflict" (b) or long-distance evacuation among several TAZs (c).

Table 1
BPR coefficients from the 1985 *Highway Capacity Manual.*

Coefficient	Freeways			Multilane Highways		
	70 mph	60 mph	50 mph	70 mph	60 mph	50 mph
α	0.88	0.83	0.56	1.00	0.83	0.71
β	9.8	5.5	3.6	5.4	2.7	2.1

Source: Highway Capacity Manual (1985). The terms "free" and "multilane highways" refer to modern interstate and state highways (lower-design roadways with red lights).

this Eq. (6), the traffic demand between two nodes in nearby TAZs is calculated based on the number of evacuating vehicles and their destination distribution ($H_s(0)/\sum_{\mathscr{S}\in \mathrm{TAZ_D}} H_{\mathscr{S}}(0)$), which follows the traditional gravity model: the larger the population, the larger the attraction (Erlander and Stewart, 1990). Given the population, the evacuation rate essentially determine the traffic flow, which, based on Eq. (5), is a monotonously increasing function of travel time. Thus, $P^{OD}(\tau)$ can be estimated by minimizing the travel time.

Put together, the evacuation reconstruction model can be expressed mathematically as follows:

$$\min_{\overrightarrow{x}^{\tau},P^{OD}(\tau)\in[0,1]} Z(\overrightarrow{x}^{\tau}) = \sum_a \int_0^{x_a} t_a(w)dw \tag{7}$$

with the following constraint:

$$\sum_{\mathrm{k}\in\psi_{\mathrm{rs}}} f_k^{rs}\left(\tau\right) = D_{rs}\left(P^{OD}(\tau)\right), \forall r\in R, \forall s\in S \tag{8}$$

$$f_k^{rs}(\tau) \geq 0, \forall k, r, s \tag{9}$$

$$x_{\mathrm{a}}^{\tau} = \sum_r\sum_s\sum_k f_k^{rs}\left(\tau\right)\delta_{a,k}^{rs}, \forall k, r, s \tag{10}$$

$$\sum_{\mathrm{m}\in\mathscr{H}} \mathrm{t_m}(x_m^{\tau}) \geq \sum_{\mathrm{m}\in\mathscr{H}} \mathrm{t_m}(x_o^{\tau}) \tag{11}$$

in which $\mathscr{H}$ is the set of the main highway sections; x_o^{τ} is the observed traffic flow at time τ (assumed to be uniform along the main highway); and $\mathrm{t_m}\left(x_m^{\tau}\right)$ and $\mathrm{t_m}\left(x_o^{\tau}\right)$ are the predicted and observed travel time, respectively, on road *m* at time τ. The constraint in Eq. (11) is used to incorporate the available data on traffic flows on the main highways between nearby TAZs by requiring simulated (minimum) traffic time on the main highway to be not smaller than the observed traffic time cost. Noticing that the main highways are the shortest distances between nearby TAZs in daily traffic, we use the traffic time cost through the main highway between two centroid nodes ($\mathrm{r_O}\in \mathrm{O}, \mathrm{s_D}\in D$) in the two analyzed TAZs as a benchmark for the traffic assignment (see the example in Fig. 2a).

This evacuation reconstruction model is essentially an adjusted static UE model. The static UE assumption requires that all the demands be cleared in a given time period (otherwise the dynamic UE is needed). Thus, when the clearance time (main highway traffic time) for the system is over 3 h (our data frequency), we extend the time window of UE symmetrically forward and backward to match the clearance time and use the traffic simulation results under the extended window to estimate the traffic demand for the original time window. The reconstruction analysis can be performed by using Python 2.7 for data processing and the QGIS package AequilibraE to calculate the network equilibrium (Camargo and AequilibraE, 2015).

b) "Conflict" Analysis

In Part a), we reconstruct the traffic between every nearby TAZ pair. We can then merge the traffic flow on each road and traffic demand in each TAZ by linear combination. However, when performing the nearby TAZ analysis, we must first assume that the road network is empty before we assign the traffic. Thus, for a road selected by people from two or more OD pairs at the same time, the traffic time on that road based on linearly combining the nearby TAZ analysis results is an underestimation. For example, as shown in Fig. 2b), the vehicles going from Port St. Lucie ⑥ to Orlando ⑦ will meet vehicles driving from Tampa ⑤ to Orlando ⑦ if they choose the green dashed route, which increases the estimated traffic time on the green route, invalidating the static equilibrium established in Part a). Thus some traffic demand should be reduced to relieve such "conflict."

Here we apply a random selection method to eliminate the excess traffic demand. For all such conflicted road sections, we calculate the OD distribution of the vehicles on the road and also the route choice distribution following Feng et al. (2020a). Specifically, the probability of an individual car on road *a* having a specific OD, *r-s*, is estimated as

$$\Pi_{a,rs} = \frac{\sum_{k\in\psi_{rs}} f_k^{rs}\delta_{a,k}^{rs}}{x_a}. \tag{12}$$

The probability of an individual car on road *a* with an assigned OD, *r-s*, having a specific route, *rt*, is estimated as

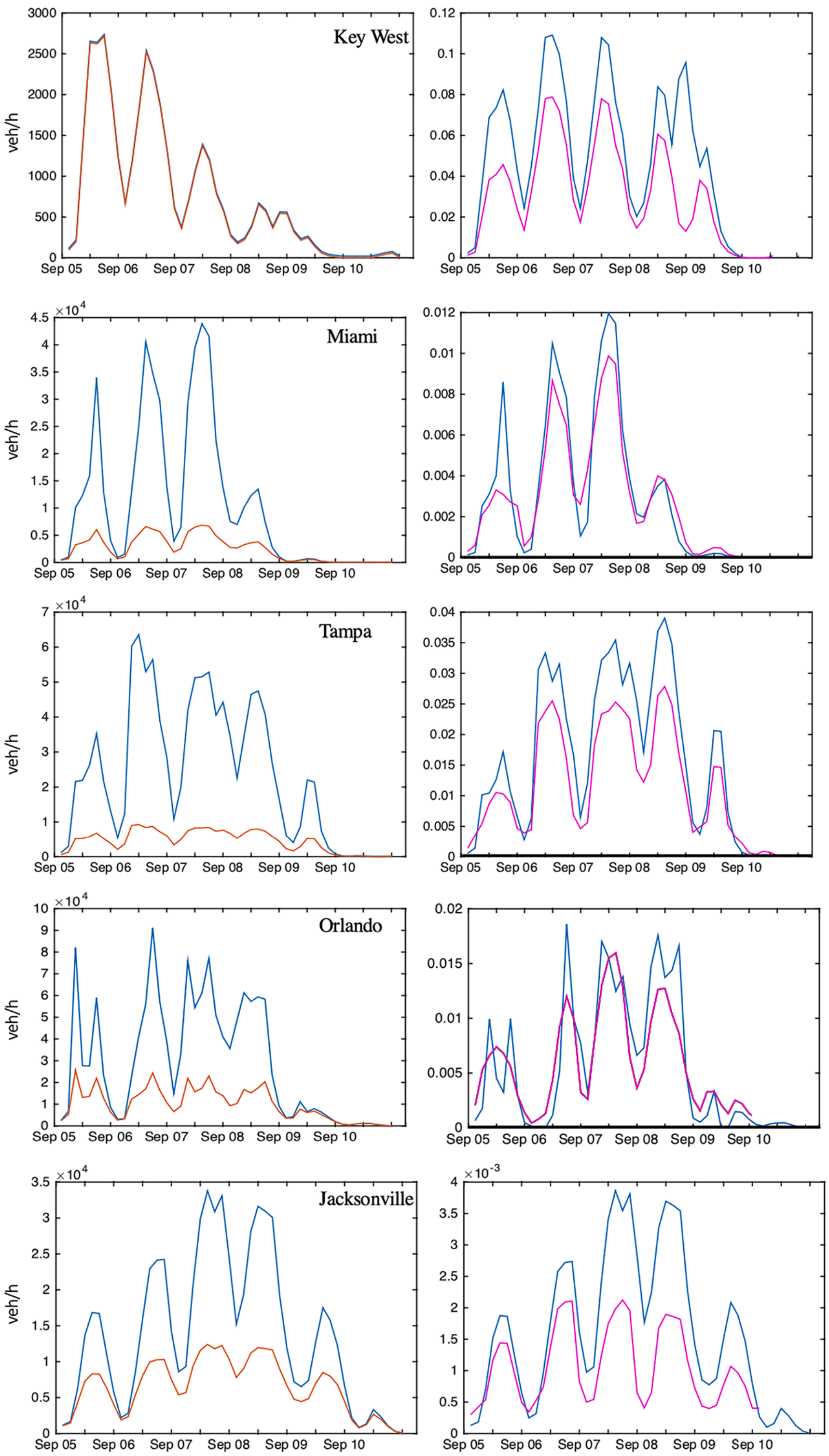

Fig. 3. The evacuation traffic (vph; left panels) and evacuation rate (%/h; right panels) reconstructed for Key West ①, Miami ③, Tampa ⑤, Orlando ⑦ and Jacksonville ⑩. Blue curves show the reconstructed traffic flow (left panels) and evacuation rate (right panels). The observed traffic on the main highway is shown in orange in the left panels. The evacuation rate from the empirical model is shown in magenta in the right panels, while red vertical lines show the time points when the local government released the evacuation order.

$$\Pi_{a,rt}^{rs} = \frac{f_{rt}^{rs}\delta_{a,rt}^{rs}}{\sum_{k\in\psi_{rs}} f_k^{rs}\delta_{a,k}^{rs}} \tag{13}$$

Then, for every conflicted road section, we randomly select a vehicle on the section and assign it an OD pair and a route based on Eqs. (12) and (13), and we calculate the travel time of that vehicle taking that route. If the travel time is longer than the main highway travel time, we remove the car from the demand matrix D_{rs} and the route-based traffic flow f_{rt}^{rs}, and we recalculate the time cost of the route. Then we randomly select another road section from the conflicting route and repeat the analysis until there is no "conflict." In this way, no evacuator would choose a route other than the shortest one, reaching the equilibrium assumed in Part a). Once the iteration is finished, we recalculate the $P_r^{OD}(\tau)$ for every OD pair to obtain the adjusted evacuation rate.

c) Long-Distance Traffic Compensation

An example of long-distance evacuation is shown in Fig. 2c. People may go directly to Orlando from Miami using the lower green line rather than going through Port St. Lucie by the main highway. This long-distance traffic demand is not considered in the nearby evacuation analysis discussed in Parts a) and b) above. Here we apply a simple compensation method to incorporate this long-distance traffic demand into the data reconstruction process. That is, we gradually add traffic demand to the long-distance direct route until the travel time for the long-distance evacuation is no longer shorter than that for the indirect routes. Then we assign the direct long-distance traffic demand into the road network and apply the random selection method discussed in Part b) again to eliminate possibly induced route conflict. After this step, we count all the traffic flow heading out of each TAZ and recalculate the adjusted evacuation rate $P_r^{OD}(\tau)$.

In reality, when the long-distant traffic demand is much lower than the nearby traffic demand, direct long-distance evacuation may take a shorter travel time than the indirect nearby evacuation through main highways, which invalidates our assumption that the travel times are equal. Thus, the simple compensation method assuming equilibrium cannot guarantee an unbiased estimation for long-distance traffic demand. Nevertheless, news reports for Hurricane Irma (Osowski 2017; Yanofsky 2017) show that the long-distance traffic demand was comparable to the nearby traffic demand.

2.3. Reconstruction results and traffic flow analysis

Applying the analysis discussed above, we obtain the estimated evacuation traffic amounts for all the defined TAZs and also the traffic volume time series for all highway road sections in Florida during Hurricane Irma. Fig. 3 shows the results for Key West, Miami, Tampa, Orlando, and Jacksonville. In the left panel, the orange curves show the observed evacuation volume for the main highway, and blue curves show the estimated total evacuation volume for all highways. In the right panel, blue curves show the estimated evacuation rate (the evacuating population out of the remaining population at the time point), and magenta curves show the evacuation rate estimated from an empirical travel demand model (Gudishala and Wilmot 2013), to be discussed below. Red lines are the time points when the local government released evacuation orders.

The estimated total evacuation demand for Key West is almost the same as the observed traffic on the main highway, which is reasonable because only one highway runs from Key West Region ① to Key Largo and Homestead ②, and it always takes less than 3 h to drive. This consistency indicates that our reconstruction model converges on the only feasible solution. The estimated evacuation demand changes over time for Key West and has apparent peaks on the fifth and fourth days before the hurricane landfall. The evacuation order was released in the afternoon of Sep. 5, and the evacuation rate was steady over time (with fluctuations due to day-night differences) until Sep. 9, 12 h before the landfall of the hurricane. The estimated total evacuation rate of Key West was as high as 90.1%, thanks to (among other reasons) the effective door-to-door warnings released by local police officers in the city (Florida Department of Emergency Management, 2018). This large evacuation number matches the information obtained by the authors during an impact survey for Key West soon after Hurricane Irma (Xian et al. 2018). Also, according to news reports, Irma's evacuation is considered "the largest and possibly the most successful mass evacuation in state history" (Hughes and Sarkissian, 2017). The result of evacuation for the Florida Keys under Irma differs significantly from the hurricane evacuation in Florida caused by Hurricane Wilma (2005). At that time, a mandatory evacuation of residents was ordered for the Florida Keys in Monroe County. However, media reports pointed out that as many as 80% of the residents might have ignored the evacuation order. The improved evacuation behavior during Irma may be attributed to the efforts of the government and media, impact of Hurricane Harvey in Texas 7 days earlier, and generally improved hurricane awareness of Floridians. Nevertheless, Hurricane Irma caused 14 deaths in Key West, 15% of the total fatalities (John et al. 2018). Considering that only about 2000 households remained without evacuating, the fatality rate for people left in the Florida Keys was as high as $\sim$ 0.7%.

The evacuation demand of Miami changed dramatically, totaling 4 to 7 times the main highway traffic. This large difference is due to the traffic network in Miami, which contains many outwards highways, and also its multiple destinations such as Tampa and Orlando. The evacuation rate of Miami was much lower than the evacuation rate of Key West, as the risk for Miami was estimated to be much lower than for Key West, which was supposed to face a direct landfall impact. Also, many airlines and shelters in Miami helped local people to leave through other means than evacuation via the traffic network. The low gasoline availability (38.7% shortage reported) during that period may have impacted the evacuation decision of Miami's people on Sep. 8 (Egan, 2017). The peak traffic occurred at noon on Sep. 7 although the evacuation order was released at noon on Sep. 6. This delay in the traffic peak reflects the fact that people often need 6 to 12 h for preparation and tend to avoid evacuating at night (Lindell et al. 2005). In total, ~1,870,000 vehicles evacuated from Miami; supposing there were 4,000,000 vehicles in the Miami region based on the census data, about 46% of Miami residents evacuated.

The evacuation traffic flow in Tampa was also much higher than main highway traffic flow. In total $\sim$ 1,110,000 vehicles evacuated from the Tampa region (52.6%). The evacuation peak came around Sep. 6, while the evacuation rate kept increasing on Sep. 7 and 8. The evacuation order was released on Sep. 7 at noon, which led to the increase of evacuation willingness on the later dates. A large portion of the evacuation flow (~63%) went to Orlando from Tampa for their first stop, as shown in the reconstruction model. Meanwhile, we notice that the evacuation order was released to the Miami region on Sep. 6 at noon (with ~ 53% of the evacuation flow heading towards Orlando in the model), and the peak traffic from Miami arrived in the Orlando region on Sep. 7. The traffic from these two places merged in the Orlando region, leading to a great traffic jam on Sep. 7 at I-75 (camera 106) and I-95 (camera 412). This traffic congestion triggered a later traffic jam in lower Florida (FDOT, 2017).

We further analyzed the traffic out of Orlando, which received enormous numbers of evacuating vehicles from the Miami and Tampa regions. -The modeled traffic peak happened on Sep. 6 and 7. There were multi-peaks led by different incoming flows from different regions, as shown in Fig. 3. This phenomenon is shown more clearly in the evacuation rate analysis. The outflow from Orlando was ~ 530,000 (~22.1% of the local population). The local evacuation rate in Orlando was much lower than the coastal regions' rate, which is consistent with the predicted lower hurricane risk. About 67% of vehicles leaving Orlando during Hurricane Irma came from Tampa and Miami. This observation indicates the special role Orlando plays in Florida's traffic network. As Florida is geographically long and narrow, people who evacuate from lower Florida need to go through the Orlando region. Thus, Orlando may be regarded as a bottleneck in Florida's traffic network, and special policy approaches should be considered and applied to relieve the traffic load there. We also analyzed a northern city: Jacksonville. As in Orlando, the residents in Jacksonville did not have much willingness to evacuate. Only 7.1% of local people evacuated, in our estimation. About 90% of the traffic passing through Jacksonville came from lower Florida heading to Georgia (based on the news report of Yanofsky 2017 and our analysis).

To better understand the information the reconstruction results conveyed, we compared the evacuation rate, shadow evacuation (those who evacuated even though they might not have been required to), and shelter capacity (Scott and Maul 2018) for these five cities in Fig. 4. These figures reveal the risk perceptions of local people. Among all places, Tampa has the highest shadow evacuation rate (40% of total evacuated population), and Key West has the lowest shadow evacuation rate (10% of total evacuated population). Also, the sum of Tampa's evacuated population and shelter capacity is over 100%, which means the governmental preparation was sufficient to meet the sheltering demand of the local people. On the other hand, the shelter capacity is much lower in Orlando and Jacksonville, so that 70% of the remaining population (estimated in this study) would not have shelter protection although in this case the hurricane risk was lower in these two places. Displaying the evacuation rate, shadow evacuation, and shelter capability in various places as in Fig. 4 provides a vivid way to understand people's behaviors and the impact of governmental policies during hurricane evacuation.

Among their various applications in traffic modeling and evacuation analysis, the reconstructed traffic data can be used to evaluate evacuation demand models. Here, we compared the evacuation rate estimated based on our model with estimations from the sequential logit dynamic travel demand model of Gudishala and Wilmot (2013). The model is empirically based and performs logit regression to predict the evacuation rate based on several variables related to the hurricane and the household, including the evacuation order (a Boolean factor for voluntary or mandatory evacuation), forecast hurricane category, time of day (i.e., morning, afternoon, or evening), time-dependent distance, and forecast storm surge height. The parameters were fitted based on both the revealed preference data from Hurricane Gustav (2008; landfall in Louisiana) and the stated preference data of a choice survey.

The estimated evacuation rate from this travel demand model is shown as the magnate curve in the right panels of Fig. 3. The empirical model predicts a lower evacuation rate in this event. Based on the empirical model, the total evacuation demand for Irma would be around 3.2 million, which is 20% lower than the 4 million evacuations estimated in our reconstruction. Also, the shadow evacuation (the evacuation ahead of the evacuation order indicated by the red line) revealed in this event is much higher than the empirical model's prediction. This higher evacuation willingness indicates that more people believed that they were at risk before the government officially stated so during Hurricane Irma than for previous events. This extra precaution may be deduced by the fact that Hurricane Harvey, which happened and was widely reported just two weeks before Hurricane Irma, had a devastating impact on Houston, but no evacuation order was released to Houston's citizens (Andone 2017). When the government makes evacuation decisions, it is important to take such specifics into consideration and perform more precise predictions of the evacuation rate. We also see that, when cross-comparing the results of survey, cell phone (see below), and reconstructed traffic data, the evacuation number estimated by the survey is the lowest.

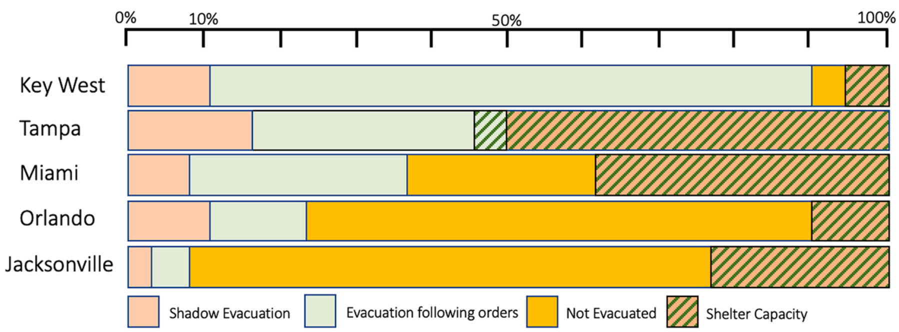

Fig. 4. The histogram of evacuation rate, shadow evacuation rate, rate of remaining population, and shelter occupancy for five cities in Florida.

3. Model evaluation

3.1. Comparison with existing model

By applying the static UE model to estimate the OD, we were able to reconstruct the traffic flow of the Irma evacuation process for the whole Florida traffic network (with over 10,000 links and 4,500 nodes). However, it is worth investigating whether our static model, while being computationally more efficient, can capture the essential features of the traffic flow under evacuation that can be simulated by a dynamic traffic assignment-based OD estimation model.

The traditional DODE model is usually applied to small networks with fewer than 300 nodes and 1000 links (e.g., Balakrishna et al. 2008), except that Ma et al. (2020) applied their DODE method to a larger network with ~ 1000 nodes and 3000 links (10 counties). Thus, the dynamic OD estimation is usually applied to city-level commuting traffic, so it has not yet been applied in a large-scale (e.g., the whole of Florida) evacuation analysis. Mathematically, both Balakrishna et al. (2008) and Ma et al. (2020) solved the GLS problem using a bi-level model, which minimizes the square difference between predicted traffic flow (based on the given traffic assignment model) and real observations. Balakrishna et al. (2008) applied the SPSA method to solve the GLS problem. Similar to the Frank-Wolfe method (which we applied to capture the static UE), SPSA is also a gradient-based non-linear optimization tool. However, it further stochastically perturbates the gradient to enable the optimization solution to jump out of local minimal points in non-convex optimization problems. Ma et al. (2020) made the loss of the general DODE framework differentiable by linearizing the dynamic traffic assignment model. They then employed a matured deep learning framework to backwardly propagate gradients for their DODE model and optimize the OD estimation. Our model uses real observations as model constraints given the limitation of the observation, while the model of Ma et al. (2020) minimizes the differences between observations and simulations through optimization. Here we compare simulation results from our static model to those from the dynamic models of Balakrishna et al. (2008) and Ma et al. (2020). As the traffic assignment methods differ for these three models, we modify the simulation-based models in Balakrishna et al. (2008) and Ma et al. (2020) to a classical stochastic traffic assignment model (Daganzo and She, 1977). Also, due to the high computational cost, we test these three models only on the Miami region (~1000 nodes and 3000 links). Simulations constrained on this region could help us better compare the results and efficiency for these three models.

The evacuation flow comparison is shown in Fig. 5. The experiment shows that these three models, though different in mechanisms and procedures, produce comparable results. Our model slightly overestimates the total evacuation rate, compared to the two dynamic models. This overestimation may be explained by the fact that we estimate ODs by static assignment, while the methods of Balakrishna et al. (2008) and Ma et al. (2020) use the simulation-based real-time stochastic assignment method. Simulation-based methods can continuously model congestions, while static models have to relax congestions by spreading them over time, which may overestimate the number of vehicles passing the region over the peak time. Such an overestimation is a common flaw of static UE models.

On the other hand, our model shows significant computational advantages. All the experiments in this section are conducted on a desktop with an Intel Core i7-9900 K CPU 4.30 GHz × 8,4400 MHz 4 × 16 GB RAM, 4 TB SSD. For the Miami region (~1000 nodes and 3000 links), Balakrishna et al.'s (2008) method takes about 8 h to converge, and Ma et al.'s (2020) method takes about 24 h. Our static UE based model takes only 30 mins to converge for the Miami region. For the simulation of all of Florida, our static UE-based model takes around 75 h to converge. Consider that static traffic assignment is an $O(n^3)$ algorithm, where n is the number of nodes; the dynamic OD estimation couples an $O(n)$ gradient-based OD estimation algorithm with the static traffic assignment model, which is approximately on the order of $O(n^4)$. In this sense, our model would be the only one among the three models that can finish the full OD estimation and reconstruction for the entire state of Florida with moderate computational resources.

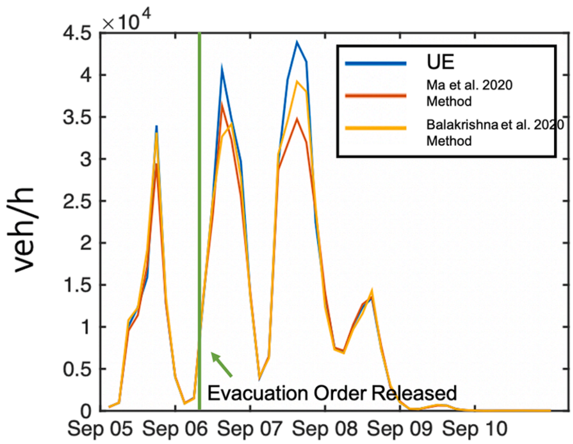

Fig. 5. Comparison of the out-flow from Miami during Irma evacuation estimated using three traffic reconstruction models.

3.2. Validation with multi-resources data

Directly and fully validating our model from traffic flow data is difficult because there is no observation other than the traffic flow on the main highways. Also, we cannot perform cross-validation by removing some observed traffic data from our training set because all the (quite limited) main highway data are necessary benchmarks for reconstruction. However, other sources, such as cellular data, survey data, and twitter data, can be used to evaluate the model. The validation of our model includes two parts: OD estimation and traffic condition estimation.

For the global OD estimation, we partially validate the evacuation rate for each region using a smartphone location dataset (Long et al. 2020). Long et al. (2020) conducted a retrospective analysis of smartphone location data to infer a smartphone user's approximate home location for Florida and Texas. Then, for three hurricanes (Matthew and Irma in Florida; Harvey in Texas), Long et al. (2020) estimated whether residents evacuated from their home locations for at least 24 h during the hurricane. For Hurricane Irma, Long et al. (2020) included all 1,321,571 smartphone users in Florida. A hurricane "evacuation" is defined as a smartphone user spending $>$ 24 continuous hours at least 100 m away from their home area, over a period beginning 4 days before the first alert until 4 days after all alerts were discontinued (Sep. 3–15, 2017, for Irma). Our reconstructed data show that the evacuation rates for the five representative cities–Key West, Miami, Tampa, Orlando, and Jacksonville–in Florida are about 90.1%, 38.7%, 52.6%, 22.1%, and 7%, respectively, while their results are 93%, 45%, 56%, 27%, and 5%, respectively. Our OD estimation can generally match the observations from the smartphone data except that our estimates are slightly lower than the smartphone data results. This relatively small discrepancy may be mainly explained by the fact that their model uses a very low evacuation threshold (i.e., 100 m) while our model considers only long-distance evacuation (i.e., $>$ 50 miles). In a survey for the Louisiana region, Cheng (2010) found that usually $\sim$ 7% people would travel less than 50 miles. Thus, our model would naturally give a lower number than the results in Long et al. (2020).

The higher-level OD estimation (e.g., the portion of evacuation from Miami to Orlando compared to that from Miami to Jacksonville) can also be validated with the smartphone location data. We employ a smartphone dataset (with $\sim$ 300,000 users) anonymized following Long et al. (2020) to validate our model. We aggregate the smartphone users' location data to the TAZ level. We build the OD matrix for every major evacuation day during the Irma evacuation (Sep. 6 to Sep. 8, 2017), by capturing each smartphone user moving from the home TAZ to another TAZ (the location of the phone user is attached to its nearest TAZ) in a day as one evacuator. Also, we employ an agent-based model described in Feng et al. (2020b) to trace the OD distribution of evacuees on each single day. The comparison results for destination distributions at different TAZs are shown in Fig. 6a. The x-axis shows the percentage of evacuated people relative to the local population reconstructed from our model; the y-axis shows the data we rebuild from smartphones. We show only the results for evacuation from Miami and Tampa regions because those two TAZs generated the largest evacuating population, and their evacuation behaviors are most representative. The blue points show the evacuation from Miami; the orange points show the evacuation from Tampa. Different points mean different destinations and different time points. The evacuation rate for upper Florida is very small, and thus the smart phone data may contain large amounts of noise (e.g., mixtures of daily traffic information, sampling noises, etc.). The reconstruction results compare well with the smartphone data, which confirms the ability of our reconstruction model to capture the OD distribution during the whole evacuation period.

Moreover, the smart phone data can also be used to validate the modeled traffic conditions during the evacuation from Irma. As in the OD comparison, we extend the smartphone data analysis for the traffic validation. The smartphone data cannot continuously trace every user on record, and thus we use the minimal possible time cost to represent the traffic conditions. For each time window (3 h), we chose the 20% lower quantile of all traffic times between two TAZs to represent the traffic time between the two TAZs. Here, we show only the results for evacuation from Miami and Tampa following the same reasons as stated in the OD comparison. The comparison of traffic times between TAZs are shown in Fig. 6b, where the longest traffic time for each day is shown. The blue points show the evacuation from Miami; the orange points show the evacuation from Tampa. Different points mean different destinations and different days. The reconstruction result compares well with the smartphone data, which confirms the ability of our reconstruction model to

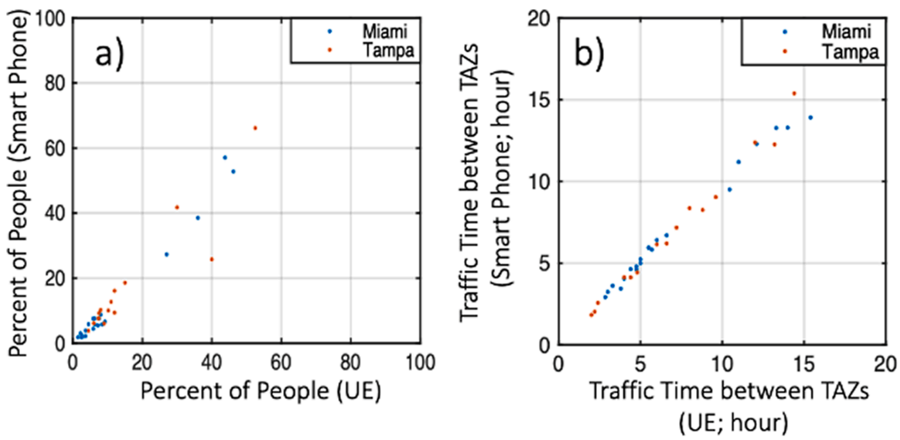

Fig. 6. Comparisons of a) OD and b) traffic conditions between traffic reconstruction and smartphone data.

capture the traffic conditions, including the congestions, during the whole evacuation period.

In addition, we partially validate the model for traffic condition using Twitter records, in which some evacuators reported their origins, destinations, and time costs. For example, one person reported that he drove from Miami to Gainesville for 14 h on Sep. 7. Our model estimates that, if he left Miami between morning and noon on Sep. 7, it would take him 12 $\sim$ 14 h to reach Gainesville. Another person tweeted that it took her 5 h in the afternoon of Sep. 8 to travel the distance that usually took her 2 h; our model estimates that the time cost for a normal 2-hour trip was between 4 $\sim$ 10 h on Sep. 8, depending on which direction she was heading. The Twitter data, however, are highly unstructured. We obtained about 30 records to validate our model. To protect privacy, the data are not shown here.

4. Conclusion

In this paper we have presented an evacuation traffic reconstruction model based on the static UE assumption. We have largely reduced the reconstruction computational cost by recognizing the typical one-directional property of evacuation in Florida during hurricanes. Thus, we enable reconstruction of the 6-day evacuation process for the entire Florida region efficiently. We have applied the model to estimate the temporal changing traffic on all highways in Florida during Hurricane Irma based on available main highway traffic data. The reconstructed traffic flow compares well with the traffic flow simulated by dynamic models (tested for the Miami region). The global reconstructed traffic pattern was also validated with smartphone data, news reports, and Twitter records.

Traffic records of 5 main evacuating cities–Key West, Miami, Tampa, Orlando, and Jacksonville–were analyzed. The largest evacuation in the US history, Hurricane Irma may have caused $\sim$ 38% of Miami residents, $\sim$53% of Tampa residents and $\sim$ 90% of Keys residents to evacuate. The total traffic amount was estimated to be much higher (3 $\sim$ 7 times) than the traffic observed on the main highway for Miami and Tampa regions. In total, $\sim$ 4 million vehicles evacuated. The evacuation rate differs from place to place and generally increases with predicted hurricane risk.

We also found that the peak evacuation traffic flows from Tampa and Miami arrived at the Orlando region almost simultaneously. This event triggered the catastrophic congestion through the entire state. Thus, we argue that the evacuation process may be improved through better coordination between local governments (e.g., Miami and Tampa) to stagger the evacuation peaks.

We have compared the evacuation rates estimated with the reconstruction model and predicted by using an empirical model and found that, for this event, the empirical model underestimates the real evacuation demand. The shadow evacuation is especially underestimated. This comparison illustrates that the reconstruction data can be used as a benchmark to evaluate traditional survey-and-experiments-based methods of predicting evacuation demand.

The developed reconstruction method may be applied to other large-scale hurricane evacuation events. However, the model requires the evacuation network to be directional by design. This model yields a good approximation in Florida since the state is geographically long and narrow. The model may not work well for others such as Hurricane Florence (2018) in North Carolina (2018), for example. For a wide and open traffic network as in North Carolina, evacuation may not be as difficult as for the long, narrow network in Florida; for example, evacuation for Florence ($\sim$1 million vehicles; Bacon and Rice, 2019) did not lead to a long-lasting global traffic jam. Meanwhile, traditional reconstruction models (Dixit et al. 2011) would still work for open network regions, in spite of their much higher computational cost.

The reconstructed traffic dataset can be used to study evacuation decision-making and travel behavior, facilitating the improvement of evacuation orders and governmental risk management. In future studies, we will utilize this detailed dataset to better understand evacuation behavior and develop new evacuation models and optimization-based methods to manage evacuation.

Declaration of Competing Interest

The authors declared that there is no conflict of interest.

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