Household Flood Evacuation Route Choice Models at Sub-district Level

Hector LIM, Jr., Ma. Bernadeth LIM, Mongkut PIANTANAKULCHAIR

Sirindhorn International Institute of Technology, Thammasat University, Pathum Thani, 12121, Thailand
E-mail: hector151981@yahoo.com
E-mail: dae032004@yahoo.com
E-mail: mongkutp@gmail.com

Abstract: Flood evacuation route choice modeling studies gained its momentum in recent years. However, understanding how various explanatory variables determine flood route choice behavior of evacuees has not been fully investigated. The goal of this study is to understand flood evacuation route choice behavior of households at Bahay Toro and Sto. Domingo sub-districts in Quezon City, Philippines. Binary logit and probit models were estimated with variables selected through backward elimination stepwise method. Results include the presence of elderly person, departure timing, and mode used in evacuating as explanatory variables of households’ route choice at Bahay Toro Sub-district. On the other hand, the number of family members, level of education and type of work of the household head, house ownership and the mode are variables that determine route choice of households at Sto. Domingo. Modeling evacuation route choice behavior representing the entire city can be further explored in future research.

Keywords: Flood, Evacuation, Route Choice, Evacuation Modeling, Travel Behavior

1. INTRODUCTION

The withdrawal stage in evacuation process is described as the movement of evacuees to their destination. It can be considered as the heart of the evacuation process (Lim et al., 2013). One of the core aspects of withdrawal is evacuation routing, which much of the evacuation research focused on. One of the impetus for this is that the travel demand during emergency evacuation exceed the capacity of the transportation networks (Pel et al., 2010), and congestion is likely to happen. In the studies, optimal evacuation routes that determine the least possible time for evacuees to reach safety are evaluated (e.g. Ng and Waller, 2010; Sayyady and Eksioglu, 2010; Campos et al., 2012; Na et al., 2012; Bish and Sherali, 2013). In doing this, planners initially analyze the baseline scenario; after which, the effect of routing strategies for the movement of evacuees from origins to their destinations to evacuation clearance time are evaluated. Once the strategies have desirable results, these are put in the form of an evacuation plan. Desirable results of strategies include the substantial reduction of clearance time against the lead time of the hazard. It is expected that when the evacuation plan is carried out, damage, loss of lives as well as chaos and delay are minimized.

The use of simulation-based models assists planners to determine the most probable scenario during an evacuation. In simulating routing strategies, assumptions on the routes taken by evacuees are usually made (e.g. Dow and Cutter, 2002; Robinson and Khattak, 2010). However, these and other assumptions do not necessarily capture the behavior of the decision makers. For example, Fang and Edara (2013) investigated the effects of these assumptions to the sensitivity of evacuation travel time. The authors found out that travel times realized
during an evacuation is underestimated. The magnitude of underestimation shows the
importance of understanding the route choice behavior of evacuees. Additional empirical
studies on observed route choices of evacuees are then valuable. Travel behavior could be
incorporated in evacuation simulations in order to identify optimal routing strategies (Fang
and Edara, 2013). This recommendation is also consistent with previous studies that
recognized route decisions of evacuees as an important part of evacuation simulation/traffic
modeling (e.g. Dow and Cutter, 2002; Pel et al., 2010; Pel et al., 2011).

Recently, research attempt to fill this gap by shifting efforts to understanding how
 evacuees choose the route they take during evacuation (e.g. Akbarzadeh and Wilmot, 2015;
Sadri et al., 2014; Lim et al., 2015). Researchers are becoming more adept to solve
 evacuation problems that will generalize how evacuees (e.g. individuals/households) decide
on certain aspects (e.g. evacuation decision, departure time, destination, mode, and route)
whenever a disaster strikes. However, in places where household characteristics are
heterogeneous, households’ decisions might considerably vary. Household decisions can be
affected by culture, demography, and environment, among others. Hence, it is an imperative
to understand household’s preferences in different communities in making decisions during
certain events such as evacuation.

In line with the above gaps, this study aims to understand key explanatory variables that
determine household evacuation route choice behavior. Understanding the variables that affect
 evacuees’ choice can assist emergency planners in preparing future evacuation plans, for
instance in determining which route can be congested and which routes to recommend for
 evacuees to take in order to reach destination in a timely manner. In this study, variables were
identified based on previous evacuation travel behavior studies. The variables included in the
analysis are socio-demographic information of evacuees, some hazard-related and
evacuation-related information. Effects of these variables were analyzed with data collected
from Bahay Toro and Sto. Domingo sub-districts based on the recommendation of Quezon
City Government (QCG) in the Philippines. With explanatory variables identified through
backward elimination stepwise method. The models were estimated using binary logit and
probit modeling techniques. Then, model specifications were validated as well as performance
and goodness-of-fit were assessed.

There are four remaining sections of this paper. Section 2 presents the existing literature
on evacuation route choice modeling. Specifically variables that determine route decision
making are highlighted. Section 3 presents the methods employed towards obtaining the goal
of this study. Section 4 presents and discusses the data and results of model estimation.
Section 5 gives the summary, conclusions and identified future research based from the
findings of the study.

2. LITERATURE REVIEW

In the past, studies in evacuation route choice were mostly considered under evacuation traffic
simulation modeling, while very few are focused on modeling travel behavior. Evacuees in
most studies consider nearest/shortest or familiar route during evacuation (Murray-Tuite et al.,
2012). The former choice is particularly evident in most simulation modeling studies such as
the works done by Huibregtse et al. (2010) and Pel et al. (2010). With the latter, Wu et al.
(2012) in their review mentioned that evacuees rely on personal familiarity, time, safety or
convenience. These similar conditions are assumed on en route scenario (Hobeika and Kim,
1998; Sheffi et al., 1981) as evacuees will not distribute themselves optimally over the
available routes. In most cases, behavior and traffic simulation are modeled separately.
Nevertheless, travel behavior such as evacuation route choice can give an added value to recent practices in traffic simulation studies by investigating the preferences of the evacuees in disaster events.

Explanatory variables to route choice behavior were investigated in the following studies. Three routing strategies was used for analysis in Sadri et al. (2014)’s work in understanding route preferences of hurricane evacuees. These are usual/familiar route, the route recommended by officials and updated route. Routes taken by interviewees in the Akbarzadeh and Wilmot (2015)’s hurricane study were categorized according to route attributes in terms of familiarity, accessibility, availability of services and road type. In Lim et al. (2015)’s study in the context of flood evacuation, analysis was done in 2 types of route choice categorized into familiar (main road) and shortest one. A common approach used in these studies in identifying choice sets for route choice analysis is that when interviewees have indicated that they would evacuate, they were asked to state the route they choose to reach their destination. The routes listed are then categorized according to similar attributes with reference to similar origins and destinations. The summary of the routing strategies used for analysis in evacuation route choice studies are presented in Table 1.

### Table 1. Route categories used in evacuation route choice literature

<table>
<thead>
<tr>
<th>Authors</th>
<th>Routes/routing strategies</th>
<th>Characteristics/description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lim et al. (2015)</td>
<td>Familiar (main road)</td>
<td>Main road usually taken during normal days. (There is only 1 main road among possible routes for evacuees)</td>
</tr>
<tr>
<td></td>
<td>Nearest/shortest route</td>
<td>Route other than the main road that is shorter. Route-specific characteristics that were investigated include familiarity with route, availability of fuel and shelter, road type and accessibility</td>
</tr>
<tr>
<td>Akbarzadeh and Wilmot (2015)</td>
<td>Identified interstate highways grouped according to origin and destination</td>
<td>Usual route/familiar/shortest route combined in one due to possible overlap.</td>
</tr>
<tr>
<td>Akbarzadeh and Wilmot (2015)</td>
<td>Usual/familiar route</td>
<td>Route recommended by the government officials</td>
</tr>
<tr>
<td>Sadri et al. (2015)</td>
<td>Recommended route</td>
<td>For evacuees that updated route because of traffic congestion once they tries initial route</td>
</tr>
<tr>
<td>Sadri et al. (2015)</td>
<td>Updated route</td>
<td></td>
</tr>
</tbody>
</table>

Explanatory variables that determine route choice behavior of evacuees are related to transportation infrastructure and the available services that are located along given routes. Akbarzadeh and Wilmot (2015) investigated the effect of travel time, familiarity with the route, availability of fuel and shelter, road type, and accessibility of the route on evacuees’ route choice. They also tested whether the importance given by evacuees assign to the variables determining route choice varies with time. By using multinomial logit model, findings show that the longer a route is, the less likely it will be selected. Interstate highways are expected to be more attractive for evacuation than other highways. Perceived service, which is the product of familiarity and service, will attract evacuees to that route. Accessibility, which shows the distance between a route and the residence suggest that evacuees prefer routes that are more accessible to them. Moreover, statistical comparison of parameters for risk-averse (evacuees during the first half) and risk-tolerant (evacuees during the second half) show that as the storm gets closer, people are more likely to take freeways rather than arterial routes. Also, as the storm gets closer, distance becomes less important, while perceived service becomes more important. This may indicate that as the storm gets closer, people become less discriminating about less significant issues and just want to get out
of the area. On the other hand, because congestion is likely as the storm gets closer and being stranded on the road without services is highly undesirable, availability of service facilities becomes more important. In addition to these findings, the authors noted that the variables included in their model are not necessarily the only variables affecting route-choice behavior of evacuees.

The inclusion of socio-demographic information in transportation planning has become necessary in discrete choice modeling (Train, 2009). Researchers that studied the relationship of information to evacuation travel behavior includes Fu and Wilmot (2004), Stopher et al. (2004), Hasan et al. (2011), and Mesa-arango et al. (2013) to name a few. Understanding how socio-demographic characteristics of evacuees affect their route choice decision is still understudied. Among the recent studies in line with this were conducted by Sadri et al. (2014) and Lim et al. (2015). Sadri et al. (2014) considered age, income and number of children in the family as variables that influence the route decision from alternatives of familiar route and route recommended by authorities. Their findings showed older evacuees are likely to detour or update their routes. Evacuees having a high annual household income of USD 40,000 or more are less likely to prefer the recommended routes. High income households may prefer to stick with their plan instead of following recommendations because they have better access to in-vehicle and other real-time travel information. Evacuees having children less than 18 years old are more likely to follow the routes recommended by the emergency officials rather than any of the other two route options. Lim et al. (2015), on the other hand, found that age of household head has a level of influence to route decision-making, although it might differ in other areas in the Philippines. Older household heads are more likely to evacuate through the nearest route than the younger ones. Additionally, households having their own vehicle are more likely to evacuate through the nearest route.

Flood disaster warning plays an important role in the evacuation compliance. Studies show that warning in general may include the source, message and the characteristics and possible impact of the hazard (EMA, 2005; Dash and Gladwin, 2007). It was found out in Sadri et al. (2014) that when a household receives an evacuation notice early enough, they could find more information about the traffic conditions and learn the evacuation routes specified for that particular area. Because of the predetermined routing strategy, evacuees are more likely to follow the recommended route or switch to the routes based on prevailing traffic conditions. However, the variable indicating the households receiving evacuation notice from radio or television instead of any other source (friend, relative, or newspaper) indicate that evacuees are more likely to take the route familiar to them rather than taking recommended evacuation routes.

Traffic simulation modeling studies for flood disasters used degeneration of road network over time in the event of flood hazards (Huibregtse et al., 2010). This has been applied over a number of simulation modeling studies such as Pel et al. (2011) and Lammel et al. (2010). Knowing that in reality this might happen regardless of the limitation of models, variables related to the hazard such as flood level, distance from source of flood, and distance to evacuation destination should also be considered in the analysis of evacuation route choice through discrete choice modeling technique. Such characteristics are attributed as environmental cues in the study conducted by Siebeneck and Cova (2013). The more distance the evacuees need to travel during evacuation, the more likely that the evacuee will update or switch their route (Sadri et al., 2014). Findings in Lim et al. (2015) also indicate a level of influence of the flood level to route choice. Households that experienced higher than one meter from earlier flood events are more likely to evacuate through the nearest route when compared to others that experienced lower flood level.

The effect of variables related to evacuation such as evacuation decision, destination
choice, departure time choice, and mode choice have also been investigated in studies on hurricane and flood (e.g. Sadri et al., 2014; Lim et al., 2015). Evacuating households may decide to evacuate some members of the household (partial) or all members (full) (e.g. Stopher et al., 2004; Hasan et al., 2011). They can also choose to evacuate prior to or when the hazard strikes their vicinity (Lindell et al., 2005; Charnkol and Tanaboriboon, 2006; Akbarzadeh and Wilmot, 2015). The destination of the households may include public shelter, friends/relatives, hotels/motels, church, workplace and others (Milet et al., 1992; Chen, 2005; Modali, 2005; Lindell and Prater, 2007; Cuellar et al., 2009; Wu et al., 2012; Mesa-arango et al., 2013). And in order to reach their destinations, evacuees could walk, cycle, or use their own car or vehicle provided by authorities (Lindell et al., 2007; Siebeneck and Cova, 2012; Deka and Carnegie, 2010; Lindell et al., 2011; Wu et al., 2012). Sadri et al. (2014) found that if an evacuee wants to evacuate to a friend or relatives’ house, majority of the evacuees, when they evacuate to a familiar destination, are likely to select their familiar routes from their previous visits to those destinations. In addition, when evacuees are departing well ahead of time, they do not necessarily follow recommended evacuation routes or switch routes; rather, they would prefer to drive through the routes which they are familiar with.

In the study of Lim et al. (2015), results indicate that mode and evacuation destinations in addition to others have some level of influence to route choice. Findings on the effect of mode indicate that households that walked when evacuating prefer to take the nearest route than those who evacuate by other modes such as vehicle provided by the government and rented vehicle. The effect of destination choice differ among households that evacuated prior to and during the flood event. Households that evacuated before the flood, and who are evacuating to the church, seminary, and to their friends and relatives are more likely to take the nearest route. Households that evacuated during the flood, and evacuating to friends and relatives house are less likely to choose the nearest route compared to those going to a church, seminary, and to their friends and relatives.

This study builds on identified explanatory variables to route choice behavior in literature discussed above to further investigate significant factors to route decision-making. Specifically, behavior in this context is analyzed with data from households at sub-districts in Quezon City, Philippines in the context of flooding. Whether variables that determine the route choice behavior of households at sub-districts analyzed here are consistent with earlier findings is also taken into account.

3. METHODOLOGY

3.1 Study Area, Sampling and Data Preparation

In the initial stage of this research, we sought the recommendation from QCG. QCG recommended five sub-districts suitable for the study due to their history of evacuation and the number of vulnerable households on flood. Bahay Toro and Sto. Domingo sub-districts were among the recommended areas aside from Bagong Silangan that served as a study area in understanding flood evacuation route choice behavior in the earlier study (Lim et al., 2015). These sub-districts are located in flood prone areas in Quezon City as shown in Figure 1.

According to QCG (2013), Bahay Toro has an estimated number of population of 74,987 while Sto. Domingo has around 15,560. These areas were badly affected by the floods brought about by the monsoon rains and Tropical Cyclone Trami in Mid-August of 2013. During that period, households were mandated to evacuate. Records show that about 500 and 533 households from Bahay Toro and Sto. Domingo, respectively, evacuated to public shelters
(SSDD, 2013). This excludes the number of households that evacuated to their friends/relatives’ house.

Figure 1. Map of Flood Prone Areas in Quezon City
Source: QCG (2013)

A post flood survey was conducted at Bahay Toro and Sto. Domingo sub-districts using the survey instrument used in Lim et al. (2015). Villages in each sub-district located in the flood prone areas with recorded history of evacuating during the Mid-August 2013 flood were identified. Researchers do not have prior knowledge on detailed socio-demographic information of households in every village to pinpoint households to interview. Hence, households were randomly approached for face to face interviews. The researchers made sure that samples were collected as possible in every block of village areas covering households of different number of members, type of houses, house ownership and other household information. Interviewees were the head of each household.

The interviewers asked the households questions that elicit socio-demographic and other household related information as well as their evacuation experience during the Mid-August 2013 flood event. Information gathered from households included age, marital status, educational attainment, number of household members, age of members, the presence of small children and senior citizens, monthly household income, number of years the household has been living in that residence, type of house materials, the number of house floor levels, vehicle ownership and pet ownership. Additional information inquired from the households are the level of flood in their house, the number of days they were flooded, the type and timing of evacuation, their evacuation destination, the mode they used when evacuating, and the route they took were inquired. The type of evacuation was full and partial. Full evacuation was noted for households that evacuated all members of the household and partial evacuation when some of the members were left at home. The timing of their evacuation was classified into evacuation during and before the flood, representing risk-tolerant and risk-averse households, respectively. The modes households took ranged from vehicles provided by the government, rented or personal vehicle and walking.
Routing strategies available to households were identified and included in the survey instrument. The route recommended by the government, usually available in other studies was not made available to households in this current study during issuance of evacuation warning. During the interviews, a map of possible routes to identified evacuation centers were shown from which interviewees were asked which route they took during evacuation to their specific destinations. They were then asked of the reason of taking such route rather than taking other available ones. From these, three routing options were identified including the route that they usually take during normal days (most familiar route to them that was also confirmed as not the nearest to their destination), the nearest route or where they thought they can take to evacuate faster, and the route without flood waters. These were the list of options made available to households during the rest of interviews in addition to “others” in case of the existence of route option not identified during the pilot survey. After data collection, however, the third option was removed from analysis as it was found that such route was not available to them that time or it is the only route available. In addition, there were no “other” route options made available in the data collected. The 2 remaining routes are then used for analysis in this study. These route options are defined as nearest and familiar (the main road most familiar that they usually take during normal days but not the nearest).

150 and 142 households were interviewed from Bahay Toro and Sto. Domingo, respectively. After the face to face interviews, data collected was summarized and tabulated. The data were verified for any inconsistency on required information. All observations with invalid and several missing information was not included for analysis. For instance, observations without the information on the route taken during evacuation and/or other information such as household income were excluded from analysis. Hence, not all collected samples were used for model construction. Details on the number and descriptions of data used for analysis are presented in Section 4.1.

3.2 Model Formulation, Parameter Estimation and Validation

The data were analyzed using the discrete choice model. Discrete choice model has been widely used in various fields due to its ability to model outcomes in categorical/nominal form. Binary logit and probit models as outlined in Train (2009) are employed in this study. Binary logit models give the probability of an outcome as a function of other explanatory variables. It was used in number of studies in evacuation modeling (e.g. Fu and Wilmot, 2004; Stopher et al., 2004; Charnkol et al., 2007) and has the ability to capture behavioral complexities of certain decision being investigated. The binary logit model is derived under the assumption that the unobserved factors are not correlated over the outcomes/alternatives, known as the independence from irrelevant alternatives (IIA) property. Despite this, it is widely used due to its simplicity and closed form estimation. The utility of household \( h \) choosing route \( i \) (the nearest, or familiar route) is represented by the utility function as shown in Equation 1. In this study, familiar route serves as the basis of analysis.

\[
U_{i,h} = \beta_i X_{i,h} + \epsilon_{i,h}
\]  

Where,

\( U_{i,h} \) : the utility of household \( h \) choosing route choice \( i \);

\( \beta_i \) : vector of parameters to be estimated;

\( X_{i,h} \) : vector of the explanatory variables for route choice; and

\( \epsilon_{i,h} \) : error term accounted for the impact of unobserved attributes of household \( h \) and
differences in preferences on observed route choice \( i \).

The probability that nearest or familiar route is presented by \( P_h(i) \) in Equation 2.

\[
P_h(i) = \frac{e^{\beta_i x_i}}{\sum e^{\beta_i x_i}}
\]  

(2)

On the other hand, probit models can address the IIA limitation in logit as well as handles difference in random tastes (Train, 2009). The probit model is derived under the assumption of correlated random error term which follows normal distribution.

The probit model (Greene, 2003) uses a latent variable \( y \), as shown in Equation (3) to determine evacuation route outcomes, where \( x_i \) is a vector of explanatory variables; \( \beta \) is a vector of the coefficients for the explanatory variables; and \( \varepsilon \) is a random error term following standard normal distribution.

\[
Y^* = \alpha + \beta x_i + \varepsilon
\]  

(3)

However, \( Y^* \) is observed only as a binary or dichotomous variable \( Y \) which is defined by the threshold model shown in Equation 4

\[
Y = \begin{cases} 
1 & \text{if } Y^* > 0 \\
0 & \text{if } Y^* \leq 0 
\end{cases}
\]  

(4)

The probability of a household choosing a route to take during evacuation is shown in Equation 5, where \( \Phi \) is the cumulative distribution function of the standard normal distribution, and \( x_i \) is a vector of explanatory variables for route choice; and \( \beta \) is a vector of parameters of explanatory variables to be estimated.

\[
P_h(\text{route} = 1/ x_i, \beta) = \Phi(x_i, \beta)
\]  

(5)

The stepwise selection method was employed to identify variables that are included in the models. This method provides fast and effective way to screen a large number of variables, and to fit logit models simultaneously (Steyeberg et al., 2004). The variables were subjected to statistical tests which indicate the significance of the variable to affect the route decision making. Variables with very high p-values are removed and remaining variables are repeatedly subjected to statistical test until desired significant model is obtained.

After selection of explanatory variables included in the model, parameters are determined by the maximum likelihood estimation method. The t-statistics is used to determine the significance of variables to route choice. The odds ratio is also obtained to determine the effect of an increase in one unit of certain variable when all others are held constant, to the probability of the route choice. It is estimated by exponential term raised to the power of the coefficient of the explanatory variable (\( e^{\beta_i} \)).

The McFadden pseudo \( R^2 \) is used to evaluate the goodness of fit of the models. However, as this is usually not a good measure for logit and probit models, the likelihood ratio index and the correct rates (CCR). The area under the Receiver Operating Characteristics (ROC), AUC is also calculated in this study to determine the discrimination ability of the models. With values between 0 and 1, AUC indicates the capability of the classifier model to distinguish a randomly chosen positive case (sensitivity) higher than a randomly chosen negative case (specificity). Generally, AUC indicates outstanding discrimination with values
from 0.9 to 1, excellent discrimination with values from 0.8 to less than 0.9, and acceptable discrimination with values from 0.7 to less than 0.8 indicates (Hosmer and Lemeshow, 2000). Another method employed to validate specifications of the model is the bootstrap method. An internal validation, the method employs part of the data for model estimation and another for testing the model results (Giancristofaro and Salmaso, 2003). It is an efficient validation method resulting in models with stable variance results and low bias (e.g. Efron and Tibshirani, 1997; Steyberg et al., 2004). Besides providing more accurate point estimates for prediction error, another advantage of bootstrapping is it provides a direct assessment of variability for estimated parameters in the prediction rule. In the method, sample generation from the original set of samples is repeated with replacement of the same number with that of the original samples (Kohavi, 1995). For efficient results with stable variance and low bias, at least 1,000 bootstrap replication is needed (Hesterberg et al., 2003).

4. RESULTS AND DISCUSSIONS

The results of the parameter estimation and validation for Bahay Toro and Sto. Domingo sub-districts are presented in this section.

4.1 Selected Variables and Their Descriptive Statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>Classification</th>
<th>Bahay Toro</th>
<th></th>
<th>Sto. Domingo</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>N</td>
<td>%</td>
<td>N</td>
<td>%</td>
</tr>
<tr>
<td>Number of household members (MEM)</td>
<td>1-4 members</td>
<td>-</td>
<td></td>
<td>34</td>
<td>41.5</td>
</tr>
<tr>
<td></td>
<td>&gt;5 members</td>
<td>-</td>
<td></td>
<td>48</td>
<td>58.5</td>
</tr>
<tr>
<td>Presence of elderly person citizen (SEN)</td>
<td>No elderly person in the household</td>
<td>88</td>
<td>85.4</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Presence of elderly person</td>
<td>15</td>
<td>14.6</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Educational attainment of the head of the household (EDUC)</td>
<td>Elementary</td>
<td>-</td>
<td></td>
<td>15</td>
<td>18.3</td>
</tr>
<tr>
<td></td>
<td>High School</td>
<td>-</td>
<td></td>
<td>46</td>
<td>56.1</td>
</tr>
<tr>
<td></td>
<td>Diploma and Undergraduate</td>
<td>-</td>
<td></td>
<td>17</td>
<td>20.7</td>
</tr>
<tr>
<td></td>
<td>Graduate</td>
<td>-</td>
<td></td>
<td>4</td>
<td>4.9</td>
</tr>
<tr>
<td>Type of work of the head of the household (TWORK)</td>
<td>Part time worker</td>
<td>-</td>
<td></td>
<td>32</td>
<td>39.0</td>
</tr>
<tr>
<td></td>
<td>Full time worker</td>
<td>-</td>
<td></td>
<td>50</td>
<td>61.0</td>
</tr>
<tr>
<td>House ownership (HOWN)</td>
<td>Rented</td>
<td>-</td>
<td></td>
<td>42</td>
<td>51.2</td>
</tr>
<tr>
<td></td>
<td>Owned</td>
<td>-</td>
<td></td>
<td>40</td>
<td>48.8</td>
</tr>
<tr>
<td>Departure timing (TDEC)</td>
<td>Evacuated during flood</td>
<td>81</td>
<td>78.6</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Evacuated before the flood</td>
<td>22</td>
<td>21.4</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Mode of evacuation (MDEC)</td>
<td>Other modes</td>
<td>44</td>
<td>42.7</td>
<td>42</td>
<td>51.2</td>
</tr>
<tr>
<td></td>
<td>Walking</td>
<td>59</td>
<td>57.3</td>
<td>40</td>
<td>48.8</td>
</tr>
</tbody>
</table>

-not relevant to Sub-district

In the analysis of route choice decision making, data show that in Bahay Toro with a total of 103 observations used for analysis, 31.1% of households took the route familiar to them, while 68.9% took the nearest route available to them. In Sto. Domingo, 82 observations was used in the analysis. The composition of data is 36.6% and 63.4% for households that took the familiar and nearest route, respectively. For each sub-district, the backward elimination
stepwise selection of variables was done to identify appropriate explanatory variables to be included in the model. Sixteen variables were tested for significance and inclusion in the models. These are age, gender, type of work, and marital status of the household head, number of household members, presence of small children aged less than or equal to 10 years old, and presence of elderly aged greater or equal to 60, presence of pet and vehicle ownership, flood level, distance of household from the source of flood, and the evacuation household decisions variables (evacuation decision, departure time, destination, and mode choice). The variables were assessed for inclusion in the model using statistical test with resulting p-values. Insignificant variables were removed one at a time. After a variable is removed, the variables left were subjected to statistical test. The process is repeated until the desired combination of variables that gave a significant model is met. Table 2 gives a summary of the selected variables for each sub-district model and the percentage in the data. Presence of elderly person, departure time and mode used in evacuating are variables included in the model for Bahay Toro. While number of household members, educational attainment and type of work of the household head, house ownership, and mode used in evacuating are variables included in the model for Sto. Domingo.

4.2 Parameter Estimation Results and Model Validation

The binary logit and probit route choice models for households choosing the nearest route (main route used as base for estimation) was estimated with STATA v. 12.0. Parameter estimates for Bahay Toro and Sto. Domingo are presented and discussed here. Table 3 shows the summary of logit and probit model parameters, named Model 1 and Model 2, respectively, for Bahay Toro sub-district. Table 4 presents the resulting logit (Model 3) and probit (Model 4) parameter estimates for Sto. Domingo sub-district.

4.2.1. Bahay Toro model results

All explanatory variables in both Models 1 and 2 are significant at 90% confidence interval. Both Models show the same signs with slight differences in coefficients. The resulting positive coefficients for households having elderly member in both Model 1 and 2 indicate that these households are more likely to evacuate through the nearest route compared to households that don’t have elderly members. Further, the households that evacuate prior to the flood are more likely to take the nearest route than the households that evacuate during the flood. They would probably take the route they have been taking during normal days without flood. Similar to the result here, departure timing was also found to affect route decision making in earlier studies such as Sadri et al. (2014). However, thresholds for comparison differ in these studies such as the context, the type of hazard and the routing strategies made available to the evacuees. Lastly, households that choose to walk are more likely to choose the nearest route than those that traveled using other modes of transport available to them. The effect of mode taken when evacuating is also consistent with findings in Lim et al. (2015) in a study of route choice behavior in another sub-district in Quezon City, Philippines.

Models are compared here with the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC). These are measures that allow direct model comparison for models (Burnhaman and Anderson, 2004). The model with lower BIC and AIC has better fit when compared to other models. BIC for Model 1, 134.506, is slightly lower than that of Model 2, 137.848 which indicates better fit. The same is true with the AIC values of 126.967 for Model 1 and 127.309 for Model 2. The models also show CCR values of 74.76% compared to the base CCR of 57.144% indicating that the models are better than prediction by
chance. Given the low and slight difference in the Models’ pseudo-\( R^2 \), the LR test was performed to further compare the goodness-of-fit of the Models. The LR statistic of Model 1, 8.68, is higher than that of Model 2 which is 8.34. These are both larger than the \( \chi^2 \) value of 7.81 at 0.05. Although Model 1 shows better fit than Model 2 with an improvement in CCR compared to base CCR rate, both Models’ capacity to discriminate, measured by AUC of 0.680 are a bit lower than acceptable level (Hosmer and Lemeshow, 2000). Hence, further analysis is needed in order to develop predictive model for route choice behavior in Bahay Toro.

Table 3. Bahay Toro logit and probit model estimation results

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Logit model (Model 1)</th>
<th>Probit model (Model 2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \beta )</td>
<td>Std. Error</td>
</tr>
<tr>
<td>Indicator variable for SEN (1 for the presence of elderly person, 0 otherwise)</td>
<td>1.442**</td>
<td>0.820</td>
</tr>
<tr>
<td>Indicator variable for TDEC (1 for households that evacuated before the flood, 0 for those that evacuated the during flood)</td>
<td>1.190**</td>
<td>0.645</td>
</tr>
<tr>
<td>Indicator variable for MDEC (1 for walking, 0 for other modes)</td>
<td>0.896**</td>
<td>0.478</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.088</td>
<td>0.399</td>
</tr>
<tr>
<td>No of observations</td>
<td>103</td>
<td>103</td>
</tr>
<tr>
<td>Initial log-likelihood</td>
<td>-63.823</td>
<td>-63.823</td>
</tr>
<tr>
<td>Final log-likelihood</td>
<td>-59.483</td>
<td>-59.655</td>
</tr>
<tr>
<td>LR ( \chi^2 ) (3)</td>
<td>8.68</td>
<td>8.34</td>
</tr>
<tr>
<td>Pseudo R(^2)</td>
<td>0.068</td>
<td>0.065</td>
</tr>
<tr>
<td>Prob &gt; ( \chi^2 )</td>
<td>0.034</td>
<td>0.040</td>
</tr>
<tr>
<td>AUC</td>
<td>0.680</td>
<td>0.680</td>
</tr>
<tr>
<td>AIC</td>
<td>126.967</td>
<td>127.309</td>
</tr>
<tr>
<td>BIC</td>
<td>134.506</td>
<td>137.848</td>
</tr>
<tr>
<td>CCR (%)</td>
<td>74.760</td>
<td>74.760</td>
</tr>
<tr>
<td>Base CCR (%)</td>
<td>57.144</td>
<td>57.144</td>
</tr>
</tbody>
</table>

*significant at 5% level; **significant at 10% level

4.2.2. Sto. Domingo model results

Results of Model 3 estimation for Sto. Domingo demonstrates that the educational attainment of the head of the household, and the mode used when evacuating, are significant at 95% confidence interval. While the type of work of the head of the household, and house ownership variables are significant at 90% confidence interval. For Model 4, resulting coefficients have slight difference in the level of significance compared to Model 3 results. Educational attainment is significant at 99% confidence interval of the head of the household, and the mode used when evacuating, are significant at 95% confidence interval. The type of work of the household head and house ownership are significant at 90% confidence interval. The number of household members appears to be insignificant at 0.10. However, it is included in the Models due to indications from household interviews that they take this into account when choosing the route to take. It was also outlined in Ben-Akiva and Lerman (1985) that variables believed to have some level of influence on the decision, can be included in the
model.

All coefficients for both Model 3 and Model 4 have the same signs. For the level of education, result indicates that household heads educated higher than elementary level are more likely to choose the nearest route compared to those with elementary level education. Household heads that have full time work have less likelihood of taking the nearest route compared to those working part-time. Households that own their house have higher likelihood to choose the nearest route over those who are just renting their house. These characteristics of household indicate important effects in decision-making. Hence, knowing these characteristics of the population in the sub-district allow government officials and planners to identify which population group will take certain route. Information can then be used to predict volume of traffic on specific routes in future evacuations. On the other hand, households that walk when evacuating as indicated by positive coefficient prefer to take the nearest route.

Table 4. Sto. Domingo model estimation results

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Logit model (Model 3)</th>
<th>Probit model (Model 4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β</td>
<td>Std. Error</td>
</tr>
<tr>
<td>Indicator variable for MEM (1 for greater than 4 members, 0 for less than or equal to 4)</td>
<td>-0.909</td>
<td>0.565</td>
</tr>
<tr>
<td>Indicator variable for EDUC (1 for higher than elementary, 0 for elementary)</td>
<td>1.057*</td>
<td>0.423</td>
</tr>
<tr>
<td>Indicator variable for TWORK (1 for full time worker, 0 for part time worker)</td>
<td>-1.111**</td>
<td>0.574</td>
</tr>
<tr>
<td>Indicator variable for HOWN (1 for owned, 0 for rented)</td>
<td>1.059**</td>
<td>0.570</td>
</tr>
<tr>
<td>Indicator variable for MDEC (1 for walking, 0 for other modes)</td>
<td>1.383*</td>
<td>0.560</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.423</td>
<td>0.645</td>
</tr>
</tbody>
</table>

| No of observations | 83 | 83 |
| Initial log-likelihood | -54.302 | -54.302 |
| Final log-likelihood | -44.747 | -45.008 |
| LR chi²(5)          | 19.110 | 18.590 |
| Pseudo R²           | 0.176  | 0.171  |
| Prob > chi²         | 0.0018 | 0.0023 |
| AIC                  | 101.494 | 102.017 |
| BIC                  | 116.007 | 116.530 |
| AUC                  | 0.791  | 0.786  |
| CCR (%)              | 78.31  | 73.49   |
| Base CCR (%)         | 53.59  | 53.59   |

*significant at 5% level; **significant at 10% level; ***significant at 1% level

The BIC for Model 3, 116.007 is slightly lower than Model 4, 116.530. In addition, the AIC value of 101.494 for Model 3 is also lower than that of Model 4, 102.017. These indicate better fit for Model 3. Moreover, the LR statistics for Model 3 and 4, both larger than the χ² value are 19.11 and 18.59, respectively. This also indicates better goodness-of-fit for Model 3. The CCR values of 78.31% and 73.49% for Models 3 and 4, respectively compared to the base CCR of 53.59% indicate that the models are much better than prediction by chance.
AUCs for both models (Model 3 = 0.791) and (Model 4 = 0.786) are acceptable (Hosmer and Lemeshow, 2000). These results show a preference for Model 3 over Model 4.

4.2.3. Comparison of Bahay Toro and Sto. Domingo model results

A significant variable common to both sub-district Models is the mode of evacuation. This is an indication that the mode available to households when evacuating can be one of the most dominating explanatory variables to be included in a generalized route choice model for the flood affected households in Quezon City. Their effect to the household decision on route choice seems to be consistent regardless of the geographical location of the data source. Consistent result is demonstrated in findings in Lim et al. (2015) in case of Bagong Silangan sub-district in Quezon City, Philippines. Despite these, performance of the Model developed for Bahay Toro is questionable while Model 3 in Sto. Domingo shows good performance.

Empirical findings show that age, income, presence of children less than 18 years old and the destination type do not significantly affect the route choice behavior of households. These variables were found to significantly affect the route choice behavior in the context of hurricane. Sadri et al. (2014) found that older evacuees as likely to detour or update their routes rather than taking the most familiar or government recommended routes. They also found out that evacuee with children less than 18 years old are more likely to take the routes recommended by the government which are less likely in the case of those with high incomes. High income households are more likely to take recommended routes. Moreover, evacuees that went to friends and relatives’ house have higher probability of using the route most familiar to them. In another study, Lim et al. (2015) in their study of binary route outcomes found that older household heads with their own vehicles are more likely to evacuate through nearest route. Although these variables are also investigated in this study, some other variables resulted to have significant effect to route choice decision-making in this context. The difference in the context as well as the hazard type might have contributed to difference in results. Also, the thresholds used in some investigated variables in this study are very much different compared to past studies. Characteristics of routes in this study are not available in the data and hence not investigated here. Also small number of samples used for data analysis might have contributed to the insignificance of these variables. Collecting more data will be helpful in developing useful prediction models.

4.2.4 Model validation by bootstrap method

An internal validation is conducted to assess the validity of each model’s specifications. Bahay Toro and Sto. Domingo models are estimated at 1000 bootstrap samples for high accuracy estimations (Hesterberg et al., 2005) subjected to 100 iterations. Tables 5 and 6 present the bias-corrected bootstrap estimates for both Bahay Toro and Sto. Domingo, respectively. The internal validation result for Bahay Toro Model 1 indicates the presence of elderly to be a significant explanatory variable at 0.10 level. However, the timing and mode of evacuation becomes insignificant with 1,000 bootstraps For Model 2, presence of elderly and mode of evacuation remains to be significant at 0.10. However, departure timing becomes insignificant at 0.10 level as well. Hence, the presence of elderly and mode of evacuation indicates a strong influence on the route choice behavior of households at Bahay Toro.

The validation results for Sto. Domingo Model 3 shows that the level of education and the mode used when evacuating are significant at 0.10 level, while the number of household members, and the type of work of the household head becomes insignificant at 0.10 level. For Model 4, only the level of education remains to be significant at 0.05 level. Other variables
became insignificant at 0.10. For Sto. Domingo, the level of education and the mode of evacuation seems to have the strongest influence to household’s decision making.

Table 5. Internal validation results using bootstrap technique for Bahay Toro sub-district

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Bootstrap for Logit (Model 1)</th>
<th>Bootstrap for Probit (Model 2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β</td>
<td>Std. Error</td>
</tr>
<tr>
<td>Indicator variable for SEN (1 for the presence of elderly person, 0 otherwise)</td>
<td>1.442*</td>
<td>0.644</td>
</tr>
<tr>
<td>Indicator variable for TDEC (1 for households that evacuated before the flood, 0 for those that evacuated the during flood)</td>
<td>1.190</td>
<td>0.843</td>
</tr>
<tr>
<td>Indicator variable for MDEC (1 for walking, 0 for other modes)</td>
<td>0.896</td>
<td>0.574</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.088</td>
<td>0.448</td>
</tr>
</tbody>
</table>

*significant at 5% level; **significant at 10% level

Mode of evacuation appears to have some level of consistency in affecting route choice behavior of evacuees in Sto. Domingo, while inconsistent in Bahay Toro. However, further investigation is needed as the mode might be a significant variable that determines route choice whenever the datasets of the Bahay Toro, Sto. Domingo and Bagong Silangan (Lim et al., 2015) sub-districts will be combined as a single dataset for future modeling studies.

Table 6. Internal validation results using bootstrap technique for Sto. Domingo sub-district

<table>
<thead>
<tr>
<th>Explanatory Variables</th>
<th>Bootstrap for Logit (Model 3)</th>
<th>Bootstrap for Probit (Model 4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β</td>
<td>Std. Error</td>
</tr>
<tr>
<td>Indicator variable for MEM (1 for greater than 4 members, 0 for less than or equal to 4)</td>
<td>-0.909</td>
<td>0.747</td>
</tr>
<tr>
<td>Indicator variable for EDUC (1 for higher than elementary, 0 for elementary)</td>
<td>1.057**</td>
<td>0.569</td>
</tr>
<tr>
<td>Indicator variable for TWORK (1 for full time worker, 0 for part time worker)</td>
<td>-1.111</td>
<td>0.750</td>
</tr>
<tr>
<td>Indicator variable for HOWN (1 for owned, 0 for rented)</td>
<td>1.059</td>
<td>0.847</td>
</tr>
<tr>
<td>Indicator variable for MDEC (1 for walking, 0 for other modes)</td>
<td>1.383**</td>
<td>0.757</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.423</td>
<td>0.808</td>
</tr>
</tbody>
</table>

*significant at 5% level; **significant at 10% level

5. SUMMARY AND CONCLUSIONS

In recognition of the need for more studies in understanding the route choice behavior of
evacuees, this study builds on identified explanatory variables in past studies to further investigate what determines the decision making process. Specifically, this study sought to analyze route choice behavior of households at sub-districts in Quezon City, Philippines. Whether variables that determine the route choice behavior of households from two sub-districts are consistent with earlier findings, is also analyzed.

Binary logit and probit models were estimated and validated based on household post flood interviews conducted in two sub-districts. Empirical findings provide insights in route choice behavior of evacuees that are useful for emergency planning and management. An understanding of how evacuees choose the route they take during flood events help evacuation planners and managers predict behavior that can be incorporated in evacuation traffic models. Particularly, it can assist emergency planners and evacuation managers to plan and prepare according to existing facilities. Specifically, it can help them determine which route can be congested and which routes to recommend to evacuees when providing the evacuation warning. This further helps in effective evacuation operations in the future.

Empirical findings indicate that different sub-districts decide differently based on some specific variables that determine household evacuation route choice. This is an indication that households have their own uniqueness based on their characteristics and the circumstance they face during an emergency. However, the result show the mode of evacuation available to the households, consistent in both sub-districts, is a variable that is dominating factor households’ decision making. Households that walk when evacuating prefer to take the nearest route. Implication of this in future evacuation is that, the nearest routes to destinations can be designated for those who will walk. Evacuees on other modes (e.g. by motorcycle, tricycle, vehicles provided by the government) can be designated to main roads or other longer routes available. This is to avoid traffic congestion of multi modes in the nearest routes. Specific to Bahay Toro Sub-district, a strong explanatory variable consistent with the bootstrap validation result is the presence of elderly person in the household. When they decide to evacuate, there is a higher probability of taking the nearest route when compared to households that do not have elderly person. On the other hand, Sto. Domingo Model result shows that dominating factors in addition to the mode of evacuation are educational attainment of the head of household, and the type of work of the household head. Household heads that are educated higher than elementary level, those that own their house and walk when evacuating are more likely to choose the nearest route. These results of preference on the nearest routes of specific characteristics of households indicate possible congestion on nearest routes. The government officials can plan accordingly, designate nearest to those that walk, and provide vehicles to those with elderly as possible in future evacuations. Motorized vehicles used during evacuation should be designated to the main road or other longer routes. In preparation, signage should be put in place and evacuation drills to different routes conducted for more organized evacuations in the future.

Some of the variables found in this study that are consistent with earlier findings include the timing of evacuation and mode of evacuation. Sadri et al. (2014) found that those that evacuate well ahead of time choose to take routes that are familiar to them. In another study, Lim et al. (2015) found that older household heads with their own vehicles are more likely to evacuate through nearest route. In both sub-districts households do not give importance to hazard-related characteristics compared to that in Bagong Silangan Sub-district investigated in an earlier study (Lim et al., 2015). It is also interesting to note that some important variables found to influence route decision making in earlier studies are not significant in the context of the current study. These variables include income, presence of small children. The difference in the context as well as the hazard type might have contributed to difference in results. Also, the small number of samples used for data analysis might have
contributed to the insignificance of these variables. Collecting more data will be helpful in developing useful prediction models. Since the routes recommended by the government officials are not made available to households in the study area, this information should be included in evacuation warning messages in future evacuations. It is important that once routes that may be congested during evacuation are identified, distribution of evacuees to other routes available should be done to avoid delays in future evacuation.

Logit models estimated for the sub-districts showed better performance and goodness-of-fit compared to probit models. This indicates that correlation between random terms might not be as strong as expected. Although Sto. Domingo Model shows good performance, further analysis is needed for Bahay Toro in order to develop useful predictive Model. The use of multinomial logit and probit modeling approach can be explored in future research whenever the Philippine government, through the local flood early warning system (LFEWS) program provides recommended route to evacuees. In addition, the disaggregate models estimated in this study can be very specific to the study area. Hence, estimating a generalized model for the whole city using samples taken in selected sub-districts combined can be. Specific studies may focus on pedestrian and gender-based flood evacuation route choice behavior. Moreover, other significant explanatory variables which are attributed as socio-demographic information are likely due to the ethnic majority in the area which can be further investigated. This information is not available and can be collected in future studies.

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REFERENCES


Technologies for Homeland Security, Boston, MA, USA.


Quezon City Government (QCG) (2013) Quezon City actual and projected population by district and by barangay. Unpublished report collected from the QCG office.


