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The transferability of the Gravity Model for evacuations to friends and relatives was also tested in this study by applying the model estimated on the Hurricane Floyd data in South Carolina to data from Hurricane Andrew in Louisiana. Transferability was tested by comparing the trip length frequency distributions from the two data sets, the similarity of friction factors from models estimated on each data set, and the ratio of the Root-Mean-Square-Error (RMSE) of destination predictions of a locally-estimated model to a transferred model on the Andrew data. No significant statistical difference was found between the trip length frequency diagrams or the sets of friction factors at the 95 percent level of significance. The ratio of RMSEs on the Andrew data was 0.67, indicating that the average error of a locally-estimated model was 67 percent that of the transferred model.

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Modeling Hurricane Evacuation Traffic: Testing the Gravity and Intervening Opportunity Models as Models of Destination Choice in Hurricane Evacuation

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ABSTRACT

In this study, the ability of standard trip distribution models, such as the Gravity Model and Intervening Opportunity Model (IOM), to model evacuation destination choice was tested. The test was conducted by estimating the models on a portion of evacuation data from South Carolina following Hurricane Floyd, and then observing how well the models reproduced destination choice at the county level on the remaining data. The tests showed the models predicted destination choice on the remaining data with similar accuracy. The Gravity Model predicted evacuation to friends or relatives in 110 different counties with an average error of 1.55 evacuations over all destinations, while the corresponding error for the IOM was 1.64. For evacuation to hotels or motels in 70 different counties, the Gravity Model gave an average error of 1.48 evacuations and the IOM an average error of 1.50. However, when the IOM was modified to make the sequencing of opportunities sensitive to the direction of evacuation relative to the path of the storm, the modified IOM performed slightly better than the Gravity Model with average errors of 1.55 and 1.43 evacuations to friends and relatives, and motels and hotels, respectively.

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IMPLEMENTATION STATEMENT

The results of this study will be useful in modeling the destination choice of hurricane evacuees. The study demonstrates that both the Gravity and the Intervening Opportunity Models are capable of reproducing observed evacuation trip patterns at the aggregate level. The transfer of a Gravity Model estimated on data from Hurricane Floyd in South Carolina to data collected in Louisiana following Hurricane Andrew, shows that the transferred model reproduces observed destination choice with an error that is 50 percent greater than that achieved with a locally-estimated model. No significant difference is observed in the trip length frequencies and the friction factors between the transferred and locally-estimated model. This shows that the Gravity Model is reasonably transferable in this particular case, but it is not known how transferable it will be in other situations. A model that is transferable can be used to estimate the impact of changes to a local situation such as the introduction of contraflow on freeways that lead out of the area, or policies that affect the attractiveness of a destination, such as the opening of additional shelters or the availability of hotel rooms in potential destination cities.

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INTRODUCTION

Hurricane evacuation management, as currently practiced, is primarily an operational activity where emergency managers, state police, and elected local officials use current conditions, along with their expectation of future conditions, to manage and direct the evacuation process. This has the benefit of allowing actual conditions to shape decisions, resulting in a customized response to each storm. However, it usually does not allow sufficient time for decision makers to test alternative strategies so that optimum tactics can be selected. For example, as a hurricane approaches, emergency managers want to know when to issue an evacuation order, what type of evacuation order to use, and which areas to target. They also want to know when to introduce and terminate contraflow on the evacuation routes, and what the consequences of alternative decisions will be. To get answers to these questions requires planning and analysis in advance of the storm.

Advance planning for hurricane evacuation involves evaluation of alternative operational strategies for a range of storm and local conditions to identify the best response in each scenario. The optimum response strategies are typically compiled into "contingency plans" used to direct their operational decisions under different scenarios. The development of a contingency plan is typically achieved by:

1. Identifying storm scenarios that account for the range of storm conditions that are likely to occur.
2. Estimating the evacuation travel demand that will result from each storm scenario and each alternative policy or strategy that emergency managers are likely to implement to facilitate evacuation.
3. Evaluating the outcomes to identify the policies and strategies that provide the best handling of the different storm scenarios.
4. Preparing detailed contingency plans.

Evacuation demand estimation involves if, when, and where evacuation will take place. In this report, we are specifically concerned with the "where" of the evacuation trip. That is, assuming we already know which households will evacuate and when they will do so, what determines where these households will evacuate to? In urban transportation planning, this activity is termed trip distribution. Several trip distribution models are available in urban transportation planning packages to perform this function. Two of the most popular aggregate trip distribution models, namely the Gravity and Intervening Opportunity Models, are tested in this study to see if they can distribute evacuation trips with sufficient accuracy to warrant their use in evacuation demand modeling. The initial aspects of evacuation demand, namely the "if" and "when" evacuation takes place, are addressed in LTRC Technical Report 408 *[1]*.

OBJECTIVE

The objectives of this study are to:

- Test whether the Gravity and Intervening Opportunity Models can successfully reproduce aggregate evacuation destination choice observed in evacuation behavior from Hurricane Floyd.
- Compare the performance of the Gravity and Intervening Opportunity Models in modeling evacuation destination choice.
- Test the transferability of the Gravity Model by applying the model estimated from the Floyd data to the data from Hurricane Andrew.

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SCOPE

The scope of this study is to test the Gravity and Intervening Opportunity Models' ability to reproduce observed evacuation destination choices at the aggregate level, and to observe how well a model estimated on data from one hurricane can reproduce evacuation behavior in another. The focus of the study is on developing advance planning procedures, rather than the operational procedures used during a storm. Clearly, there is a need for both planning and operational models, but this research is restricted to the consideration of planning models.

The research reported in this document is part of a more comprehensive study addressing other topics related to evacuation planning. These topics are addressed in separate LTRC reports. Specifically, LTRC Technical Report 400 addresses contraflow as a means of increasing evacuation capacity, and reports on research conducted on the effectiveness of alternative initiation and termination configurations of contraflow evacuation systems *[2]*. LTRC Technical Report 402 *[3]*, documents the investigation into a mobile traffic counter capable of providing real-time traffic flow and speed information at remote locations. It describes the specification, evaluation, and acquisition of a trailer that uses radar detection of volume and speed over multiple lanes, and uses a cellular phone to transmit information back to a central location at time intervals of the user's choice. LTRC Technical Report 408 *[1]* addresses the estimation of time-dependent hurricane evacuation demand and reports on the development of a sequential logit model that estimates whether a household will evacuate or not, and if it does decide to evacuate, when they will choose to leave. The development of a methodology to establish hurricane evacuation zones in a systematic and reproducible manner was also conducted as part of this study, and is reported in Transportation Research Record 1922 *[4]*. The procedure uses postal Zone Improvement Plan (ZIP) areas as basic building blocks in a GIS-based process that progressively combines these blocks into evacuation zones of similar flooding potential.

METHODOLOGY

Approach

This study concentrates on the modeling of destination choice in hurricane evacuation. Southworth *[5]* has suggested that evacuees choose their destination in one of the following ways:

- They choose the closest destination (in terms of distance or travel time) beyond the at-risk area.
- They head for pre-specified destinations according to an established evacuation plan.
- They display some degree of dispersion in their selection of destinations, depending on factors such as the location of friends and relatives, characteristics of the hazard, and the traffic conditions on the network.

The first assumed method of choosing a destination may work effectively in modeling small urban systems or rural evacuations when the hazard is approaching rapidly. It may also apply when the hazard is great and avoidance is of paramount importance, such as in a radioactive, chemical, or biological release. This method is also likely to apply in post-event evacuations where a hazard remains, such as following a volcanic eruption or the explosion of a dirty bomb.

The second approach to choosing an evacuation destination applies when well-publicized evacuation plans, and clear instructions for individual portions of an urban area, have been prepared and disseminated to the population in advance. Large cities may favor this approach because it allows more effective use of the evacuation routes than would likely occur if the choice of route were left entirely to the discretion of evacuees. Past experience has shown that providing little or no guidance to evacuees on which route to choose in evacuation results in an uneven use of facilities. Southworth *[5]* suggests that a good plan supplemented by effective policing of traffic flow could make this option the best method for evacuation.

The third option, while more complicated, is closer to reality, since approximately two-thirds of households evacuating from hurricanes in the past report that they go to stay with friends and relatives *[6], [7]*. Thus, for these evacuees, their destination is relatively fixed (depending on the number of options open to them), and, subsequently, they are likely to simply seek the quickest way to reach their destination.

In this study, we built our model based on the third assumed method of destination choice, although we also recognized that storm characteristics and network properties can still play a role in destination choice.

Gravity Model

To date, the most widely used trip distribution model in urban transportation planning has been the Gravity Model *[8]*. Gravity Models are founded on the notion that trip patterns are primarily determined by the amount of activity at the origin, the relative attractiveness of a destination, and the difficulty of making the trip between the origin and destination *[9]*. In urban transportation planning, these three assumed determinants of trip distribution are represented by productions, attractions, and travel impedance respectively. In evacuation demand modeling, productions are replaced with evacuations, attractions with the number of opportunities of refuge, and travel impedance with some measure of travel time or travel distance combined with directionality of travel away from the hazard. In the Gravity Model, travel impedance is the only deterrent to travel, and in urban transportation planning, travel time irrespective of direction is a good measure of the deterrence to travel. However, in evacuation destination choice using the Gravity Model, the deterrence should be reduced for travel away from a hazard and increased for travel toward it.

In urban transportation planning, trips are distinguished by trip purpose. Separate Gravity Models are estimated for each trip purpose because the travel patterns for different trip purposes are so distinct. However, in evacuation modeling, only one trip purpose exists, and travel behavior is found to be influenced more by the type of destination (i.e. friends/relative, hotel/motel, or public shelter) than by anything else. The opportunities for safe refuge at these locations are likely to change significantly over time, as they are consumed, meaning that it is very important to model the evacuation process dynamically. This is in contrast to regular urban transportation planning where travel demand modeling is typically conducted using static models.

Intervening Opportunity Model

Formulation

The initial concept of an Intervening Opportunity Model originated with Stouffer *[10]*, as applied to population migration. The model was originally formulated as:

$$\delta P = K/V, \text{ or}$$

$$P = K \ln V + C_1$$

where V = total number of opportunities within a radius R from the town of origin, and

P = number of migrants who find destinations within a radius R from their starting place

The application of the Intervening Opportunity Model in urban transportation planning was first conducted by Morton Schneider of the Chicago Area Transportation Study (CATS). The model assumes that trip makers consider potential destinations sequentially, in order of their impedance from the origin *[11]*. The model is formulated as follows:

Let i = origin zone

$j = j^{th}$ destination in order of travel impedance (distance or travel time) from the origin zone

A_j = number of destination opportunities in the j^{th} zone

V_j= the sum of destination opportunities available from the origin zone to the j^{th} zone, ranked by travel impedance from the origin zone

U_j = probability of traveling beyond zone j

L = the constant probability of accepting a destination if it is considered

$P(V_j)$ = probability of finding an acceptable destination in V_j opportunities

$P(A_j)$ = probability of finding an acceptable destination in the A_j opportunities of zone j

Assuming a constant L, we have

$$U_j = U_{j-1}(1 - LA_j)$$

$$-LA_j = (U_j - U_{j-1})/U_{j-1}$$

but $A_j = V_j - V_{j-1}$

hence, $-L(V_j - V_{j-1}) = (U_j - U_{j-1})/U_{j-1}$

Assuming many destinations, U and V can be taken as continuous functions

hence, $$-LdV=dU/U \qquad (1)$$

Integrating both sides, we have $U = Ke^{-LV}$, where K is a constant of integration

The number of trips from zone i which terminate in zone j will be the total number of trips originating from i times the probability that the trip ends in zone j.

hence, $T_{ij} = O_i(U_j - U_{j-1})$

$$U_j = Ke^{-LVj}$$

hence, $$T_{ij} = KO_i(e^{-LVj-1} - e^{-LVj}) \qquad (2)$$

Applying the production constraint, assuming all trips from origin i are distributed, and there are n zones, we have

$$\sum_j T_{ij} = O_i K(1 - e^{-LVn}) = O_i$$

hence, $K = \dfrac{1}{1 - e^{-LVn}}$

so we get the common formulation of the Intervening Opportunity Model:

$$T_{ij} = \frac{O_i (e^{-LV_{j-1}} - e^{-LV_j})}{1 - e^{-LV_n}} \qquad (3)$$

This formulation is known as the *forced Intervening Opportunity Model*, which is a singly (production) constrained model.

If we use another constraint – the constraint that all trips must be made – we get the *free Intervening Opportunity Model [12]* where the probability of traveling beyond the origin, U_0, is equal to 1.

$$U_0 = Ke^{-LV_0}$$

hence K = 1, and

$$T_{ij} = O_i (e^{-LV_{j-1}} - e^{-LV_j})$$

Similarity of the Intervening Opportunity Model and the Gravity Model

This finding of the similarity of the Gravity Model and Intervening Opportunity Model is due largely to CATS. An alternative explanation is also provided by Zhao et al. *[13]*.

Using equation (3) and noting that $V_j = V_{j-1} + A_j$

$$T_{ij} = O_i K(e^{-LV_{j-1}} - e^{-LV_j}) = O_i K(1 - e^{-LA_j})e^{-LV_{j-1}}$$

If L is small, say in the order of 0.1 or less, then $1 - e^{-LA_j}$ is nearly equal to LA_j, *[14]*. Therefore,

$$T_{ij} \approx KO_i A_j Le^{-LV_{j-1}}$$

Applying the production constraint $\sum_j T_{ij} = O_i$

$$\sum_j T_{ij} = \sum_j KO_i A_j Le^{-LV_{j-1}} = K_i O_i \sum_j A_j Le^{-LV_{j-1}} = O_i$$

$$\Rightarrow K = \frac{1}{\sum_j A_j L e^{-LV_{j-1}}}$$

Therefore,

$$T_{ij} = O_i \left\{ \frac{A_j e^{-LV_{j-1}}}{\sum_j A_j e^{-LV_{j-1}}} \right\} \tag{4}$$

which is the production-constrained Gravity Model with exponential impedance function with travel time replaced with the number of opportunities passed up (V_{j-1}). A doubly constrained Intervening Opportunity Model can be interpreted in a similar fashion *[14]*.

The Intervening Opportunity Model is shown to be a unique kind of Gravity Model and can subsequently be calibrated as a Gravity Model, as demonstrated later. It is interesting to note that while the Intervening Opportunity Model does not take impedance explicitly into account as does the Gravity Model, it takes it into account implicitly by considering the opportunities in order of increasing impedance.

Maximum Likelihood Estimation of the Intervening Opportunity Model

Rogerson *[11]* has derived a maximum likelihood estimation method to estimate the L value in the Intervening Opportunity Model. The major restriction of his method is an assumption that the spatial distribution of opportunities is uniform, which is unrealistic in transportation, particularly in evacuation. However, Eash *[14]* uses a method of maximum likelihood for calibration of the Intervening Opportunity Model without the assumption of uniform opportunities and has successfully coded a binary search program that solves for L values.

Eash *[14]* formulated a likelihood function L_i for zone i as:

$$L_i = \prod_{j=1}^{n} P_{ij}^{N_{ij}}$$

where L_i = the likelihood value for zone i

P_{ij} = probability of an interchange between zone i and zone j estimated by the distribution model

N_{ij} = number of survey trip interchanges from zone i to zone j

n = total number of zones

Substituting the probability of trip interchange by the opportunity model:

$$L_i = \prod_{j=1}^{n} \left\{ e^{-LV_{j-1}} - e^{-LV_j} \right\}^{N_{ij}}$$

By summing over all the destination zones and taking the log of the likelihood function, we have the log likelihood to maximize:

$$\ln L_i = \sum_{j=1}^{n} N_{ij} \ln \left\{ e^{-LV_{j-1}} - e^{-LV_j} \right\}$$

A simple one dimensional search algorithm can solve the above problem for value of L.

Graphical Method of Calibrating the IOM

A convenient method of calibration of the intervening opportunities model involves the use of a graphical solution *[12]*. This can be explained as follows:

Define V_{j-1} (as before) as the total number of intervening opportunities up to zone j, and U_j as the probability of traveling beyond that zone. Let P be the probability of a trip terminating among the opportunities in volume V, that is, P = 1 - U and dU = -dP. Substituting these relations into equation (1), we have

(1-P) LdV = dP

dP/(1-P) = LdV,

Integrating both sides of the equation, we have the relationship:

-ln (1 - P) = LV + k

Hence we can evaluate P and V for a series of time intervals from each origin zone and use regression techniques to obtain the values of L. This method of calibration is simple and straightforward. It can evaluate multiple L values for different origins and different travel distances.

Theoretical Extension to the Intervening Opportunity Model

The conventional Intervening Opportunity Model uses the order and magnitude of destination opportunities to model destination choice. However, hurricane evacuees are likely to order their choice of destinations by their distance from the projected path of the storm. Since the Intervening Opportunity Model orders the opportunities by travel impedance, we investigated modifying travel impedance to become direction sensitive. The formulation of the modified model is described below. Its performance in reproducing observed travel destination choice is presented, together with that of the Gravity Model and conventional IOM, in the next section.

In the classic IOM, travel impedance is portrayed as a series of concentric circles around the point from which the impedance is measured. In the original presentation of the model, Stouffer *[10]* showed the ordered sequence of intervening opportunities by concentric circles of increasing impedance, with the center of the circles at the origin, and the opportunities shown as dots in the diagram in figure 1.

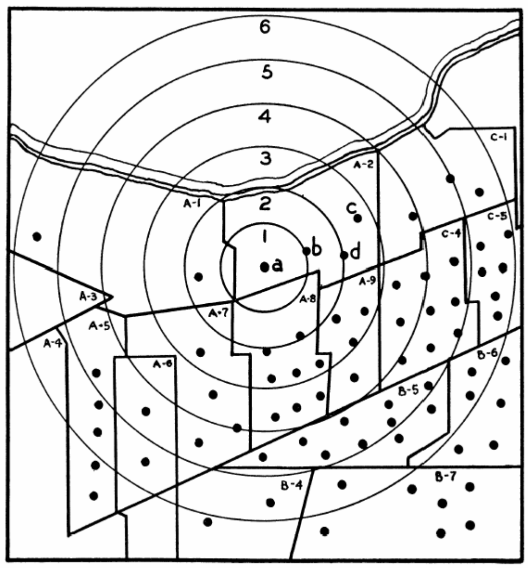

Figure 1

Stouffer's model

Circular contours of impedance imply uniform impedance from the origin in all directions. However, direction is important when evacuating from a hurricane, since evacuating in the direction of the hurricane would bring virtually no relief, while evacuating away from it (say, at right angles to the path of the hurricane) would bring maximum relief. Incorporating this concept

into impedance contours, with the notion of a "good" direction and a "bad" direction, results in impedance contours that form a series of ellipses instead of circles, as shown in figure 2.

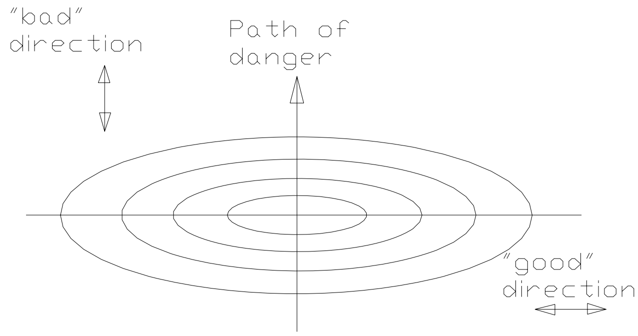

Figure 2

Effect of path of danger on impedance contour lines

If destinations along the path of danger are highly undesirable, and the hazard bisects the area of interest, the ellipses will compress along the "bad" direction and perhaps be better represented by the "bowtie" pattern shown in figure 3. The contours of equal impedance can also be termed contours of equal destination attractiveness as determined by location.

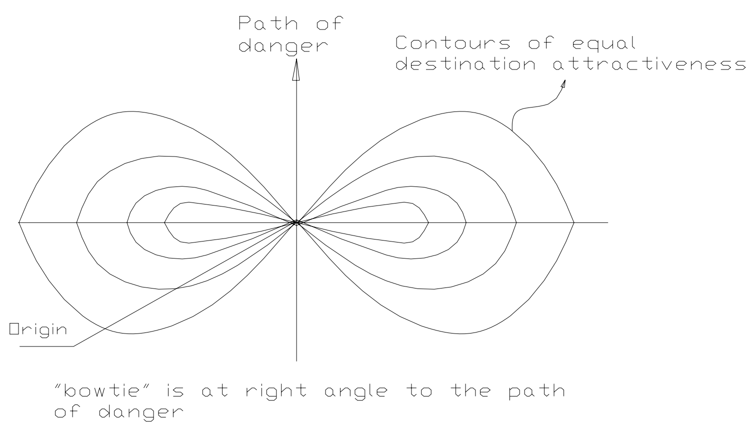

Figure 3

Contours of equal destination attractiveness

When an origin is close to the coastline, it is intuitively expected that the axes of the bowtie pattern needs to be changed from 90° to the path, to something else to reflect the desire to flee inland and away from high winds and flooding. See figure 4.

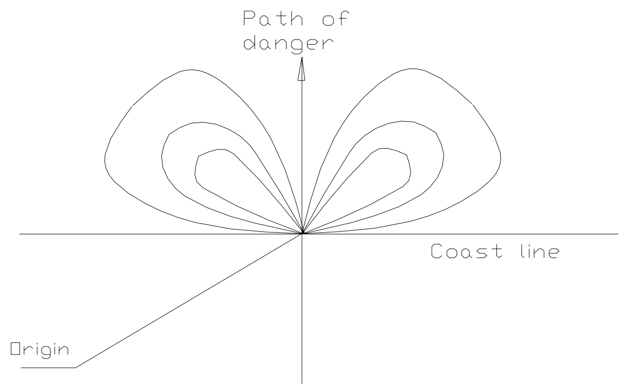

Figure 4

The effect of coastline on the contours

Similarly, when an origin is not in the path of danger, the contours of equal attractiveness can reasonably be expected to be asymmetrical, as shown in figure 5.

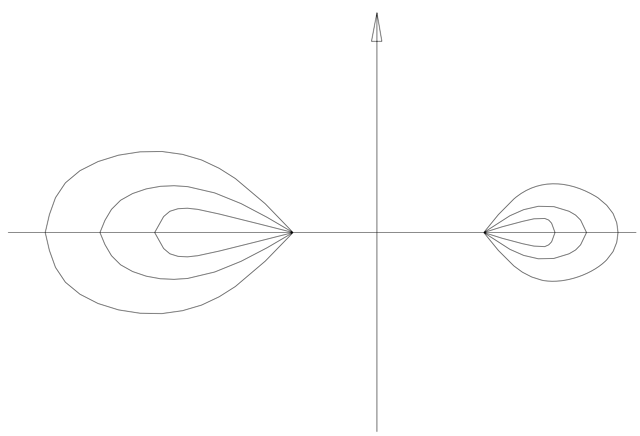

Figure 5

Asymmetrical contours of equal destination attractiveness

Using these assumptions, destinations can be ordered according to their new impedance or attractiveness. The application of the modified Intervening Opportunity model is described in the section "Analysis and Results".

Goodness of Fit Measures for Trip Distribution Models

Goodness-of-fit of aggregate trip distribution models is often measured by the fit of the trip-length frequency distribution from the model with that observed from the survey data. However, considering that the parameters of trip distribution models are adjusted to reproduce the observed trip-length frequency distribution as closely as possible, this statistic gives an optimistic impression of goodness of fit.

An alternative approach is to measure how well the model reproduces the observed O-D matrix. Since the product of an aggregate trip distribution model is an O-D matrix, measuring how well the final product matches what it should be seems a more appropriate test than comparing trip length frequency distributions. However, the tests are not all that dissimilar. Both compare aspects of trip interchange behavior; one groups trips by trip length and the other by O-D pair.

In this study, we have concentrated on comparing O-D matrices as a measure of performance. The statistics used for this purpose are described below.

Coincidence Ratio

One measure of the similarity of two matrices is the coincidence ratio *[13]*:

$$\text{Coincidence} = \sum_{n=1}^{N} \min\{\frac{E_n}{\sum_{n=1}^{N} E_n}, \frac{O_n}{\sum_{n=1}^{N} O_n}\}$$

$$\text{Total} = \sum_{n=1}^{N} \max\{\frac{E_n}{\sum_{n=1}^{N} E_n}, \frac{O_n}{\sum_{n=1}^{N} O_n}\}$$

$$\text{Coincidence ratio} = \frac{Coincidence}{Total}$$

The coincidence ratio lies between zero and one, with zero indicating two disjoint distributions and one indicating identical distributions.

Dissimilarity Index

The Dissimilarity Index (DI) is defined by:

$$DI = \frac{1}{2}\sum_{n=1}^{N}\left|\%O_n - \%E_n\right|$$

where $\%O_n$ = percentage of observed trips in cell n, and

$\%E_n$ = percentage of estimated trips in cell n

The dissimilarity index has a minimum value of 0, indicating two identical distributions, and a maximum value of 100. The lower the value, the better fit we have for the two distributions.

Root Mean Square Error

The Root Mean Square Error (RMSE) is a measure of average error. It can be used to measure the average difference between any paired set of data. In this case, RMSE is defined as:

$$RMSE = \left[\sum_{n=1}^{N}\frac{(O_n - E_n)^2}{N}\right]^{1/2}$$

Standardized Root Mean Square Error (SRMSE)

A problem with the Root Mean Square Error (RMSE) is that it is an absolute value and, therefore, its magnitude depends on the units of measurement used. One solution is to use the standardized RMSE (SRMSE) which, as a relative measure, does not have units. One definition of SRMSE (there are others) is as defined by Zhao et. al *[13]*:

$$\text{SRMSE}=\left[\frac{\sum_{n=1}^{N}\frac{(O_n - E_n)^2}{N}}{\sum_{n=1}^{N}O_n^2/N}\right]^{1/2}$$

The SRMSE statistic has a lower limit of zero, indicating a completely accurate set of predictions, and an upper limit of 1.0 when all predictions are zero. When the predictions cannot be negative (as in our case), a value of 1.0 for SRMSE indicates the maximum error possible.

Information Gain

Information gain is calculated as:

$$\text{I}=\sum_{n=1}^{N}O_n \ln\left[\frac{O_n}{E_n}\right]$$

It has a lower value of zero corresponding to a perfect set of predictions and upper limit of infinity. Cells with a zero estimated value are not included in the calculation.

DATA

Data collected on evacuation behavior in Hurricanes Andrew and Floyd were used to estimate Gravity and Intervening Opportunity Models, test their goodness of fit, and observe the transferability of a Gravity Model from Floyd to Andrew data. This data was supplemented with highway network data containing information on the attributes of the highway system such as type of facility, number of lanes, lane width, speed limit, whether the route is an evacuation route or not, etc. The data is explained in greater detail in the following sections.

Hurricane Floyd Behavioral Data

The U.S. Army Corps of Engineers commissioned a survey to obtain evacuation travel behavior during Hurricane Floyd. The survey was conducted by Professor Earl J. Baker of Florida State University. The questionnaire contained 91 questions, including questions such as “Did you go to a public shelter, a friend or relative’s house, a hotel, or somewhere else?”, “In what city is that (evacuation destination) located?”, “In which state is that located?” etc. In South Carolina, 1,887 telephone interviews were conducted in the coastal counties surrounding the metropolitan areas of Charleston, Beaufort, and Myrtle Beach. These three metropolitan areas were considered the only three origins of trip distribution models estimated on the data.

The data were cleaned and reformatted to serve as the input to the model. Destinations were identified by county or city, and were observed as far away as North Carolina, Georgia, and Tennessee. The type of destinations for the Floyd data out of South Carolina are shown in table 1.

Table 1

Evacuation destinations in the Hurricane Floyd South Carolina survey

Origin	Destination Type							Total
	Friends/ Relative	Hotel/ Motel	Shelter	Church	Work place	Mobil e home	Other	
Beaufort	211	170	8	4	2	1	212	608
Charleston	259	122	6	4	3	1	232	627
Myrtle Beach	210	75	9	9	4	0	345	652
Total	680	367	23	17	9	2	789	1887

Only the data with the complete and correct information were used in this study. In total, 1,042 households evacuated to either the homes of friends/relatives or to hotels/motels. Of these, 941 households evacuated to the four states of South Carolina, North Carolina, Georgia, or Tennessee. Only destinations in these four states were considered in this study. Of the 941 households, 852 had complete and identifiable destination information. These 852 households were use in this study. Detail of the data used is shown in table 2.

Table 2

Percentage of data utilization from Floyd Data

	Friends/Relatives	Hotel/Motel	Total
Number Valid and Used	534	318	852
Number in Survey	680	367	1047
Data Usage	78.5%	87.8%	81.8%

The trip length distributions for the three most common destinations are shown in figure 6, using data from Hurricane Floyd. The distributions were drawn using travel times reported by respondents in the survey. The graph shows that the trip length distributions are different for the three types of trip destinations; distances to public shelters are typically short while trips to hotels and motels are typically longer than those to shelters and to friends and relatives. Therefore three different models for the above mentioned three destination choices were generated. However, after investigation of the data, the data for the shelters was found to be insufficient to build a separate model. As a result, separate models were estimated for the destination of homes of friends or relatives, and for the destination of hotels or motels, only in this study.

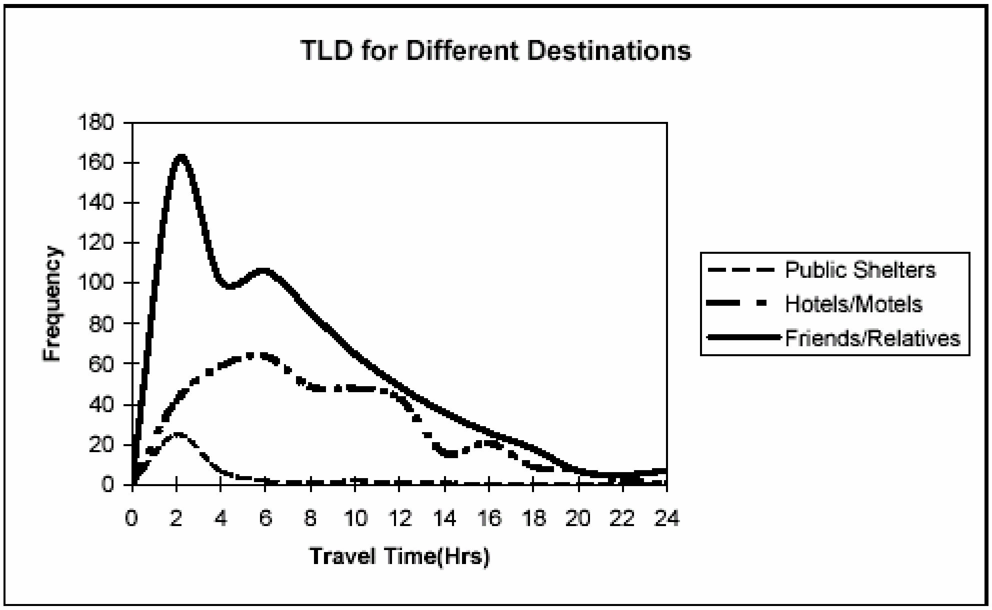

Figure 6

Trip length frequency distributions for different destination types

Lewis *[15]* suggested that transportation modeling for evacuation is best performed on a county-by-county basis because evacuation orders are generally issued at county level. Thus, the origins and destinations of the evacuation trips in the Floyd data were assigned to the centroids of their counties or metropolitan areas. In the Floyd data, evacuation trips originated from either Myrtle Beach, Charleston, or Beaufort, South Carolina (see figure 7). They terminated in locations spread throughout South Carolina, North Carolina, Georgia, and Tennessee. Those that evacuated to the homes of friends or relatives were observed to terminate in 110 different counties or metropolitan areas as shown in Figure 8. Those that went to hotels and motels terminated at 70 counties or metropolitan areas as shown in Figure 9. Separate origin-destination matrices were established for evacuation trips to friends and relatives, and to hotels/motels.

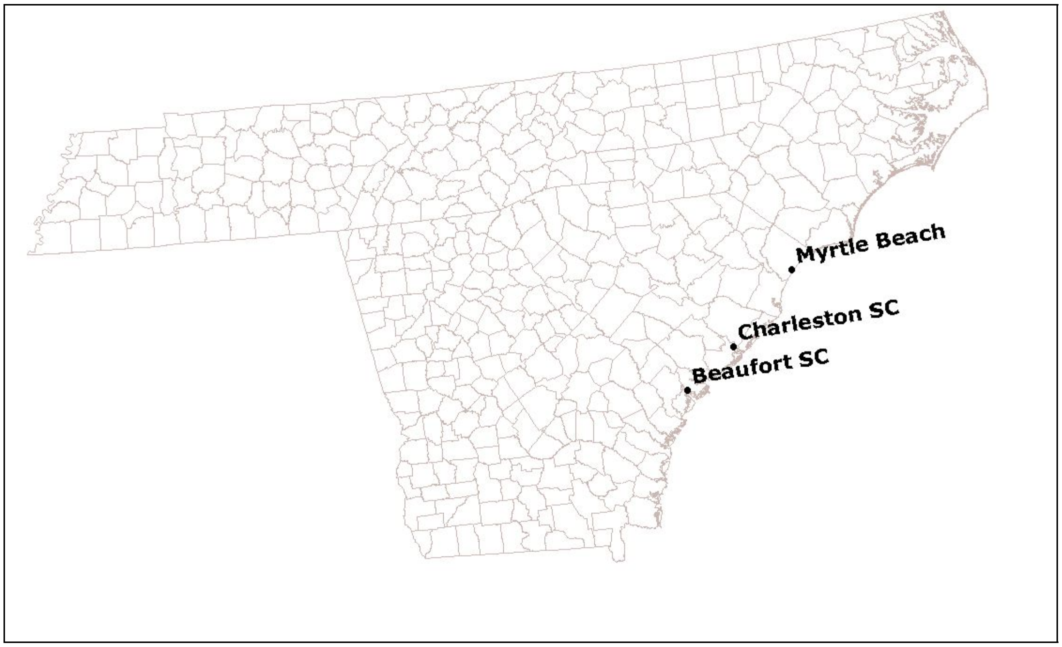

Figure 7

Origins of Evacuation Trips

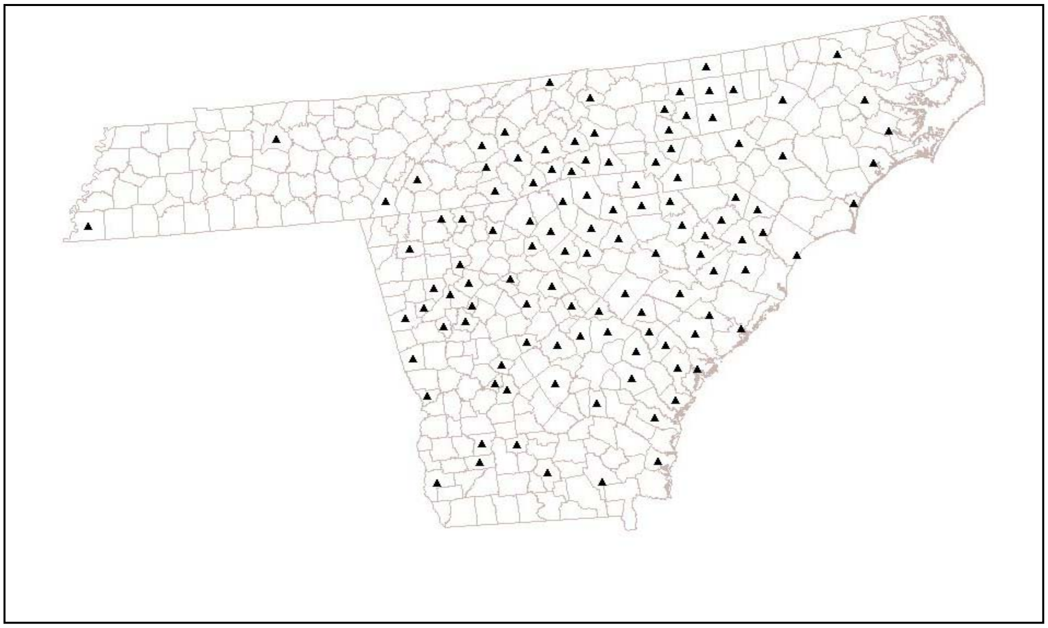

Figure 8

Origins and destinations for trips to friends or Relatives

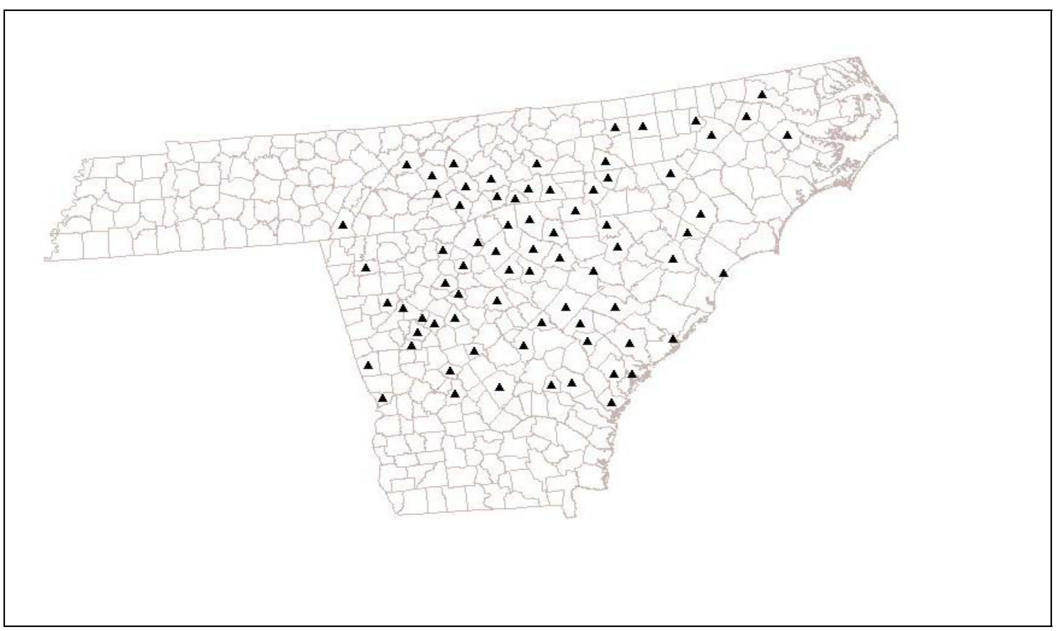

Figure 9

Origins and destinations for trips to hotels and motels

Hurricane Andrew Behavioral Data

A survey was conducted by Louisiana Population Data Center in September 1995, with the objective of gathering information about the experiences of respondents who were living in affected parishes in southwest Louisiana when Hurricane Andrew struck in August 1992. The data were collected in telephone interviews, using computer-assisted telephone interviewing (CATI) technology. In total, 651 households were surveyed, among which 466 households were living in an affected parish when Andrew struck or had evacuated from the parish because of Hurricane Andrew. This study was conducted on the data from these 466 households. Of these 466 households, 194 evacuated during Andrew.

Building an Opportunity Matrix

To establish an opportunity matrix, the destinations were ranked in terms of travel distance from each origin, and the cumulative opportunities passed were observed. The opportunities used in the model for those evacuating to friends or relatives were the population of the county or city passed. Population was used as a surrogate for the true opportunity of having a friend or relative in a location since they are expected to be proportional to each other. For evacuation to hotels or motels, the number of licensed hotel and motel facilities as recorded in the 1997 Economic Census was used.

Highway Network

The US highway file included with the TransCAD software was used to establish the highway network used in this study. The network includes interstate, US, and state highways. The length, name, and functional classification of each road link is included in the data. Travel distance on the network was used to rank destinations in increasing impedance from the origin.

ANALYSIS AND RESULTS

Model Estimation

Travel Time Matrix

The travel time matrix is the matrix of shortest path travel time between zones. The time reported in the matrix is the shortest time taken to travel from one zone to the other zone using the highway network in the present study. Since travel time is assumed as the impedance in the present study, the travel time matrix is considered as the impedance matrix to run the Gravity Model. Travel time is taken as the impedance because the main objective of the evacuees is to reach a safe destination in the shortest possible time. Hence, travel time is the main cost function in the evacuation process.

The observed travel to friends and relatives in the study area ranged between 1.27 hours to 29.83 hours. The mean travel times from the three origins ranged from approximately 9 hours to 11 hours. A travel time between 27.14 hours and 29.23 hours was needed to reach Shelby, TN, from the three origins. This was the most distant destination observed for those going to the house of friends or relatives.

The observed travel times to hotels and motels ranged between 1.75 hours to 17.69 hours. The mean travel times from the three origins ranged from approximately 9 to 10 hours. A travel time between 15.56 hours and 17.69 hours was needed to reach Hamilton, TN from the three origins . This was the most distant destination observed for those going to hotels and motels.

Trip Length Distribution

Trip length distributions (TLDs) are graphs plotted between travel time intervals and the number of trips made during each travel time interval. The shortest path matrix and the observed O-D matrix are the required inputs to calculate the observed TLD. The output is the number of trips in each travel time interval plotted on a graph. A travel time interval of one hour was used. Since most respondents in the survey evacuated to a safe place within 24 hours, the maximum TLD was taken as 24 hours. Different TLD’s were drawn for the two different types of trip destinations considered in this study (friends/relatives or hotel/motel).

Calibration of the Intervening Opportunity Model

The procedure used to calibrate a Gravity Model in TransCAD, was used to calibrate the IOM using an opportunity matrix in place of an impedance matrix, as explained in the Methodology section. The calibration requires input of an O-D matrix and an impedance matrix (in this case, the opportunity matrix). An impedance function in the form of an exponential function must be chosen. The model was calibrated for the parameter L of the IOM. The model was calibrated to reproduce the observed opportunity distribution. The model's calibration fits to the observed data are shown in Figures 10 and 11 for the friend/relative and hotel/motel destinations, respectively. A constant speed of 40 mph was assumed on all links so that the ranking of opportunities on travel time is identical to ranking them by distance.

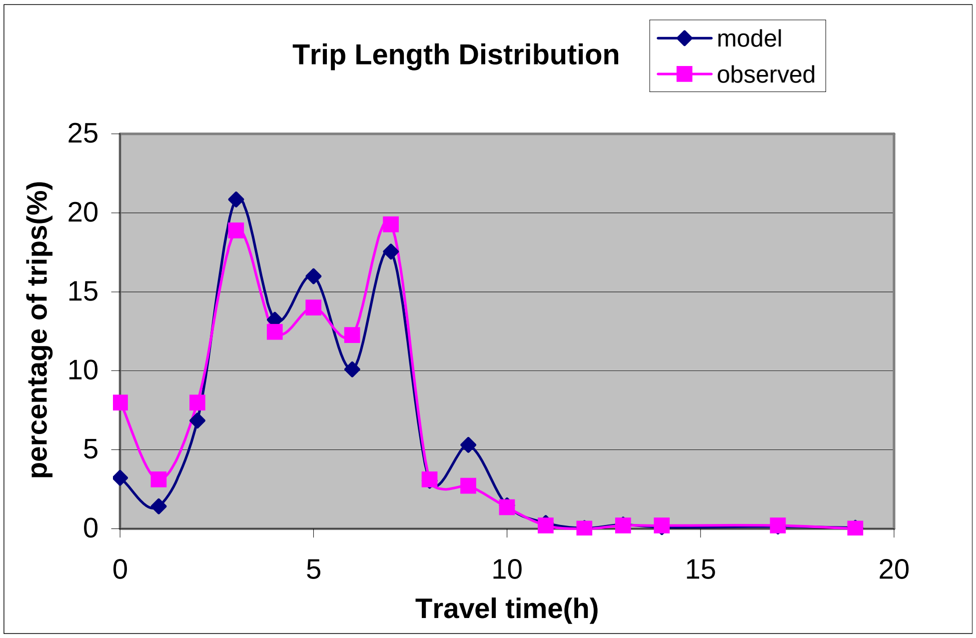

Figure 10

TLD for Intervening Opportunity Model for friends/relatives destination

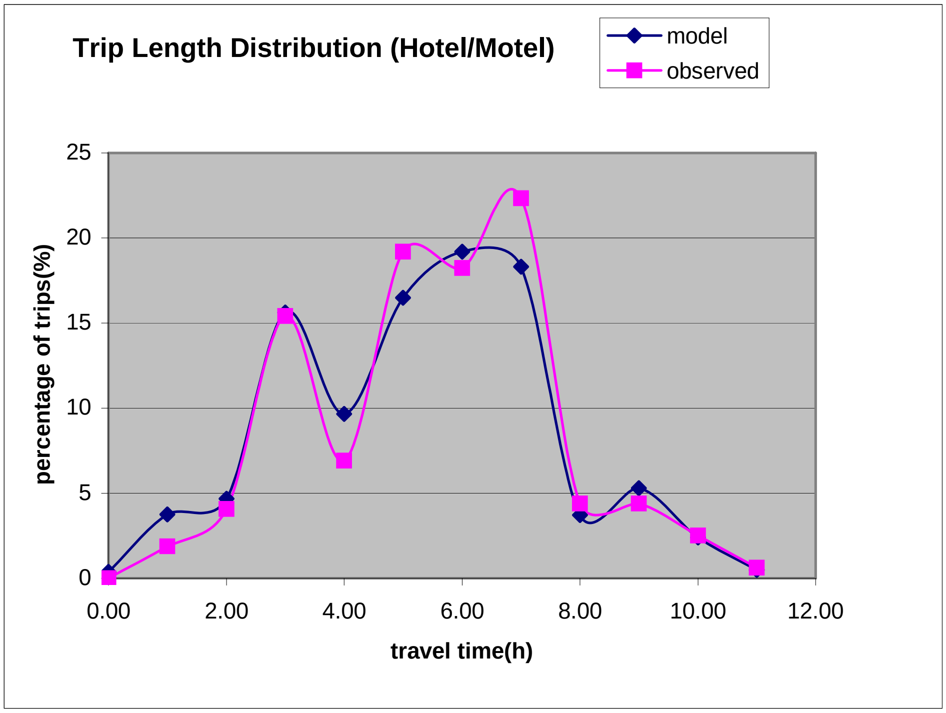

Figure 11

TLD for Intervening Opportunity Model for hotel/motel destination

The performance of the calibrated IOM was evaluated graphically and statistically. Individual cell values of the O-D table produced by the IOM were graphically compared with observed O-D values, as shown in figures 12 and 13. Each dot in the graphs represents an origin destination pair; its value on the x-axis represents the observed number of trips, and its value on the y-axis is the number of trips estimated by the model.

If a line is fitted to the data using linear regression, the coefficients can be interpreted and a statistical test of the comparison is provided in the form of the Coefficient of Multiple Correlation (R^2). Ideally, the regression line should pass through the origin and have a slope of 1.0 if the observed and estimated values are the same. In this case, the friends and relatives model produced a fitted line that has a constant of 0.289, a slope of 0.8485, and an R^2 value of 0.8485. For the hotels or motels model, a constant of 0.3788, a slope of 0.7392, and an R^2 value of 0.7437 was obtained. The results show a reasonable fit to observed data.

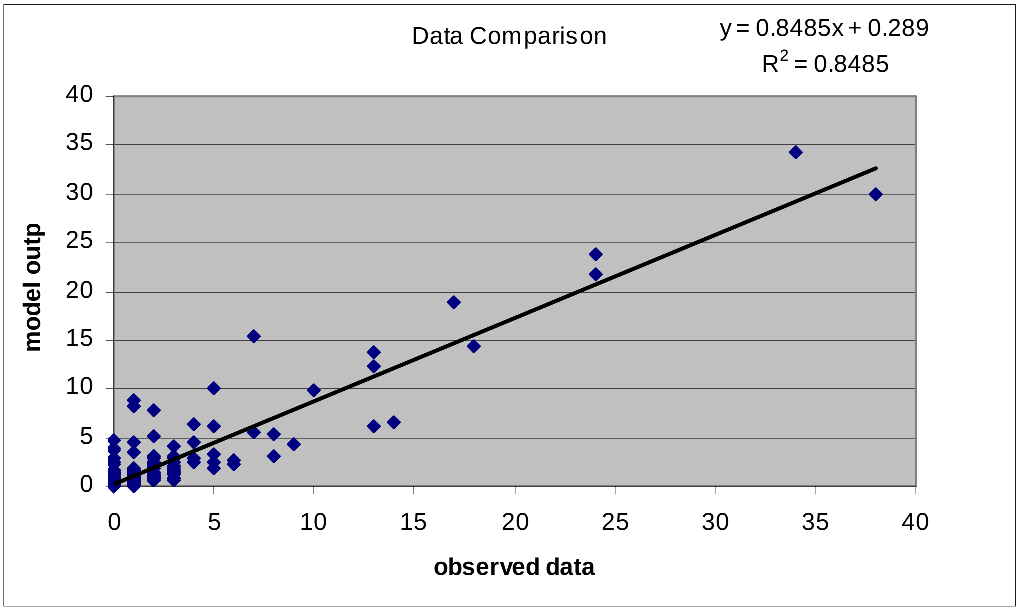

Figure 12

Predicted and observed O-D values for trips to friends and relatives

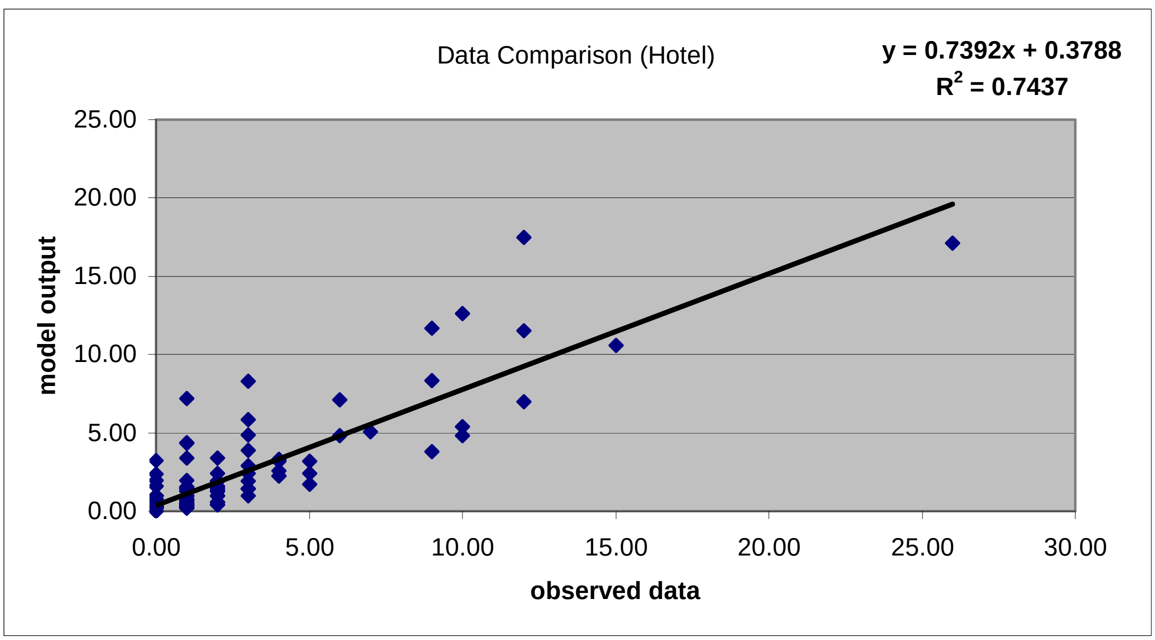

Figure 13

Predicted and observed O-D values for trips to hotels and motels

Calibration of the Extended Intervening Opportunity Model

The IOM was modified to incorporate the effect of the path of the hurricane on the trip distribution of hurricane evacuation trips. This was achieved by making the ordering of opportunities sensitive to the direction in which the opportunities lay with respect to the path of the storm. As described in the Methodology section, this involved identifying the expected path of the storm and then establishing contours of equal destination attractiveness that take into account the fact that evacuees will try to evacuate in a direction that takes them away from the storm as quickly as possible. To accomplish this, a Cartesian coordinate system for each evacuation origin was established which was aligned to the path of the storm. In establishing the coordinate system, three basic assumptions were made:

1. The path of the hurricane is a straight line.
2. The coordinate system does not take into account the spherical curvature of the earth.
3. A separate coordinate system was established for each of the three origins considered in this study.

To rotate the axes of the coordinate system anti-clockwise by an angle of θ, the following coordinate transform formulae were used:

$$x' = x\cos\theta + y\sin\theta$$
$$y' = y\cos\theta - x\sin\theta$$

In the case of Hurricane Floyd, the path of the hurricane was nearly parallel to the coastline in both South Carolina and North Carolina. The three evacuation origins, Beaufort, Charleston and Myrtle Beach are all located on the seashore nearly in a straight line. Therefore the direction of Beaufort to Charleston was used as an axis reflecting the "bad" direction after rotation. The "good" direction was, obviously, at right angles to the "bad" direction.

As stated earlier, the contour lines in the new model are expected to have a bow-tie shape. To simulate this, a beta distribution curve was selected. The probability density function of the beta distribution is given by:

$$f(x) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)*\Gamma(\beta)} * x^{\alpha-1} * (1-x)^{\beta-1}$$

Where $\Gamma(\gamma) = (\gamma - 1)!$

By selecting different parameters for α and β, curves with different shapes are obtained. By noting the pattern of destinations chosen from a particular origin among the survey respondents, the parameters were selected as follows:

$\alpha = 3$ and $\beta = 2$.

So $f(x) = 12x^2(1-x)$

Every point on the same contour line is assumed to have the same destination attractiveness. Let i represent this value. To accommodate the fact that x is limited to values between 0 and 1 and to obtain consecutive contour lines, the beta-distribution curve must be scaled by a factor for each i. To achieve this:

Let m_i = scale factor for x for the i_{th} destination attractiveness

And, n_i = scale factor for f (x) for the i_{th} destination attractiveness

Thus, the contour line function becomes:

$$\frac{f(x)}{n_i} = 12\left(\frac{x}{m_i}\right)^2 * (1 - \frac{x}{m_i})$$

If i is the distance along the scaled x axis, then since the beta distribution curve is defined on the interval of [0,1], $m_i = i$. Further, to ensure that every contour line has the same shape and is similar with each other with no intersection, we have

$$n_i = k * m_i = ki,$$

Where k=constant.

The new contour line functions are then:

$$\frac{f(x)}{ki} = 12\left(\frac{x}{i}\right)^2 (1 - \frac{x}{i})$$

$$f(x) = \frac{12k}{i} x^2 (1 - \frac{x}{i}),$$

Let $k_0 = 12k$,

Then,

$$f(x) = \frac{k_0}{i} * x^2 (1 - \frac{x}{i})$$

$$\therefore i = \frac{k_0 x^2 \pm \sqrt{k_0{}^2 x^4 - 4 f(x) k_0 x^3}}{2 f(x)}$$

If $x = x_0$ unchanged, f (x) ↓ then intuitively i ↓

$$\therefore i = \frac{k_0 x^2 - \sqrt{k_0^{\,2} x^4 - 4 f(x) k_0 x^3}}{2 f(x)} \qquad (5)$$

Where $f(x) \neq 0$

For (1) to have meaning, it must satisfy $k_0^{\,2} x^4 - 4 f(x) k_0 x^3 \geq 0$

i.e. $f(x) \leq \frac{k_0}{4} x$

For every point that satisfies the above condition, we have one corresponding *i* value. The value of *i* defines which contour line (*x, y*) is on. The *i* value is inversely related to the attractiveness of a destination, meaning that low values of *i* reflect attractive destinations and high values of *i* reflect unattractive destinations. The value of k_0 was taken as 10, in order to cover most of the destinations in the map. Larger values are possible but not without changing the shape of the contour lines.

To draw a contour line, a grid of "*i*" values is first built. Then contour lines are established on the *i* values. In this case, the contour lines were established in TransCAD. Contour lines with Beaufort as the origin are shown in figure 14. Obviously, there are certain areas along the coast that have no attractiveness because they are too close to the path of the storm.

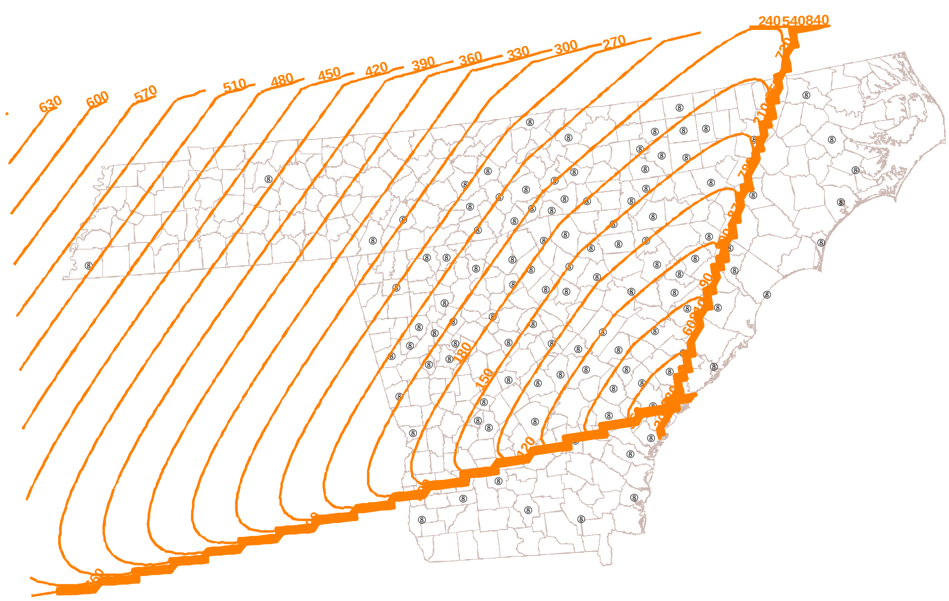

Figure 14

Contour lines for an origin in Beaufort, k_0=10

By altering k_0, the contour lines assume similar but different shapes. Figure 15 shows how the contour lines appear k_0 is altered to 5.

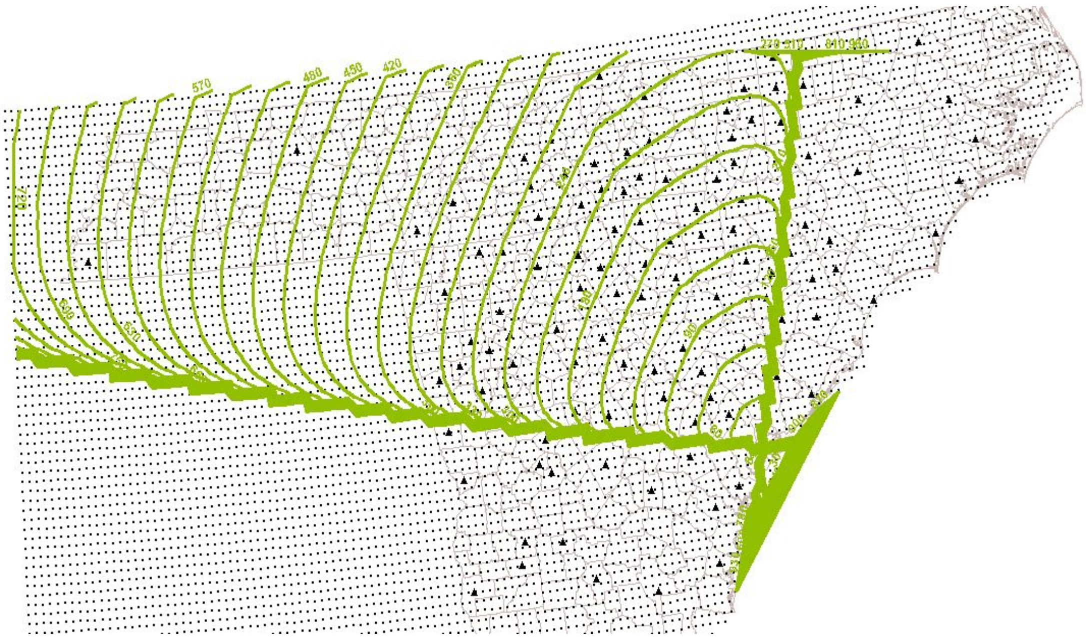

Figure 15

Contour lines for an origin in Beaufort, k_0=5

The only difference between the Extended IOM and the original IOM is the way the destinations are ordered. For the Extended IOM, opportunities are ordered in terms of their i-value, rather than in terms of travel time. If a destination is outside the region in which i-values were calculated, they were ranked behind the destinations with i-values and ordered based on their distance to the origin.

After updating the opportunity matrix, calibration of the Extended IOM was carried out in TransCAD. Similar to the original IOM, the exponential form of impedance function was selected and the opportunity matrix was used as the impedance matrix. For the friends and relatives model, the calibration converged after 6 iterations, with an L value of 0.0018. For the hotel/motel, the calibration converged after 5 iterations, producing an L value of 0.0008.

Calibration of the Gravity Model

In regular urban transportation planning, the inputs required to calibrate a Gravity Model are the productions and attractions for each zone, a productions/attractions matrix, and a travel time matrix. The same system can be used in evacuation modeling, although several changes need to be made. First, the productions and attractions in evacuation modeling are the number of evacuating departures and arrivals, respectively. Second, the P-A matrix is the matrix of evacuating trip interchanges. In the data used in this study, there are only three origin zones (Beaufort, Charleston and Myrtle Beach) from which trips are produced. The data shows there are 110 zones to which evacuees traveled to be with friends and relatives, and 70 zones to which evacuees traveled to seek shelter in hotels or motels. Trips to these zones form the attractions. The travel time matrix is identical between urban transportation planning and evacuation planning while calibrating a Gravity Model.

The calibration of the Gravity Model in this study was conducted in TransCAD using friction factors as the measure of impedance in the model. The model was calibrated on 1-hour intervals over a period of 24 hours. Calibration involved adjusting the parameters in the model until the trip length frequency distribution (TLD) generated by the model matched the observed trip length frequency from the survey data. The observed and estimated trip length frequency distribution for friends and relatives is shown in figure 16. The curve is not as smooth as that shown in figure 6 because smaller time intervals were used in compiling the curve in figure 16. The individual peaks represent cities at different distances from the origins. A total of 427 households evacuated to homes of friends and relatives, with a median travel time of 10 hours.

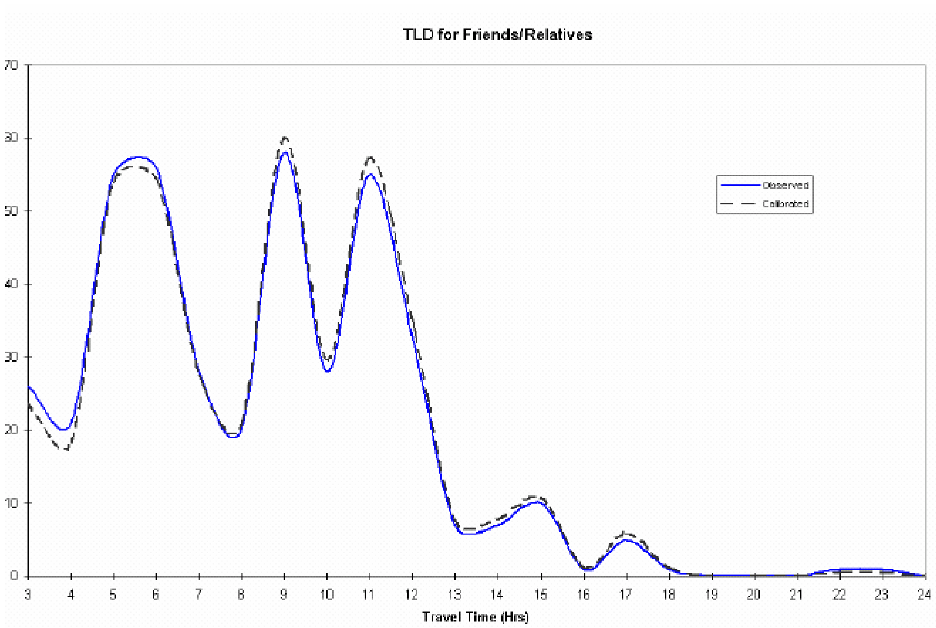

Figure 16

Observed and estimated TLD for friends and relatives

The TLD for hotels and motels is shown in figure 17 below. The TLD plot is similar to the observed TLD for friends and relatives with peaks occurring at approximately the same travel time, although the TLD for hotels and motels has proportionally fewer short trips (5-6 hours). Also, it seems as though no distant trips (>18 hours) were made to hotels and motels. The median travel time to hotels and motels was 10 hours.

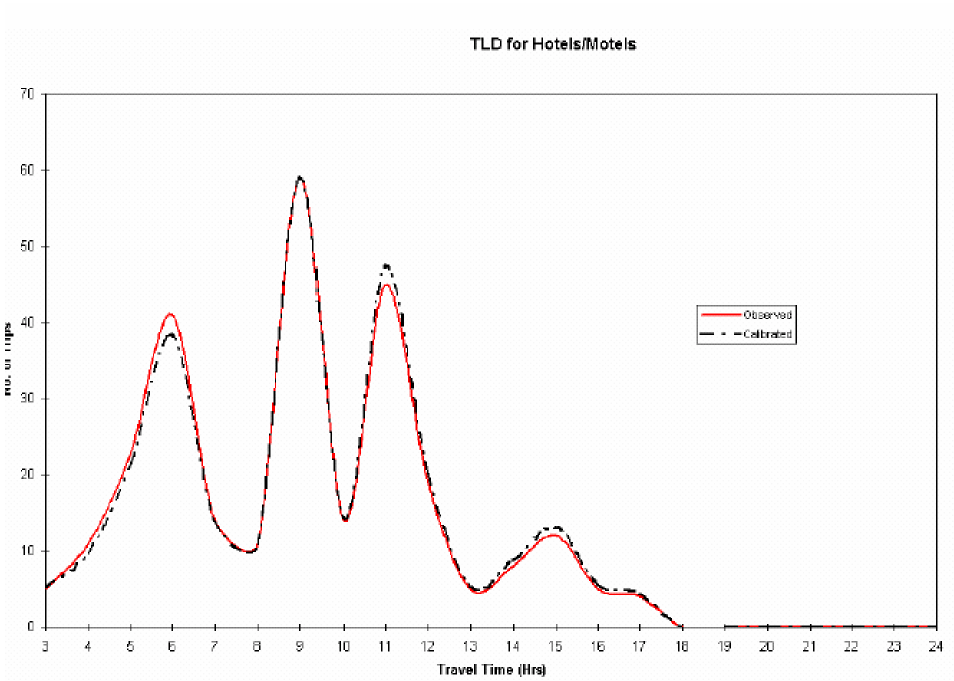

Figure 17

Observed and estimated TLD for hotels and motels

Calibration of the Gravity Model on the input data from the Floyd data produced the friction factors shown in table 3 below.

Table 3

Friction Factors From Calibration Of Gravity Model

Time interval (hrs)	Friction Factors	
	Friends/Relative	Hotel/Motel Model
0 - 1	4.4	9.5
1 - 2	34.7	69.0
2 - 3	25.8	33.1
3 - 4	10.1	16.9
4 – 5	5.4	15.8
5 – 6	4.5	9.2
6 – 7	6.6	7.9
7 – 8	4.3	11.8
8 – 9	4.0	6.2
9 – 10	3.1	2.4
10 – 11	6.5	5.8
11 – 12	3.4	3.0
12 – 13	3.1	1.0
13 – 14	2.8	3.3
14 – 15	2.0	2.3
15 – 16	1.0	2.1
16 – 17	3.2	6.5
17 – 18	1.8	0.0
18 – 19	0.0	6.1
19 – 20	5.1	1.0
20 - 21	0.0	1.0
21 – 22	6.2	1.0
22 – 23	11.3	1.0
23 – 24	5.1	1.0

Model Transferability

The issue of transferability is important in this study because the model needs to be able to predict trip distribution under different conditions than those that existed at the time of calibration. The different conditions the model must be able to accommodate are different storm conditions, changes in the population, and the impact of alternative strategies and policies implemented by the evacuation authorities.

Model transfer can occur in two ways, full transfer and partial transfer. Full transfer is the transfer of an entire model while partial transfer is the transfer of any portion of the original model. In this study, only full transfer was conducted.

The Gravity Model estimated on Floyd data was applied to Hurricane Andrew data in Southwestern Louisiana. Hurricane Andrew data was obtained though a survey similar to the survey conducted for Hurricane Floyd in that it was a post-event telephone interview of randomly selected households in the region impacted by the storm. The data contain information about the socio-economic characteristics of the household interviewed, the location of the residence, the destination of the household if they evacuated, the type of destination, etc. The model for the friends/relatives destination type was used to test the transferability of the Floyd model on the Andrew data.

Gravity Models are calibrated on trip length frequency. Thus, it seemed that comparing the trip length frequency that would be generated by a model transferred into an area with that of the local data would be an effective measure of transferability. Another measure of transferability used in this study was to compare the friction factors between the transferred model and a locally estimated model. The results from both these tests are described below.

Comparing Trip Length Frequency Diagrams

The model estimated on the Floyd data was applied to the Andrew data to produce an O-D matrix from which trip lengths were established using the shortest paths between the origins and destinations. From this, a trip length frequency distribution was established which represented the distribution of trip lengths assumed by the transferred Floyd model. The trip length frequency of the local model was assumed to be the same as the observed trip length frequency in the Andrew data.

The trip length frequencies from the Floyd and Andrew data were compared using the Kolmogorov-Smirnov (KS) two-sample test. The test statistic 'T' in the two sample KS test is defined as the maximum difference between the two cumulative distribution functions of two distribution functions being tested. The two-sample KS test determines whether the two distributions belong to the same distribution or not. Thus the null hypothesis for this test is that the distributions of the transferred model and the locally estimated model are the same and the alternate hypothesis is that they are different. The null hypothesis is rejected if the value of the T statistic calculated is greater than the critical value of T at a given level of significance.

In the test of the similarity of the Floyd model's trip length frequency distribution with the local trip length frequency distribution, the value of T obtained was 0.1364. The critical value of T at the 5 percent level of significance is 0.3636. Thus, the null hypothesis cannot be rejected suggesting that no statistical difference between the two trip length frequency distributions could be observed.

Comparison of Friction Factors

The transferability of the Floyd model to the Andrew environment was tested by comparing the friction factors of the Floyd model with the friction factors of a model estimated on the Andrew data. The paired sample t-test was used to make the statistical comparison. The paired sample t-test computes the difference between the paired variables, and tests whether the differences are collectively different from zero. The null hypothesis is that there is no significant difference between the two sets of variables. The null hypothesis is rejected if the value of t calculated is greater than the critical value of t.

The paired sample t-test of the friction factors for the Floyd and Andrew models produced a t-value of 0.748. The critical value of t at the 5 percent level of significance for 24 degrees of freedom is 2.064. Thus, the null hypothesis cannot be rejected, suggesting that no statistical difference between the two sets of variables were observed.

Relative Aggregate Transfer Error (RATE)

The Relative Aggregate Transfer Error (RATE) is the ratio of the Root-Mean-Square-Error (RMSE) of the predictions of a locally estimated model to the RMSE of a transferred model *[16]*.

$$RATE = \frac{RMSE_i(\beta_i)}{RMSE_i(\beta_j)}$$

where,

$RMSE_i(\beta_i)$ = RMSE of a locally estimated model

$RMSE_i(\beta_j)$ = RMSE of a model transferred from j and applied in i.

A transfer is considered good if the RATE value tends to 1 and it is considered bad if the RATE value tends to zero.

The RMSE was calculated on the modeled and observed trip interchanges. The RMSE of the locally estimated model obtained was 0.14 and the RMSE of the transferred model obtained was

0.21. Thus, the RATE is 0.14/0.21 or 0.67. The RATE value suggests a relatively good transfer, which is consistent with the findings of the previous two tests of model transferability described above (i.e. comparison of TLD and friction factors).

DISCUSSION OF RESULTS

The comparative performance of the Intervening Opportunity Model (IOM), the Gravity Model and the Extended Intervening Opportunity Model (EIOM) is evaluated below in terms of several statistics. The statistics used for comparison are average trip length, coincidence ratio, RMSE, SRMSE (Standard Root Mean Square Error), and information gain.

Average Trip Length

According to the report of TMIP (Travel Model Improvement Program) of USDOT, the most standard validation check of trip distribution models are comparisons of observed and estimated trip lengths. Modeled average trip lengths should generally be within five percent of observed average trip length. Trip length is expressed in terms of travel time in table 4 below. Travel time was estimated based on a uniform travel speed of 40 mph over the network, and is therefore, proportional to travel distance.

Table 4

Comparison of average trip length

Model	Average Trip Length in Hours (Error in %)			
	Survey Data	IOM	Gravity Model	EIOM
Friends/Relatives	4.90	4.76 (3%)	4.87 (0.6%)	4.79 (2%)
Hotel/Motel	5.24	5.45 (4%)	5.26 (0.4%)	5.22 (0.4%)

The Gravity Model produces average trip length much closer to the survey data than the other models. The EIOM provides improved performance over the IOM in terms average trip length.

Coincidence Ratio

The Coincidence Ratios for the three models are shown in table 5. The trip length distributions were aggregated using one-hour intervals in the compilation of this statistic.

Table 5

Comparison of Coincidence Ratio

Model	Coincidence Ratio		
	IOM	Gravity Model	Extended IOM
Friends/Relatives	0.825	0.882	0.897
Hotel/Motel	0.858	0.859	0.853

Since higher Coincidence Ratios indicate higher coincidence between observed and estimate values, the results in table 5 indicate that for the friends/relatives destination type, the EIOM performed best, followed by the Gravity Model, and then by the IOM. For the hotel/motel destination type, the Gravity Model performed marginally better than the IOM, followed by the EIOM.

RMSE

The root mean square errors of different models in prediction evacuation trips are compared in table 6. The values in the table represent the average in error in predicting the number of trip interchanges by cell, where no cell was allowed to have observed values of less than five.

Table 6

Comparison of RMSE

	RMSE		
	IOM	Gravity Model	Extended IOM
Friends/Relatives	1.64	1.55	1.55
Hotel/Motel	1.50	1.48	1.43

For the friends/relatives destination type, the Gravity Model and the EIOM appear to have similar average error, with the IOM having a marginally larger average error than the Gravity Model and the EIOM. This result is reasonably consistent with the Coincidence Ratio results. However, for the hotel/motel destination type, the EIOM has the lowest average error, and yet it has the lowest coincidence ratio among the three models. Thus, these results are inconsistent between the two tests (i.e. coincidence ratio and RMSE), but the difference in the results are marginal.

SRMSE

The Standardized Root Mean Square Errors (SRMSEs) of the different models for the two destination types considered in this study (i.e. friends/relatives and hotel/motel) are shown in table 7.

Table 7

Comparison of SRMSE

	SRMSE		
	IOM	Gravity Model	Extended IOM
Friends/Relatives	0.0852	0.0802	0.0804
Hotel/Motel	0.1377	0.1356	0.1309

The SRMSE statistic depicts the proportion of the maximum possible error that the model predicts, when maximum error is achieved by predicting zero (the lowest possible value) in each cell where observations occur. Multiplied by 100, it can be interpreted as the percentage of maximum error committed by the model. For the friends/relatives destination type, the Gravity and Extended IOM models have lower percentage errors than the IOM model; the same result was obtained with the coincidence ratio and the RMSE measurement. For the hotel/motel destination type, the Extended IOM provides the lowest percentage error, followed by the Gravity model and then the Intervening Opportunity Model. However, as before, the difference in the results from the different models is marginal.

Information Gain

Table 8 shows the information gain result for the three models. The smaller the information gain, the better the performance of the model. For both destination types, the Extended IOM performs best, followed by the Gravity Model and then the Intervening Opportunity Model. The results are reasonably consistent with the results from the other measures of model performance above.

Table 8

Comparison of information gain

	Information Gain		
	IOM	Gravity Model	Extended IOM
Friends/Relatives	198	177	169
Hotel/Motel	118	116	109

The results from all the tests are summarized in Table 9. The model with the best performance in each item is shown in bold to facilitate evaluation. Of the five measures included in Table 9, the Extended IOM was found to be best, or equally as good, on seven of the ten measures, and the Gravity Model on five of the ten measures. The IOM was not best, or equally as good, on any of the measures. However, as emphasized before, the difference in the results is small, suggesting that while the IOM was not found to be the best model on any measure, it's performance was comparable to the other models.

Table 9

Summary of results of comparisons

Item		IOM	GM	EIOM
Average Trip Length (Error)	Friends/Relatives model	2.86%	**0.61%**	2.24%
	Hotel/Motel model	4.01%	**0.38%**	**0.38%**
Coincidence Ratio	Friends/Relatives model	0.825	0.882	**0.897**
	Hotel/Motel model	0.858	**0.859**	0.853
RMSE	Friends/Relatives model	1.64	**1.55**	**1.55**
	Hotel/Motel model	1.50	1.48	**1.43**
SRMSE	Friends/Relatives model	0.0852	**0.0802**	0.0804
	Hotel/Motel model	0.1377	0.1356	**0.1309**
Information Gain	Friends/Relatives model	198	177	**169**
	Hotel/Motel model	118	116	**109**

CONCLUSIONS

This study investigated whether the Gravity and Intervening Opportunity Models can successfully distribute hurricane evacuation trips to observed destinations. Data from Hurricane Floyd was used to test the model's ability to reproduce observed destination choices. The IOM was also extended to include sensitivity to the direction in which evacuation takes place relative to the path of the storm, and this "extended" IOM was tested along with the Gravity and conventional IOMs with respect to their ability to successfully distribute evacuation trips.

When evacuation trips are distinguished by the three main destinations observed in the data, namely friends/relatives, hotel/motel, or public shelter, the trips display different trip length frequency distributions. Since trip distribution models are calibrated on trip length frequency distributions, it is necessary to estimate separate evacuation trip distribution models on each destination type. Because of a shortage of data, models could only be estimated on the friends/relatives and hotel/motel destination types in this study. Models were estimated on 75 percent of the data, and tested on the remaining 25 percent.

The model's performances were assessed by observing how well the models reproduced observed values in the test data. One measure related to average trip length, but several statistics were used to observe how well the models reproduced the observed origin-destination matrix. The results are summarized in table 9, and show all three models (Intervening Opportunity Model, Gravity Model, and Extended Intervening Opportunity Model) performed well with relatively little difference in performance among them (less than four percent error in average trip length, and average error in numbers evacuating to different destinations of less than two). If the small differences in performance are taken into account, the Extended IOM performed best, followed by the Gravity Model, followed by the IOM. The improvement observed in the Extended IOM over the IOM suggests that adjustments to existing models to accommodate features relevant to evacuation can produce improvements in model performance, and should be pursued further.

The results suggest that conventional trip distribution models used in urban transportation planning can be used in evacuation planning when such modeling is performed at the aggregate level. However, the results are based on one data set, and the test data set is very similar to the data set on which the models were calibrated. It is not known whether similar studies on other data sets will produce similar results.

When the gravity model calibrated on the Floyd data from South Carolina was transferred to the Andrew data from Louisiana, the transferred model produced an average error in trip distribution (i.e. in origin-destination assignments) that was 50 percent higher than a locally-estimated model. The friction factors of the transferred model and the locally-estimated model were not significantly different at the five percent level of significance. Thus, while this is again a single observation of transfer of an evacuation trip distribution model, the results are encouraging regarding the inherent transferability of such models.

RECOMMENDATIONS

It is recommended that the investigation into models of trip distribution (i.e. destination choice) of evacuation trips be continued. Specifically, models should be developed that are sensitive to factors commonly influencing destination decisions, such as the location of the destination relative to the projected path of the storm, the level of congestion on the evacuation routes, and the availability of accommodation at the destination. In addition, the models investigated in this study are static models in that they do not recognize how conditions change over time, or how behavior can be affected by such changes. The introduction of dynamic trip distribution models is of utmost importance since many of the factors affecting destination choice vary considerably over time (e.g., congestion on the network, and availability of accommodation at the destination).

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