# A Destination Choice Model for Hurricane Evacuation

By

# **Guangxiang Cheng**

PE, PTOE

Department of Public Works City of Baton Rouge/ Parish of East Baton Rouge Baton Rouge, LA 70821 Tel: (225) 389-3192, Fax: (225) 389-8541, email: <u>gcheng@brgov.com</u> (Corresponding author)

### **Chester G. Wilmot**

Associate Professor, PE Department of Civil and Environmental Engineering Louisiana Transportation Research Center Louisiana State University, Baton Rouge, LA 70808 Phone: (225) 578-4697, Fax: (225) 578-8652, email: <u>cewilm@eng.lsu.edu</u>

#### Earl J. Baker

Associate Professor Department of Geography Florida State University, Tallahassee, FL 32306 Phone: (850) 644-8380, fax: (850) 644-5913, email: jbaker@coss.fsu.edu

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## ABSTRACT

A disaggregate destination choice model for hurricane evacuation was developed with post hurricane Floyd survey data collected in South Carolina in 1999. Because destination choice is a choice between discrete, independent alternatives, the multinomial logit model was selected as a convenient model form. It was used to investigate the effect of risk areas in the path, or projected path, of a hurricane, and destination socioeconomic and demographic characteristics on destination choice behavior. Models were developed for persons evacuating to friends or relatives, or hotels or motels separately. The models were tested by comparing the observed destination choices with predicted values. No significant difference was found.

**Keywords**: Destination models, multinomial discrete choice model, trip distribution, gravity model, travel demand, hurricane, evacuation, trip length distribution

#### **1 INTRODUCTION**

In keeping with the four-step modeling paradigm used in urban transportation planning, the hurricane evacuation planning process can be considered as involving evacuation trip generation, destination choice (trip distribution) and evacuation route traffic assignment. The research described in this paper is aimed at testing whether a multinomial logit model can successfully be used to model hurricane evacuation destination choice.

Destination choice is a critical step in evacuation planning and emergency management since output from this process is input to traffic assignment and is necessary for the accurate assessment of network congestion and delay. However, despite its importance to hurricane evacuation modeling, it has received relatively little attention in the past; probably because hurricane evacuation is a fairly rare phenomenon. Current practice is, predominantly, to assign evacuees to destinations, or evacuation routes, subjectively (NCDOT, 2000; Jha et al., 2004; Radwan et al., 2005). Wilmot, Modali, and Chen (2006) investigated the use of the gravity model, intervening opportunity model and extended intervening opportunity model on hurricane evacuation destination choice. Through a series of tests between the predicted trips by the models and observed trips, the study suggested that the conventional urban transportation planning trip distribution models are able to model hurricane evacuation trip distribution at the aggregate level. Cheng (2006) estimated alternative impedance functions for gravity models used in hurricane evacuation trip distribution. The impedance function found to most closely reproduce observed destination patterns was a combination of a negative exponential curve, which accommodates the travel distance impedance, and a left skewed Rayleigh curve which accommodates the impact of hurricane threat on destination zones. The model produced satisfactory trip distribution results.

Although the aggregate models mentioned above can provide satisfactory results, they lack the ability to capture behavioral influences at the disaggregate level. Specifically, evacuation destination choice is, intuitively, likely to be significantly influenced by conditions facing individual households and, therefore, is more likely to be successfully modeled using disaggregate discrete choice models.

Urban transportation planning models typically require detailed and numerous Traffic Analysis Zones (TAZs). This prohibits the application of destination choice modeling at disaggregate level in urban transportation planning. However, the travel pattern of hurricane evacuation is different from urban transportation in that evacuation trips are mostly long distance intercity journeys. In evacuation modeling, TAZs can be large areas, thereby limiting the number of TAZs and making destination choice by disaggregate modeling feasible again.

The objective of the study is to test whether discrete choice models can successfully reproduce evacuation destination choice observed in evacuation behavior from Hurricane Floyd. Beside the disaggregate variables that will be included in the model specification, the influence of aggregate destination socioeconomic, demographic, and hurricane threat characteristics will also be investigated. An attempt will be made to make the mode sensitive to storm conditions and alternative emergency management actions.

## **2 DATA DESCRIPTION AND TAZ SPECIFICATION**

#### 2.1 Data Description

Intuitively, hurricane evacuation destination choice is dependent on the characteristics of the alternative destinations and the properties of the hurricane. Therefore, if a model is to be estimated on existing evacuation data, it is necessary that it contain information on the

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characteristics of alternative destinations and the characteristics of the hurricane which prompted the evacuation. The data used in this study is from a telephone survey of hurricane Floyd evacuation conducted on behalf of the U.S. Army Corps of Engineers shortly after the storm in 1999. The data contains socio-economic information of the households responding to the survey, as well as details regarding their evacuation behavior during the hurricane. Approximately 1,800 households were surveyed in the metropolitan and surrounding areas, of Charleston, Myrtle Beach, and Beaufort in South Carolina. Those areas are the only three origins in the model. Since destination types generate different trip length frequency diagrams (Wilmot, Modali and Chen, 2006), the data was divided into four major destination types: 1) home of friends and relatives; 2) hotels/motels; 3) public shelters and churches; 4) and others. Each of these subsets of data could be used to build a different model, but there are only 40 households in the data that chose shelters or churches as their destination type, and 56 households that chose "other" destination types such as a second home, a hospital, state park, office, truck stop, etc. Thus, models for public shelters or churches, and "other" destination types were not considered due to insufficient data for modeling. On the other hand, 680 households chose the home of friends and relatives as their destination, and 360 households chose hotels or motels as their destination, which was sufficient for modeling purposes. Other studies found similar percentages for destination types in other hurricane evacuation cases (Irwin et al. 1995, RDS 1999). The data set was separated into two data sets for these two types of destination – one for the friend/relative model and the other for the hotel/motel model.

#### **2.2 TAZ Specification**

The majority of the evacuation destinations from South Carolina were located in the states of South Carolina, North Carolina, Georgia and Tennessee. Trips farther away to other states were dropped from the data sets due to limited observations. All destination locations in the survey data were categorized by county.

In conventional urban transportation planning models, TAZs are units of geography that can range from large areas in the suburbs to city blocks in central business districts. In defining TAZs in urban transportation planning, several criteria are typically adopted (Baass, 1981; Ortuzar and Willumsen, 1994). Generally, these criteria can be stated as: the zones should be as homogeneous with respect to the socioeconomic characteristics as possible; intrazonal trips should be minimized; the border of the zones should give considerations to administrative limits such as census tracts, county boundary and physical geographic separators such as railway lines and rivers; one zone should not encircle another, and each zone should contain a similar number of households, population, area, or trips generated and attracted.

In the case of hurricane evacuation, origin zones are concentrated in threatened coastal areas, and destination zones are spread inland to neighboring counties and states. Some guidelines have been suggested on the creation of origin evacuation zones (USACE 1986, 1994, 1995, PBS&J 1992, Wilmot and Meduri, 2005), but little has been suggested on establishing destination evacuation zones. Since evacuation travel patterns are less complex than the multi-purpose, multi-directional travel encountered in everyday urban travel, the TAZ's used in evacuation planning can generally be less comprehensive. In addition, they can become progressively less comprehensive as distance increases from the origin since fewer and fewer evacuees are left to reach a destination, and the need to accurately estimate network conditions in terms of congestion and delay is reduced due to the lower traffic volumes. Thus, a process that aggregated counties into progressively larger evacuation TAZs as the distance from the coast

increased, was instituted. The aggregation process also created a manageable choice set for disaggregate modeling and allowed a reasonable number of observations in each origindestination pair. The TAZ aggregation process we employed used the following criteria in establishing evacuation TAZs for this application:

*1. Location risk due to hurricane*. Figure 1 shows a Hurricane Floyd wind speed map. As can be seen, the hurricane ran roughly parallel to the coastline of Georgia, South Carolina and North Carolina, creating a band of counties along the coastline which were subject to gale force winds and which represented at-risk areas that all evacuees would want to avoid as a destination. Figure 2 is the trip length distribution, which shows the trip frequency versus travel distance at every 50 miles for the total trips and the two major types of destinations. The trip length distribution (Figure 2) shows that there were few trips within 50 miles from origin. Therefore, the at-risk coastal counties could be aggregated into a single origin evacuation zone.

2. Distance from origin to destination. It was assumed that travelers would try to evacuate to close safe places as much as possible once beyond the at-risk area (Southworth 1991). Figure 2 shows that most evacuees traveled distances longer than 50 miles and less than 300 miles. The size of destination TAZs were set proportionally to the distance from origin to destination. The closer the destination was to the origin, the smaller the TAZ, as there were more observations in closer counties than counties farther away. As a result, more destination zones were established in South Carolina and fewer destination zones in other states.

*3. Natural geographic feature.* Significant geographic features can be a factor in aggregating the zones. In this case, the Appalachian range goes through Tennessee, North Carolina, western South Carolina and northern Georgia. It can be seen as a natural barrier and, therefore, a feature that defines a TAZ.

4. *Metropolitan area*. Metropolitan areas can be major destination choices due to their ability to accommodate many evacuees. Counties surrounding mega-metropolitan area can be aggregated into one TAZ representing the metropolitan area because most trips will be going to locations in the metropolitan area.

5. *Existing regions*. Some states, such as Georgia, have been divided into several regions. Each region has its own distinct geographic feature and economic characteristics. These regions can be further aggregated into larger TAZs.

Based on the above factors, 28 destination TAZs were created and are shown in Figure 3. The three origin zones, and the at-risk area, consisting of the area experiencing gale force winds (i.e. winds in excess of 38 miles per hour), are also shown in Figure 3.

Destination socioeconomic and demographic information for the study area was obtained from the standard GIS data files provided with TransCAD software. Hurricane Floyd's track and speed data was obtained from National Hurricane Center website. The total number of hotels of a destination was found in 1997 Economic Census Reports for Accommodation from U.S. Census Bureau website.



FIGURE 1 Hurricane Floyd wind speed map (source: FEMA).



FIGURE 2 Trip length distribution of evacuation trips.



#### FIGURE 3 Aggregated traffic analysis zones.

#### **3 METHODOLOGY**

#### **3.1 Discrete Choice Models**

Evacuees choose one destination out of a set of mutually exclusive alternative destinations. Qualitative choice from a set of distinct alternatives can be modeled using discrete choice models. Discrete choice models are based on the assumption that people are utility maximizers. To apply this theory here, we suggest evacuees will try to maximize the utility of their evacuation experience by choosing the most attractive destination to them out of all possible destinations. Although it is obvious that this assumption is a simplification of human behavior since people generally operate under more constraints and influences than can be included in a utility function, models based on this assumption obtain results that are expected to be better than those obtained with aggregate models that do not attempt to capture individual behavior.

There are different types of discrete choice models. The most common, the multinomial logit (MNL) model takes the following form:

$$P_i = \frac{e^{\beta \mathbf{x}_i}}{\sum_{j=1}^J e^{\beta \mathbf{x}_j}}$$

where:

 $P_i$  = probability of choosing alternative i;

 $\mathbf{x}_i$  = vector of attributes of alternative i;

 $\beta$  = parameters;

J = number of alternatives

Destination choice models are relatively rare in urban transportation planning modeling because of the large number of destination choices typically encountered in urban transportation. However, as discussed above, the number of TAZs has been aggregated to a limited number (28) in this application. Therefore the MNL model seems to be an appropriate method here.

## **3.2 Model Preparation**

The model used in this application is based on the idea that evacuation consists of only one activity; namely, the activity of evacuating from a hurricane threat to a safe destination. The alternatives inherent in the choice are the aggregated TAZs as described in prior sections. The variables in the utility function of the discrete choice model have been chosen based on former studies which have analyzed factors influencing travel behavior in intercity destination choice (Sharma, 1995). The variables which will be used in the proposed trip distribution model will explain the cause of attraction to the destinations. The variables will include:

- 1. Travel costs (distance) to the destination (DIST in the model). This describes the impedance to go from one place to another. The shortest path distance between origin and destination was used in this case since link flows, and subsequently link travel times, are not known at this stage.
- 2. Destination population (POP in the model) was used for the friend/relative model.
- 3. Number of hotels/motels at destination (HOTEL in the model) was used for the hotel/motel model.
- 4. Risk indicator was used to indicate a destination's vulnerability to a hurricane (DANGER in the model). This variable was entered in the format of a dummy variable. It distinguished destination zones that were in the area experiencing gale force winds from those areas that did not. In Figure 3, the red shaded and red striped TAZs are given a dummy variable value of 1 and all other TAZs (i.e. the destination zones) were given the value of 0.
- 5. Destination ethnic percentage (ETHPCT in the model). This variable describes the White population percentage in each zone.
- 6. Metropolitan area indicator (MSA in the model). MSA is ascribed the value of 1 if a TAZ contains a major metropolitan area, and 0 otherwise.
- 7. Interstate highway proximity indicator (INTERSTA in the model). INTERSTA has the value 1 if a TAZ contains an interstate highway and 0 otherwise.

The variables above include both disaggregate and aggregate variables. Specifically, travel distance (DIST) is a disaggregate variable relating the travel distance each household traveled to get to their destination, while the remainder are aggregate variables describing the characteristics of destination zones. However, the aggregate characteristics of the destination zones are used to characterize the destination alternatives for each respondent, and therefore, are used as disaggregate variables.

## **4 RESULTS**

Based on the variables suggested above, models were estimated for households evacuating to friends/relatives, or to a hotel/motel separately. The variables in each model were selected if they were found to be significant using a t-test, and were discarded if found to be insignificant. The results are shown in Tables 1 and 2.

|           |                               |           | Standard |                | Approx  |
|-----------|-------------------------------|-----------|----------|----------------|---------|
| Parameter | Description                   | Estimate  | Error    | t Value        | Pr >  t |
| DIST      | O-D Distance                  | -0.004655 | 0.000752 | -6.19          | <.0001  |
| POP       | <b>Destination</b> Population | 1.66E-07  | 3.21E-08 | 5.16           | <.0001  |
| DANGER    | Risk Indicator                | -0.5171   | 0.1626   | -3.18          | 0.0015  |
| MSA       | Metropolitan Area             | 1.5562    | 0.1353   | 11.5           | <.0001  |
| ETHPCT    | White Percentage              | 0.6711    | 0.2193   | 3.06           | 0.0022  |
|           |                               |           |          | Estrella       | 0.6903  |
|           |                               |           |          | McFadden's LRI | 0.1613  |
|           |                               |           |          |                |         |

Table 1. Friend/Relative Model Results.

In the friend/relative model, the parameter values shown in Table 1 are all significant and have the correct signs. DIST has a negative sign, which indicates that evacuees consider increased evacuation distance a negative utility. The parameter for the population variable (POP) has a positive sign indicating that the size of population is proportional to destination attraction (or utility). The parameter for the DANGER variable has a negative sign which indicates that hurricane threatened areas are clearly less attractive as destinations than those outside the at-risk areas. MSA has a strongly positive effect, over and beyond that provided by population (POP), suggesting that evacuees have a clear preference for a metropolitan area over other areas. ETHPCT has a positive sign which indicates that the higher the percentage of white population at the destination, the more likely people will evacuate to that destination. This result should be seen in the context that most residents, and therefore evacuees, of coastal South Carolina are white, and therefore are more likely to have family and friends who are of the same ethnic background. Because POP and HOTEL are correlated, HOTEL was not present in the friend/relative model. INTERSTA was deleted from the model because this variable was found to be insignificant. Estrella's index and McFadden's LRI are measures of goodness of fit of the model to the disaggregate data. They show a reasonably good fit.

To test the performance of the model, we compared the model predictions with those in the data. Ideally, one would want to test model performance on other data than those on which the model was estimated, but our data was insufficient to divide into a calibration and testing subsets. We also chose to compare the results at the aggregate level rather than at the disaggregate level. There were several reasons for this. First, in trip distribution (or destination choice) modeling, it is only the aggregate number of trips from origin to destination that is used in trip assignment. Second, trip distribution models in urban transportation planning are calibrated on trip length frequency diagrams, demonstrating the significant role trip length frequencies are assumed to play in describing trip patterns. Third, the percent correctly predicted statistic is notoriously dependent on the number of alternatives and the distribution of choices among them, and therefore is not a reliable measure of performance. For example, with only two alternatives and 99 percent of the choices favoring one alternative, a model that always chooses the more popular alternative (thereby displaying no predictive power at all), would produce a "percent correctly predicted" (PCP) of 99 percent. The same poor model would produce a PCP of 50% if each alternative occurred equally in the data set, and 25% if there were four alternatives that were equally likely.

The comparison of the observed trip length distribution for evacuation to friends or relatives with that predicted by the model is shown in Figure 4. The trip length distributions of the observed OD matrix and estimated OD matrix were first compared using the Kolmogorov-Smirnov (KS) two sample test. Trip frequency was determined for every 50 mile distance from

the origin centroids as measured on the shortest path between the origin and destination . The evacuation travel range was 0 to 550 miles. Therefore, the sample size was 11. The test statistic D obtained was 0.09 with a p-value 0.985 and the critical value of D at the 5% level of significance was 0.522 with a sample size of 11. Thus, the null hypothesis could not be rejected, suggesting no statistical difference between the two trip length frequency distributions.

The model was further tested with a paired samples t-test. The t-statistic obtained was 1.81 with a p-value 1.00. The two-tailed critical value was 2.23 with 10 degrees of freedom. Thus, the null hypothesis again could not be rejected and there was no significant difference between the two trip length frequency distributions.



FIGURE 4 Trip length distributions for friend/relative model.

|           |                         |           | Standard |                | Approx |
|-----------|-------------------------|-----------|----------|----------------|--------|
| Parameter | Description             | Estimate  | Error    | t Value        | Pr> t  |
|           |                         |           |          |                |        |
| DIST      | O-D Distance            | -0.005882 | 0.000981 | -6             | <.0001 |
| HOTEL     | Destination # of Hotels | 0.002279  | 0.000387 | 5.88           | <.0001 |
| DANGER    | Risk Indicator          | -1.57     | 0.2331   | -6.74          | <.0001 |
| INTERSTA  | Interstate Proximity    | 0.1324    | 0.0497   | 2.66           | 0.0078 |
| ETHPCT    | White percentage        | 0.8705    | 0.3178   | 2.74           | 0.0062 |
|           |                         |           |          | Estrella       | 0.6881 |
|           |                         |           |          | McFadden's LRI | 0.1613 |

| Table  | 2. | Hotel | /Motel | Model | <b>Results</b> |
|--------|----|-------|--------|-------|----------------|
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The signs of the variables in the hotel/motel model are similar to the signs of the variables in the friend/relative model for those variables that are common among them. The parameter for the HOTEL variable has a positive sign which indicates the number of hotels positively contributes toward the attraction of the destination. INTERSTA has a positive effect to attract evacuees if a destination contains interstate highway. MSA was deleted from the model because this variable was not significant in the model. The Estrella index and McFadden's LRI produce similar values of goodness-of-fit to that achieved with the friend/relative model.

The estimated and observed trip length distributions for the hotel/motel model are shown in Figure 5. The statistic D of KS test obtained was 0.28 with a p-value 0.736 with sample size 11, and the critical value of D at the 5% level of significance was 0.522. Therefore, no statistical difference was observed between the two trip length frequency distributions. The t-statistic of the paired samples t-test was 1.81 with a p-value 0.81. Thus, no significant difference between the two distributions was detected using the paired sample t-test.



FIGURE 5 Trip length distributions for hotel/motel model.

### **5 CONCLUSIONS**

Modeling hurricane evacuation destination choice is a relatively undeveloped area in transportation modeling at the moment. However, it is important to make progress in this area since the entire ability to model hurricane evacuation depends on being able to model each aspect of evacuation behavior adequately.

Destination choice using discrete choice models has not, to the author's knowledge, been used in hurricane evacuation destination choice modeling before. Aggregating destinations to a manageable number (in this application 28), makes it a feasible proposition to model destination choice using discrete choice theory. Other research has shown that the trip length frequencies of evacuation trips vary depending on whether evacuees are heading to stay with friends or family, or whether they are heading to shelter in a hotel or motel in a safe area. Thus, separate models have been established for those evacuating to friends and relatives, and those evacuating to hotels or motels. This means that the trip generation model that precedes these models will have to estimate evacuation generation by destination type.

The MNL models estimated on evacuation data from South Carolina in response to hurricane Floyd both show likelihood ratio statistics of 0.16 or Estrella statistics of 0.69, suggesting a reasonably good fit to the data. Comparing the model's predictions of trip length frequency distribution to that observed in the data, shows that they are not significantly different from each other. At the same time, by observing the distributions for the two destination types, it is obvious that they are different from each other.

The hurricane risk indicator shows that the path of the hurricane has a significant impact on the distribution of trips from their origins. Having the variable within the model specification allows estimation of the impact of alternative storm trajectories. When a major hurricane approaches, the risk indicator can be assigned to destinations depending on the different hurricane path projections, and thus provide different scenarios for emergency management agencies.

The variable POP (population) appears to function as a reasonable surrogate for the likelihood of a friend or relative being at a destination, just as the number of hotels represents the opportunity to find hotel or motel accommodation in a location. The trip length distributions show peaks at the around 200 miles and 300 miles. The first peak is due to people evacuating to get beyond the at-risk area but not wanting to go further than necessary. The second peak can be explained by the large population or number of hotels in the Atlanta area, which is located approximately 300 miles from evacuation zones, which attracts a large number of evacuees. The population variable does seem to be modified by the matching of ethnic similarities between the origin and destination.

The models do indicate that, all else being equal, evacuees do choose closer safe destinations to more distant ones. As expected, this is more pronounced among those evacuating to hotels and motels than those going to friends or relatives where the choice of destination is more restricted. Clearly, distance may not be a good representation of impedance, particularly if congestion is experienced on some links and not on others, and at some times and not at others so that different trips in the data base experience different travel times over the same routes. However, to remedy this would require trip assignment in an iterative distribution/assignment process that was beyond the scope of this study. Alternatively, a dynamic trip destination choice model could be developed to capture the time-dependent destination availability, real-time travel time and real-time hurricane threat to the destinations. These are considered possibilities for future research.

Destination choice models of the type estimated in this study can be used to test likely evacuation patterns resulting from different storm trajectories, different levels of evacuation, and the spatial location and size of metropolitan areas in safe locations relative to the path of the storm. However, further testing of the model with other data, reflecting different storm and local conditions, is needed before the results of this study can be considered typical or representative of evacuation behavior in general.

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