Title: A novel state-transition model for real-time forecasting of evacuation demand

Authors

Xiangyang Guan[1] and Cynthia Chen[1]

[1]Civil and Environmental Engineering, University of Washington, Seattle, WA

Introduction

Increasing frequencies and intensities of natural disasters such as hurricanes make evacuation, the primary action to protect human life from natural disasters, no longer rare events. Timely and accurate forecast of evacuation demand is key for emergency responders to plan and organize orderly evacuation before/during a disaster. Exiting efforts in evacuation demand forecasting comprise two lines of work. On one hand, behavior-based models leverage regression models and survey data from previous disasters to investigate how certain factors affect evacuation demand; and forecasts of evacuation demand can be made by applying fitted regression models to a given disaster context. On the other hand, flow-based models apply machine learning and other dynamic methods in quest of modeling and predicting large-scale population movement under a disaster. These two lines of work have three critical limitations. First, behavior-based models are static. The factors incorporated in behavioral models, such as social-demographics, environmental cues and geographical characteristics, are usually collected by surveys. This means the behavioral models can not be implemented in real time, and are unable to utilize real-time evacuation information as a disaster unfolds. Second, flow-based models typically have short prediction time windows, ranging from minutes to hours. This limits the amount and timeliness of preparations emergency responders can make before large-scale population movement happens. Third, flow-based models and certain behavioral models are formulated at aggregated zone levels, and overlook individual heterogeneities within zones.

This study addresses these limitations in evacuation demand forecasting, and develops a state-transition model that is dynamic, has a prediction window of days, and accounts for individual heterogeneities. The state-transition model formulates evacuation as a stochastic decision making process at the individual level regarding whether to evacuate at time t+1 if the individual has not evacuated at time t. To accomplish this task the state-transition model faces two challenges. First, capturing dynamic decisions made by individuals requires the model to have time-varying transition probabilities, which is non-trivial. To overcome this challenge, we develop a survival model formulation for the state-transition model, which allows the transition probabilities to be history dependent. Second, large-scale population movement usually happens suddenly during evacuation, leading to a surge in evacuation demand. Making demand forecasts before the surge occurs is critical for emergency response but faces the difficulty in lack of data, as there could be few to no evacuation before the demand surge. To overcome this challenge, we integrate insights from behavioral models into the state-transition model, which grants the state-transition model a hyperopic view of possible future changes in evacuation demand at the early stage of a disaster.

Methodology

The state-transition model describes the following decision process: on each day, an individual can decide either to evacuate or to stay at home, if the individual stayed on the previous day. Let $\tau_{i,t}$ be the number of days individual *i* has stayed on day *t*. The two possible decisions on day *t* can be denoted by state transitions as follows.

- Evacuation on day *t*: $H_{t-1} \rightarrow D_t \middle| \tau_{i,t}$;
- Stay at home on day *t*: $H_{t-1} \rightarrow H_t \middle| \tau_{i,t}$.

The symbols H_t and D_t represent staying at home and evacuating on day *t*, respectively. Two properties of the above state transitions are worth noting: first, they are history dependent, influenced by how long a person has already stayed at home; and second, they vary from individual to individual, indicated by the individual-specific $\tau_{i,t}$.

Let T_i be a random variable denoting the number of days individual *i* stays at home before he/she evacuates (i.e. the survival time). The probabilities of the transitions can be expressed as in equations (1)-(2).

$$P\left(H_{t-1} \rightarrow D_t \middle| \tau_{i,t}\right) = P\left(T_i \leq \tau_{i,t} \middle| T_i > \tau_{i,t-1}\right) = \lambda\left(\tau_{i,t}\right), \tag{1}$$

$$P\left(H_{t-1} \rightarrow H_t \middle| \tau_{i,t}\right) = P\left(T_i > \tau_{i,t} \middle| T_i > \tau_{i,t-1}\right) = \frac{P\left(T_i > \tau_{i,t}\right)}{P\left(T_i > \tau_{i,t-1}\right)} = \frac{S\left(\tau_{i,t}\right)}{S\left(\tau_{i,t-1}\right)}, \tag{2}$$

where $\lambda\left(\tau_{i,t}\right) \equiv P\left(\tau_{i,t} \geq T_i > \tau_{i,t-1} \middle| T_i > \tau_{i,t-1}\right)$ is the hazard function, and $S\left(\tau_{i,t}\right) \equiv P\left(T_i > \tau_{i,t}\right)$ is the survival function. The term $T_i > \tau_{i,t-1}$ indicates that individual *i* has not evacuated by day *t-1*, and the term $T_i \leq \tau_{it}$ indicates that individual *i* has evacuated by day *t*.

From a state-transition perspective, the likelihoods of individual *i* evacuating or staying on day t_i can be formulated as in equations (3) and (4), respectively.

$$\begin{aligned} L_i^E(t_i) &= P\left(H_1 \middle| \tau_{i,1}\right) \cdot \prod_{t=2}^{t_i-1} P\left(H_{t-1} \rightarrow H_t \middle| \tau_{i,t}\right) \cdot P\left(H_{t_i-1} \rightarrow D_{t_i} \middle| \tau_{i,t_i}\right) \\ &= S\left(\tau_{i,1}\right) \cdot \frac{S\left(\tau_{i,2}\right)}{S\left(\tau_{i,1}\right)} \cdot \frac{S\left(\tau_{i,3}\right)}{S\left(\tau_{i,2}\right)} \cdot \ldots \cdot \frac{S\left(\tau_{i,t_i-1}\right)}{S\left(\tau_{i,t_i-2}\right)} \cdot \lambda\left(\tau_{i,t_i}\right) = S\left(\tau_{i,t_i-1}\right) \cdot \lambda\left(\tau_{i,t_i}\right) = f\left(\tau_{i,t_i}\right), \end{aligned} \tag{3}$$

$$\begin{aligned} L_i^H(t_i) &= P\left(H_1 \middle| \tau_{i,1}\right) \cdot \prod_{t=2}^{t_i} P\left(H_{t-1} \rightarrow H_t \middle| \tau_{i,t}\right) \\ &= S\left(\tau_{i,1}\right) \cdot \frac{S\left(\tau_{i,2}\right)}{S\left(\tau_{i,1}\right)} \cdot \frac{S\left(\tau_{i,3}\right)}{S\left(\tau_{i,2}\right)} \cdot \ldots \cdot \frac{S\left(\tau_{i,t_i}\right)}{S\left(\tau_{i,t_i-1}\right)} = S\left(\tau_{i,t_i}\right). \end{aligned} \tag{4}$$

where $f\left(\tau_{i,t}\right) \equiv P\left(T_i = \tau_{i,t}\right)$ is the survival density function. Equations (3) and (4) show that under the survival model formulation, the likelihoods of state transitions reduce to simple forms. This allows employing likelihood-based methods such as maximum likelihood estimation or Bayesian inference to estimate and forecast T_i for each individual i, and collectively the evacuation demand on a daily basis.

To integrate behavioral model insights into the state-transition model, the likelihood function needs to account for not only observed evacuations by a given day as in equations (3) and (4), but also possible future evacuations predicted by behavioral models. Therefore, when behavioral model insights are integrated, the likelihood on a given day *t* becomes a composite function weighing the likelihood for observed evacuations and the likelihood for future trends of evacuation demand predicted by behavioral models, as in equation (5).

$$L^*(t) = f\big(obs(t), P\big(\Delta p(t)\big), P\big(\Delta p(t+1)\big); \boldsymbol{w}\big), \quad (5)$$

where $obs(t)$ is the likelihood of observed evacuations by day t, which can be calculated from $L_i^E(t_i)$ and $L_i^H(t_i)$, $\Delta p(t)$ is the behavioral-model predicted change in evacuation demand from day *t* to *t*+1. The weights $\boldsymbol{w}$ determine how much observed evacuations and behavioral model predictions each contribute to the likelihood $L^*(t)$.

Results

Using Hurricane Harvey in 2017 as a case study, we apply the proposed state-transition model (without behavioral model insights) to forecast the evacuation demand in southern Texas from August 21 to August 31, considering that the hurricane made landfall in this area on August 25. The forecast is made daily, given the observed evacuation up to the day. The results are shown in Figure 1.

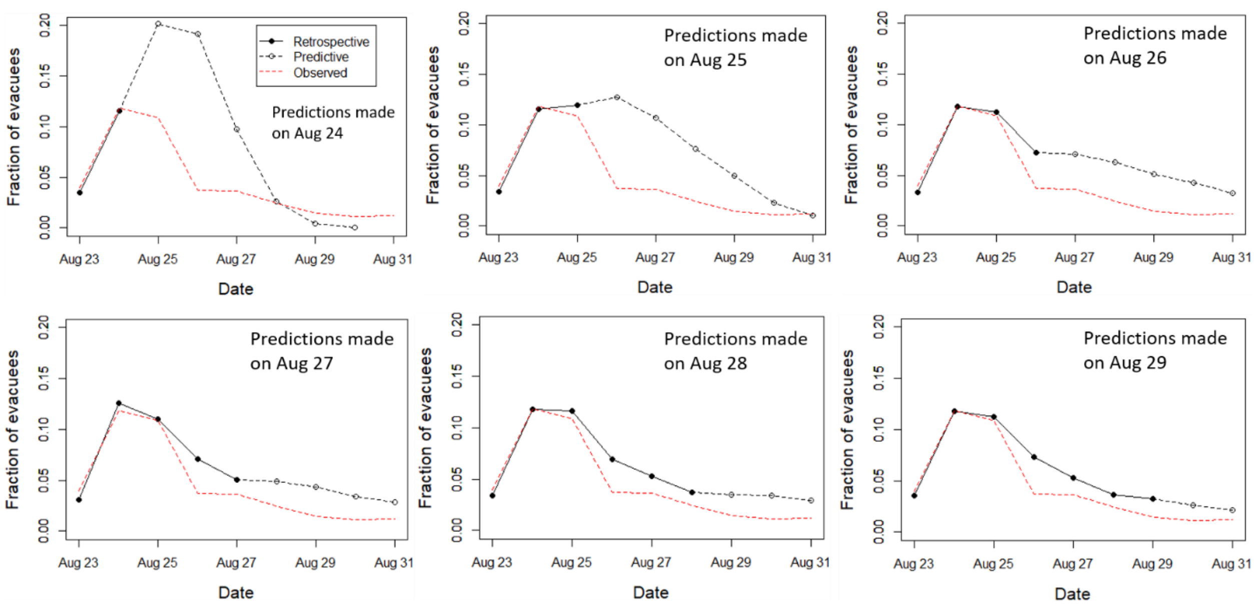

Figure 1. State-transition model predictions of evacuation demand in comparison to observed evacuation demand.

There are two key messages from Figure 1. First, as the state-transition model takes in newly observed evacuations over time, it is capable of adjusting the forecasts to approach the observations. Second, the state-transition model (without behavioral model insights) can not accurately forecast the peak evacuation demand before it happens.

When behavioral model predictions are integrated into the state-transition model, we test 5 scenarios with different evacuation demand patterns from behavioral models. The results are shown in Figure 2.

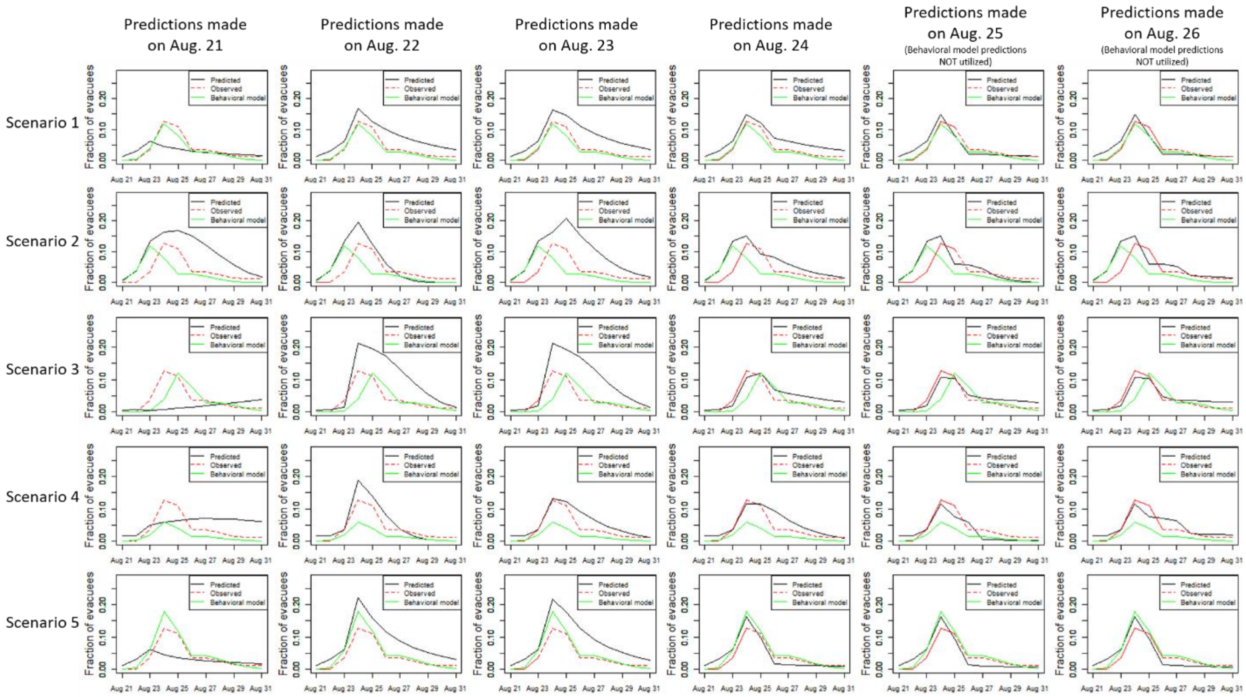

Figure 2. Scenario analysis to test the performance of state-transition model after integrating different behavioral model predictions.

The key finding from Figure 2 is that when behavioral model predictions, even if inaccurate with respect to the observations, are integrated into the state-transition model, the state-transition model gains the ability to early capture the peak evacuation demand, at least in terms of it timing.

Conclusion

This study develops an innovative state-transition model with survival formulation and integrated behavioral model insights. Its novelties are two-fold. For model development, this study extends the conventional state-transition model to account for time-varying and individually heterogeneous transition probabilities. And for evacuation demand forecasting, it addresses the challenge of early prediction of sudden surge in evacuation demand. Our case study results show that the model can accurately forecast the timing of peak evacuation demand generally 2 days ahead, and consistently over-predict its magnitude. The results suggest potential value of the methodology in assisting emergency responders to plan, prepare and organize evacuations.

Note

This extended abstract is based on an ISTTT24 paper that is to be presented in July 2021 in Beijing and is also under review for possible publication at Transportation Research Part E. This abstract is submitted for presentation only at the ISTDM21 conference.