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Development of a Mode Choice Model to Estimate Evacuation Transit Demand

by

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16. Abstract

Since Hurricane Katrina, transit evacuation service has been seen to serve critical needs in affected cities and an increasing number of hurricanes have struck the east coast where more people rely on public transportation to evacuate. Thus, it is important to model mode choice in evacuation for a better estimation of evacuation transit demand. In this study, a joint mode and destination type choice model was estimated based on multiple post-storm behavioral surveys from the northeastern seaboard to the Gulf Coast. A nested logit model specification was used to estimate this joint choice model. The estimated model showed significant linkage between mode and destination type choice, which validated the choice of a nested structure for the model. Selected variables include both household and zonal characteristics, reflecting the attributes of alternatives, the characteristics of households, and the interactions between them. Most of the selected variables are significant at a confidence level of 95%. The estimated model was then applied in two different cases and the prediction errors are small. This study also estimated a new model in a situation that zonal data is only available at a relatively coarse level. The new estimated model was applied in three different cases. The prediction errors in all cases are larger in comparison with the previous applications, but they are still within an acceptable range. Overall, the findings of this study provide insight into the factors affecting mode and destination type choice of residents during hurricane evacuation. It also provides discussion on model transferability in applications with different characteristics.

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ABSTRACT

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EXECUTIVE SUMMARY

The purpose of this study was to develop a model that can predict what mode of travel people will choose when they evacuate from a hurricane. One problem is that mode of travel is often influenced by the type of refuge people evacuate to. For example, use of transit is possible if someone is evacuating to a public shelter to which transit service is provided, but evacuating to a hotel/motel, or the home of a friend or relative, typically requires an automobile. For this reason, a joint mode and destination type model was developed in this study rather than just a mode choice model.

The joint model developed in this study is sensitive to the characteristics of the evacuee, the community they live in, and the transportation system that serves them. Characteristics of interest include the socio-economic composition of communities, the level of social interaction within them, transit service provided, and the accessibility and affordability of different destination types (e.g., hotel rates divided average household income). The model is estimated on evacuation behavior observed in hurricanes Irene and Sandy in New York and Hurricane Gustav in New Orleans. The model is tested by applying it to Hurricane Georges in New Orleans and comparing model predictions with observed values. The results are shown in the table below where the predicted number of evacuating households is shown above the line and observed number below the line in each cell. As can be seen, the model produces the same pattern of evacuation as that observed in Hurricane Georges although individual cell values do not match exactly.

Predicted and observed joint mode/destination type choices for Hurricane Georges

County/Parish	Home of friends or relatives				Hotel or motel				Public shelter				Other	
	own	ride	transit	other	own	ride	transit	other	own	ride	transit	other	own	other
Jefferson	53 / 43	1 / 0	0 / 0	0 / 0	17 / 25	1 / 0	0 / 0	0 / 0	1 / 4	0 / 0	0 / 0	0 / 0	5 / 7	1 / 1
Orleans	44 / 38	1 / 3	0 / 0	0 / 0	18 / 18	1 / 0	0 / 0	0 / 0	1 / 4	0 / 0	0 / 0	0 / 0	6 / 10	1 / 1
Plaquemines	28 / 19	1 / 1	0 / 0	0 / 0	10 / 18	1 / 0	0 / 0	0 / 0	1 / 2	0 / 1	0 / 0	0 / 0	3 / 3	1 / 0
St. Bernard	20 / 15	1 / 0	0 / 0	0 / 0	5 / 6	0 / 1	0 / 0	0 / 0	0 / 4	0 / 0	0 / 0	0 / 0	2 / 2	0 / 0
St. Tammany	19 / 19	0 / 1	0 / 0	0 / 0	10 / 8	1 / 0	0 / 0	0 / 0	1 / 3	0 / 1	0 / 0	0 / 0	3 / 2	1 / 0
Hancock	10 / 8	0 / 0	0 / 0	0 / 0	5 / 2	0 / 0	0 / 0	0 / 0	1 / 4	0 / 0	0 / 0	0 / 0	2 / 4	0 / 0
Harrison	18 / 23	0 / 0	0 / 0	0 / 0	8 / 4	0 / 0	0 / 0	0 / 0	1 / 0	0 / 0	0 / 0	0 / 0	3 / 4	1 / 0
Jackson	15 / 14	0 / 0	0 / 0	0 / 0	6 / 5	0 / 0	0 / 0	0 / 0	1 / 4	0 / 0	0 / 0	0 / 0	2 / 0	0 / 1

How accurately the model will predict in other areas with different conditions and different storms is not known at this time; more testing of the model's predictions on past storms with observed responses (as shown in the table above with Hurricane Georges) is needed before an estimate of the model's prediction accuracy can be determined.

This model forms part of a sequential series of models developed at LTRC that collectively predict if, when, where, how, and by what route people evacuate from a hurricane. The models are currently being integrated into a package that allows a user to estimate the impact of evacuation management decisions on evacuation traffic from an affected area. In using the package, a user first chooses from a list of past hurricanes or selects an active hurricane being tracked by the National Hurricane Center in real time. Once a storm is identified, its time-dependent characteristics, including the projected path and future properties of the storm, are automatically downloaded from the National Hurricane Center's webpage using either historical records or real time projections. The user then specifies the area they want to analyze evacuation from, and enters a scenario of time-related evacuation management decisions to test. Detail of the transportation network and transit service for the area must be specified. The model then produces time-dependent estimates of the evacuation that will follow given the characteristics of the storm, the transportation system, and the selected evacuation management decision scenario. Output is 6-hourly reports on the number of departures from each zone, arrivals at destinations by destination type, shelter occupancy relative to capacity, average evacuation time, clearance time, levels of congestion on individual links, total delay, total vehicle hours, and total vehicle miles traveled. By running the package with different evacuation management decision scenarios and observing the results, the consequences of alternative evacuation management decisions can be evaluated.

At first the model package will be applied to past known storms and the predictions compared with observed behavior. If sufficient accuracy is achieved and the model package produces results within, say, 30 minutes for each run, the ultimate use of the package will be tested; its application in real time to an active hurricane. The aim is to estimate the traffic impact of one or two management decision scenarios in each 6-hour storm advisory period. If this proves possible, emergency managers will be able to estimate the consequences of alternative evacuation management decisions at progressively shorter forecasting horizons before having to implement the decisions. This should lead them to identify what management decisions to make and when to implement them to achieve the best evacuation experience.

ACKNOWLEDGMENTS

IMPLEMENTATION STATEMENT

The model developed in this study will be integrated into the Hurricane Evacuation Modeling Package being developed in LTRC project 17-3SS. Its function will be to distinguish the mode and destination type of evacuating households in each time interval. When the package is applied, it will first be used to validate its performance by being able to replicate evacuation behavior from past storms. The correct functioning of each component model will be assessed by comparing their predictions with observed values.

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INTRODUCTION

Current models of hurricane evacuation demand use subjectively determined evacuation participation rates to estimate evacuation demand. However, as it was shown in past studies, evacuation behavior is sensitive to the dynamic properties of a hurricane, the evacuation network, operational decisions made by emergency managers, the conditions the population are exposed to, and their ability to withstand them. In trying to accommodate these influences in a modeling framework, Louisiana Transportation Research Center (LTRC) has developed hurricane evacuation demand models over the last decade.

What is currently missing among the LTRC models is the ability to estimate the use of other modes of transportation in evacuation beside the private vehicle. Of particular interest is the use of transit and the ability to model it as a function of the level of transit service provided, location of shelters, characteristics of the population, etc. Transit use during an evacuation virtually confines the choice of destination type to public shelter, so a close link exists between mode choice and destination type choice. This also extends to other combinations of destination type and mode such as evacuation to friends and family, which essentially requires the use of a private vehicle. For this reason, it was considered appropriate to model mode choice and destination type jointly in this study.

Generally speaking, in any evacuation, part of the decision-making activity of a person or household involves deciding what type of facility they are going to evacuate to (i.e., destination type choice) and how they are going to get there (i.e., mode choice). From the perspective of an emergency manager, people's collective choices affect what kind of preparation must be made to accommodate the resulting movement (such as contraflow) and what resources need to be provided (such as public transportation and shelter service). Emergency managers' decisions consequently affect the performance of the whole evacuation system. Thus, understanding evacuation mode choice of households is an important issue and is becoming increasingly so with the increasing frequency of hurricane strikes in areas that have higher population density and less hurricane experience. This study also benefits areas that are attempting to find out how to improve evacuation bus service during hurricanes.

Literature Review

Research Background

Historically, Atlantic hurricanes more frequently affect states on the Gulf Coast and the lower eastern seaboard areas of the U.S., where most of the cities are car-oriented. High vehicle ownership, a low level of public transportation service, long evacuation distances,

and the desire to protect their own vehicular property make using their own private vehicle the most preferred mode choice during hurricane evacuation in these areas. In a survey conducted after Hurricane Andrew (1992) in the coastal parishes of Louisiana, about 85% of the respondents used their own vehicles for evacuation and almost all the remainder rode with others in their vehicles. Another survey conducted after Hurricane Floyd (1999) in Florida, Alabama, Mississippi, and Louisiana showed that about 95% of the respondents relied on their own vehicles for evacuation. In both surveys, the percentage of respondents who used public transportation service was less than 1%. Thus, mode choice studies did not receive much attention for a long time because the private vehicle dominated mode choice in the areas where most hurricanes were making landfall. In addition, the revealed preference surveys that were typically conducted after each hurricane did not provide enough data to effectively model mode choice where transit was one of the alternatives. Therefore, stated preference surveys using hypothetical cases became the primary data source for modeling evacuation mode choice in past studies *[1][2]*.

Within the past few years, however, northern cities like New York have been struck by several deadly hurricanes, such as Hurricane Irene in 2011 and Hurricane Sandy in 2012. Evacuation behavior data collected from a transit-oriented city like New York is likely to capture transit choice during evacuation more fully than data collected from car-oriented cities for two reasons. First, the higher level of public transportation service and lower household vehicle ownership make transit a more likely choice in all circumstances. Second, evacuation distances in New York have been observed to be shorter than the intercity evacuations typically observed in the Gulf Coast, making evacuation by local transit a more feasible choice. Specifically, 83% of the respondents evacuated to a place within the study area in the post-Irene survey conducted for US Army Corps of Engineers (USACE) in 2013. In the same survey, over half of the respondents (54%) did not leave their own county and 12% chose public transportation (bus, ferry, subway, and taxi). In a post-Sandy survey funded by New York City Emergency Management Department and completed in 2014, 16% of evacuees used transit to evacuate from Sandy. It is recognized that the shorter evacuation distances are likely to be the result of more factors than the availability of local transit; a rapid increase in topographical elevation from the coastline, the general direction of storms (parallel to the coast on the eastern seaboard and perpendicular to the coast in the Gulf), and more opportunities for refuge in large metropolitan areas, may be additional factors favoring shorter evacuation distances. No matter the reason, the value of these surveys is that they capture a high proportion of actual transit choice during an evacuation.

Since the number of people in transit-oriented cities that rely on public transit system for evacuation is large, this research is obviously important to these cities. But this research can

also benefit car-oriented cities as well. In these locations, there are a portion of the population who have to rely on transit for evacuation. They are usually characterized as people who are carless, disabled, low-income, and low English proficiency. Cities like New Orleans and Miami have already established evacuation assistance program to help them evacuate. But the estimation of demand is usually based on the local emergency managers' judgment or experience. Obviously, this research can assist their decisions, such as what demand to expect and where to locate pick-up points.

Even though mode choice during evacuation is of much importance in practice, this subject has received little attention in past academic research. Among the handful of studies that have been conducted on the subject, the focus has been on using the demographic characteristics of each household in explaining mode choice behavior. Several other factors affecting mode choice have typically been overlooked. For example, the level of public transportation service and accessibility to destinations are intuitively expected to play an important role in people's mode choice and yet they have seldom been included in past studies. Second, social factors have also been neglected in the past. Factors such as a household's social network size and social interaction level in the community where they live are likely to play a role in the choice of destination type and mode choice. Specifically, these types of factors are likely to influence whether a carless household will ride with neighbors and whether they can find a friend/relative with whom to stay. This study searches potential explanatory variables more thoroughly than past studies.

Models estimated in the past studies have sometimes incorporated variables that are difficult to predict, such as whether the household changed their destination from the originally chosen destination while evacuating, and how much time passed between the decision to evacuate and the actual evacuation. This study aims to develop a model that can operate where such information is not necessary. Therefore, variables that cannot be collected from large open databases are carefully avoided in this study.

Beyond selection of explanatory variables that are most likely to influence a decision and are predictable, it is also possible to change the structure of model for better estimation. Evacuation mode choice and destination type choice have usually been analyzed and modeled separately. However, there is dependence between mode and destination type choices in many cases. For example, to evacuate to the home of friends or relatives living in an area not served by public transportation, a household would either have to have their own vehicle or ride with someone else. During an emergency, public transportation is typically directed at serving public shelters, making a strong link between public transportation and the choice of a public shelter.

Evacuation Modeling on Mode and Destination Type Choice

      Choice Composition. In evacuation modeling, alternatives of travel mode are often composed of driving your own vehicle, riding with others, taking transit, and using other modes. In order to protect their own property, many households choose to evacuate in their own vehicles so as to remove their vehicles from the possibility of damage. Empirical studies even show that the number of vehicles taken by a household in evacuation ranges between 1.3 to 1.7 which is higher than occupancy levels in ordinary urban travel *[3]*. Riding with others is usually a second choice of a household, especially for residents living in car-oriented cities and facing longer evacuation distances.

Types of destination typically include the home of friends/relatives (FR), hotels/motels (HM), public shelters, and others. FR is the most common destination type during hurricane evacuation. Whitehead et al. surveyed residents who have experienced three actual hurricanes. According to the responses, they found that over 65% of the respondents chose FR; about 11% went to shelters; and others went to HM *[4]*. Similar results have been found in other empirical research on different hurricanes *[3]*.

      Structure of Models. In evacuation modeling studies of mode and destination type, the two choices have usually been analyzed and modeled separately. The following types of models have typically been applied to model them independently: Multinomial Logit (MNL), Nested Logit (NL), logistic regression, and decision trees *[1, 2, 5-9]*. Regarding the specification of nests in NL models, evacuation bus and regular bus have been distinguished from each other within the nest of bus, and public shelters and hotels have been included in a nest of public facilities. They are different from the proposed nest structure in this study. In fact, only one past study linked evacuation mode choice and destination type choice together *[2]*. In that research, destination types were entered as dummy variables in the modeling of mode choice and were found to be significant in that model. This provides evidence to support the assumption that mode choice and destination type choice are related. Clearly, the structure of a MNL model does not apply in this situation where the independence of irrelevant alternatives (IIA) property is not sustained.

There have been studies that simultaneously modeled mode choice with other choices in non-emergency situations. For example, since residential location and travel behavior are not independent of each other, Yang, Zheng, and Zhu treated residential location, travel mode, and departure time as a joint choice *[10]*. They estimated the model with both NL and cross-nested logit (CNL) structures and found CNL outperforms NL in the process of estimation. CNL belongs to the family of Generalized Extreme Value (GEV) models; MNL and NL are special cases of CNL *[11]*. CNL allows alternatives to belong to more than one nest instead

of a single nest as in NL model. Therefore, CNL is capable of handling correlations among alternatives in complex situations. In another case, Ding et. al tested MNL, NL, and CNL in modeling commuter joint choice behavior of travel mode and departure time *[12]*. In their research, NL and CNL were found to perform better than MNL, and CNL was found to perform better than NL. Although both studies found CNL models to have the best performance, whether such a model can be successfully estimated depends largely on the sample size. Both of the above two studies tested CNL structure with over 10,000 observations. With the complexity of a model structure increasing, it generally requires a larger number of observations for model estimation.

Regarding the impact of sample size on model form, another example is the study of Mesa-Arango et. al on modeling of destination type choice during Hurricane Ivan *[6]*. To capture the heterogeneity of household behavior, mixed multinomial logit (MMNL) was tested but it was found that the random parameters are not significantly different from zero and thus adopting fixed parameters is reasonable. It is possible that the number of observations (about 1,400) restricted the performance of MMNL. Due to the limitation on sample size in the research of hurricane evacuation in this study, the effort to pursue a more complex model than NL was expected to offer only marginal benefits.

Variable Selection. In the utility function of a discrete choice model such as various logit models described earlier, the portion of the utility that can be observed by an analyst (i.e., V_{it}) is generally considered as being composed of three parts: the attributes of the alternatives, the characteristics of the decision maker, and any interaction that may exist between the attributes of alternatives and the characteristics of the decision maker *[13]*.

Mode choice models that have been estimated in the past focused mainly on the characteristics of a single household from three aspects: (1) vehicle ownership and other characteristics that could reflect a household's disadvantaged status, such as language spoken and disability status; (2) characteristics that might pose restrictions on a household's mode choice, such as the presence of children or people with special needs and presence of animals or pets; and (3) hurricane-related household characteristics such as past experience.

For destination type choice models, variables of the following five types were most often used: (1) economic status of a household, such as vehicle ownership, income level, education level, and home ownership; (2) social status of a household, such as years of residence and marital status; (3) characteristics that might pose restrictions on a household's destination type choice, which are similar to those listed under modeling mode choice; (4) other demographic characteristics of a household, such as language spoken, household size, and

race; and (5) variables that reflect hurricane characteristics, such as hurricane strength and distance from the approaching hurricane to a household.

Beside the household characteristics listed above, zonal level data can reflect the contextual characteristics of the surrounding environment and thus have an effect on a household's choice, such as level of social interaction within a zone. As often stated in sociology research, a household's family context, kin relationship, and level of community involvement must be taken into account in the study of human behavior in disasters [14-17]. Therefore, at household level, length of residence has been used as a proxy variable to measure a household's social network in modeling evacuation choices [7]. As stated in some sociology studies, communities with strong social ties can improve evacuation performance [18]. Sampson investigated which factors affect local friendship ties and community attachment at both household and community levels [19]. In the research reported in that paper, length of residence, labor force participation, marital status, age, social class, children in household, and fear of crime were investigated at household level. At community level, urbanization, community density, residential stability, family structure (percent divorced or separated), socioeconomic status (education and income), age composition/life cycle (number of children under 16), and unemployment rate, fear, and victimization rate for serious predatory crime were investigated. In that study, it was found that length of residence at household level and residential stability at community level are more significant than other variables that measure local friendship ties and community attachment.

In past studies, variables related to the attributes of mode and destination type have seldom been considered even though they intuitively would be expected to be influential. Take mode choice of transit as an example. Transit level of service would clearly be expected to affect a households' choice of transit and yet it has not been used in mode choice in evacuation modeling before. It could be measured directly by the extensiveness of the network, frequency of service, number of operating vehicles, or capacity of the network. It could also be reflected indirectly by the number of commuters who take transit on regular days. For destination type choice, an example of a factor that could affect the choice of hotel/motel but has not been used before is the average availability of hotel rooms (i.e., hotel occupancy). Another example is the price of hotel accommodation relative to the household income.

Accessibility is another factor that has been neglected in modeling destination type and mode in the past. As pointed out by Bhat et. al, accessibility is a combined assessment considering both transportation system and land use patterns [20][21]. According to them, accessibility can be measured in terms of three factors: an impedance factor, a destination factor, and a traveler factor. The attributes used to reflect each of the above factors can be fine or coarse in

its areal unit, which is generally based on data availability and the problem under study. For example, in measuring the impedance factor, whether there is shade or a bench at a bus stop can reflect impedance (more specifically, comfort) at a fine level, while total travel time can reflect impedance at a coarse level. In measuring the destination factor, whether ADA access is provided can reflect the convenience of a destination at a fine level, while the number of employees in a zone is a coarse measure. In measuring the traveler factor, personal preference is a measure at a fine level and annual household income is a measure at a coarse level. Regarding forms of formulating the measurement using above factors, there are different variants that are based on the Gaussian function, gravity function, or cumulative opportunity function. No matter what is under study or which form of measurement is selected, an accessibility measure should: (1) obey several widespread axioms, which will be specified in greater detail in measuring accessibility; (2) have a behavioral basis; (3) be technically feasible; and (4) be easy to interpret *[22][23]*. A few questions that can assist in formulating accessibility measure are: what is the degree and type of disaggregation desired; how are OD defined; how is attraction measured; and how is impedance measured *[24]*. The authors of this study paid attention to the above questions in formulating an accessibility measure in this study.

OBJECTIVE

Overall, the objective of this study was to develop a joint mode/destination type choice model for hurricane evacuation, and demonstrate its use in New Orleans. To achieve these objectives, the following activities were conducted:

1. Use data from real hurricanes to better capture evacuation behavior that is the consequence of all the factors influencing choices as a hurricane approaches. This is done because it allows the use of detailed information about storm and local conditions that is almost impossible to include in the description of a hypothetical situation.

2. Pool data from several post-storm behavioral surveys. This is done because it allows researchers to have a dataset with greater diversity and more observations. The underlying assumption is that households with the same characteristics and facing the same conditions will behave the same even though they are from different areas.

3. Consider mode and destination type choice as a joint choice. Theory on discrete choice models was thus used in this study. Types of logit models under investigation included Multinomial logit (MNL) model, Nested Logit (NL) model and other types of Generalized Extreme Value (GEV) models. The type of model was selected based on their characteristics and suitability to the subject of this study.

4. Consider a wider variety of variables, such as sociologic and contextual factors, than have typically been considered in the past. In considering a wider range of alternatives as influencing mode and destination choice, the following two hypotheses were tested:

   Hypothesis 1: destination type choice = f(characteristics of the household, characteristics of the destination type, characteristics of the transportation system)

   Hypothesis 2: mode choice = f(destination type choice, characteristics of the household, characteristics of the transportation system)

5. Estimate parameters and calibrate the model. Models were estimated with household choice behavior data from a pooled dataset. Two models were estimated separately to accommodate the availability of zonal data at either a fine or a coarse zonal level. The one with the best performance was selected in each case for application and prediction purpose.

6. Apply the selected model on other post-storm behavioral surveys. These surveys were conducted after different hurricanes or covered different study areas. By doing this, the application performance of the estimated model can be observed more fully.

Assess the predicted results. The estimated choices were compared with recorded choices in that survey. Prediction error was calculated for each application to assess the prediction power of the estimated model in different situations.

SCOPE

The scope of this study is limited to the development of a joint mode/destination type choice model for hurricane evacuation but its application is meant to be geographically universal. That is, use of the model is based on the premise that evacuation behavior is determined primarily by the variables in the model, and the geographic location of its application is not significant beyond those features captured in the variables of the model.

In order to appreciate the role of the joint mode/destination type choice model developed in the whole LTRC evacuation modeling process, its position and function of the whole process are presented first. Following this, the study areas in which the post-storm behavioral surveys that provided the data on which the joint choice model was estimated, are shown. Although they represent only a limited number of areas, they do represent a diverse range of conditions representative of the conditions that could be encountered on the east coast and Gulf Coast of the U.S.

The Scope of the Model

The general structure of the entire evacuation modeling process adopted in this study is similar to the four-step travel demand modeling process used in regular urban transportation planning. That is, demand estimation is conducted in a sequence of steps with the output of one step serving as input to the next until at the end, the last step produces estimated travel on the network. However, the number of steps and the nature and the sequence of steps are different in evacuation and urban travel demand modeling. To illustrate, Figure 1 shows both the regular urban transportation planning process and the evacuation demand estimation processes, with dotted lines linking similar activities between the two systems. For example, the trip generation process in regular urban transportation planning is replaced with two activities in evacuation modeling: the decision to evacuate and when to do so. The third step in evacuation demand modeling is to decide what type of destination to evacuate to and what mode to choose, which is similar to mode choice in regular urban transportation planning. Similarly, route choice in evacuation demand modeling is similar to trip assignment in regular urban transportation planning although the criteria for route choice are more comprehensive in evacuation demand modeling than the sole criterion of travel time used for route choice in urban transportation planning.

Regular travel demand modeling process

Trip generation	→	Trip distribution	→	Mode choice	→	Trip assignment

Evacuation?	→	When?	→	To what? & How?	→	Where?	→	Route?

Evacuation modeling process
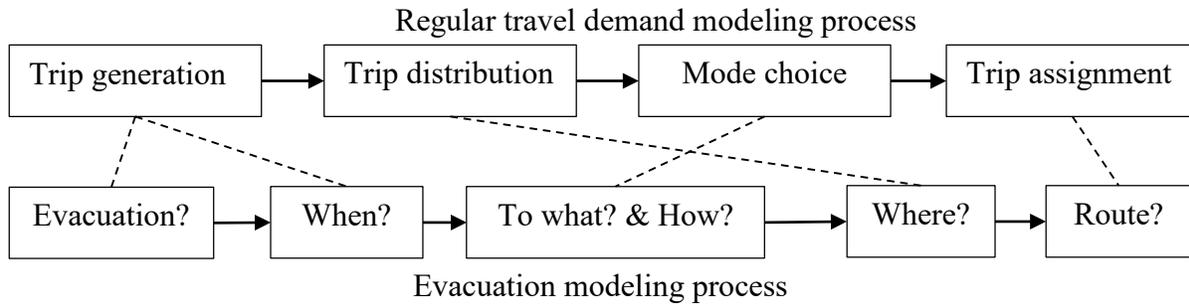
Figure 1
Process of evacuation modeling

This study is a part of the above-mentioned evacuation modeling process. The authors focus on modeling mode/destination type choice (i.e., To what? and How?). Thus, how many people decide to evacuate and when to evacuate are assumed known in this study and serve as input. The output from this study is the type of destination chosen and the mode used. This information is, in turn, fed into the model of destination choice (Where?) where the location of the trip end is identified. The product of the destination choice model, the number of households from origin to destination by mode in each time period, is converted to vehicle trips and input to the route choice process. Vehicles are then assigned to routes linking the origins and destinations to produce a time-dependent representation of evacuation traffic flows.

The Scope of the Study Area

Household behavior was extracted from three evacuation behavioral surveys conducted after Hurricane Gustav (Aug 25–Sep 05, 2008), Hurricane Irene (Aug 21–Aug 30, 2011), and Hurricane Sandy (Oct 21–Oct 31, 2012). Hurricane tracks and their categories are shown in Figure 2. The track of Hurricane Georges is also shown in the following figure because data from that storm were used in the process of model application.

Figure 2
Hurricane tracks (source: https://coast.noaa.gov/hurricanes/)

As can be observed from Figure 2, Gustav and Georges affected southern states, while Irene and Sandy had significant impacts on northeastern states. Table 1 is a description of the extent of the study area in each survey. The number in each bracket is the year in which hurricane took place.

Table 1
Study area of post-storm surveys

Survey	Study area
Georges (1998)	Five coastal parishes in southeastern Louisiana and three coastal counties in Mississippi
Gustav (2008)	Ten coastal parishes in southeastern Louisiana
Irene (2011)	New York City, Nassau, Suffolk, and Westchester County
Sandy (2012) I	New York City
Sandy (2012) II	New York City and coastal counties of New Jersey

METHODOLOGY

Approaches to Model Choice Behavior

A choice process is composed of four elements: the decision-maker, the alternatives, the attributes of alternatives, and the decision rule *[13]*. In this study, the decision-maker is each household in the sample when a model is being estimated, and each household in the population when the model is being applied. The alternatives available to each household are assumed to be the same for all households. That is, each household can choose from the same set of destination types and the same set of modes. The alternatives are described in terms of their attributes, and these can be both generic and alternative specific attributes as discussed in the next chapter. The decision rule and the models that will execute those rules are discussed below.

A decision-maker is usually assumed to make rational choices which are consistent and transitive. A common rational decision rule is utility maximization where a decision maker is assumed to always choose the alternative with the greatest utility. According to probabilistic choice theory, the utility function is assumed to be two parts: a portion that is observed to an analyst and a portion that is known to the decision maker but is unknown, or unobserved, to an analyst:

$$U_{ni} = V_{ni} + \varepsilon_{ni} \tag{1}$$

where,

U_{ni} is the utility of alternative i to decision-maker n;

V_{ni} is the portion of the utility that can be observed by an analyst. It can be expressed as $\beta_i X_{ni}$, where X_{ni} is a vector of independent variables relating to alternative i for decision maker n, and β_i is a vector of parameters common among all decision-makers;

ε_{ni} is the portion of the utility that cannot be observed by an analyst. Because an analyst cannot observe it (although a decision maker includes it in the decision making process), the analyst formulates it as a random error term in the utility function. Different assumptions about the distribution of the error term lead to different mathematical forms of a discrete choice model *[13]*. For example, if it is assumed that the error terms are independently and identically Gumbel distributed across alternative and decision makers, it leads to the multinomial logit (MNL) model.

As is well known, the above-mentioned assumption of the MNL model will lead to the wrong results when it is applied to choices that do not have the independence of irrelevant alternatives (IIA) property and the degree of error will depend on the level of dependence among the alternatives [25]. One solution to this problem is to use a Nested Logit (NL) model where alternatives that are correlated are nested together. This allows the common attributes of alternatives in each nest to cancel out in a utility comparison among alternatives. The NL model lets unobserved factors have the same correlation for all alternatives within a nest and no correlation for alternatives in different nests. Equation (2) is a general expression of a NL model [26][27][28].

$$P_{ni} = \frac{\exp(\frac{V_{ni}}{\lambda_k})(\sum_{j \in D_k} \exp(\frac{V_{nj}}{\lambda_k}))^{\lambda_k - 1}}{\sum_{l=1}^{K}(\sum_{j \in D_l} \exp(\frac{V_{nj}}{\lambda_l}))^{\lambda_l}} \tag{2}$$

where,

P_{in} is the choice probability for decision maker n choosing alternative i, where i belongs to a nest D_n^k;

V_{in} is the utility for decision maker n choosing alternative i;

λ_k is the nesting coefficient or logsum coefficient.

When $\lambda_k = 1$, it means there is no correlation in unobserved utility among the alternatives within nest k. When $\lambda_k = 1$ is true for all k, it means all the alternatives in all the nests are not correlated. The model then reverts to the same structure as a MNL model. Thus, λ_k is a measure of the degree of independence in unobserved utility among the alternatives in nest k, while $(1 - \lambda_k)$ is a measure of their correlation.

To illustrate the functioning of a NL model, equation (2) can be decomposed into the product of two logits. The derivation is shown below [25].

$$P_{in} = \frac{\exp\left(\frac{V_{in}}{\lambda_k}\right)\left(\sum_{j \in D_n^k} \exp\left(\frac{V_{jn}}{\lambda_k}\right)\right)^{\lambda_k - 1}}{\sum_{l=1}^{K}\left(\sum_{j \in D_n^l} \exp\left(\frac{V_{jn}}{\lambda_l}\right)\right)^{\lambda_l}} \tag{3}$$

$$= \frac{\exp\left(\frac{V_{in}}{\lambda_k}\right)}{\sum_{j \in D_n^k} \exp\left(\frac{V_{jn}}{\lambda_k}\right)} \cdot \frac{\left(\sum_{j \in D_n^k} \exp\left(\frac{V_{jn}}{\lambda_k}\right)\right)^{\lambda_k}}{\sum_{l=1}^{K}\left(\sum_{j \in D_n^l} \exp\left(\frac{V_{jn}}{\lambda_l}\right)\right)^{\lambda_l}} \qquad (\text{Let } V_{in} = W_n^k + \lambda_k Y_{in}^k)$$

$$= \frac{\exp\left(\frac{W_n^k + \lambda_k Y_{in}^k}{\lambda_k}\right)}{\sum_{j \in D_n^k} \exp\left(\frac{W_n^k + \lambda_k Y_{jn}^k}{\lambda_k}\right)} \cdot \frac{\left(\sum_{j \in D_n^k} \exp\left(\frac{W_n^k + \lambda_k Y_{jn}^k}{\lambda_k}\right)\right)^{\lambda_k}}{\sum_{l=1}^K \left(\sum_{j \in D_n^l} \exp\left(\frac{W_n^l + \lambda_l Y_{jn}^l}{\lambda_l}\right)\right)^{\lambda_l}}$$

(Because $e^x b^c = e^{x + c \ln b}$)

$$= \frac{\exp\left(\frac{W_n^k}{\lambda_k}\right) \exp\left(Y_{in}^k\right)}{\exp\left(\frac{W_n^k}{\lambda_k}\right) \sum_{j \in D_n^k} \exp\left(Y_{jn}^k\right)} \cdot \frac{\exp(W_n^k)\left(\sum_{j \in D_n^k} \exp\left(Y_{jn}^k\right)\right)^{\lambda_k}}{\sum_{l=1}^K \exp(W_n^l)\left(\sum_{j \in D_n^l} \exp\left(Y_{jn}^l\right)\right)^{\lambda_l}}$$

(Let $I_{D_n^k} = \ln \sum_{j \in D_n^k} \exp\left(Y_{jn}^k\right)$)

$$= \frac{\exp\left(Y_{in}^k\right)}{\sum_{j \in D_n^k} \exp\left(Y_{jn}^k\right)} \cdot \frac{\exp\left(W_n^k + \lambda_k I_{D_n^k}\right)}{\sum_{l=1}^K \exp\left(W_n^l + \lambda_l I_{D_n^l}\right)}$$

$$= P_{in|D_n^k} \cdot P_{D_n^k}$$

where,

V_{in} is the utility for decision maker n choosing alternative i;

W_n^k is the mean of V_{in} over all alternatives in nest D_n^k and D_n^k is nest k to which decision maker n belongs;

Y_{in}^k is the deviation of V_{in} from the mean W_n^k;

$P_{in|D_n^k}$ is the conditional probability of decision maker n choosing alternative i given that the nest D_n^k is chosen by the decision maker n, $i \in D_n^k$;

$P_{D_n^k}$ is the marginal probability of decision maker n choosing an alternative in nest D_n^k;

$I_{D_n^k}$ is called logsum because it is the log of a sum, i.e., $\ln \sum_{j \in D_n^k} \exp\left(Y_{jn}^k\right)$;

λ_k is the nesting coefficient or logsum coefficient.

The purpose of this derivation is to show that if a set of alternatives can be subdivided into nests in which unobserved utility is correlated among alternatives within a nest and no unobserved utility is correlated between nests, the nested logit model reduces to the product of a marginal probability of a choice among the nest and a conditional probability within each nest. Each probability (marginal and conditional) is a multinomial logit model with IIA properties. The difference is that the marginal probability has the so-called "inclusive value"

(or "logsum") term as an added variable in its utility function. It reflects the influence alternatives in each nest collectively have on the choice of that nest. Thus, influence is carried between subsets of alternatives and the nests they belong to but it is achieved without violating the IIA assumption of the MNL models constituting the nested logit model.

Assume there are two alternatives from two nests, say $i \in D_n^k$ and $m \in D_n^l$. Then, based on the new expression of two logits, the ratio of probabilities between the alternatives for individual n is:

$$\frac{P_{in}}{P_{mn}} = \frac{P_{in|D_n^k} \cdot P_{D_n^k}}{P_{mn|D_n^l} \cdot P_{D_n^l}} \tag{4}$$

When $k = l$, that is i and m are in the same nest, equation (4) becomes $\frac{P_{in|D_n^k}}{P_{mn|D_n^k}}$, which means that the ratio of probabilities between alternatives i and m are independent of any changes in all other alternatives. That is, IIA holds among alternatives within the same nest. However, when $k \neq l$, that is i and m are in different nests, the ratio depends on the attributes of all alternatives within D_n^k and D_n^l. That is, IIA does not hold among alternatives across nests. In addition, the ratio does not depend on the attributes of alternatives that do not belong to the named two nests.

NL and Other GEV Models. NL is the most widely used type of GEV model. Typically, GEV relaxes the restrictions present in models such as logit and thus allows any pattern of correlation among alternatives. Beside the NL model, the GEV family includes many other models, such as the generalized nested logit (GNL) model, cross-nested logit (CNL) model, and spatially correlated logit (SCL) models. For a detailed review on GEV models, please refer to the work of Bekhor and Prashker *[29]*. As mentioned in the literature review, GEV models (with the exception of NL) have typically required large datasets (over 10,000 observations) to successfully estimate a model in the past. The number of available observations is much less in this study, which is presented in a following section. Therefore, an NL was selected as the model structure to be used in this study. The specific structure of the NL model used in this study is discussed in detail in the next section.

Specific Structure of the NL Model

The nested logit structure shown in Figure 3 was selected for use in this study for the following reasons. First, the assumption of a dependency between destination type and mode makes the use of a regular multinomial logit model inappropriate in this situation. Thus, NL and other GEV models are potential choices to handle this situation. The assumption of dependence between destination type and mode choice can be tested by observing whether

the logsum parameters in the model are significantly different from 1. Second, among all the GEV models, the NL model was selected because of the relatively small sample size available in this study. As discussed in the previous section, those studies using a GEV structure other than NL typically require large samples. In this study, even if observations with missing values are imputed and then pooled across all the surveys, the maximum number of observations available is less than 2,000. Third, the NL model enjoys widespread use, estimation procedures are commonly available, and it is easy to interpret the estimation and application results. In contrast, other GEV models have not been fully exploited in the research area and thus have not been widely applied in practice. Therefore, considering all the above reasons, the NL model appears to be a better choice for the purpose of this research and subsequent applications in practice.

In this study, a potential structure of the NL model is to put destination type on the upper level nest and mode choice on the lower level nest. During model estimation, other potential nesting structures were also tested during model estimation. However, other nesting structures did not produce results that were as good as those produced by the structure shown in Figure 3. Specifically, this structure was chosen because it provides satisfying results in consideration of multiple statistical criteria, such as likelihood ratio index (rho square), significance of parameters, and whether logsum parameters are within a feasible range (0 to 1). These statistics are explained in the next section.
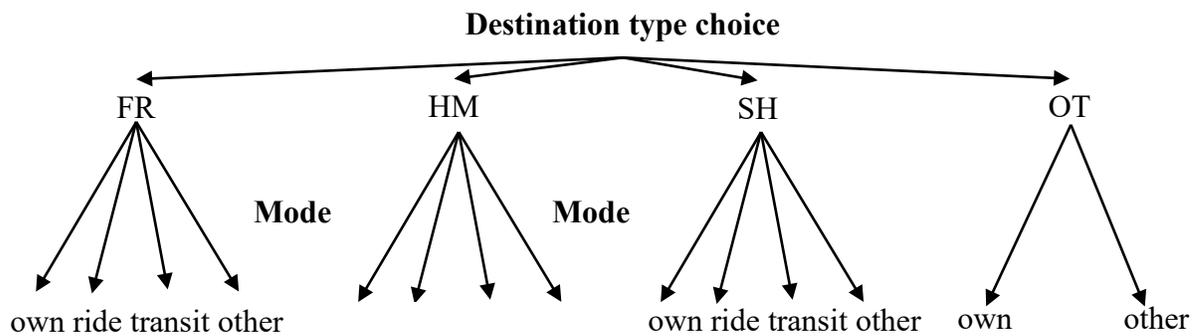
Figure 3
The structure of model
(FR: Friends/Relatives; HM: Hotels/Motels; SH: Public shelters; OT: Other destination type; own: driving your own vehicle; ride: riding with others; transit: taking transit; other: other modes)

Under the nest of FR, HM, and SH, there is a full set of mode choice alternatives in the form of using your own private vehicle to evacuate (own), ride with others (ride), use transit (transit), or use any mode of transport (other). However, under the nest of "other" destination

type (OT), mode choice is only distinguished by whether the household used their own private vehicle to evacuate or not. This is due to the few observations in the OT destination type but where using your own vehicle is still the dominant mode of transportation. During evacuations, emergency managers and traffic engineers pay attention to the amount of traffic flow on the road network so that strategies like contraflow can be applied on time. Therefore, a choice of driving your own vehicle can have a significant impact on the number of vehicles on the road network. Even with a rough estimation, it can be helpful for the management of traffic flows.

<div align="center">Statistics Used in an NL Model</div>

This section presents statistics that are used to evaluate an estimated NL model.

Test of Overall Goodness-of-Fit (GOF). The goodness-of-fit of a model to the data on which it is estimated can be described by rho-squared value (ρ^2) or adjusted rho-squared value ($adj\ \rho^2$). Both are based on log-likelihood values and measure how well the model performs in fitting the data. The difference is that adjusted rho-squared values consider the number of parameters in the model. Rho-squared values vary between zero and one with one indicating a perfect fit of the model to the data, and zero indicating no fit at all.

$$\rho^2 = 1 - \frac{LL(\hat{\beta})}{LL(0)} \tag{5}$$

$$adj\ \rho^2 = 1 - \frac{LL(\hat{\beta}) - K}{LL(0)} \tag{6}$$

where,

$LL(\hat{\beta})$ is the log-likelihood for the estimated model;

$LL(0)$ is the log-likelihood for a model with coefficients equaling zero;

K is the number of parameters used in the estimated model.

Different from the interpretation of R-squared in regression, a rho-squared value does not indicate the percentage of variation in the dependent variable that has been captured or explained by the estimated model. It only stands for the proportional increase in the log likelihood from its value when all coefficients in the model are set equal zero, to its value when the coefficients have reached their maximum likelihood value at convergence. Therefore, it is not as easily interpreted as R-squared. But there is still something in common between rho-squared and R-squared values: they both range from 0 to 1 with 0 and 1 having

the same meanings of no fit and perfect fit, respectively. Because the log likelihood is a non-linear function, rho-squared values cannot be interpreted in linear terms. In maximum likelihood estimation, predicted probabilities on chosen alternatives are maximized, resulting in good model predictions producing likelihood values approaching 1 on each choice alternative, and a poor model predictions producing likelihood values that approach zero on each choice alternative. However, because the log of these likelihood values is taken, poor fits are exaggerated by the large negative value of the log of a small value, while the reverse is true of the log of a value approaching 1. The result is a poor model fit is exaggerated on the log likelihood scale and a good model fit is under-estimated if a linear interpretation of the log likelihood values is made. Since rho-squared is a statistic compiled from log likelihood values, this deviation from a linear scale is carried through. In general, if a rho-squared value is less than 0.1, it means the estimated model has a poor performance in fitting the data; if it is over 0.2, it means the estimated model is acceptable; if it is over 0.3, it means the estimated model performs well; if it is over 0.4, it means the estimated model is excellent.

It should be noted that two models that are estimated on different samples or with a different set of alternatives for any sampled decision maker cannot be compared based on their likelihood ratio index values.

Test of Individual Parameters. The purpose is to find out whether an estimated parameter is significantly different from zero and, therefore, whether the selected variable with which the parameter is associated has a significant impact on household choice behavior. As with other modeling processes, this task can be fulfilled by applying a standard t-test.

$$t - statistic = \frac{\widehat{\beta_k} - \beta_0}{S_k} \tag{7}$$

where,

$\widehat{\beta_k}$ is the estimated parameter for the kth variable;

β_0 is the hypothesized value for the kth parameter;

S_k is the standard error of this estimate.

Tests on each individual logsum coefficient are the same as shown in equation (7), but β_0 equals one in this situation. This test can also be performed to find out whether a portion of the nesting structure can be eliminated.

Test of the NL Structure. As mentioned in a previous section, a NL model is reduced to a MNL model when all the logsum coefficients equals one. Therefore, a likelihood ratio test can be used to identify whether a NL model is a significant improvement on a MNL in a particular case *[13]*. When the following statistic is greater than the Chi-squared statistic χ_n^2 (where, n is the number of logsum parameters), the null hypothesis that a MNL is the correct structure is rejected.

$$-2 \times [LL(MNL) - LL(NL)] \tag{8}$$

where,

$LL(MNL)$ is the log-likelihood of the MNL model, i.e., restricting all logsum coefficients to one;

$LL(NL)$ is the log-likelihood of the NL model, i.e., without restrictions on logsum coefficients.

Data at Household Level

As stated earlier, this research used revealed preference (RP) data from several post-storm behavioral surveys. RP data is generally preferred over stated choice (SC) data because it is believed to be more reliable. One example is the choice on shelter: respondents usually overstate their likelihood of using shelter by a factor of two *[30]*. However, the problem of using RP data is that each post-storm behavioral survey only provides a limited number of observations. The consequence is that some of the joint choice alternatives have only a few observations. In order to have sufficient observations and add more diversity, a compromise was made to pool all datasets together. That is to say, the assumption was made that households living in different areas will display the same behavior under similar conditions. As long as the major impact factors are included in the model and data is available on these factors, we expect that households will make the same decisions no matter where they are. The concern about pooling datasets is similar to that raised in model transferability: do the models capture all the factors dictating behavior? However, if at least the main impacts are successfully captured in a model, the model can reasonably be expected to have good performance when it is transferred and applied in another situation *[31]*.

In this study, household data were collected from three post-storm behavioral surveys. This

section presents information of each survey, how the data were processed, and an analysis on household behavior and their socio-demographic characteristics.

Post-Storm Behavioral Surveys Used in Model Estimation

All of the surveys include questions regarding characteristics of household, as well as details regarding the household's evacuation behavior during the hurricane. The research reported in this study focused on households who chose to evacuate and their choice behavior on destination type and mode. The study area in each survey and the number of population is shown graphically in Figure 4. Due to the availability of variables on geographic unit in each survey and also to keep consistency, ZIP code tabulation areas (ZCTA) were chosen as the geographic spatial unit.
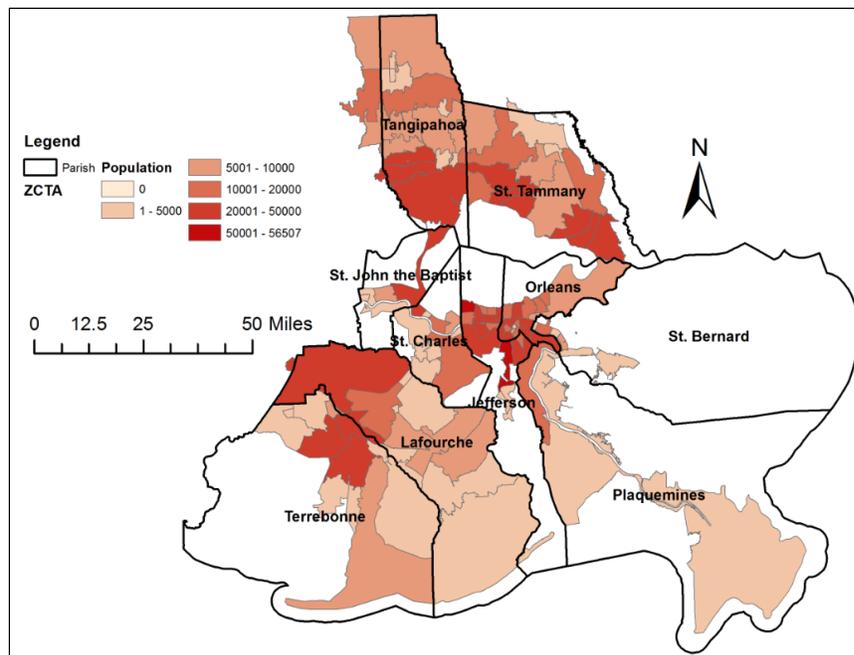
(a) Study area in the survey of Hurricane Gustav (LA)
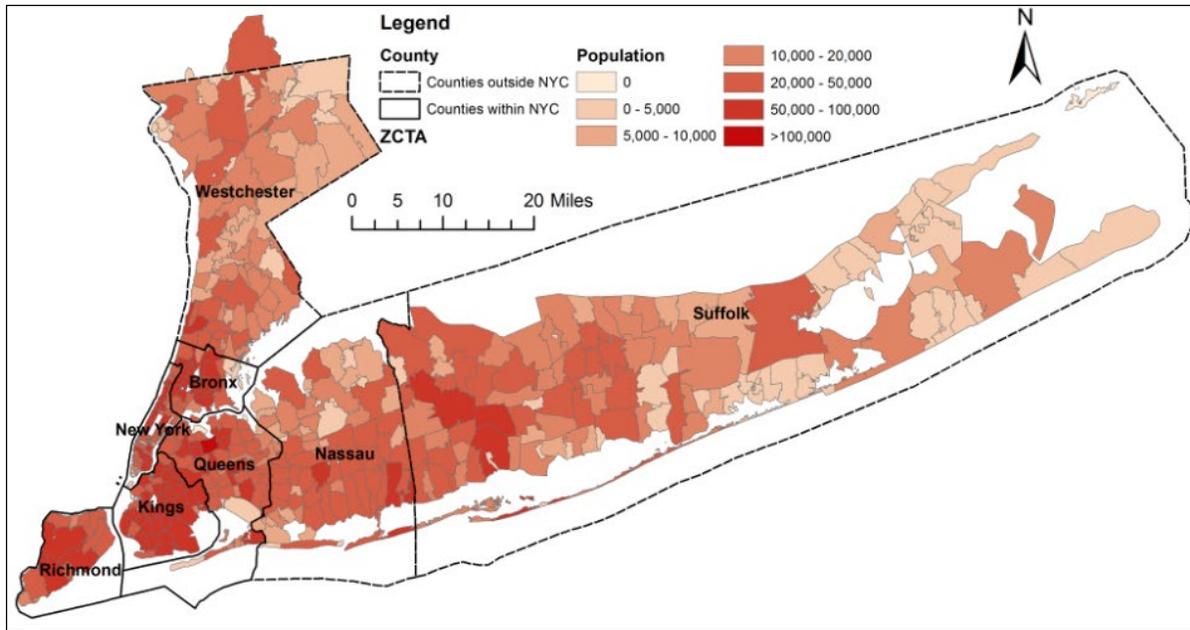
(b) Study area in the survey of Hurricanes Irene and Sandy (NY)
Figure 4
Study area

Table 2 shows the number of respondents (i.e., households in the sample), number of evacuees (i.e., households who chose to evacuate), and the number of evacuees without any missing value on the reported questions and the composition of their choice. Destination type choice (DTC) is categorized as the home of a friend or relative (FR), a hotel or motel (HM), a public shelter or church (SH), and other (OT). OT includes a second home, workplace, campground, clubhouse, etc. Mode choice (MC) is categorized as driving your own vehicle (own), riding with others (ride), taking transit (transit), and using other modes (other). Travel modes within transit include bus, ferry, subway, train, and taxi. Other modes include renting a vehicle, taking an airplane, using an ambulance, walking, cycling, and using a motorcycle.

As shown in the table, there are both similarities and differences in choice behavior across surveys. An analysis on the household choice behavior will be presented in the following section.

Table 2
Description of post-storm surveys

		Gustav (2008)	Irene (2011)	Sandy (2012)
Number of respondents		310	1,600	3,506
Number of evacuees		233	418	637
Number of observations without missing value		170	240	429
DTC:				
	FR	92 (54%)	198 (83%)	356 (83%)
	HM	60 (35%)	25 (10%)	28 (7%)
	SH	4 (2%)	2 (1%)	18 (4%)
	OT	14 (8%)	15 (6%)	27 (6%)
MC:				
	own	165 (97%)	188 (78%)	254 (59%)
	ride	4 (2%)	18 (8%)	58 (14%)
	transit	1 (1%)	29 (12%)	69 (16%)
	other	0 (0%)	5 (2%)	48 (11%)

Household Choice Behavior

Regarding destination type choice, all the surveys present the following similarities: the majority of the respondents went to FR; SH is the least likely choice among respondents. However, as pointed out before, there are also differences among surveys. First, the aggregate choice during Irene is more similar to that during Sandy. An explanation towards this finding lies in the similarity in study area between the two surveys. Second, it can be seen that respondents to Irene and Sandy are even more likely to go to FR and less likely to choose HM than those respondents in Gustav. This finding may seem surprising given that southern states are generally believed to have stronger family ties than areas in the northeast, and the fact, validated by statistics from tourism and economy sector, that there is less hotel accommodation per capita in the New Orleans area than in New York. As will be discussed in the next section, an explanation was found for this phenomenon.

For mode choice, one significant similarity across all the surveys is that a large proportion of the respondents chose to evacuate by their own vehicle. However, mode choice is more similar between Irene and Sandy than with Gustav. Specifically, within Gustav driving own vehicle dominates (over 95%) and taking a transit is barely chosen (less than 1%). In contrast, within Irene and Sandy, the proportion of choice on own vehicle decreases to below 80%, while the proportion of taking transit increases to over 10%. Considering the high level of transit service in NY and the fact that NY residents have been used to rely on transit for commuting in normal days, this reality may encourage some of them to keep using transit

during evacuation. A finding that supports this point of view is that respondents to Sandy are more likely to take transit than those to Irene and New York City provides a higher level of transit service than its surrounding counties. Therefore, factors reflecting the level of transit service appear to be important in choosing transit for evacuation.

Four alternatives in each of the four choices formed 16 possible alternatives in total in their joint choice. However, the destination type "other" has only two mode choices due to limited observations in that destination type, resulting in 14 possible alternatives. Table 3 lists the composition of joint choice in each post-storm behavioral survey.

Table 3
Composition of joint choice without imputation

DTC_MC	Gustav	Irene	Sandy
FR_own	90	160	214
FR_ride	2	15	51
FR_transit	0	21	58
FR_other	0	2	33
HM_own	58	14	16
HM_ride	2	3	3
HM_transit	0	5	4
HM_other	0	3	5
SH_own	3	0	8
SH_ride	0	0	2
SH_transit	1	1	3
SH_other	0	1	5
OT_own	14	14	16
OT_other	0	1	11

As shown in Table 3, there are only a few observations when the choice is transit or shelter. Each single survey cannot provide enough data for model estimation. Therefore, the objective becomes achieving enough observations. Imputation is one of the methods employed to save records that otherwise would not be useable due to missing information on individual items in the survey responses. Another choice is to pool all or a part of the above datasets to add diversity while achieving an adequate number of observations at the same time. Both of them were tested in the process of model estimation.

Household Socio-demographic Characteristics
Table 4 shows the mean, minimum, and maximum of several household characteristics. To observe difference across surveys, statistics are reported for each of them. Although the table only presents five household variables, many more variables were considered in model

estimation. All the household variables in common across the three surveys were entered for test during the model estimation. Those excluded variables are house structure (e.g., detached single family home), house ownership (i.e., own/rent), number of children in a household, whether a household has pets, race or ethnicity, language spoken at home, age of a household head, and education level.

Table 4
Statistics of household characteristics

Variable description and abbreviation	Gustav (2008)			Irene (2011)			Sandy (2012)		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Household size (**HHSize**)	2.71	1	10	2.7	1	5	2.92	1	13
Indicator variable for household vehicle ownership (1 if a household owns at least one vehicle, 0 otherwise) (**HHVeh**)	0.97	0	1	0.81	0	1	0.74	0	1
Indicator variable for presence of disabled people in a household (1 if there is a disabled person in the household, 0 otherwise) (**HHDisab**)	0.08	0	1	0.13	0	1	0.12	0	1
Residential length in years (**HHResYears**)	17.69	0.25	54	37.53	1	82	44.21	2	93
Household income in $1,000 (**HHInc**)	64.77	15	150	67.52	15	100	64.93	15	100

HHSize. The average household size is similar across surveys, which is about three persons per household.

HHVeh. The proportion of households who own at least one vehicle are significantly different across surveys. Households in Gustav survey are the most likely to own a vehicle. About 97% of them own at least one vehicle. In contrast, only 81% of the households in the Irene survey own a vehicle. There are even fewer households (74%) who own a vehicle in the Sandy survey. This indicates that residents living in counties around NYC have a higher vehicle ownership rate than those who live within NYC.

HHDisab. The proportion of households with disabled household members is only slightly different between Gustav and the other two. Generally, about 10% of the households reported they have disabled household members.

HHResYears. Average length of residence in a local area presents significant difference across surveys. Households in Gustav survey reported much shorter residential length. This may be due to Hurricane Katrina (2005) happening only three years before Hurricane Gustav (2008). As is well known, a large number of households were forced to change residential places due to Hurricane Katrina.

HHInc. Contrary to what may be expected, average annual household income (HHInc) does not vary a lot among the Gustav, Irene, and Sandy survey respondents, which is around $65,000. The reason is that only evacuated households were analyzed, so that the statistic actually states that average income of evacuated households is similar across the three surveys. The minimum and maximum value are exactly the same because the original question on household income offers categorical options instead of asking for an exact value.

Data at Zonal Level from ACS

The American Community Survey (ACS) provides data about residents and housing in the U.S. Information on residents includes population, age, disability, education, employment, income, insurance, language, marital & fertility status, citizenship, race or ethnic origin, etc. Topics about housing include basic count, financial characteristic, occupancy characteristic, and physical characteristic. Depending on the requested variable and year, data is provided at geographical units which range from state to census block.

Zonal Unit Discussion

Zonal variables are used as contextual factors, which potentially can influence household evacuation behavior. To associate the zonal data with household data, the selected zonal unit must be available in both the ACS data and all household post-storm surveys. In Table 5, available zonal units in each survey are listed from fine to coarse.

Table 5
Available zonal unit in post-storm surveys

	Gustav (2008)	Irene (2011)	Sandy (2012)
Zonal unit	Longitude/Latitude Census tract ZIP code County City State	ZIP code County City State	ZIP code County City State

Regarding the specific zonal unit to be used in model estimation, ZIP code tabulation areas (ZCTA) is preferred because it is the finest available in all the above surveys. It is a generalized areal representation of United States Postal Service (USPS) ZIP code service areas. Another advantage of using ZCTA is that industrial data are usually provided at this zonal level. For example, it is useful when data from the hotel industry (NAICS industry code 7211: Traveler accommodation) is used in this study.

Zonal Socio-demographic Characteristics

Table 6 shows the mean, minimum, and maximum of several zonal characteristics, which were collected at ZCTA level. If data are not available for the exact year, data from the closest year to that event were collected. The table only presents variables that are found significant in the model estimation. However, all available variables from the ACS were considered and tested in the process of model estimation.

Within the study area of Gustav, Irene, and Sandy, some of the ZCTAs may not have any respondents. Instead of removing them from the following zonal comparison, the reported statistics incorporate all ZCTAs as long as they have residents and are within the border of the surveyed counties.

　　　　ResStab. Residential stability was considered a potential surrogate for social networking. That is, the longer residents remain in an area, the more social links they are expected to develop. Residential stability was measured by the proportion of households who moved into their current dwelling before 2005. The reason that 2005 was chosen as the cutoff point for this variable is due to the availability of data. For all three storms, this portion of the data is only available from "2011 ACS 5-year estimates," which provides the percentage of households who "Moved in 2005 or later." For the data collected before 2011, this variable is actually not available. For data collected later, in 2012, the categories change to "Moved in 2010 or later" and "Moved in 2000 to 2009." Both of them are not that suitable for the calculation of residential stability: "Moved in 2010 or later" presents, on average, too short a

period in which local friendship ties can develop, while "Moved in 2000 to 2009" presents too long a period to effectively distinguish those forming local friendship ties from those who have not. Therefore, one minus the proportion of household who "Moved in 2005 or later" was used for the calculation of residential stability in this study. For Irene and Sandy, residents would have lived in the local area for about seven or eight years before they experienced the need to evacuate. For Gustav, residents would have lived in their local communities for about four years before they evacuated. In both cases, residents have lived in the local area over three years, which is considered long enough to establish local friendship ties. As shown in Table 6, the average length of stay (reflected in **ReStab**) for Gustav is less than the others, possibly due to the disruption caused to communities by Hurricane Katrina three years earlier. This fact is also reflected in the household characteristic of duration of residential stay (**HHResYears**) shown in Table 4.

      PropNoVeh. The variable describing the proportion of households having no vehicle, PropNoVeh, equals 0.08 for the ten coastal parishes in Louisiana, while this value is 0.51 for New York City. When three additional counties were incorporated in the Irene survey, the value of PropNoVeh decreases to 0.25, which means vehicle ownership in these counties is much higher than in New York City.

Other zonal characteristics also reflect differences in the three surveys. First, New York generally has a higher level of public transportation use (**CommutebyTransit**), a larger value of average household income (**AvgInc**), greater community density (**ComDensity**), and more non-U.S. citizens (**PropNonCitizen**). Second, coastal parishes of Louisiana have more disabled people than the other two study areas (**PropDisab**). Third, **PropAge** also shows a slight difference among study areas, reflecting a difference in age distribution, but it is not as significant a difference as with the other variables.

Table 6
Statistics of zonal characteristics: ACS

Variable description and abbreviation	Gustav (2008)			Irene (2011)			Sandy (2012)		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Residential stability (Proportion of households moved in before 2005) (**ResStab**)	0.50	0	1	0.61	0	1	0.57	0	0.80
Proportion of workers using transit (excluding taxi) for commuting purpose (**CommutebyTransit**)	0.02	0	0.28	0.29	0	1	0.52	0	1
Proportion of households that do not own any vehicle (**PropNoVeh**)	0.08	0	0.51	0.25	0	0.88	0.51	0.04	0.89
Average household income in $1,000 (**AvgInc**)	60.3	22.9	119	113.9	30	398	89	31.1	387
Community density (Proportion of households living in multiple dwelling units, i.e., number of units in structure is greater than 2) (**ComDensity**)	0.15	0	0.86	0.45	0	1	0.78	0.003	1
Proportion of people who are not U.S. citizen (**PropNonCitizen**)	0.02	0	0.17	0.11	0	0.53	0.16	0	0.45
Proportion of people with disability (**PropDisab**)	0.16	0	0.41	0.09	0	0.33	0.09	0	0.33
Proportion of people who are less than 18 or over 65 (**PropAge**)	0.38	0.19	0.73	0.37	0	0.88	0.33	0	0.88

Data at Zonal Level Based on a Calculated Measure of Accessibility

In this study, the average accessibility of a zone measures how accessible residents living in that zone are to different destination types in all the other zones that contain potential destinations. Since accessibility is measured at a zonal level in this study, it is assumed that all residents in a zone enjoy the same accessibility. In this study, accessibility measures the relative ease with which evacuees can access refuge by destination type. This factor was not

given any attention in previous evacuation modeling studies but it was found significant in this study.

According to some leading authors in this subject area, the measurement of accessibility should abide by the following principles: "the order of opportunities should not affect the value of the measure; the measure should not increase with increasing distances or decrease with increasing attractions; and opportunities with zero value should not contribute to the measure" [21]. Based on the above principles, the following formulation of an accessibility measure was developed in this study.

       Define Destinations. Potential destinations are defined as places where over 80% of the survey respondents were found to evacuate to in past evacuation surveys. For Irene and Sandy, potential destinations were found to be New York City and the three surrounding counties (i.e., Nassau, Suffolk, and Westchester). For Gustav, potential destinations were the inland parishes of Louisiana and seven states that are adjacent or close to Louisiana. When measuring accessibility where surveys have not been conducted, the analyst can identify destination zones manually based on judgment.

       Measure Attraction. A safety indicator is used to distinguish between safe and unsafe destination zones for the storm under consideration. If a zone is marked as dangerous, its attraction is reduced to zero no matter how attractive it otherwise would be. For New York, hurricane evacuation zones (HEZs) that received evacuation orders during Irene or Sandy were identified as unsafe destinations for those storms. If an area receiving an evacuation order is over 50% of the area of a ZCTA, the whole ZCTA is considered an unsafe area and thus receives a safety indicator of 0. The mathematical expression of a safety indicator for destination zone j is shown in equation (9). For Louisiana, all ZCTAs in coastal parishes that received evacuation orders were marked as unsafe destinations and, therefore, were given safety indicator values of zero.

$$safety_j = \begin{cases} 1, if \frac{Area\ receiving\ an\ evacuation\ order\ in\ ZCTA\ j}{Area\ of\ ZCTA\ j} < 0.5 \\ 0, otherwise \end{cases} \quad (9)$$

If a zone is marked as safe, it is proposed that the attraction of that zone for evacuation is reflected by its capacity to accommodate people. To quantify the capacity to accommodate evacuees at the homes of friends and relatives (FR) in a zone, the population in that zone is used as a proxy. Data were collected from the ACS, as stated before, to provide this information. To reflect the capacity of a zone to accommodate hotel/motel (HM) guests, the number of hotel employees in that zone was selected as a proxy. The underlying assumption is that there is a direct correlation between the number of hotel employees and the number of

guests that can be accommodated. This part of data was collected from County Business Pattern (CBP) data set, which offers data at zip code level. For the capacity of shelters (SH) in a zone, shelter capacities were collected from available online resources. For the New York area, established shelters are schools or colleges. Therefore, the number of students in that institution was used as a proxy to for the capacity of shelters on that campus. This portion of data was collected from National Center for Education Statistics (NCES). For Louisiana, the capacity of each shelter was collected directly from the government website *[32]*.

Measure Impedance. Travel impedance is typically measured in terms of distance, time, money, or other forms of cost. In this study, distance between zones was picked as the measure of impedance because, unlike travel time, it remains fixed and known. If a zone itself is marked as safe, intra-zonal evacuation is considered possible. The intra-zonal distance is calculated as a half the distance between this zone and its nearest neighboring zone.

Formulate Accessibility. For people living in zone i, their accessibility to zone j with respect to FR is assumed to be directly related to the population in zone j and inversely related to the distance between the two zones. To account for the fact that only safe zones can effectively serve as destinations, accessibility to zone j is formulated as $\frac{Pop_j \times safety_j}{Distance_{ij}}$. Then the accessibility to FR was summed up for zone i and divided by the number of safe residential zones in the study area. Taking the average instead of using the total accessibility is based on the assumption that a household only stays at one destination during their evacuation. As an example, evaluate accessibility for the following two situations:

Situation 1: there is only one safe zone for a household to evacuate to. That zone has a large population ($4P$) and it is D miles away from that household.

Situation 2: there are four safe zones, each of them have a population of P and all of them are D miles away from the household.

It could be argued that the total accessibility in the two situations is the same: $\frac{4P}{D}$. However, the average accessibility in the two situations is $\frac{4P}{D}$ and $\frac{P}{D}$, respectively. Since a household can only choose one destination, it is obvious that they will have more opportunities in the first situation than the other for two reasons. First, assume a household has a fixed number of friends or relatives. The chance for that household to have a friend or relative in a particular zone increases when the number of zones decreases and the population in each zone

increases. That is, if people are more concentrated, there is a larger chance that a household has a friend or relative in one of the zones. Second, a larger zone can offer more opportunity for a household to find more friends or relatives who have enough room in their house to accommodate them. Therefore, accessibility was measured based on an average, which reflects an average opportunity of finding an available FR at one location. The complete expression of $accessFR_i$ is shown in the equation below. It represents the average accessibility in terms of FR from zone i to all the other safe residential zones within the study area.

$$accessFR_i = \frac{\sum_{j=1}^{J} \frac{Pop_j \times safety_j}{Distance_{ij}}}{\sum_{j=1}^{J}(safety_j \times Resid_j)} \tag{10}$$

where,

$accessFR_i$ is the average accessibility to FR for residents living in zone i;

$safety_j$ is the safety indicator of zone j;

$Resid_j$ is the residential indicator of zone j. It equals 1 if zone j has residents and 0 otherwise;

Pop_j is the number of population in zone j;

$Distance_{ij}$ is the distance between zone i and zone j.

Regarding the calculation of accessibility to HM and SH, the method is similar to that described above. For HM and SH, population in zone j is replaced by the number of hotel employees or the capacity of shelters, respectively. As before, the average accessibility represents an average opportunity that a household can find a hotel room or shelter space at one destination. The expressions for the accessibility to HM and SH destinations are shown in equations (11) and (12), respectively.

$$accessHM_i = \frac{\sum_{j=1}^{J} \frac{HotelEmployee_j \times safety_j}{Distance_{ij}}}{\sum_{j=1}^{J}(safety_j \times Hotel_j)} \tag{11}$$

where,

$accessHM_i$ is the average accessibility to Hotel/Motel for residents live in zone i;

$Hotel_j$ is the hotel industry indicator of zone j. It equals 1 if zone j has any hotel/motel (NAICS industry code 7211: Traveler accommodation);

$HotelEmployee_j$ is the number of hotel employee in zone j.

$$accessSH_i = \frac{\sum_{j=1}^{J} \frac{ShelterCapacity_j \times safety_j}{Distance_{ij}}}{\sum_{j=1}^{J}(safety_j \times Shelter_j)} \qquad (12)$$

where,

$accessSH_i$ is the average accessibility to shelters for residents live in zone i;

$Shelter_j$ is the shelter indicator of zone j. It equals 1 if zone j has any shelter;

$ShelterCapacity_j$ is the capacity of shelters in zone j.

The calculated accessibility for different survey areas and destination types are shown in Table 7. Longer evacuation distance and lower population density makes the average of **accessFR** smaller in Louisiana than in New York. This fact also applies to **accessHM** and **accessSH**. Accessibility has a potential to explain households' choices toward different modes in the sense that with greater accessibility a household becomes less dependent on autos and has more choice options, such as walking and cycling. Accessibility measures cannot be compared across destination types because they use different variables in their formulation.

Table 7
Statistics of zonal characteristics: accessibility (Unit: ×10^{-2})

Variable description and abbreviation	Gustav (2008)			Irene (2011)			Sandy (2012)		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Average accessibility to Friend/Relative house (**accessFR**)	1.9	1.8	2	155	18	329	157	18	331
Average accessibility to Hotel/Motel (**accessHM**)	0.025	0.022	0.027	2.6	0.17	27	2.5	0.16	25
Average accessibility to Shelter (**accessSH**)	0.19	0.15	0.23	9.4	1	29	9.4	1	29

Data at Zonal Level from Other Sources

Hotel price (**HotelPrice**) and occupancy rate (**HotelOccupy**) can have an impact on the choice of HM by locals depending on the price of a hotel room relative to average local income, and the availability of hotel accommodation when it is sought on short notice. To address this issue, the quarterly average daily rate and monthly occupancy rate of hotels were collected from Statista and NYCEDC *[33][34]*. Due to the availability of data, it can only be collected at a regional level, i.e., New York City and New Orleans. Average household income was obtained from the ACS database.

Table 8 shows the quarterly average daily rate of hotels, which was based on data from Statista. It is an average across multiple years. As shown, the price of a hotel in NYC is about twice that of New Orleans and yet their average household income (shown in Table 4) is very similar (approximately $65,000 per year).

Table 8
Quarterly average daily rate of hotels (Unit: $/night)

	Q1	Q2	Q3	Q4
NYC (2010-2014)	261	332	316	364
New Orleans (2012-2015)	175	163	140	171

Table 9 shows the monthly average occupancy rate of hotels across multiple years. The hotel occupancy rate in New York City was provided by NYCEDC. But such data is not available for New Orleans. Therefore, the statistics for the whole U.S., provided by Statista, was used as a substitution for New Orleans in the model estimation. As shown, NYC has a much higher hotel occupancy rate than the national average.

Table 9
Monthly average occupancy rate of hotels (2011-2015) (Unit: %)

Area	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
NYC	74.4	78.2	87	90.4	91.2	90.6	90.8	92.6	90.8	92	88	89.4
U.S.	50.9	58.8	64.2	63.9	64.7	70.5	72.0	69.1	64.7	65.9	57.5	50.5

The above two tables also show seasonal variations. Instead of using above multiple year average, Table 10 shows the original values of hotel price and occupancy for the year and quarter/month when the hurricane event actually occurred. Hotel prices during Irene and Sandy in NY are about triple of that during Gustav in New Orleans. In addition, HotelPrice during Irene and Sandy are not the same because the time of the events are different in year and seasonal quarter. NY has higher hotel prices and most of the hotels were almost fully occupied during the months of the storms of Irene and Sandy. These conditions would likely decrease the probability of a household choosing HM as a destination type in the NY area. The two factors were not considered in previous modeling studies because they did not get a chance to observe household evacuation behavior across regions. This illustrates the benefit of using data from multiple study areas.

Table 10
Statistics of zonal characteristics: hotel price and occupancy

Variable description and abbreviation	Gustav (2008)	Irene (2011)	Sandy (2012)
Hotel price in the local area (**HotelPrice**)	135	323	380
Hotel occupancy rate in the local area (**HotelOccupy**)	0.693	0.926	0.920

DISCUSSION OF RESULTS

In this chapter, results from model estimation and application are presented. The best model estimated with zonal data of ZCTA level is analyzed in detail with an interpretation on the coefficients of selected variables. This best estimated model was then applied in two cases: Hurricanes Gustav and Sandy. The prediction error in each case is used to evaluate model performance in different situations. The last section discusses a situation in which zonal data is only available at a relatively coarse level: county or parish. A new model was estimated with zonal data collected at county/parish level. This new estimated model was applied in the two above-mentioned cases for comparisons and one additional case covering five coastal parishes of Louisiana.

Model Estimation and Discussion with Zonal Data of ZCTA Level

Two issues were studied in model estimation. The first issue is the size of data. Generally, there are two solutions to achieve enough observations: imputing data and pooling data from different sources. Both of these strategies were tested in this study. The second issue is the nest structure. That is, which choice should be on the upper level: mode choice or destination type choice? This was tested by formulating a structure with each option. Models that were estimated based on the same dataset were compared and selected based on goodness-of-fit (GOF) statistics, signs of the parameters, and their significance. Models that were estimated based on different datasets were compared based on the validity of nested structure, model stability, and prediction ability. After a large number of trials, this study found the best estimated model was reached when the three datasets (i.e., Irene, Sandy, and Gustav) were pooled and records with imputed values were not incorporated. The nest structure of the best model has destination type choice on the upper level and mode choice on the lower level.

Table 11 shows the composition of choices in the pooled dataset. OT_ride and OT_transit were merged into OT_other in the model estimation because of the small number of observations in each of the named alternatives. Utility scaling was not used in this case.

Table 11
Choice of Households: Irene + Sandy + Gustav without imputation

	Own	Ride	Transit	Other	Total
FR	464 (55.3%)	68 (8.1%)	79 (9.4%)	35 (4.2%)	646 (77%)
HM	88 (10.5%)	8 (1.0%)	9 (1.1%)	8 (1.0%)	113 (13.5%)
SH	11 (1.3%)	2 (0.2%)	5 (0.6%)	6 (0.7%)	24 (2.9%)
OT	44 (5.2%)	2 (0.2%)	5 (0.6%)	5 (0.6%)	56 (6.7%)
Total	607 (72.3%)	80 (9.5%)	98 (11.7%)	54 (6.4%)	839

The best estimated model is shown in Figure 5. The model specification resulted in a model with a large rho square, which means the estimated model fits the data very well. Most of the selected variables presented in Figure 5 have coefficients with t-statistic significant at the 95% level of significance.

The logsum coefficients, designated by theta in Figure 5, are all significantly different from one. The larger the logsum coefficient, the greater the independence among alternatives. When it equals one, it indicates that no correlation exists among the error terms of the alternatives within a nest. When all of the logsum coefficients are equal to one, it indicates that the nest structure is not necessary and the model reduces to a MNL. Since they are shown significantly different from one in this model, it can be concluded that the nest structure is accommodating dependence among alternatives and the assumption of joint choice is validated.

At the upper level of destination type choice, zonal residential stability (**ResStab**), which is a surrogate for the strength of a social network in a community, was found to have a positive effect on the choice of evacuating to FR. That is, households, who live in a zone with high residential stability, are more likely to evacuate to FR than those who live in areas of low residential stability. As defined previously, residential stability is measured by the proportion of households who moved in before 2005. Residents living in zones with high residential stability are more likely to have stronger community attachment and establish more local friendship ties. Both increase the chance that a household will reach out for help during evacuation. Therefore, a positive sign is appropriate. Similarly, it is suggested that the length of stay of a household in an area (**HHResYears**) can function as a surrogate for the size of a household's social network. That is, the longer a household lives in an area, the more social connections they are expected to develop and the greater their social network. The positive sign indicates the longer households live in an area, the more likely they are to evacuate to FR because they are more likely to have a larger social network.

Destination Type Choice

FR (646)

ResStab = 2.45 (t = 3.31)
HHResYears = 0.01 (t =1.87)
Theta = 0.31 (t = -3.35)

own (464)

HHVeh = 3.63 (t =10.99)

ride (68)

HHResYears = 0.03 (t = 4.17)
ResStab = 2.64 (t = 2.03)
CommutebyTransit = 3.59 (t = 3.61)
Constant = -3.37

transit (79)

CommutebyTransit = 3.08 (t = 2.38)
accessFR = 0.55 (t =1.93)
Constant = -1.20

other (35)

accessFR = 1.04 (t =3.88)
Constant = -1.61

HM (113)

AvgInc/HotelPrice = 1.21 (t = 1.75)
HotelOccupy*accessHM = -15.63 (t = -1.87)
CommutebyTransit = -6.19 (t = -4.56)
PropNoVeh = 4.41 (t = 3.25)
Constant = 0.30
Theta = 0.20 (t = -4.57)

own (88)

HHVeh = 3.11 (t = 3.64)
HHInc/AvgInc = 1.58 (t = 1.42)

ride (8)

HHSize = 0.33 (t =1.98)
Constant = 0.20

transit (9)

PropNoVeh = 7.60 (t = 2.93)
Constant = -2.87

other (8)

ComDensity = 82.55 (t =1.95)
Constant = -78.57

SH (24)

PropNonCitizen = 6.47 (t = 2.18)
PropDisab = 15.54 (t = 3.10)
Constant = -3.70
Theta = 0.24 (t = -2.17)

own (11)

HHVeh = 1.98 (t =1.66)

ride (2)

PropAge = 150.14 (t = 1.02)
Constant = -63.93

transit (5)

PropNoVeh = 2.83 (t = 1.25)
Constant = -0.58

other (6)

accessSH = 21.97 (t = 1.63)
Constant = -1.41

OT (56)

Constant = -2.56

own (44)

HHVeh = 2.98 (t = 2.86)

other (12)

Constant = 1.33

Figure 5
The best estimated model with zonal data of ZCTA level
(Statistics: LL(Zero) = -2214.17; LL(End) = -1044.30; Asymptotic rho squared = 0.5284; Adjusted rho squared = 0.5098)

Regarding choice on HM, households living in an area with higher average income relative to local hotel prices (**AvgInc/HotelPrice**) are more likely to stay in a hotel or motel. In past research, a simple indicator variable of high household income was often used to explain a household's choice of HM *[6]*. The impact of hotel price was not taken into consideration. This is because past research was usually conducted in a single local area at a specific time, where a single average hotel price prevails. When multiple areas and different years are under investigation, average hotel price can vary considerably and a variable considering average household income relative to **HotelPrice** is more likely to allow replication of observed household choices more accurately. The significant positive sign of the parameter for **AvgInc/HotelPrice** variable in the model confirms that this "general affordability" variable indeed plays a significant role in the choice of a hotel or motel as a destination type.

HotelOccupy*accessHM represents the spatial distribution of hotel resources where a high value indicates nearby hotels are fully occupied and available hotels are far away. Conversely, nearby hotels with low occupancy produce low values of the variable. Thus, a negative sign for the parameter of the variable indicates that a combination of unavailability and inaccessibility to hotels makes it is less likely for a household to choose HM as a destination type.

The parameters for **CommutebyTransit** and **PropNoVeh** are negative and positive, respectively, and both are significant in choosing HM as destination type. This reflects that carless households evacuating to HM are more likely to take a taxi than to use other forms of transit. That is, a zone with a high proportion of carless households but, at the same time, with a low proportion of commuting trips by public transportation (except taxi), is likely to have more HM users. A good example from the survey is Manhattan, where household vehicle ownership is low and taxi trips form a large proportion of commuting trips than elsewhere. In the post-Irene survey, 21% of the respondents living in Manhattan evacuated to HM while this proportion was much lower elsewhere (9% overall). Thus, given that regular transit (except taxi) is less likely to serve HM destinations well, the negative sign for the parameter of **CommutebyTransit** and positive sign for the parameter of **PropNoVeh** are logically correct in choosing HM as a destination type.

With respect to SH choice, the proportion of non-citizens in an area (**PropNonCitizen**) and the proportion of disabled in an area (**PropDisab**) are found to have a positive effect on the choice of public shelter. This portion of the population includes those who have special needs and require special transit vehicles during evacuation as well as those who have difficulty evacuating on their own.

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The positive signs of **HHVeh** for choice of own vehicle under FR, HM, SH, and OT show that a household is more likely to use their own vehicle during evacuation if they own at least one vehicle. This finding is consistent with other empirical and modeling studies. In addition, **HHInc/AvgInc** has a positive effect on choice of own vehicle under HM. That is, a household earning a higher income relative to the local average is more likely to use their own vehicle given that the household chose HM as the destination type.

Variables that have a significant effect on FR_ride include **HHResYears**, **ResStab**, and **CommutebyTransit**. **HHResYears** and **ResStab** indicate that, as expected, social networking plays an important role in the FR_ride choice. The positive parameter value for the variable **CommutebyTransit** for riding with others to FR indicates that transit commuters are more likely to ride with others when evacuating to FR.

For HM_ride, **HHSize** has a positive effect. That is, given that HM has been chosen as the destination type, the larger the household the more likely they are to ride with others. The model is suggesting that, all else being equal, larger households are more likely to need at least some of their members to ride with other households than smaller households would.

For SH_ride, **PropAge** has a positive effect. This suggests that this portion of shelter users (those under 18 or over 65 years of age) may have difficulties on driving alone/using transit or are not accessible to any vehicular resources, thus they are more likely to be dependent on receiving a ride with someone else. Zones with school dorms or many retirement homes are examples for this situation. However, the small t-statistic of this variable also show that it has a large variance in its estimated value.

For the choice of using transit, **CommutebyTransit** and **accessFR** have significantly positive effect on FR_transit, which means a higher level of public transportation service and an easily reached friend or relative home will increase the possibility for a household to choose transit. This can be supported by the fact that there is a larger proportion of respondents who chose FR_transit in New York than in Louisiana. For HM_transit and SH_transit, **PropNoVeh** has positive effect for both of them. The sign is correct in the sense that carless residents are more likely to depend on transit during evacuation.

For other mode choices, accessibility and community density have a significant effect on them. Because other mode choices are mainly composed of walking, bicycling, and motorcycling, which generally serve short distance trips, higher accessibility is expected to be a good explanatory variable. This is shown to be the case for FR_other and SH_other in Figure 5. However, for HM_other, community density is a better explanatory variable than accessibility. Collectively this suggests that as community density and accessibility increases,

other modes (walking, cycling, motorcycle, etc.) becomes a more attractive means of evacuation to hotels and motels.

Model Application and Assessment with Zonal Data of ZCTA Level

The presented model specification was applied in two different cases. Details of the applications are defined in Table 12.

Table 12
A summary of applications

Application	Dataset used	Imputation	Zonal unit	Year	Study area
1	Gustav	No	ZCTA	2008	Ten coastal parishes in southeastern Louisiana
2	Sandy II	Yes	ZCTA	2012	New York and New Jersey

Although the model selected operates at a disaggregate level, assessment of the models' performance is typically made at the aggregate level *[13]*. Therefore, the disaggregate prediction table with household ID on each row and different alternatives on each column was transformed to predictions at an aggregate level. More specifically, for each alternative, the predicted household choice probability was aggregated by the zonal ID associated with each household. After this process, a zonal prediction table was produced with each row representing different zonal IDs (such as ZCTA ID in this section or County ID in a later section) and each column representing different alternatives (from FR_own to OT_other).

The survey also recorded the real decision made by each household. The observed household choice table was aggregated in a similar manner to the above-mentioned process to produce a zonal observed table. The zonal prediction table was then compared with the zonal observed table through three statistics to measure the accuracy of prediction: correlation coefficient, and two types of the percentage Root-Mean-Square Error (%RMSE). A correlation coefficient of over 0.7 is usually considered as an indication of a strong correlation and, hence, a high level of accuracy. In contrast, a small value of %RMSE means a better prediction since it reflects the difference between the two tables. A value less than 30% is generally considered acceptable. The following equation shows the calculation of %RMSE in a general form.

$$\%RMSE = \sqrt{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(\frac{y_{ij}-\hat{y}_{ij}}{y_{ij}})^2} \times 100\% \qquad (13)$$

where,

y_{ij} is the observed number of households who choose alternative j in zone i;

$\hat{y}_{ij}$ is the predicted number of households who choose alternative j in zone i.

However, %RMSE is infinite when the denominator (i.e., y_{ij}) equals zero. It is exactly the case in this study, because the distribution of the joint choice is extremely skewed resulting in many cases of zero observations in sparsely populated alternatives. Therefore, the calculation of %RMSE was adjusted to overcome this disadvantage and produce a statistic that is a more reasonable measure of accuracy. First, the adjustment adds 1 to the denominator. This solves the problem of reaching infinity when y_{ij} equals zero. Second, the adjustment assigns larger weights to cells with a larger number of observations. This reduces the weight assigned to observations when y_{ij} is close to zero.

Two different ways of assigning weights were considered. First, each zone was considered equally important. The adjusted %RMSE was calculated for each zone i. Then the average of above calculated zonal %RMSE was used to stand for the average prediction error for the whole study area. It is called the first adjusted %RMSE in the following text.

$$adjusted\ \%RMSE_i = \sqrt{\sum_{j=1}^{n}\left(\left(\frac{y_{ij}-\hat{y}_{ij}}{y_{ij}+1}\right)^2 \times w_{ij}\right)} \times 100\% \qquad (14)$$

$$w_{ij} = \frac{y_{ij}+1}{\sum_{j=1}^{n}(y_{ij}+1)} \qquad (15)$$

$$\sum_{j=1}^{n}w_{ij} = 1 \qquad (16)$$

$$average\ adjusted\ \%RMSE = \frac{1}{m}\sum_{i=1}^{m}adjusted\ \%RMSE_i \qquad (17)$$

Second, zones with more observations/evacuees were considered more important. This version of calculation considered the weight of each zone. It is called the second adjusted %RMSE in the following text.

$$adjusted\ \%RMSE = \sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} \left(\left(\frac{y_{ij} - \hat{y}_{ij}}{y_{ij} + 1} \right)^2 \times w_{ij} \right)} \times 100\% \qquad (18)$$

$$w_{ij} = \frac{y_{ij} + 1}{\sum_{i=1}^{m} \sum_{j=1}^{n}(y_{ij} + 1)} \qquad (19)$$

$$\sum_{i=1}^{m} \sum_{j=1}^{n} w_{ij} = 1 \qquad (20)$$

As shown, the sum of the weight equals one, which follows the basic rules of weighting. When observations are equally distributed across cells, above weights reduce to $w_{ij} = \frac{1}{n}$ or $\frac{1}{mn}$. The second adjusted %RMSE is the same as the general form of calculation for %RMSE in this situation, except the change on the denominator (i.e., y_{ij} in equation (13) and ($y_{ij} + 1$) in equation (18)).

Application 1: Gustav (ZCTA)
Application 1 used a part of the dataset that was used in the model estimation, and where the zonal unit was the ZCTA. The purpose of this application is to provide a baseline. The results of Application 1 are shown in Table 13.

Table 13
Prediction error in Application 1

	Correlation	The first adjusted %RMSE	The second adjusted %RMSE
Application 1	0.882	19.3%	22.0%

The correlation coefficient is over 0.8. It means the predicted results are highly correlated with the observed results. The two types of %RMSE are both less than 30%. It means the prediction error is within a general acceptable range.

Application 2: Sandy II (ZCTA)
To distinguish it from the previous Sandy data that were used for model estimation (called "Sandy I" in the following text), this dataset is from another post-storm behavioral survey of Hurricane Sandy (2012) covering the area of NYC, Long Island, and New Jersey while Sandy I covered NYC only. The study area is shown in Figure 6.
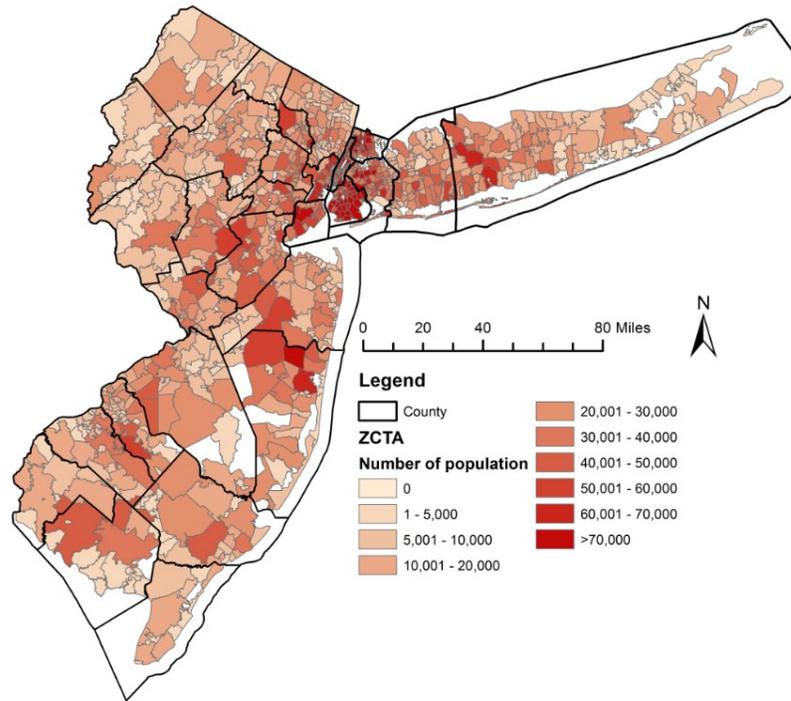
Figure 6
Study area in the survey of Hurricane Sandy II (NJ and NY)

Of the 1101 observations, 300 households chose to evacuate. The composition of household choice on mode and destination type is shown in Table 14. As five of the households did not report one of the choices, the total number of observations decreased to 295. Compared to other post-storm behavioral surveys in the area, the distribution of choice during Sandy II looks similar to that of Irene. However, it also has its own characteristics. On DTC, there are relatively few households evacuating to their friend or relative's home and more to shelter. On MC, there are less transit users and more driving their own vehicles.

Table 14
Choice of households: Sandy II without imputation

	Own	Ride	Transit	Other	Total
FR	190 (64.4%)	19 (6.4%)	8 (2.7%)	6 (2.0%)	223 (75.6%)
HM	25 (8.5%)	4 (1.4%)	0 (0%)	0 (0%)	29 (9.8%)
SH	6 (2.0%)	1 (0.3%)	0 (0%)	3 (1.0%)	10 (3.4%)
OT	28 (9.5%)	0 (0%)	1 (0.3%)	4 (1.4%)	33 (11.2%)
Total	249 (84.4%)	24 (8.1%)	9 (3.1%)	13 (4.4%)	295

Processing Household Data. Although choices were not imputed, other household data with missing values were imputed using the hot deck imputation method. As there is no question related to household disability, this dataset was pooled with records without any missing values from the Sandy I dataset for imputation purposes. Variables entering into the process of imputation included: vehicle ownership (52), whether there is a disabled household member (295), whether their house is rented (10), residential length (17), household size (17), whether there is an elderly household member (13), household income (90), and education level (15). The number in brackets is the frequency of missing values for each variable. Except the situation that no question about disability was included in this survey, household income still holds the largest number of missing values.

Collecting Zonal Data from ACS. This process is the same as what has been done for model estimation. The data were collected for each ZCTA in Application 2.

Calculating Accessibility. Two major issues in this process are defining the study area and the safety indicator. The two issues were solved separately for New York (NY) and New Jersey (NJ), but the solution was based on similar criteria discussed before.

As found from the survey, over 80% of the respondents from NY evacuated to a location within New York City and three surrounding counties (i.e., Nassau, Suffolk, and Westchester). Therefore, the study area was restricted to those counties, which is the same as the case of Sandy I. Regarding the safety indicator, it was defined using the same equation as in the case of Sandy I, which is equation (9). Thus the calculated accessibility for Sandy I was used directly in Application 2 because both cases used the same storm, study area, and geographic unit.

For those respondents from NJ, over 74% of them evacuated to places within NJ. Therefore, the study area for NJ was restricted to itself. The population, hotel employees, and shelter capacity were thus collected for all ZCTAs within NJ in Application 2. Regarding the definition of a safety indicator, the barrier islands from Sandy Hook to Cape May received mandatory evacuation order at that time. Therefore, ZCTAs that cover those barrier islands were marked as dangerous zones and received a safety indicator equaling zero. The calculation of accessibility was conducted in a similar manner to that shown in equations (10)-(12).

Collecting Other Zonal Data. For NY, the hotel price and occupancy rates are the same as those used in Sandy I. For NJ, the assumption is that hotel price and occupancy rate are the same as NY, because of the similar economic status in the two states in the areas covered by the surveys.

The accuracy of prediction is shown in Table 15. The accuracy of prediction in Application 2 is satisfying because the correlation coefficient is over 0.8 and the values of the two types of %RMSE are less than 30%.

Table 15
Prediction error in Application 2

	Correlation	The first adjusted %RMSE	The second adjusted %RMSE
Application 2	0.839	22.6%	29.3%

The two types of %RMSE slightly increase (3% and 7%) in comparisons with Application 1. It means the estimated model still keeps good transferability in a situation of changing study area. A few reasons why the estimated model can predict the joint choice for Sandy II at the level of ZCTA (i.e., Application 2) quite well are as follows. First, Sandy II is a post-storm behavioral survey of the same hurricane as the subject storm for the Sandy I survey. The similarity on the event's year and study area may make the household behavior more similar in the two datasets. Second, Sandy I household data were used in the imputation process of Sandy II household data. This operation may reinforce the relationship between the two datasets.

Model Estimation and Application with Zonal Data of County Level

Best Estimated Model with Zonal Data of County Level
Household data remained the same in the pooled dataset, but zonal data were updated by using data collected at county level. After a large number of trials with different explanatory variable combinations, the best model is presented in Figure 7. Most of the selected variables are the same as the previous estimation made with zonal data of ZCTA level, especially under the nest of FR. Therefore, the coefficients can be interpreted in the same fashion as the previous model. The next three sections focus on applying this new estimated model in different cases.

Destination Type Choice

FR (646)

ResStab = 3.56 (t = 2.78)
HHResYears = 0.01
(t = 2.31)
Theta = 0.24 (t =-3.54)

own (464)

HHVeh = 3.84 (t = 11.30)

ride (68)

HHResYears = 0.03
(t = 4.21)
ResStab = 6.79 (t = 1.71)
CommutebyTransit = 3.32
(t = 2.37)
Constant = -5.78

transit (79)

accessFR = 0.11 (t = 3.51)
Constant = -6.54

other (35)

HM (113)

AvgInc/HotelPrice = 2.71 (t = 2.12)
CommutebyTransit = -3.49
(t = -2.02)
PropNoVeh = 2.46 (t = 1.91)
Constant = 0.33
Theta = 0.17 (t = -3.47)

own (88)

HHVeh = 3.91 (t = 5.29)

ride (8)

HHSize = 0.34 (t = 2.10)
Constant = -0.49

transit (9)

other (8)

accessHM = 5.17 (t = 1.92)
Constant = -0.74

SH (24)

HHDisab =1.43
(t = 3.24)
Constant = -0.50
Theta = 0.09
(t = -1.64)

own (11)

HHVeh = 2.18
(t=1.96)

ride (2)

HHResYears = 0.03
(t = 1.07)
Constant = -1.72

transit (5)

PropNoVeh = 3.00
(t = 1.48)
Constant = -0.47

other (6)

ComDensity = 3.78
(t = 1.58)
Constant = -1.66

OT (56)

own (44)

other (12)

Constant = 1.25

Figure 7
The best estimated model with zonal data of county level
(Statistics: LL(Zero) = -2214.17; LL(End) = -1072.62; Asymptotic rho squared = 0.5156; Adjusted rho squared = 0.4989)

Application 3: Gustav (County)

Application 3 used the same household data as Application 1, but zonal data at county level was used instead of at ZCTA level. The accuracy of prediction by applying the new estimated model is shown in Table 16. This application serves as a baseline in the following comparisons.

Table 16
Prediction error in Application 3

	Correlation	The first adjusted %RMSE	The second adjusted %RMSE
Application 3	0.984	20.5%	22.1%

Predicted choices were also compared with observed choices by county in Table 17. Predicted choices were rounded to integers and reported in this table which makes the following phenomenon possible. Even though no households are predicted to choose a particular alternative in all counties, the total number of households choosing that alternative (in the last row) is a non-zero value, e.g., FR_ride. Overall, the distribution of predicted choices is close to what observed in the survey.

Table 17
Predicted /observed choices by county: Application 3

CountyID	County Name	FR				HM				SH				OT	
		own	ride	transit	other	own	ride	transit	other	own	ride	transit	other	own	other
22051	Jefferson	34/30	0/1	0/0	0/0	18/23	1/0	0/0	0/0	1/0	0/0	0/0	0/0	4/6	1/0
22057	Lafourche	7/6	0/0	0/0	0/0	3/5	0/0	0/0	0/0	0/0	0/0	0/0	0/0	1/0	0/0
22071	Orleans	8/8	0/0	0/0	0/0	8/7	0/0	0/0	0/0	0/1	0/0	0/0	0/0	2/4	0/0
22075	Plaque-mines	1/2	0/0	0/0	0/0	1/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0
22087	St. Bernard	1/2	0/0	0/0	0/0	2/1	0/1	0/0	0/0	0/0	0/0	0/0	0/0	1/0	0/0
22089	St. Charles	4/4	0/0	0/0	0/0	2/2	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0
22095	St. John the Baptist	2/2	0/0	0/0	0/0	1/1	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0
22103	St. Tammany	17/18	0/0	0/0	0/0	12/12	1/1	0/0	0/0	1/0	0/0	0/1	0/0	2/2	0/0
22105	Tangipahoa	2/2	0/1	0/0	0/0	1/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0
22109	Terrebonne	16/16	0/0	0/0	0/0	7/7	0/0	0/0	0/0	1/2	0/0	0/0	0/0	2/2	0/0
Sum		90/90	1/2	0/0	0/0	55/58	3/2	1/0	1/0	4/3	0/0	0/1	0/0	12/14	3/0

Application 4: Sandy II (County)

Application 4 used the same household data as Application 2, but it used zonal data collected at county level. The accuracy of prediction is shown in Table 18. Compared to Application 2, the coefficient of correlation increases in Application 4 which is at least partially due to fewer cells being compared because of fewer number of zones. The values of the two types of %RMSE are over 30%, which seems less desirable. However, the calculation of %RMSE was adjusted as shown in equations (14)-(20) in this study and more weights were assigned to cells with larger number of observations. Therefore, the critical value of 30% used in general cases may not apply well enough in this situation. A comparison between applications to find out the relative changes on the adjusted %RMSE is more proper. The values of the two types %RMSE increase about 14% and 18% compared with the baseline application (i.e., Application 3). The increments are more significant than Application 2, which are 3% and 7% from its baseline application (i.e., Application 1). Table 19 presents predicted and observed choices for more direct comparisons. They are generally the same in most of the cells as shown.

Table 18
Prediction error in Application 4

	Correlation	The first adjusted %RMSE	The second adjusted %RMSE
Application 4	0.970	34.9%	40.8%

Although the new estimated model has a similar specification (i.e., the model structure and variable selections) as the model estimated with data of ZCTA level, the four applications indicate more accurate results were achieved when the model was estimated and applied with data of ZCTA level. It can be understood as the loss of information can cause a significant impact on the results of predictions. That is, data collected at county level only provide a general description and average status of an area while data collected at ZCTA level can provide much more detailed information of this area. This is especially important in this situation in which zonal data are expected to describe the characteristics of a community where a household resides.

Table 19
Predicted /observed choices by county: Application 4

CountyID	County Name	FR				HM				SH				OT	
		own	ride	transit	other	own	ride	transit	other	own	ride	transit	other	own	other
34001	Atlantic	13/10	0/1	0/0	0/0	3/4	0/0	0/0	0/0	1/0	0/0	0/0	0/0	2/4	0/0
34003	Bergen	1/1	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0
34009	Cape May	14/20	0/1	0/0	0/0	8/5	0/0	0/0	0/0	1/0	0/0	0/0	0/1	4/2	1/0
34013	Essex	1/1	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0
34017	Hudson	7/7	0/0	0/0	0/0	1/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	1/2	0/2
34023	Middle-sex	2/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/1	0/2	0/0
34025	Mon-mouth	23/25	0/0	0/0	0/0	4/3	0/1	0/0	0/0	1/1	0/0	0/0	0/0	2/1	0/0
34029	Ocean	49/51	0/3	0/0	0/2	10/2	0/1	0/0	0/0	2/2	0/0	0/0	0/1	5/7	1/0
34039	Union	1/0	0/0	0/0	0/0	0/1	0/0	0/0	0/0	0/1	0/0	0/0	0/0	0/0	0/0
36005	Bronx	2/2	0/0	0/0	0/0	0/1	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0
36047	Kings	15/14	1/0	1/2	1/0	1/1	0/1	0/0	0/0	0/0	0/1	0/0	0/0	2/2	0/1
36059	Nassau	31/26	1/5	0/0	1/0	3/5	0/0	0/0	0/0	1/1	0/0	0/0	0/0	2/2	0/0
36061	New York	6/2	0/1	1/3	0/3	2/0	0/0	0/0	0/0	0/0	0/0	0/0	0/0	1/2	0/0
36081	Queens	18/18	1/3	3/3	1/1	1/0	0/1	0/0	0/0	1/0	0/0	0/0	0/0	2/1	0/1
36085	Rich-mond	5/2	1/3	0/0	0/0	0/1	0/0	0/0	0/0	0/0	0/0	0/0	0/0	0/1	0/1
36103	Suffolk	14/11	0/2	0/0	0/0	2/2	0/0	0/0	0/0	0/1	0/0	0/0	0/0	1/2	0/0
Sum		202/190	6/19	6/8	3/6	37/25	1/4	1/0	1/0	7/6	0/1	1/0	1/3	23/28	5/5

Application 5: Georges (County)

The last application is a local case. Hurricane Georges (Sep 15–Oct 01, 1998) affected several southern states. The post-storm behavioral survey used in this research covers five coastal parishes in Louisiana and three coastal counties in Mississippi as shown in Figure 8. Of the 1624 respondents, 606 chose to evacuate.
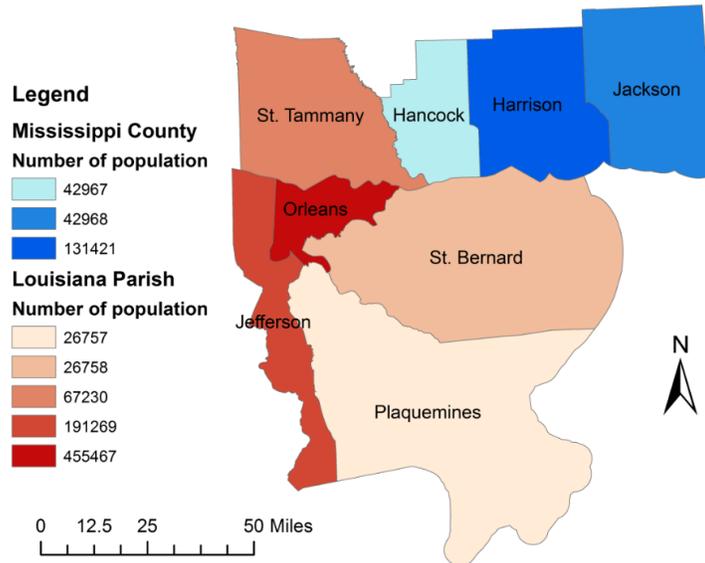

Figure 8
Study area in the survey of Hurricane Georges (LA and MS)

The composition of household choice is shown in the following table. The choice during Georges is similar to those made during Gustav although, in Georges, there are more shelter users.

Table 20
Choice of households: Georges without imputation

	Own	Ride	Transit	Other	Total
FR	179 (53.8%)	5 (1.5%)	0 (0%)	0 (0%)	184 (55.3%)
HM	86 (25.8%)	1 (0.3%)	0 (0%)	0 (0%)	87 (26.1%)
SH	25 (7.5%)	2 (0.6%)	0 (0%)	0 (0%)	27 (8.1%)
OT	32 (9.6%)	2 (0.6%)	0 (0%)	1 (0.3%)	35 (10.5%)
Total	322 (96.7%)	10 (3%)	0 (0%)	1 (0.3%)	333

Processing Household Data. Imputation was not conducted in this case even though 273 of the 606 households who evacuated had missing data on at least one of the variables. The application was conducted with the 333 records without any missing values.

Collecting Zonal Data from ACS. The process employed was similar to that used in model estimation with the geographic unit of county. In addition, ACS does not provide data for 1998. Therefore, data from the closest year (i.e., 2000) to the event was collected.

Calculating Accessibility. The two major issues in this process are defining the study area and the safety indicator. Potential destinations were all parishes of Louisiana, all counties of Mississippi, and six states that are adjacent to or close to the two states. Overall, potential destinations are similar to those defined in the case of Hurricane Gustav. Then population and the number of hotel employees were collected from ACS. However, the list of open shelters during the storm was not available. Therefore, the list of shelters used in Hurricane Gustav was used as a substitute. The calculation of accessibility was also based on equations (10)-(12).

Collecting Other Zonal Data. Data about hotel price and hotel occupancy are not available for the year of the event (1998). As a substitute, they were assumed to be the same as the data used in Hurricane Gustav, because both cases generally cover similar areas.

The accuracy of prediction is shown in Table 21. The correlation coefficient is over 0.9 in this application. The values of the two types of adjusted %RMSE are about 35%, which are about 15% larger than the baseline application (i.e., Application 3).

Table 21
Prediction error in Application 5

	Correlation	The first adjusted %RMSE	The second adjusted %RMSE
Application 5	0.962	35.3%	34.2%

Table 22 presented both predicted and observed choices of each county. Although values in most of the cells are close, large differences exist in some cells, such as FR_own and SH_own. It is partly due to the reason that zonal data were collected from ACS 2000 instead of 1998 exactly. After a major hurricane, local areas may experience significant changes which makes data from 2000 not fully reflecting the situation in 1998. In addition, some information was assumed the same as the case of Hurricane Gustav (2008), which may bring additional errors. For example, the capacity of shelters in Gustav may be less than that in

Georges. Therefore, less households evacuated to shelters in Gustav. This may cause the underestimation of shelter users in this application on Georges. Another potential source of error can originate from the fact that the survey was conducted in 2001, three years after the hurricane, and this increases the possibility that some households may not have reported their choices accurately.

Table 22
Predicted /observed choices by county: Application 5

CountyID	County Name	FR				HM				SH				OT	
		own	ride	transit	other	own	ride	transit	other	own	ride	transit	other	own	other
22051	Jefferson	53/43	1/0	0/0	0/0	17/25	1/0	0/0	0/0	1/4	0/0	0/0	0/0	5/7	1/1
22071	Orleans	44/38	1/3	0/0	0/0	18/18	1/0	0/0	0/0	1/4	0/0	0/0	0/0	6/10	1/1
22075	Plaque-mines	28/19	1/1	0/0	0/0	10/18	1/0	0/0	0/0	1/2	0/1	0/0	0/0	3/3	1/0
22087	St. Bernard	20/15	1/0	0/0	0/0	5/6	0/1	0/0	0/0	0/4	0/0	0/0	0/0	2/2	0/0
22103	St. Tammany	19/19	0/1	0/0	0/0	10/8	1/0	0/0	0/0	1/3	0/1	0/0	0/0	3/2	1/0
28045	Hancock	10/8	0/0	0/0	0/0	5/2	0/0	0/0	0/0	1/4	0/0	0/0	0/0	2/4	0/0
28047	Harrison	18/23	0/0	0/0	0/0	8/4	0/0	0/0	0/0	1/0	0/0	0/0	0/0	3/4	1/0
28059	Jackson	15/14	0/0	0/0	0/0	6/5	0/0	0/0	0/0	1/4	0/0	0/0	0/0	2/0	0/1
Sum		205/179	4/5	0/0	1/0	77/86	5/1	2/0	1/0	6/25	1/2	1/0	0/0	25/32	5/3

CONCLUSIONS

The diversity of household behavior has been increased in this research by using datasets from different storms (i.e., Hurricanes Gustav, Irene, and Sandy) and study areas (i.e., Louisiana and New York) in the U.S. The variation in behavior provides an opportunity to capture the impact of factors that influence evacuation but are often stable in individual data sets. Examples of such variables are the level of transit service in a study area, average hotel/motel prices, and general levels of private vehicle ownership. As a result of this data diversity, factors affecting household behavior are expected to have been identified more fully than in previous research. This expectation appears to be supported by the fact that the estimated models reasonably predicted mode and destination type choice in two post-storm behavioral surveys (i.e., Hurricanes Georges and Sandy) covering different study areas (i.e., Louisiana and Mississippi; New York and New Jersey). This is especially true in the case of applying the model estimated with data of ZCTA level. The error of prediction only increases about 7% from the baseline case.

The first contribution of this work is modeling mode and destination type choice jointly. The nested logit model was chosen because it provided the flexibility to test the linkage between the two choices through the significance of the logsum coefficients. It was proved in this study that they were linked choices. This finding is consistent with a prior research which indicates the relation between them through adding destination type choices as a dummy variable to explain mode choices. This result is also consistent with the experience that shelter users are more likely to be transit-dependent.

The second contribution is the selection of variables. Some variables have seldom been considered in previous mode or destination type choice modeling studies. The first example of this is neglecting to include social interactions as a factor in past studies. Residential stability was used as a surrogate measure of social interaction as it reflects the level of community interaction and the likelihood of collaborative evacuation behavior. The second example of incomplete variable selection in the past, is the failure to consider at least most of the attributes of alternatives. Transit level of service is an example of omission of important variable in the past. It clearly reflects how attractive public transit is for evacuees and is relevant to mode choice. The third example of the failure of past studies to include relevant variables in their model formulations is to take into account the characteristics of the study area. One of the most interesting illustrations of this is the case of choice of hotels/motels. Only 10% of the respondents living in New York chose hotels/motels as their destination, while the ratio was much higher in Louisiana (35%). Louisiana is generally believed to have stronger family ties than New York in most people's impressions so respondents from

Louisiana were expected to be more inclined than New Yorkers to evacuate to friends or relatives' houses instead of going to hotels or motels. As found in this study, this likely resulted from the low availability and high price of hotels in New York which discouraged households from choosing them during evacuation.

Estimating models on multiple data sets from different locations increases the likelihood that application of the models could be used to predict joint choice behavior in the scenario of hurricane evacuation in the U.S. This would improve current practice because the demand on transit vehicles has not been well understood, the location choice on pickup points and shelters can be better optimized, and a more precise prediction on traffic flow on the network can be expected.

The developed joint choice model would be easy to apply elsewhere because data are generally available for all the selected variables. Synthetic households can be generated by common transportation planning tools (such as TransCAD). The inputs to create synthetic households come from two sources. The first part is a household database, which provides rich information on household and personal characteristics. The Public-Use Micro Data Sample (PUMS) from the U.S. Census is a common choice. The second part is a zonal database, which contains aggregate marginal household statistics. Zonal level data can be easily collected from American Community Survey (ACS) and other named open data sources in this study.

RECOMMENDATIONS

Future researchers will be able to build upon this work by incorporating additional variables or alternatives to explain new emerging choice behavior. An area of particular significance is the emergence of ride-sharing programs. Commercial ride-sharing programs (such as Uber and Lyft) have become more popular in recent years and compete with taxis in some areas. The choice behavior on them can be understood based on the choice of taxis at this stage, because both of them provide door-to-door service and pick-up activities are both for profit. In addition, some areas consider designing non-profit ride-sharing programs for evacuation. This type of ride-sharing program differs from the regular "riding with others" in the sense that it is not based on collaborative efforts and requires less community attachment from the rider. The choice behavior on such programs can be understood based on the choice of evacuation transit service at this stage. When enough data on this choice alternative is accumulated in the future, adding a new alternative to the current model structure will update the model to reflect the new emerging behavior.

There is a portion of the population who are barely captured in current surveys, such as the disabled who use paratransit service, tourists, and temporary residents. At this stage, changing the survey instrument to collect a sufficient sample of these people to know their choice behavior may be too ambitious and not be that helpful considering the traffic these groups generate is likely to have only a limited effect on the road network since they are likely to evacuate before local residents. Accumulating data across different surveys through time may be a better solution. Besides, when enough data can be accumulated in the future, other types of GEV model, MMNL, or a dynamic model can be estimated and compared with the current estimated model.

Overall, additional data can help this research to generate more insight on household's joint choice behavior, update the model to fit the ongoing changes of household behavior, and draw more meaningful conclusions for the benefit of emergency managers.

ACRONYMS, ABBREVIATIONS, AND SYMBOLS

ABM	Agent-based Modeling
accessFR	Accessibility to the home of Friends/Relatives (See Table 7)
accessHM	Accessibility to Hotels/Motels (See Table 7)
accessSH	Accessibility to shelters (See Table 7)
ACS	American Community Survey
CBP	County Business Pattern
CNL	Cross-Nested Logit
ComDensity	Community density (See Table 6)
CommutebyTransit	Proportion of workers using transit (excluding taxi) for commuting (See Table 6)
DOTD	Department of Transportation and Development
DTC	Destination Type Choice
FR	The home of Friends/Relatives
GEV	Generalized Extreme Value
GNL	Generalized Nested Logit
GOF	Goodness-of-fit
HEZ	Hurricane Evacuation Zones
HHDisab	Household disability status (see Table 4)
HHInc	Household income in $1000 (see Table 4)
HHIncome	Household income (an indicator variable)
HHResYears	Household residential length (see Table 4)
HHSize	Household size (see Table 4)
HHVeh	Household vehicle ownership (see Table 4)
HM	Hotels/Motels
HotelOccupy	Hotel occupancy rate in the local area (See Table 10)
HotelPrice	Hotel price in the local area (See Table 10)
HURREVAC	Hurricane Evacuation
IIA	Independence of Irrelevant Alternatives
LA	Louisiana
LTRC	Louisiana Transportation Research Center
MC	Mode Choice
MMNL	Mixed Multinomial Logit
MNL	Multinomial Logit
MS	Mississippi
NAICS	North American Industry Classification System

NCES	National Center for Education Statistics
NHC	National Hurricane Center
NJ	New Jersey
NL	Nested Logit
NY	New York
NYC	New York City
OT	Other destination types
PropAge	Proportion of people who are less than 18 or over 65 (See Table 6)
PropDisab	Proportion of people with disability (See Table 6)
PropNonCitizen	Proportion of people who are not U.S. citizen (See Table 6)
PropNoVeh	Proportion of carless households (See Table 6)
PUMS	Public-Use Micro Data Sample
ResStab	Residential Stability (See Table 6)
RMSE	Root-Mean-Square Error
RP	Revealed Preference
RtePM or RoutePM	Real Time Evacuation Transportation Planning Model
SC	Stated Choice
SCL	Spatially Correlated Logit
SH	Public shelters
USPS	United States Postal Service
ZCTA	Zip Code Tabulation Areas

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