DEVELOPMENT OF ALGORITHMS TO ESTIMATE POST-DISASTER POPULATION DISLOCATION—A RESEARCH-BASED APPROACH

A Dissertation

by

YI-SZ LIN

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2009

Major Subject: Urban and Regional Sciences

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Approved by:

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ABSTRACT

Development of Algorithms to Estimate Post-Disaster Population Dislocation—A Research-Based Approach. (August 2009)

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This study uses an empirical approach to develop algorithms to estimate population dislocation following a natural disaster. It starts with an empirical re-examination of the South Dade Population Impact Survey data, integrated with the Miami-Dade County tax appraisal data and 1990 block group census data, to investigate the effects of household and neighborhood socioeconomic characteristics on household dislocation. The empirical analyses found evidence suggesting that households with higher socio-economic status have a greater tendency to leave their homes following a natural disaster. Then one of the statistical models is selected from the empirical analysis and integrated into the algorithm that estimates the probability of household dislocation based on structural damage, housing type, and the percentages of Black and Hispanic population in block groups.

This study also develops a population dislocation algorithm using a modified Hazard-US (HAZUS) approach that integrates the damage state probabilities proposed by Bai, Hueste and Gardoni in 2007, accompanied with dislocation factors described in

HAZUS to produce structural level estimates. These algorithms were integrated into MAEviz, the Mid-American Earthquake Centers Seismic Loss Assessment System, to produce post-disaster dislocation estimates at either the structure or block group level, whichever is appropriate for the user's planning purposes. Sensitivity analysis follows to examine the difference among the estimates produced by the two newly-developed algorithms and the HAZUS population dislocation algorithm.

DEDICATION

To my Parents, Mao-Shen Lin and Yi-Chen Chen,

and the best friend of my life, Pei-Ying Hsieh

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1. INTRODUCTION

The estimation of population dislocation following a major natural disaster is critical in at least two aspects. First, it provides planners with the fundamental information to determine the immediate demand for temporary shelter, described by Quarantelli (1982a) as the second of the four phases of housing recovery. This piece of information is valuable for designation and establishment of shelters, as well as the requirement of staff and nursing personnel to operate these shelters (Quarantelli, 1982a). Second, the estimation of this population loss—which could be temporary or permanent—is one of the important factors to assess the indirect loss of local economy. This economic impact mainly comes from the disruption of money flow because of the sudden loss of people conducting the economic activities such as consumptions and services. The decline in economic activities also reduces the financial sources available to local governments because of the loss of tax in sales, business, property and personal income (Lindell & Prater, 2003; Lindell et al., 2006). For the sake of these planning issues, it is therefore essential to develop algorithms that can provide appropriate measurement of population dislocation.

This dissertation follows the style of *Journal of the American Planning Association.*

Population dislocation is a form of mass population movement attributed to natural disasters. Disaster research suggests that the pattern of post-disaster population dislocation is influenced by factors including the structural damage to housing, housing type, disaster type, weather, infrastructure disruption, job loss, and socioeconomic characteristics of households and their surrounding neighborhoods (Baker, 1991; Belcher & Bates, 1983; FEMA, 2003; Fried, 1966; Gladwin & Peacock, 1997; Haas et al., 1977; Heller, 1982; Lindell & Prater, 2003; Lindell et al., 2006; Morrow-Jones & Morrow-Jones, 1991; Peacock & Girard, 1997; Whitehead et al., 2000; Whitehead, 2005). However, the only existing algorithmic model to estimate population dislocation—the HAZUS model—relies solely on the structural damage to different housing types, without considering the other factors in play. In addition, the HAZUS population dislocation model produces census tract level estimates which in many cases are inappropriate for users' specific planning purposes.

In this context, this dissertation attempts to improve on the HAZUS model by producing population dislocation estimates at the structure level that may be aggregated at any larger unit of analysis depending on specific users' needs. It also seeks to develop population dislocation algorithm that further incorporates human socioeconomic characteristics in addition to housing structural damage and housing type as employed in the HAZUS model. This study utilizes a research-based approach that extends empirically based statistical models to the formulation of population dislocation algorithm. In particular, three research questions are the emphasis of this study. First, how do household and neighborhood socioeconomic characteristics influence post-disaster household dislocation? Second, how can the population dislocation algorithm be specified to incorporate socioeconomic factors and produce structural level estimates that allow flexibility in aggregation to meet a user's specific planning purposes? Third, how does the dislocation algorithm developed in this study perform differently from the HAZUS model?

This dissertation is structured in the following sections. Section 2 is the literature review that defines the scope of this study and summarizes previous research on the post-disaster population dislocation. The conclusion of literature review suggests seven research hypotheses. Section 3 explains the measurement, method, data source, data management, independent and dependent variables, and analytical approach employed in this study. Section 4 describes the major analyses for hypothesis testing and algorithm development. Section 5 describes the formulation of population dislocation algorithms and examines the sensitivity of the algorithms. Section 6 summarizes the major research findings and also discusses the study's limitations, as well as its theoretical and practical implications.

2. LITERATURE REVIEW

2.1 Defining Population Dislocation

As mentioned by Quarantelli (1995), the scientific jargon in a specific field has to avoid imprecision and vagueness to allow knowledge and understanding of the phenomena involved. It is therefore important to eliminate any ambiguity associated with the term *population dislocation*. In the field of sociological research, population dislocation has some synonyms being used interchangeably, such as *forced migration, forced displacement*, *population transfer* and *displaced person* (Davenport et al., 2003). Specifically, different types of *population dislocation* are often classified according to the causes of displacement, including conflict-induced, development-induced and disaster-induced, and the scale of movements, based upon whether or not people cross international borders (Eschenbächer, 2007; Mason, 2006). The term *population dislocation* in this study, to be precisely described from a taxonomic perspective, represents a post-disaster socio-demographic impact in which households are forced to move—domestically in most cases—because of the damage to structures and infrastructures caused by the natural hazards (Lindell & Prater, 2003).

In order to better understand the scope of this study, it is important to distinguish population dislocation from other types of disaster-induced population movement. Perry et al. (1981) proposed a systematic scheme to classify different types of evacuation based on the timing and duration of the evacuation event, as shown in Table 2.1. This classification scheme can also be employed as the criterion to differentiate varieties of disaster-induced population moves.

Table 2.1 Classification Scheme Based on Timing and Duration of Evacuation

		Period of evacuation	
		Short-Term	Long-Term
Timing of evacuation	Pre-impact	Preventive	Protective
	Post-impact	Rescue	Reconstructive

Source: Perry et al. (1981).

Some studies consider both evacuation and dislocation as human migration related to environmental hazards without a clear distinction between them. Plenty of the existing literatures dedicated to hazard-related population moves have focused on either preventive evacuation specifically (e.g., Baker, 1991; Dow & Cutter, 1997; Landry et al., 2007; Mileti et al., 1992; Whitehead et al., 2000; Whitehead, 2005) or a broad picture of disaster-induced migration as a whole (e.g., Belcher & Bates, 1983; Hunter, 2005; Morrow-Jones & Morrow-Jones, 1991), whereas very few have focused on population dislocation. The differences and similarities found between evacuation and dislocation can be described as the following.

The first difference is that evacuation is usually a pre-impact emergency preparedness practice adopted to protect the population while population dislocation is a socio-demographic impact regarded as a result of the structural damage caused by the natural hazards (Lindell & Prater, 2003; Perry et al., 1981). In most disaster research the term evacuation often has a narrower sense that represents the pre-impact preventive measure to minimize the negative effects of a natural disaster on the population rather than their property. In this study, population dislocation means that residents stay away from their homes after the disaster event for at least some period of time (versus those who never left). As a result, population dislocation may also include those who left during the pre-impact evacuation. To clearly demonstrate the scope of this study, the evacuation classification scheme can be modified as the following Table 2.2 to distinguish disaster-induced population moves.

Table 2.2 Topology Modified from Perry et al. (1981) to Distinguish Population Moves

		Period of population movement	
		Short-Term	Long-Term
Timing of population movement	Pre-impact	Preventive evacuation	Protective evacuation
	Post-impact	Population dislocation (People who leave home for at least some time)	

Source: Modified from Perry et al. (1981).

Second, evidence in the literature suggests that population evacuation is essentially driven by a physical threat including the potential intensity of the event and evacuation orders. This is very different from population dislocation that is essentially driven by the level of housing damage as well as disaster types, weather, infrastructure disruption, and job loss (Baker, 1991; FEMA, 2003; Gladwin & Peacock, 1997; Whitehead et al., 2000; Whitehead, 2005).

On the other hand, the similarity found in these literatures is that both evacuation and dislocation are influenced by the socioeconomic characteristics of the households and their surrounding neighborhoods (Baker, 1991; Belcher & Bates, 1983; FEMA, 2003; Fried, 1966; Gladwin & Peacock, 1997; Haas et al., 1977; Heller, 1982; Morrow-Jones & Morrow-Jones, 1991; Whitehead et al., 2000; Whitehead, 2005). The socioeconomic characteristics of a household and its neighborhood are closely related to the household's mobility in terms of facing the natural disasters. In fact, evacuation-related topics have drawn much more attention than dislocation issues have in the disaster research. The way in which the socioeconomic characteristics affect population dislocation is similar to that found in evacuation studies, which is discussed with further details in section 2.3.4.

2.2 The HAZUS Multi-Hazard Population Dislocation Model

The HAZUS Earthquake Model is designed by Federal Emergency Management Agency (FEMA) to produce loss estimates for use by different levels of governments for planning purposes. The algorithm to estimate the number of displaced households is derived from several pieces of research including Harrald et al. (1990a, 1990b), Harrald et al. (1992), Perkins (1992), and Perkins et al. (1996) that utilizes housing damage data collected from Hurricane Hugo, the Loma Prieta Earthquake, and the Northridge Earthquake to compute uninhabitable units and affected population.

To produce estimates of population dislocation, HAZUS first uses building functions that include fragility curves and building capacity curves to model residential structural damage in an earthquake scenario. The fragility curves are in the form of lognormal functions that relate the probability of being in, or exceeding, a building damage state to for a given response spectrum displacement. Median spectral displacement values and the total variability are developed for each of the model building types and damage states of interest by the combination of performance data from tests of building elements, earthquake experience data, and expert judgment. Figure 2.1 shows the fragility curves for different damage states. Each curve indicates the probability of a structure being in a particular damage state with a given level of ground shaking. The capacity curves are utilized to characterize building response with respect to ground acceleration. They describe the push-over displacement of each building type and seismic design level as a function of laterally-applied earthquake load.

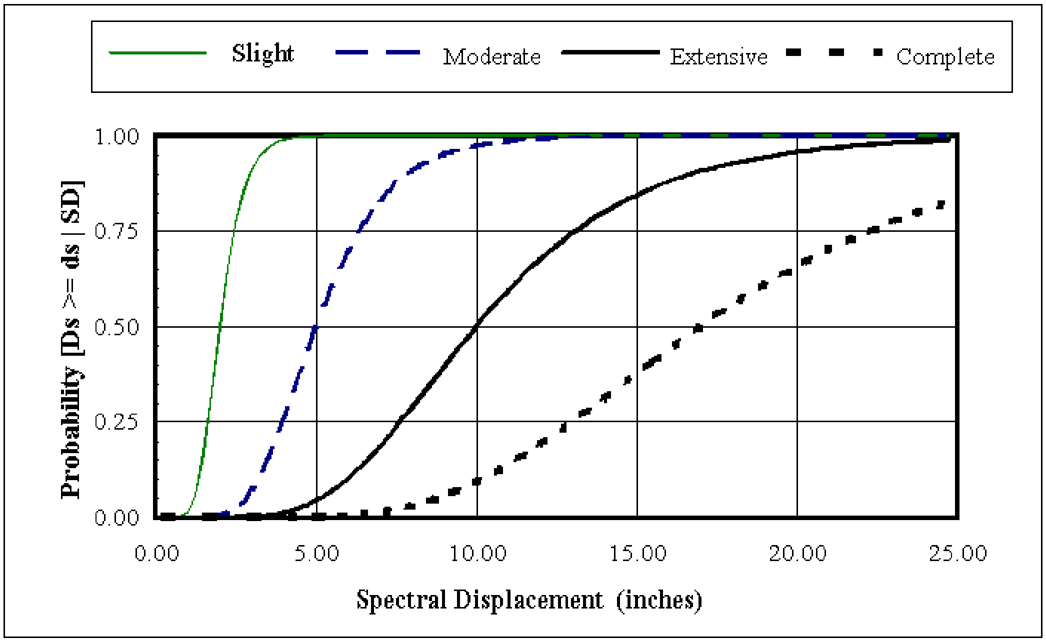

Figure 2.1 Example Fragility Curves for Slight, Moderate, Extensive and Complete Damage (Source: *HAZUS-MH technical manual*).

Input required to estimate building damage using fragility and capacity curves includes model building type (including height) and seismic design level that represent the building of interest, and the response spectrum at the building's site or at the centroid of the census tract where the building is located. The cost of damage is expressed as a percentage of the complete damage state. The assumed relationship between damage states and repair costs for both structural components is listed in Table 2.3.

Table 2.3 Percentage of Repair Cost for Damage States in HAZUS

Damage state	Percent of complete damage
Slight damage	2%
Moderate damage	10%
Extensive damage	50%

Table 2.4 lists all types of residential structures included in the HAZUS. In the population dislocation algorithm, HAZUS only includes the RES1 and RES3 occupancy classes as shown in the table.

Table 2.4 Residential Building Occupancy Classes in HAZUS

No.	Label	Occupancy Class	Description
1	RES1	Single-Family Dwelling	Detached House
2	RES2	Mobile Home	Mobile Home
3	RES3	Multi-Family Dwelling	Apartment/Condominium
4	RES4	Temporary Lodging	Hotel/Motel
5	RES5	Institutional Dormitory	Group Housing (military, college), Jails
6	RES6	Nursing Home	

After acquiring the structural damage of all single-family and multi-family buildings, HAZUS estimates the number of displaced households in a census tract with the following equations.

$$\%SF = W_{SFM} \times \%SFM + W_{SFE} \times \%SFE + W_{SFC} \times \%SFC \qquad [1]$$

$$\%MF = W_{MFM} \times \%MFM + W_{MFE} \times \%MFE + W_{MFC} \times \%MFC \qquad [2]$$

$$\#DH = (\#SFU \times \%SF + \#MFU \times \%MF) \times \left(\frac{\#HH}{\#SFU + \#MFU} \right) \qquad [3]$$

Where $\%SF$: Percent of displacement for single-family residential occupancy class;

W_{SFM}: Weighting factor for moderate structural damage in the single-family residential occupancy class;

$\%SFM$: Damage state percentage for moderate structural damage in the single-family residential occupancy class;

W_{SFE}: Weighting factor for extensive structural damage in the single-family residential occupancy class;

$\%SFE$: Damage state percentage for extensive structural damage in the single-family residential occupancy class;

W_{SFC}: Weighting factor for complete structural damage in the single-family residential occupancy class;

$\%SFC$: Damage state percentage for complete structural damage in the single-family residential occupancy class;

$\%MF$: Percent of displacement for multi-family residential occupancy class;

W_{MFM}: Weighting factor for moderate structural damage in the multi-family residential occupancy class;

$\%MFM$: Damage state percentage for moderate structural damage in the multi-family residential occupancy class;

W_{MFE}: Weighting factor for extensive structural damage in the multi-family residential occupancy class;

$\%MFE$: Damage state percentage for extensive structural damage in the multi-family residential occupancy class;

W_{MFE}: Weighting factor for complete structural damage in the multi-family residential occupancy class;

%MFC: Damage state percentage for complete structural damage in the multi-family residential occupancy class;

#DH: Total number of displaced households in the census tract;

#SFU: Total number of single-family dwelling units in the census tract;

#MFU: Total number of multi-family dwelling units in the census tract;

#HH: Total Number of Households in the census tract;

The default values for W_{SFM}, W_{SFE}, W_{SFC}, W_{MFM}, W_{MFE} and W_{MFC} are specified as the following Table 2.5. These values may be changed by users if warranted by local conditions.

Table 2.5 Default Values for Damage State Percentages (Dislocation Factors)

Weight Factor	Default Value
W_{SFM}	0.0
W_{SFE}	0.0
W_{SFC}	1.0
W_{MFM}	0.0
W_{MFE}	0.9
W_{MFC}	1.0

By default, the HAZUS model assumes that all residents in completely damaged single-family structures and completely damaged multi-family structures, and 90 percent of residents in extensively damaged multi-family structures will leave their homes after a natural disaster.

This dissertation seeks to develop population dislocation algorithms that address two major weaknesses found in the HAZUS algorithm. First, HAZUS assumes that all buildings in a census tract are located on the centroid of that census tract. Under this assumption it can only produce population dislocation estimates at census tract level, which could be inappropriate for some planning purposes. Second, HAZUS assumes that population dislocation is only affected by building structural damage and housing type. In fact, the disaster literature suggests that household dislocation involve complex interactions of many additional factors including disaster type, weather condition, infrastructure disruption, job loss and socioeconomic characteristics of households and their surrounding neighborhoods. Thus, this study will develop new population dislocation algorithms that further include the household and neighborhood socioeconomic characteristics and produce structure level estimates for aggregation at whatever unit requested by users.

2.3 Factors Affecting Population Dislocation Following Natural Disasters

Figure 2.2 is a conceptual diagram that describes the scope of population dislocation and its relationships with evacuation and housing recovery, based on different types of natural hazards. Evacuation is possible only when the natural hazard has environmental cues (Lindell & Prater, 2003; Lindell et al., 2006). Evacuation action is directly affected by evacuation orders and risk perception, with the influence of certain human socioeconomic characteristics. If the disaster does happen and cause damages in a designated area, then people are forced to leave their homes because of the damage to the residential structures and the involvement of the socioeconomic patterns in the area, as well as disaster type, weather conditions, infrastructure disruption, and job loss. Literature discussing the factors that influences the pattern of population dislocation as shown in the figure is summarized in the following sections. This study is focusing on the human socioeconomic characteristics, in addition to the housing structural damage and housing types as employed in the HAZUS model, for the development of population dislocation algorithms.

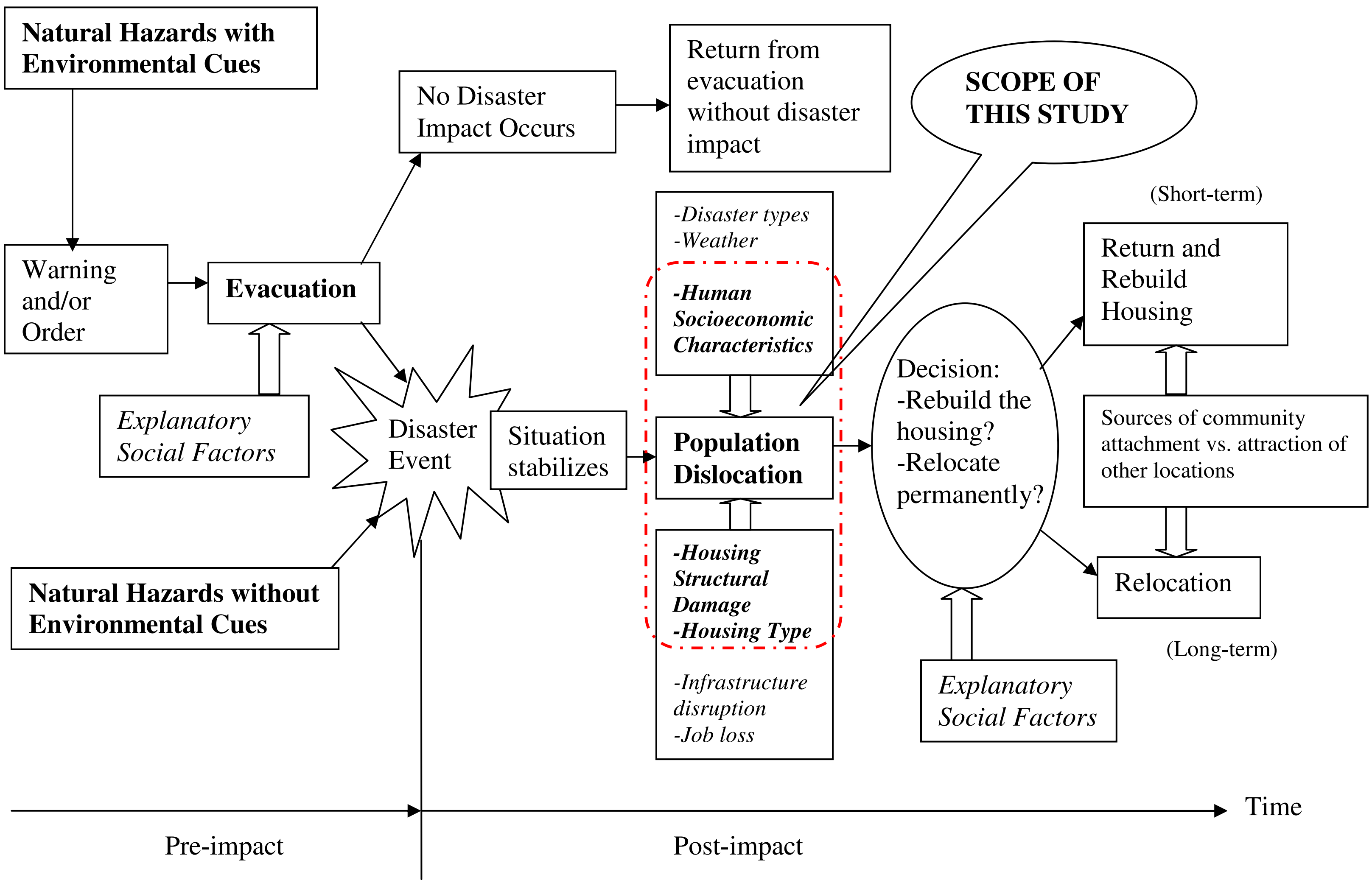

Figure 2.2 Conceptual Diagram Representing the Scope of Population Dislocation in this Study

2.3.1 Housing Structural Damage

Numerous studies point out that the level of housing structural damage is a dominant factor in influencing population dislocation (Comerio, 1998; FEMA, 2003; Harrald et al., 1992; Peacock & Girard, 1997; Quarantelli, 1982a; Smith & McCarty, 1996). These studies provide either qualitative or quantitative evidence to show that households suffering more severe housing damage have a greater tendency to leave their damaged homes.

The assessment of housing damage after a disaster is typically conducted in two steps. First, a preliminary assessment of damage is conducted by a "windshield survey" of the impacted area. This assessment provides state and local officials a basic knowledge of the extent of damage in the area so they can decide whether to ask for a presidential disaster declaration. Following the preliminary assessment, local building departments dispatch their own staffs of inspectors and engineers as well as volunteer engineers and architects provided by professional associations to conduct detailed safety assessments (Comerio, 1998).

The measurement of housing damage is also an important issue to determine its effect on population dislocation. There are several schemes to measure the level of housing damage. In most cases inspectors classify buildings into three categories based on the severity of structural damage (Comerio, 1998; Harrald et al., 1992; Perkins et al., 1996). Buildings with heavy damage and/or clear hazard are red tagged, meaning no entry is allowed. Buildings with some structural damage are yellow tagged, meaning that permission of the local building officials is required to enter the buildings. Buildings found to have minimal or no structural damage are given green tags that mean they are safe to enter. A problem associated with this classification is that inconsistencies tend to occur as structures are assessed and reported by inspectors in different jurisdictions where different criteria are employed (Comerio, 1998). The other common classification approach is the HAZUS scheme which classifies damage into four categories namely slight, moderate, extensive, and complete, based upon the percent of building repair cost.

The logic that housing damage affects population dislocation is straightforward as households have to stay away from their homes because of the loss of housing habitability and safety concerns. However, in many cases, the level of housing damage is not the only factor to influence a household's decision to leave. A household may want to leave because of the aftershocks of a major earthquake, undesirable weather conditions, infrastructure disruption, and so on. The most important of all, the household must have the ability to leave and stay away from home, which is determined by its internal and external resources, and its social networks (Bolin, 1982).

2.3.2 Housing Type

Households' dislocation patterns also vary significantly across housing types. The HAZUS model for estimating the number of dislocated households has different rules for single-family and multi-family housing types (Harrald et al., 1990a, 1990b; Harrald et al., 1992; Perkins, 1992; Perkins et al., 1996). As noted in Table 2.5, households in multi-family structures will leave if the structures are extensively or completely damaged while single-family households will only leave completely damaged structures. Thus, it assumes that households in multi-family units have higher dislocation rates than those in single-family units. In addition, Peacock and Girard's (1997) study shows that households inhabiting multi-family structures and mobile homes are 2.76 to 10.72 times more likely to leave their damaged residences than households living in single-family units.

2.3.3 Disaster Type

Household dislocation after a natural disaster is also influenced by different types of disaster. For example, in the case of a flood disaster, households living in the flooded area have to leave and stay away from their homes for an extended period of time even though their houses are not seriously damaged. They are not able to return until the retreat of the flood and the granting of permission to reenter the area (Quarantelli, 1982b). In this case all households in the area have to leave regardless of the level of housing damage. A similar situation is also observed in the post-earthquake period when many people stay away from their slightly-damaged houses because of the fear of aftershocks. The frequency and magnitude of aftershocks may delay a household's reoccupancy decision. They may stay in commercial facilities (hotels or motels) close to their homes or, in most cases, with friends or relatives outside the impacted area as long as this social network is available (Bolin, 1982).

2.3.4 Weather Condition and Infrastructure Disruption

Infrastructure disruption could involve discontinuation of water, sewer, electric power, fuel, telecommunication, and/or transportation. In addition, unavailable groceries, supplies, schools/education, and hospital/healthcare may also increase the duration of household dislocation. The influence of weather condition on population dislocation is often interrelated with infrastructure disruption. Extreme weather conditions may increase the likelihood of household dislocation, especially when utilities are disrupted at the same time. In very cold or hot weather conditions it is difficult for households to stay in houses without heating or air conditioning even though the structures are not or only slightly damaged. People tend to seek better arrangements instead of staying in their houses during these situations. However, this type of household dislocation is also dependent upon the level of economic resource and social network available to the household.

2.3.5 Job Loss

Job loss in a disaster impact area is inevitable as businesses usually have to close if they have direct physical damage to structures, equipment, inventories, and/or disruption of infrastructure such as electric power, water/sewer, fuel, transportation and telecommunications (Lindell et al., 2006). Alesch et al. (1993), Dahlhamer & D’Souza (1997), Lindell et al. (2006), and Tierney (1997) reported that small businesses are more physically and economically vulnerable than large businesses because they are more likely to be located in non-engineered buildings, less likely to have the capacity to design and implement hazard adjustment programs, and less likely to have resources for business recovery. In addition, owners and employees of small businesses are more likely to be socially vulnerable groups such as ethnic minorities or members of low socioeconomic status. Job loss could compound the difficulty of the household recovery process especially for those of high social vulnerability. Searching for new jobs may be an incentive to out migration in this situation.

2.3.6 Human Socioeconomic Characteristics

The human social system had not yet begun to play an important part in the study of disaster impacts until White and Haas (1975) suggested that the people factors such as social, economic, and political dimensions of disasters be included in the field of hazard research. Since then the social aspect of disaster research and planning has been getting more attention. Recently, the development of the social vulnerability perspective has become popular in disaster planning both among academics and practioners (Blakie, 1994; Lindell et al., 2006). The social vulnerability model in general suggests that disaster impacts on social units with different characteristics vary, depending on the level of their social vulnerability (Blakie, 1994; Cutter et al., 2000, 2003; Lindell & Prater, 2003; Lindell et al., 2006; Peacock & Bates, 1982; Peacock & Girard, 1997). The term social vulnerability was defined by Blakie (1994) as “the characteristics of a person or group in terms of their capacity to anticipate, cope with, resist, and recover from the impact of a natural hazard”. Mileti (1999) proposes a similar concept in which he characterizes the disaster impact as the consequence of interactions of three systems—the natural system, the human system, and the constructed system.

In the case of a natural disaster, population dislocation can be described as a socio-demographic impact after a natural hazard causes physical damage in a community (Lindell & Prater, 2003; Smith & McCarty, 1996; Smith, 1996). The degree of this impact is essentially a function of the severity of physical damage caused by the natural hazard and pre-impact conditions including hazard exposure and physical vulnerability (Blakie, 1994; Cutter et al., 2000, 2003; Lindell & Prater, 2003, Lindell et al., 2006). The way in which the human social system affects population dislocation is through its effect on household mobility, which has been shown to be a result of socioeconomic status or social vulnerability of the household (Fried, 1966; Haas et al., 1977; Heller, 1982; Morrow-Jones & Morrow-Jones, 1991). In previous research socioeconomic factors affecting population dislocation can be summarized as two categories—household socioeconomic characteristics and neighborhood socioeconomic characteristics. This section of review is the focus of this study as these factors are empirically re-analyzed and then incorporated in the population dislocation algorithm.

Household Socioeconomic Characteristics

Income is one of the most common indicators to represent the socioeconomic status of a household (Blakie et al., 1994; Cutter et al., 2003; Lindell et al., 2006; Peacock & Girard, 1997). The ability of a household to get away from the disaster-damaged home is associated with its mobility, which is closely related to its socioeconomic status (Fried, 1966; Haas et al., 1977; Heller, 1982; Morrow-Jones & Morrow-Jones, 1991). Households with higher socioeconomic status often possessed favored accessibility to internal resources such as savings and insurance, and external resources such as credit and governmental aid, which provide them more opportunities during the difficult post-disaster situations (Drabek & Key, 1984; Hartman, 1964). Quarantelli's Wilkes-Barre flood case study (1982b) also found that upper-middle class people were more likely to leave their homes after the disaster than those of middle and working classes.

In the United States, the socioeconomic status of a household can also be explained by ethnicity/race as minorities tend to have limited access to social, economic and political resources (Blakie et al., 1994; Cutter et al., 2003; Lindell & Prater, 2003; Lindell et al., 2006; Peacock & Girard, 1997). Peacock and Girard's (1997) migration study provides consistent quantitative evidence to reveal the adversity faced by Black households that tried to relocate following Hurricane Andrew. However, this study did not show significant difference in post-hurricane migration for Hispanic households. This phenomenon is a result of the heterogeneity among Hispanics; Cubans in Dade County possess social, economic and political power similar to Anglos that is very different from non-Cuban Hispanics (Grenier & Morrow, 1997; Peacock & Girard, 1997).

The effect of home ownership on household dislocation remains unclear in the existing literature. Peacock and Girard's (1997) study shows inconsistent effects of home owners or renters on household relocation. Studies by Fried (1966), Anderson and Weinberg (1979), and Belcher and Bates (1983) also found inconsistent results on how home ownership affects post-disaster population moves. Morrow-Jones and Morrow-Jones' (1991) explanation of this contradiction was that home owners are usually more emotionally tied to their properties even though they also have greater access to the resources needed to relocate. Renters tend to leave once the residential structures are damaged but they also tend to have fewer transportation options and fewer resources to support relocation. The available evidence suggests that the factors promoting home owners' dislocation are almost exactly balanced by the factors inhibiting their dislocation.

In addition to income, ethnicity/race, and home ownership, household characteristics such as having homeowner's insurance, presence of the elderly, or female headed households are also indicated by past research as having a connection with households' socioeconomic status or social vulnerability (Blakie et al., 1994; Cutter et al., 2003; Lindell et al., 2006). However, the nature in which these factors affect population dislocation has not been addressed in the research. Peacock and Girard's (1997) study partly supports the proposition that insured owners are more likely to leave while insured renters are less likely to relocate after Hurricane Andrew. There do not appear to be any other factors on household dislocation that have been reported in the research.

Neighborhood Socioeconomic Characteristics

Neighborhood characteristics also affect on social impacts after a major disaster as residential segregation of ethnic minorities and low-income households has been a major component in the American urban development history (Burgess, 1928; Clark, 1986, 1989; Cowgill, 1956; Massey & Denton, 1987; Peacock & Girard, 1997; Peacock et al., 2007; Zhang, 2006). Even though progress has been made in residential integration during the past few decades, segregation still remains at high levels according to the 1990 and 2000 census data (Iceland et al., 2002).

Peacock and Girard (1997) analyzed the effects of ethnicity and residential segregation on population relocation after Hurricane Andrew. Their findings show that predominantly Black neighborhoods consistently have significantly lower rates of household dislocation. The study also points out that, with the presence of segregation, Hispanic ethnicity consistently shows no significant effects on household relocation. Peacock and Girard (1997) attribute this result to the formation of a "Cuban Enclave" as Cubans in the Miami-Dade area were better able to attain social, economic and political power than other Hispanic groups. This created heterogeneity among Hispanics and further marginalization of Blacks and Mexican Americans. The dislocation pattern of Cuban neighborhoods has not been studied in previous research.

In addition to ethnicity, neighborhoods also differ in median income, percent of renters, vacancy rate, and percent of single-family housing units. No previous research has examined the relationships between these neighborhood characteristics and household dislocation. Nevertheless, as these social characteristics of a neighborhood might also be related to its social vulnerability, it is reasonable to infer that these neighborhood characteristics might affect post-disaster household dislocation.

2.4 Research Hypotheses

As summarized in the literature review, post-disaster population dislocation is affected by the level of housing structural damage, housing type, disaster type, weather conditions, infrastructure disruption, and socioeconomic characteristics of the household and its neighborhood. The algorithms developed in this dissertation seek to improve on the HAZUS model in two ways. The first improvement is to produce structural level dislocation estimates that allow aggregation at whatever unit of analysis requested by users. Second, it attempts to include socioeconomic characteristics in addition to housing structural damage and housing type as employed in the HAZUS model. As a result, it is imperative to examine the significance of effects that these socioeconomic factors have on household dislocation. Specifically, this study addresses seven research hypotheses derived from the literature review.

The research hypotheses are presented in two groups. The first group—consisting of H1, H2, and H3—examines how household dislocation is affected by the household characteristics including building damage, household ethnicity, home ownership, and housing type. The second group—consisting of H4, H5, H6, and H7—examines how household dislocation is affected by neighborhood socioeconomic and housing characteristics. These hypotheses are presented individually below.

H1: Building damage will significantly increase the likelihood of household dislocation following a disaster.

Studies by Harrald et al. (1990a, 1990b), Harrald et al. (1992), Peacock and Girard (1997), Perkins (1992), and Perkins et al. (1996) all showed that building damage significantly increases household dislocation following a disaster. However, the degree of building damage in these studies is measured using an ordinal scale. This dissertation uses a ratio scaled variable, percent building value loss, to measure the degree of building damage. It assumes that the loss of value equals the loss of function. A ratio scaled variable is more accurate than an ordinal variable in reflecting the state of building damage, and thus may improve the precision of the statistical analysis and estimates produced by the population dislocation algorithms. Of course, this advantage in accuracy would be lost if the building inspectors cannot reliably discriminate damage levels beyond the four basic categories.

H2: Ethnic minority status of households will significantly decrease the likelihood of household dislocation following a disaster.

Households of lower socioeconomic status tend to have less access to internal or external resources that affect their post-disaster mobility. Evidence in disaster research indicates that the socioeconomic status of a household can partially be explained by ethnicity/race, as minorities tend to have limited access to social, economic and political resources (Blakie et al., 1994; Cutter et al., 2003; Lindell & Prater, 2003; Lindell et al., 2006; Peacock & Girard, 1997).

H3: Households living in single-family housing units will have a significantly lower level of household dislocation following a disaster.

This hypothesis is based on Peacock and Girard' study (1997) and the studies on which the HAZUS model is based, which both showed that households living in multi-family units or mobile homes are more likely to leave their homes than those living in single family units following a disaster.

H4: Neighborhood minority composition will significantly decrease the likelihood of household dislocation following a disaster.

H5: Neighborhood income level will significantly increase the likelihood of household dislocation following a disaster.

H6: Neighborhood renter composition will significantly increase the likelihood of household dislocation following a disaster.

H7: Neighborhood single-family housing composition will significantly decrease the likelihood of household dislocation following a disaster.

The rationale for H4, H5, H6, and H7 is that households of similar socioeconomic status such as ethnicity, income, tenure, and type of housing are often clustered because of the residential segregation as described in the literature review. Households living in neighborhoods predominantly occupied by minorities, the poor, and renters tend to have less access to resources and networks required to leave disaster-damaged homes. In addition, Peacock and Girard (1997) also found that neighborhoods predominantly occupied by ethnic minorities or population of lower socioeconomic status tend to suffer greater levels of housing damage.

3. METHODS

This study develops two population dislocation algorithms. The first algorithm utilizes a modified HAZUS approach that bases the estimation on structural damage and anticipated variations in dislocation between single and multi-family structures. The second algorithm is formulated in the following steps known as the research-based approach. First, it utilizes the South Dade County Population Impact Survey (SDPIS) integrated with the 1990 Miami-Dade County Census Data and Housing Tax Appraisal Database to empirically examine the effects of household and neighborhood socioeconomic characteristics on household dislocation. Logistic regression models are employed to test the research hypotheses. Then the socioeconomic factors are selected to formulate the algorithm based on their statistical significance, overall model performance, empirical meaningfulness, and availability of data in the MAEviz system. Finally both algorithms are implemented in MAEviz—a seismic loss assessment system developed by Mid-America Earthquake (MAE) Center at University of Illinois-Urbana Champaign and National Center for Supercomputing Applications (NCSA)—which allows sensitivity analysis and evaluation of population dislocation estimates computed according to various earthquake scenarios. This chapter introduces the data sources, data preparation, and analytical approach to be employed in the analyses and algorithm formulation.

3.1 Data Preparation

3.1.1 Datasets

South Dade County Population Impact Survey

The SDPIS was conducted by means of face-to-face interviews during the late summer and early fall of 1993, with a supplemental interviews conducted during December. In this survey, 248 Census blocks (218 regular and 30 special) were selected, mapped, and sampled, resulting in 2,990 housing units being selected (Peacock et al., 1997). Multiple visits were made to ensure that the household occupying each housing unit was interviewed to gather information on ethnic/racial status, movement by household members following the storm, insurance coverage, and residency status of each occupant for various time periods during 1993 (Peacock et al., 1997).

1990 Census Data for Miami-Dade County

Census data complement the SDPIS by providing population and housing information at multiple levels of aggregation, including states, counties, cities and towns, ZIP codes, census tracts, and census blocks. Integration of census and SDPIS data provides the survey observations with neighborhoods' population and housing characteristics. This makes it possible to assess the effects of households' and neighborhoods' socioeconomic characteristics on population dislocation. Table 3.1 summarizes the information available from two census survey forms. The short form asks a limited number of questions of every person and housing unit in the United States.

The long form has additional questions that were asked of a sample of households (generally 1 in 6).

Table 3.1 Information Available from Census Data

Survey Type		
100-percent characteristics (short form)	Sample characteristics (long form)	
	Population	Housing
	-Ancestry	
-Age	-Disability	-Farm residence
-Hispanic or Latino origin	-Grandparents as caregivers	-Heating fuel
-Household relationship	-Income in 1999	-Number of rooms and number of bedrooms
-Race	-Labor force status	-Plumbing and kitchen facilities
-Sex	-Language spoken at home and ability to speak English	-Telephone service
-Tenure (whether the home is owned or rented)	-Marital status	-Units in structure
-Vacancy characteristics	-Migration (residence in 1995)	-Utilities, mortgage, taxes, insurance, and fuel costs
	-Occupation, industry, and class of worker	-Value of home or monthly rent paid
	-Place of birth, citizenship, and year of entry	-Vehicles available
	-Place of work and journey to work	-Year moved into residence
	-School enrollment and educational attainment	-Year structure built
	-Veteran status	
	-Work status in 1999	

Source: U.S. Census Bureau (2007b)

Housing Tax Appraisal Database

These data provide a basis for computing the level of housing damage for each structure in terms of percent building value loss due to the hurricane impact. The housing tax appraisal database provides the housing values before (1992) and after (1993-1996) Hurricane Andrew. The use of these tax appraisal values is justified because the tax assessor's office starts the appraisal process in the beginning of every year to appraise the value of each structure and land parcel in the county. Hurricane Andrew hit Miami-Dade County on August 24, 1992 when the appraisal process for the year was already finished and property tax notices were on the way to owners. In the following year, the tax assessor's office re-appraised the properties to estimate the actual values of land and structures from about 5 to 10 months after the hurricane. The appraisal values in 1993 can properly reflect the state of damaged housing because the findings of Wu and Lindell's (2004) study of housing recovery after Northridge Earthquake suggests that mass reconstruction starts 4 to 5 months or more after the disaster. As a result, it is reasonable to justify the use of the housing value loss from 1992 to 1993 to represent the level of housing damage caused by Hurricane Andrew.

3.1.2 Data Integration

Figure 3.1 shows the geographic locations of SDPIS interviews in relation to the Hurricane Andrew track and the Miami-Dade County boundaries. A geographic information system (ArcGIS 9.2) and the Statistical Package for the Social Sciences (SPSS 15) were utilized to integrate the three datasets. First, the population survey data and housing tax appraisal data were geo-coded in ArcGIS. Then the point-to-point spatial join function was performed to link the two geo-coded datasets so the observations in the output dataset would have information from both the population survey data and the tax appraisal data. Second, as the population survey dataset already has variables that identify blocks and block groups in which particular observations are located, the census dataset therefore could be merged into the abovementioned output dataset in SPSS by using these identification variables as key variables. The final version of the output dataset has all the information in the housing tax appraisal data and census data at both block and block group levels.

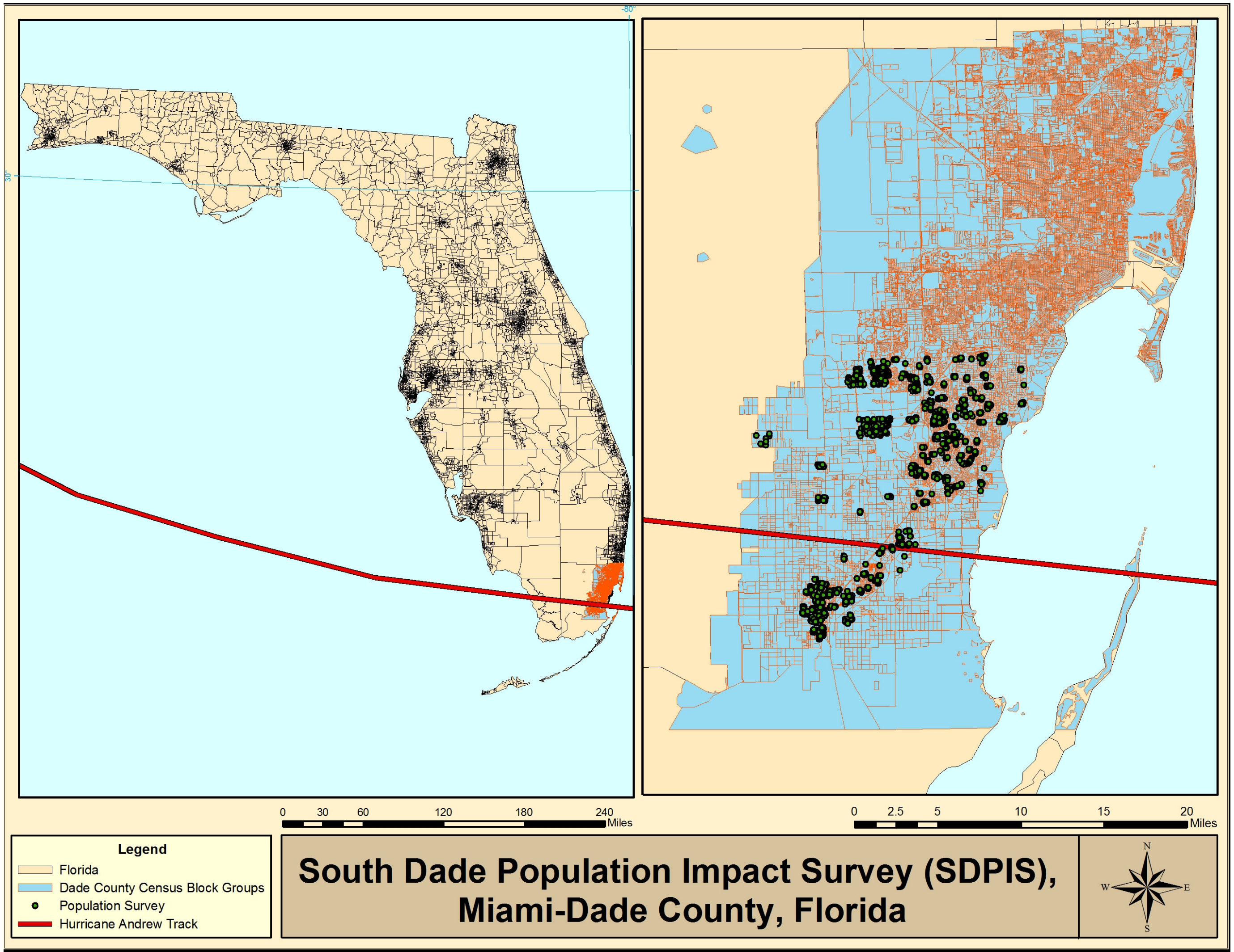

Figure 3.1 SPDIS Interviews and the Miami-Dade County Study Area

Dependent and Independent Variables

Two pieces of information collected in the SDPIS are integrated to create the dependent variable. They are the last result code indicating the final status of all interviews in the SDPIS and a question asking whether or not the household left their home due to the housing damage caused by Hurricane Andrew. The dependent variable is binary indicating whether (=1) or not (=0) household had been dislocated after Hurricane Andrew.

The independent variables are split into two major categories. The first one contains the household-level information mainly acquired from the SDPIS and tax appraisal database. These variables include household ethnic status, home ownership, housing type, and percentage of housing value loss due to damage caused by Hurricane Andrew. The qualitative information about households is coded as dummy variables. The second category has neighborhood-level information such as percentages of Black, Hispanic, Cuban, non-Cuban Hispanic, renters, vacant housing units, and single-family detached homes, as well as median household income in block groups. The independent variables to be employed in this study are listed in Table 3.2.

Table 3.2 List of Variables and Descriptions

Concept	Variable	Description	Data Source
Household Level Variables			
Dependent variable	d_dislocation	Household dislocation status: dislocated = 1; never dislocated = 0	SDPIS
Housing structural damage	pvloss_bldg	Building appraisal value loss: (BuildingValue93-BuildingValue94) / (BuildingValue93) * 100	Tax appraisal data
Household housing and socioeconomic characteristics	d_sfd	Housing structure type: single-family detached home= 1; others = 0	SDPIS
	d_white	Ethnic status: White = 1; others = 0	SDPIS
	d_black	Ethnic status: Black = 1; others = 0	SDPIS
	d_hispanic	Ethnic status: Hispanic = 1; others = 0	SDPIS
	d_other	Ethnic status: Ethnicity other than White, Black or Hispanic = 1; White, Black or Hispanic = 0	SDPIS
	d_renter	Home ownership status: Renters = 1; owners = 0	Tax appraisal data
Neighborhood Level Variables			
Neighborhood housing and socioeconomic characteristics	p_sfd_bg	Percentage of single-family detached homes	1990 block group census data
	p_whitenh_bg	Percentage of non-Hispanic White population	1990 block group census data
	p_blacknh_bg	Percentage of non-Hispanic Black population	1990 block group census data
	p_hispanic_bg	Percentage of Hispanic origin population	1990 block group census data
	p_cuban_bg	Percentage of Cuban population	1990 block group census data
	p_ncubanh_bg	Percentage of non-Cuban Hispanic population	1990 block group census data
	p_renter_bg	Percentage of renter occupied units	1990 block group census data
	p_vacant_bg	Percentage of vacant units	1990 block group census data
	mhhinc_bg	Block group median household income	1990 block group census data

3.2 Analytical Approach

In a quantitative study, the analytical approach to be adopted is primarily based on the nature of the dependent variable. Ordinary least squares (OLS) regression is the most widely employed approach to analyze pooled cross-sectional data in the social sciences studies because of its direct logic and easily comprehensible principles (Wooldridge, 2005). However, in many cases the dependent variable has substantively restricted range of values. These types of dependent variable are called limited dependent variables (LDV), such as a binary variable, a count variable, or a multi-categorical variable (Wooldridge, 2005). One frequently adopted approach to model these limited dependent variables is the use of an underlying unobserved latent variable that is specified as a linear function of one or more independent variables. The relationship between the observed and latent variables is specified based on the nature of the response variable. Commonly used examples of these relationships include the logit or probit function for binary responses, Poisson function for count responses, or Tobit function for non-negative responses.

In this study the logit model is the most appropriate approach because the dependent variable is dichotomous indicating whether (=1) or not (=0) the household was dislocated after the disaster. The logit model assumes that the natural logarithm of odds of event 1 is a linear function of a set of independent variables, which can be specified as the following equation.

$$\ln\{\Pr(1)/[1-\Pr(1)]\} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + \mu \qquad [4]$$

Here the latent variable is the logit function shown as the left part of the equation. The error component μ represents all the other factors, including unobserved and random errors or factors, which might be influencing the logit. The parameters β_0, β_1, β_2, ..., β_k are estimated by the maximum likelihood method which is different from the least squares method in the OLS model. The independent variables to be employed in the population dislocation algorithm will be selected through an empirical examination. Then the algorithm predicting the probability of household dislocation can be formulated as the following equation.

$$\Pr(1) = 1/\{1 + EXP[-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 ... + \beta_k X_k)]\} \qquad [5]$$

The default probability cutoff value is .5 which means that the households have probabilities of .5 or more are classified as dislocated households. The number of dislocated households can then be calculated at the level of aggregation based on specific planning purposes.

4. DATA ANALYSIS

4.1 Preliminary Analysis

Table 4.1 presents the descriptive statistics for the household variables from SDPIS and the neighborhood variables from the 1990 block group census data for Miami-Dade County. Several points in the descriptive statistics are worth mentioning. First, the mean of the dependent variable shows that 53.8% of the surveyed households had ever been dislocated after Hurricane Andrew. Second, the average building value loss for the surveyed households is 61.5%. These two numbers indicate that there will be enough variance in the dependent variable and one of the primary independent variables to avoid range restrictions (Lindell, 2008). Moreover, 42.07%, 24.01% and 31.06% of the surveyed households are White, Black and Hispanic respectively, which are similar to the mean White (47.86%), Black (22.77%) and Hispanic (27.20%) percentages as shown in the census data. The single-family detached housing percentage in the SPDIS (56.64%) and census data (60.70%) are also similar. These numbers show that the SDPIS sample is representative of the Miami-Dade county population at large.

Table 4.1 Descriptive Statistics of Variables

Household level variables (N=1329 when missing values excluded listwise)				
Variable	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
d_dislocation (N=2108)	.5380	.4987	.00	1.00
d_white (N=1645)	.4207	.4938	.00	1.00
d_black (N=1645)	.2401	.42729	.00	1.00
d_hispanic (N=1645)	.3106	.46290	.00	1.00
d_other (N=1645)	.0286	.1667	.00	1.00
d_sfna (N=2754)	.5664	.49565	.00	1.00
d_renter (N=2406)	.5702	.49514	.00	1.00
pvloss_bldg (N=2924)	61.4962	32.9098	.01	100.00
Neighborhood level variables (N=85)				
Variable	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
p_whitenh_bg	47.8597	25.9407	.68	87.39
p_blacknh_bg	22.7680	28.0552	.39	97.62
p_hispanic_bg	27.1956	16.1492	.67	68.00
p_cuban_bg	9.4068	7.8533	.00	35.47
p_ncubanh_bg	17.7888	12.6038	.67	61.99
p_renter_bg	30.6062	20.5815	2.36	82.58
p_vacant_bg	8.9794	8.0284	1.24	59.79
p_sfna_bg	60.6958	28.2967	0.5362	100.00
mhhinc_bg	37.6827	22.9650	8.1610	150.0010

As to the neighborhood ethnic characteristics, Black percentage has a maximum of 97.62% and a standard deviation of 28.06, which indicates a high concentration of Blacks in some block groups and a large variation among block groups. The Hispanic percentage has a lower maximum (68.00%) and standard deviation (16.15), which means predominant Hispanic neighborhoods are more mixed with non-Hispanics and thus less segregated than Blacks. Similar patterns are found when Hispanics are divided into Cuban and non-Cuban ethnic groups. Cubans are the least segregated ethnic group among the three. Regarding other neighborhood characteristics, renter percentage has a maximum of 82.58% meaning that renters in some block groups are considerably segregated. Vacant housing percentage has a mean of 8.98%, which indicates a rough 90% housing occupancy rate in this area. In addition, the majority of the housing stock in the area is single family detached housing (60.70%). Finally, the block group median household income has a mean of $37,683, a minimum of $8,161, and a maximum of $150,001, showing a large income inequality among neighborhoods in this area.

Table 4.2 lists the cross-tabulations between the dependent variable and the dummy independent variables. The table further reveals the dislocation patterns across ethnicities, tenure statuses, and housing types. Among the Black households 32.3% experienced dislocation. A similar pattern is found in Hispanic households where only 38.3% were able to leave. With regard to the home ownership, 51.2% dislocated households were renters while the rest 48.8% were owners. Finally, as to the housing types, 45.8% dislocated households were living in single-family detached homes while 54.2% of them were living in other housing types.

Table 4.2 Cross-tabulation of Variables

			d_dislocation 0	d_dislocation 1	Total
d_white	0	Count	584	317	901
		% within d_white	64.8%	35.2%	100.0%
	1	Count	367	266	633
		% within d_white	58.0%	42.0%	100.0%
	Total	Count	951	583	1534
		% within d_white	62.0%	38.0%	100.0%
d_black	0	Count	700	463	1163
		% within d_black	60.2%	39.8%	100.0%
	1	Count	251	120	371
		% within d_black	67.7%	32.3%	100.0%
	Total	Count	951	583	1534
		% within d_black	62.0%	38.0%	100.0%
d_hispanic	0	Count	653	398	1051
		%within d_hispanic	62.1%	37.9%	100.0%
	1	Count	298	185	483
		%within d_hispanic	61.7%	38.3%	100.0%
	Total	Count	951	583	1534
		%within d_hispanic	62.0%	38.0%	100.0%
d_other	0	Count	916	571	1487
		%within d_other	61.6%	38.4%	100.0%
	1	Count	35	12	47
		%within d_other	74.5%	25.5%	100.0%
	Total	Count	951	583	1534
		%within d_other	62.0%	38.0%	100.0%
d_renter	0	Count	401	319	720
		%within d_renter	55.7%	44.3%	100.0%
	1	Count	475	499	974
		%within d_renter	48.8%	51.2%	100.0%
	Total	Count	876	818	1694
		%within d_renter	51.7%	48.3%	100.0%
d_sfd	0	Count	379	449	828
		%within d_sfd	45.8%	54.2%	100.0%
	1	Count	580	491	1071
		%within d_sfd	54.2%	45.8%	100.0%
	Total	Count	959	940	1899
		%within d_sfd	50.5%	49.5%	100.0%

To preliminarily identify the relationships between the explanatory factors and their effects on population dislocation, Table 4.3 lists the bivariate pairwise correlations for all variables. Amid the household characteristics summarized in the literature review, housing structural damage has the largest with household dislocation ($r = .637$). As expected, this correlation is positive and statistically significant.

Regarding the household ethnicity, White ethnicity has a significantly positive correlation with household dislocation ($r = .069$). This is consistent with previous findings that White households generally have a higher socioeconomic status that provides them more options and greater mobility to leave their homes after the disaster. The significantly negative correlation between Black ethnicity and household dislocation ($r = -.066$) shows that Blacks are less likely to leave their homes after the disaster. In addition, Black ethnicity also has a significantly positive correlation with housing structural damage ($r = .205$). The two correlations indicate that Blacks suffered more severe housing damage but, nonetheless, they were less able to leave damaged homes. As a result, Blacks could be the major population who are in dire need of shelter after the disaster. By contrast, however, Hispanic ethnicity does not have a significant correlation with household dislocation ($r = .004$). This nonsignificant correlation could be a result of the mix of Cubans and non-Cubans in the Hispanic ethnicity. As noted earlier, Peacock and Girard (1997) identified a specific “Cuban Enclave” in the Miami area where Cubans have much stronger economic and political powers than other Hispanics.

Table 4.3 Correlations of Variables

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.
1. d_dislocation																	
2. pvloss_bldg	.367**																
3. d_sfd	-.083**	-.010															
4. d_white	.069**	-.067**	.201**														
5. d_black	-.066**	.205**	-.052*	-.479**													
6. d_hispanic	.004	-.091**	-.155**	-.572**	-.377**												
7. d_other	-.046	-.075**	-.027	-.146**	-.096**	-.115**											
8. d_renter	.069**	.081**	-.510**	-.214**	.134**	.107**	-.009										
9. p_sfd_bg	-.123**	-.063**	.564**	.174**	-.021	-.157**	-.025	-.370**									
10. p_whitenh_bg	.167**	-.033	.156**	.490**	-.492**	-.069**	.001	-.246**	.160**								
11. p_blacknh_bg	-.110**	.149**	-.042*	-.369**	.642**	-.188**	-.031	.151**	-.005	-.760**							
12. p_hispanic_bg	-.061**	-.164**	-.160**	-.112**	-.297**	.377**	.044	.106**	-.222**	-.227**	-.457**						
13. p_cuban_bg	-.059**	-.236**	.018	-.033	-.289**	.300**	.004	-.092**	.049**	-.072**	-.418**	.706**					
14. p_ncubanh_bg	-.045*	-.076**	-.222**	-.129**	-.218**	.318**	.056*	.195**	-.325**	-.258**	-.357**	.906**	.340**				
15. p_renter_bg	.007	.020	-.434**	-.310**	.218**	.126**	.009	.392**	-.661**	-.484**	.320**	.191**	-.142**	.338**			
16. p_vacant_bg	.042	.162**	-.356**	-.191**	.120**	.093**	.000	.291**	-.537**	-.164**	.120**	.069**	-.121**	.164**	.169**		
17. mhhinc_bg	-.048*	-.297**	.294**	.356**	-.360**	-.060*	.034	-.319**	.523**	.612**	-.517**	-.079**	.196**	-.222**	-.645**	-.381**	

Note: 1. ** Correlation is significant at the .01 level (2-tailed); * Correlation is significant at the .05 level (2-tailed).
2. Sample sizes range from 1465 to 2994.
3. Household-level variables: d_dislocation = dislocated; pvloss_bldg = percentage of building appraisal value loss; d_sfd = single family detached home; d_white = White ethnicity; d_black = Black ethnicity; d_hispanic = Hispanic ethnicity; d_other = other ethnicity.
4. Neighborhood (block group) -level variables: p_sfd_bg = percentage of single family detached homes; p_whitenh_bg = percentage of non-Hispanic Whites; p_blacknh_bg = percentage of non-Hispanic Blacks; p_hispanic_bg = percentage of Hispanics; p_cuban_bg = percentage of Cubans; p_ncubanh_bg = percentage of non-Cuban Hispanics; p_renter_bg = percentage of renters; p_vacant _bg = percentage of vacant housing units; mhhinc_bg = median household income.

Households living in single-family detached homes are significantly less likely to experience dislocation (r = -.083). This finding coincides with the assumption of HAZUS model and Peacock and Girard's (1997) finding that households living in multi-family homes were more likely to leave after the disaster. As to tenure status, renters have a significantly higher likelihood of household dislocation (r = .069). This is understandable as renters would escape without worrying about damage to the properties they occupy. However, owners are more emotionally tied to their properties than renters because they are more likely to spend time designing or remodeling their homes to create specific aesthetics or functions for their needs.

When it comes to neighborhood characteristics, the block group White percentage has a significantly positive correlation with household dislocation (r = .167). On the other hand, the block group Black percentage also has a significantly negative correlation with household dislocation (r = -.110). Both of them are consistent with the corresponding correlations at the household level. However, the neighborhood Hispanic percentage has a significantly negative correlation with household dislocation (r = -.061), which is inconsistent with the result found at the household level. It might be interpreted that households living in predominant Hispanic neighborhoods experience more difficulty in leaving homes after the disaster. In this case, the effect of neighborhood ethnic percentage is stronger than the effect of household ethnicity. This pattern is also found in Whites and Blacks as the magnitudes of correlations between neighborhood ethnic percentages and household dislocation are stronger than those between household ethnicities and dislocation.

When the Hispanics are divided into Cubans and non-Cubans, the correlations turn out to be inconsistent with previous findings. Both Cuban percentage (r = -.059) and non-Cuban Hispanic percentage (r = -.045) have significantly negative correlations with household dislocation. The “Cuban Enclave” effect on population dislocation is not observed in the correlation analysis. Nevertheless, it will be further tested in the logistic regression analysis.

In addition to the correlations between neighborhood ethnic percentages and household dislocation, the correlations among neighborhood ethnic percentages imply several ethnic segregation phenomena in this area. First, the significantly negative correlation between White and Black percentages (r = -.760) indicates that Whites and Blacks are extremely segregated from each other. Second, Whites are less segregated from Hispanics (r = -.227), especially Cubans (-.072). On the other hand, Blacks are highly segregated from Hispanics (r = -.457), as well as Cubans (r = -.418). Finally, Cubans and non-Cuban Hispanics are integrated but not especially strongly(r = .340).

As for home ownership, block group renter percentage has a positive correlation with household dislocation (r = .007), which is similar to the earlier finding at the household level except the correlation is weak and insignificant here. The percentage of single-family detached dwelling units in block groups has a significantly negative correlation with household dislocation (r = -.123). This is also consistent with the correlation found between single-family detached home and household dislocation. Finally, block group median household income—the essential factor that represents neighborhood socioeconomic status—has a significantly negative correlation with household dislocation ($r = -.048$). This result contradicts the findings summarized in the literature review. However, the preliminary zero-order correlation analysis explores only the relationship between each independent variable and the dependent variable. It cannot identify the causal effects or differentiate between indirect effects and direct effects. As a result, further analyses are needed to assess the unique contribution of each predictor and determine each individual variable's effect on population dislocation.

4.2 Analysis with Logistic Regression Model

To further understand the unique effect of each household or neighborhood characteristic on household dislocation when controlling for other variables, we utilize logistic regression analysis, which employs a latent logit function to transform the binary dependent variable into a continuous and unbounded variable that can be specified as a linear function of a set of independent variables.

Two sets of logistic regression models are analyzed to separately assess the effects of household and neighborhood characteristics on household dislocation. In addition to the empirical examination, the analysis also seeks to find out a model for algorithm development where a set of independent variables is selected based on the model R-square, significance of the coefficient, empirical meaningfulness of variables, and availability of building inventory and census data in the MAEviz package.

4.2.1 The Effects of Household Characteristics

The logistic regression analysis starts with the base model Model 1, which includes only housing structural damage as the independent variable. Then each of the household and neighborhood characteristics is examined controlling for housing structural damage and the other characteristics. The correlation analysis already indicates that housing structural damage is the primary factor to influence household dislocation.

Model 2 studies the effects of household characteristics on population dislocation. The independent variables employed in the analysis include percentage of building value loss, and qualitative dummy variables representing single-family detached homes, Blacks, Hispanics, and renters. Model 1 and Model 2 are specified as the following equations respectively.

$$\ln\{\Pr(1)/[1-\Pr(1)]\} = \beta_0 + \beta_1(pvloss\_bldg) + \mu \qquad [6]$$

$$\begin{aligned}\ln\{\Pr(1)/[1-\Pr(1)]\} &= \beta_0 + \beta_1(pvloss\_bldg) + \beta_2(d\_sfd) \\ &+ \beta_3(d\_black) + \beta_4(d\_hispanic) + \beta_5(d\_renter) + \mu\end{aligned} \qquad [7]$$

Table 4.4 lists the result of the logistic regression models using housing structural damage and household characteristics as independent variables to predict the logarithm of odds of household dislocation. The logistic regression result for Model 1 show that housing structural damage has a significantly positive effect on household dislocation.

For every percent increase in building value loss, the odds for household dislocation increases by 2.4 percent. However, when the household characteristics are added in the analysis, the R-square of Model 2 as well as the effect of housing structural damage decrease considerably comparing to those found in Model 1. The decrease of R-square could be a result of the huge drop in the number of valid cases in the analysis after adding the household characteristics. The household ethnic information is available mostly from completed interviews, which account for only 54% of total interview attempts in the SDPIS. The huge drop of valid cases largely decreases the strong contribution of housing structural damage to the R-square of Model 2 even though more variables are added. A further forward selection analysis reveals that all household characteristics but d_black in Model 2 have insignificant increase in the R-square.

Table 4.4 Results of Logistic Regression Models Examining the Effects of Housing Structural Damage and Household Characteristics

Variable Categories	Variables	Model 1			Model 2		
		β	EXP(β)	p	β	EXP(β)	p
Housing structural damage	pvloss_bldg	0.024	1.024	0.000	0.018	1.018	0.000
Household characteristics	d_black				-0.661	0.517	0.000
	d_hispanic				-0.076	0.927	0.593
	d_sfd				-0.207	0.813	0.131
	d_renter				0.196	1.215	0.193
Constant		1.384	0.251	0.000	-1.423	0.241	0.000
N (Total N: 2994)		2038			1329		
Nagelkerke R-square		0.174			0.114		
Cox & Snell R-square		0.130			0.084		

Black ethnicity is the only household characteristic having a significant effect on household dislocation. As shown in Model 2, the d_black has an odds ratio of 0.517 indicating that being Black households decreases the odds of dislocation by 48.3%, compared to non-Black households. As to Hispanic ethnicity, single-family detached housing and renter status, no significant effect is found for any of the three variables even though the directions of their effects are consistent with the findings in the literature.

4.2.2 The Effects of Neighborhood Characteristics

Models 3 and 4 analyze the effects of neighborhood characteristics on household dislocation, controlling for the hosing structural damage. Model 3 includes the percentages of non-Hispanic Blacks, Hispanics, renters, vacant housing units and single-family detached homes as well as median household income in block groups. Model 4 is essentially identical to Model 3 except for splitting Hispanics into Cubans and non-Cubans. The two models are specified as follows.

$$\begin{aligned}\ln\{\Pr(1)/[1-\Pr(1)]\} &= \beta_0 + \beta_1(pvloss\_bldg) + \beta_2(p\_blacknh\_bg) \\ &+ \beta_3(p\_hispanic\_bg) + \beta_4(p\_renter\_bg) + \beta_5(p\_vacant\_bg) \\ &+ \beta_6(mhhinc\_bg) + \beta_7(p\_sfd\_bg) + \mu \qquad [8]\end{aligned}$$

$$\ln\{\Pr(1)/[1-\Pr(1)]\} = \beta_0 + \beta_1(pvloss\_bldg) + \beta_2(p\_blacknh\_bg)$$
$$+ \beta_3(p\_cuban\_bg) + \beta_4(p\_ncubanh\_bg) + \beta_5(p\_renter\_bg)$$
$$+ \beta_6(p\_vacant\_bg) + \beta_7(mhhinc\_bg) + \beta_8(p\_sfd\_bg) + \mu \qquad [9]$$

Table 4.5 lists the results of the two logistic regression models. In Model 3, all neighborhood factors are shown to have negative effects on household dislocation. Specifically, three factors including percentages of non-Hispanic Blacks, renters, and single-family detached homes, have significant effects on household dislocation. Every percent increase in non-Hispanic Black population in a block group decreases the odds of household dislocation by 1%. Similarly, every percent increase in single-family detached homes in a block group decreases the odds of household dislocation by 2.4%. Results for both factors are consistent with findings in the literature. Surprisingly, the renter percentage decreases the odds of household dislocation, which obviously conflicts the findings in earlier studies. For every percent increase in renters in a block group, the odds of household dislocation decreases by 2.7%. The discrepancy might be a result of the strong positive correlation of percentages between Hispanics and renters. The percentage of renters might therefore pick up the negative effect that the percentage of Hispanic has on household dislocation because of the correlation.

Table 4.5 Results of Logistic Regression Models Examining the Effects of Housing Structural Damage and Neighborhood Characteristics

Variable Categories	Variables	Model 3			Model 4		
		β	EXP(β)	p	β	EXP(β)	p
Housing structural damage	pvloss_bldg	0.027	1.027	0.000	0.027	1.027	0.000
Neighborhood characteristics	p_blacknh_bg	-0.010	0.990	0.002	-0.011	0.989	0.001
	p_hispanic_bg	-0.005	0.995	0.239			
	p_cuban_bg				0.004	1.004	0.622
	p_ncubanh_bg				-0.011	0.989	0.064
	p_renter_bg	-0.027	0.974	0.000	-0.024	0.976	0.000
	p_vacant_bg	-0.019	0.981	0.076	-0.015	0.985	0.190
	mhhinc_bg	-0.001	0.999	0.745	-0.002	0.998	0.637
	p_sfd_bg	-0.024	0.976	0.000	-0.023	0.977	0.000
Constant		1.266	3.547	0.008	1.185	3.271	0.013
N (Total N: 2994)			2038			2038	
Nagelkerke R-square			0.245			0.246	
Cox & Snell R-square			0.184			0.185	

When the Hispanics are divided into Cubans and non-Cubans, as shown in Model 4, the coefficients for percentages of non-Hispanic Blacks, renters, vacant units and single-family detached houses, as well as median household income, are very close to those found in Model 3. Furthermore, when we conduct a 1-tailed test, the non-Cuban Hispanic percentage has a significantly negative effect on household dislocation, which is consistent with the findings in literature. However, the Cuban percentage still has no significant effect on household dislocation.

For the purpose of algorithm development, this study further analyzes two models that include the household dummy variable representing single-family detached housing and neighborhood characteristics, as housing type is a valuable piece of structure-level information available from the building inventory data in MAEviz. Similar to the earlier Models 3 and 4, Model 5 treats Hispanics as a single group while Model 6 splits them into Cubans and non-Cubans. Models 5 and 6 are specified as the following equations.

$$\begin{aligned}&\ln\{\Pr(1)/[1-\Pr(1)]\} = \beta_0 + \beta_1(pvloss\_bldg) + \beta_2(d\_sfd)\\&+\beta_3(p\_blacknh\_bg) + \beta_4(p\_hispanic\_bg) + \beta_5(p\_renter\_bg)\\&+\beta_6(p\_vacant\_bg) + \beta_7(mhhinc\_bg) + \mu\end{aligned} \qquad [10]$$

$$\begin{aligned}&\ln\{\Pr(1)/[1-\Pr(1)]\} = \beta_0 + \beta_1(pvloss\_bldg) + \beta_2(d\_sfd)\\&+\beta_3(p\_blacknh\_bg) + \beta_4(p\_cuban\_bg) + \beta_5(p\_ncubanh\_bg)\\&+\beta_6(p\_renter\_bg) + \beta_7(p\_vacant\_bg) + \beta_8(mhhinc\_bg) + \mu\end{aligned} \qquad [11]$$

Table 4.6 lists the results of the logistic regression Models 5 and 6. As shown in Model 5, the effect of household single-family detached housing surprisingly becomes significant ($p < .001$) with the presence of neighborhood characteristics in the model. For households living in single-family detached homes, the odds of dislocation decreases by 47.1%. Results for the other neighborhood variables, including the percentages of renter and vacant housing units, and median household income, are similar to those found in Model 3.

Table 4.6 Results of Logistic Regression Models Examining the Effects of Housing Structural Damage, Single-Family Detached Homes and Neighborhood Characteristics

Variable Categories	Variables	Model 5			Model 6		
		β	EXP(β)	p	β	EXP(β)	p
Housing structural damage	pvloss_bldg	0.024	1.025	0.000	0.025	1.025	0.000
Household characteristics	d_sfd	-0.637	0.529	0.000	-0.611	0.543	0.000
Neighborhood characteristics	p_blacknh_bg	-0.015	0.985	0.000	-0.017	0.984	0.000
	p_hispanic_bg	-0.007	0.993	0.1002			
	p_cuban_bg				0.009	1.009	0.209
	p_ncubanh_bg				-0.018	0.982	0.002
	p_renter_bg	-0.011	0.989	0.006	-0.008	0.992	0.083
	p_vacant_bg	0.001	1.001	0.946	0.007	1.007	0.504
	mhhinc_bg	-0.004	0.996	0.492	-0.004	0.996	0.407
	p_sfd_bg						
Constant		-0.067	0.935	0.873	-0.155	0.857	0.713
N (Total N: 2994)			1899			1899	
Nagelkerke R-square			0.210			0.214	
Cox & Snell R-square			0.157			0.161	

In Model 6, when the Hispanics are divided into Cubans and non-Cubans, the effect of non-Cuban Hispanic percentage on household dislocation becomes significant (p=0.002). The effect of Cuban percentage remains insignificant. The other three variables, percentage of renters, percentage of vacant housing units, and median household income, continue to have insignificant effects on household dislocation.

4.2.3 Model Selection for Algorithm Development

This study employs two criteria to select a set of independent variables for use in the algorithm to predict the probability of household dislocation. First, the selection of independent variables is based on the statistical significance of variables, as well as the model R-square, which represents the performance of the overall model. In this case all the independent variables have been tested for their incremental contribution to predicting household dislocation. Second, in order to provide policy implications, the selection of variables has to be theoretically meaningful and supported by the disaster research.

The selection process starts by placing two structural level variables, housing structural damage and the single-family housing dummy variable, as well as all neighborhood variables except for the percentage of single-family housing units which has been represented by the single-family housing dummy variable. Then a forward selection procedure is applied to add variables that have statistically significant effects and increase in R-square when they are placed in the model. The result shows that four variables—housing structural damage, household single-family housing, percentage of non-Hispanic Blacks, and percentage of renters—are selected by this approach. However, the significantly negative effect of renter percentage on household dislocation is inconsistent with the disaster research. Further examination reveals this is a result of the strong correlation between percentage of Hispanics and percentage of renters. Renter percentage has a stronger effect and decreases the effect of Hispanic percentage when both variables are placed into the model. When renter percentage is removed, housing structural damage, household single-family housing, percentage of non-Hispanic Blacks, and percentage of Hispanics have significant effects that increase R-square. Moreover, all the effects of these variables are all consistent with the findings in disaster literature. Model 8, which includes these four independent variables, is specified as the following equation.

$$\ln\{\Pr(1)/[1-\Pr(1)]\} = \beta_0 + \beta_1(pvloss\_bldg) + \beta_2(d\_sfd) + \beta_3(p\_blacknh\_bg) + \beta_4(p\_hispanic\_bg) + \mu \qquad [12]$$

The result of logistic regression Model 8 is listed in Table 4.7. In the next chapter, Model 8 will be extended to the population dislocation algorithm.

Table 4.7 Result of the Logistic Regression for Algorithm Development

Variable Categories	Variables	Model 8		
		β	EXP(β)	p
Housing structural damage	pvloss_bldg	0.025	1.025	0.000
Household characteristics	d_sfd	-0.502	0.606	0.000
Neighborhood characteristics	p_blacknh_bg	-0.018	0.082	0.000
	p_hispanic_bg	-0.012	0.988	0.000
Constant		-0.425	0.654	0.027
N (Total N: 2994)			1899	
Nagelkerke R-square			0.205	
Cox & Snell R-square			0.154	

5. ALGORITHM DEVELOPMENT

This section introduces the concept of incorporating the two improvements in the algorithm development. As structural damage is one of the basic inputs to estimate population dislocation, the chapter begins with the introduction of the MAEviz structural damage model and its differences from the HAZUS model. Then the development of two population dislocation algorithms—the modified HAZUS approach and logistic regression approach—is discussed. The chapter concludes with an examination of sensitivity of the algorithms.

5.1 MAEviz Seismic Structural Damage Model

The probabilistic approach employed in the MAEviz to assess the structural seismic damage is based on the study of Bai et al. (2007), which modified the damage state classification proposed by the Applied Technology Council (ATC) and then assigned damage factors to each damage state to quantify structural damage as a percentage of structural replacement cost. Similar to the HAZUS, the damage factors are calculated by a probabilistic approach that relies on the building damage functions, which include fragility curves describing the probability of reaching or exceeding different states of damage given peak building response, as well as building capacity curves used to determine peak building response.

However, two major differences are found between the MAEviz and HAZUS approaches. First, as noted in Section 2.2, the HAZUS assumes that all structures in a census tract are located on the centroid of that census tract. The assumption substantially decreases the computational complexity, but it also allows the damage estimates at the census tract level. In this case, the estimates are useless for many sub-census tract planning purposes. In the MAEviz, each structure has a unique location geographically coded by its longitude and latitude. When a user-defined earthquake scenario creates a seismic impact raster containing a distribution of peak ground acceleration (PGA) values, each structure is seismically impacted by the PGA at its geographical location. MAEviz then computes damage estimates for each individual structure.

Second, MAEviz uses a damage state scheme modified from the ATC-38. The difference in damage state schemes between the MAEviz and HAZUS could result in very different population dislocation estimates. The comparison of HAZUS and MAEviz damage state schemes is listed in Table 5.1.

Table 5.1 Comparison of HAZUS and MAEviz Damage State Schemes

HAZUS		MAEviz		
Damage state	Percent of building replacement cost (%)	Damage State	Range of percent damage (%)	Midpoint of damage range
Slight	2	Insignificant (I)	[0, 1]	0.5
Moderate	10	Moderate (M)	[1, 30]	15.5
Extensive	50	Heavy (H)	[30, 80]	55
Complete	100	Complete (C)	[80, 100]	90

The two population dislocation algorithms developed in this chapter are using the structural damage estimates generated by the MAEviz as one of the inputs. Typically, each damage state is translated into a percent of the building's value that would be lost. This is then weighted by the expected probability for each damage state. The resulting expected damage ratio is then multiplied by the value of the building to estimate repair costs. The direct economic damage to a structure is expressed as the following equation.

$$DED_k = \sum_{i=1}^{n} p(DS_i) \times DF_i \times Bldg\_Val_k \qquad [13]$$

Where DED_k is the direct economic damage to building *k*; $p(DS_i)$ is the probability of building *k* being in damage state *i*; DF_i is damage factor *i*, or percent of building value loss in damage state *i*; and $Bldg\_Val_k$ is the value of building *k*.

Both algorithms developed in this study only consider population dislocation in single and multi-family structures, represented by RES1 and RES3 respectively in the MAEviz building inventory data. MAEviz also adopts the HAZUS occupancy categories for all seismic damage analyses. Table 5.2 lists all residential structures in the Memphis Test Bed building inventory used in MAEviz for sensitivity analysis. As the table indicates, occupancy types other than RES1 and RES3 only account for 0.19% of the total residential structures in Memphis area. Similarly, some information for these types of residential structures in the SDPIS database is either unavailable or limited for population dislocation analysis. As a result, this study only includes RES1 and RES3 in the population dislocation algorithms.

Table 5.2 MTB Residential Building Inventory Data in MAEviz

HAZUS occupancy	HAZUS occupancy description	Number of buildings	Percent of buildings
RES1	Single-family residential	269,442	93.52%
RES2	Mobile home	43	0.015%
RES3A	Multi-family residential (2 units)	7,026	2.44%
RES3B	Multi-family residential (3-4 units)	1,441	0.50%
RES3C	Multi-family residential (5-9 units)	1,972	0.68%
RES3D	Multi-family residential (10-19 units)	2,100	0.73%
RES3E	Multi-family residential (20-59 units)	3,132	1.09%
RES3F	Multi-family residential (50+ units)	2,464	0.86%
RES3 (Total)		18,135	6.29%
RES4	Temporary lodging (Hotel/Motel)	331	0.115%
RES5	Institutional dormitory	59	0.021%
RES6	Nursing home	87	0.030%
	Total	288,097	100%

In addition to the difference in the estimation process, the residential building inventory data in the HAZUS and MAEviz are also different. The residential structures in HAZUS were acquired from two major sources, the Census 2000 and Department of Energy (DOE) reports (FEMA, 2003). The key information including square footage by occupancy, building count by occupancy, and general occupancy mapping was derived from the population and housing data in Census 2000. Then three reports from the DOE were used in defining regional variations in characteristics such as number and size of garages, type of foundation, and number of stories. The inventory's baseline floor area is based on a distribution contained in the DOE's Energy Consumption Report. On the other hand, the residential building inventory data utilized in MAEviz is directly acquired from the Shelby County Tax Assessor's Database in 2007. Therefore, MAEviz has a later version of building count and information. In addition, the HAZUS residential building inventory data only contains building characteristics aggregated at census tracts while each residential building in MAEviz has a unique location as well as structural and non-structural information associated with the building. The difference in numbers of residential buildings between HAZUS and MAEviz is listed in Table 5.3. With regard to the two occupancy types, RES1 and RES3, used for calculating population dislocation, MAEviz has 5.11% and 25.05% more structures respectively than the HAZUS does. This is one of the major factors contributing to the differences in population dislocation estimates between the MAEviz and HAZUS algorithms.

Table 5.3 Difference in Numbers of Residential Buildings between HAZUS and MAEviz Inventory Data

Occupancy type	Number of buildings in HAZUS building inventory (2000)	Number of buildings in MAEviz building inventory (2007)	Difference in number of buildings (MAEviz - HAZUS)	Percent increase in MAEviz building inventory
RES1	256,335	269,442	13,107	5.11%
RES2	4140	43	-4,097	-98.96%
RES3	14,502	18,135	3,633	25.05%
RES4	99	331	232	234.34%
RES5	367	59	-308	-83.92%
RES6	118	87	-31	-26.27%
Total	275,561	288,097	12,536	4.55%

5.2 Modified HAZUS Population Dislocation Algorithm

The first modification transforms the HAZUS algorithm so it can produce structural level dislocation estimates. This modified HAZUS approach bases its estimation on structural damage and anticipated variations in dislocation between single and multi-family structures. It employs damage state probabilities ($p(DS_i)$) proposed by Bai et al. (2007) weighted by dislocation factors ($DisF$) described in HAZUS and more refined estimates of the number of households per dwelling unit based on US block group census data. Displaced households for single-family structure *m* (HhD_{sf_m}) and multi-family structure *n* (HhD_{mf_n}) are estimated using the following equations respectively[2].

$$HhD_{sf_m} = \sum_{i=1}^{4} \left(DisF_{sf_i} \times p(DS_i) \right) \times AveHhDU_{bg_k} \qquad [14]$$

$$HhD_{mf_n} = \sum_{i=1}^{4} \left(DisF_{mf_i} \times p(DS_i) \right) \times NO\_DU_{jk} \times AveHhDU_{bg_k} \qquad [15]$$

Where $AveHhDU_{bg_k}$ is the average number of households per dwelling unit in block group *k* and NO_DU_{jk} is the number of dwelling units of multi-family residential structure *j* in block group *k*. The dislocation factors ($DisF$) for various damage states

[2] See APPENDIX A for example calculations using modified HAZUS algorithm.

that are utilized in the above equations are listed in Table 5.4. The users may aggregate HhD_{sf_m} and HhD_{mf_n} to any meaningful level such as block group, tract, or jurisdiction level based upon their specific planning purposes or needs.

Table 5.4 Dislocation Factors by Damage States (Modified from Table 2.5)

Proposed MAE Damage States	Dislocation factors	
	Single Family $(DisF_{sf})$	Multi-family $(DisF_{mf})$
Insignificant (I)	0.0	0.0
Moderate (M)	0.0	0.0
Heavy (H)	0.0	0.9
Complete (C)	1.0	1.0

5.3 Logistic Regression Population Dislocation Algorithm

The second modification to the population dislocation algorithm is developed by extending empirically based statistical models predicting population dislocation following Hurricane Andrew. As noted previously, disaster research suggests that population dislocation is driven not only by building damage and housing type as employed by the HAZUS population dislocation model, but also by household and neighborhood socioeconomic characteristics, weather, infrastructure disruption, disaster type, and job loss (Baker, 1991; FEMA, 2003; Gladwin & Peacock, 1997; Whitehead et al., 2000; Whitehead, 2005). While not all of these factors were available to this research, the modified algorithm does utilize a logistic regression model that includes neighborhood socioeconomic characteristics in addition to structural damage and type of residential buildings as independent variables to predict the probability that residents in a given structure be dislocated. The probability that residents of structure *j* in block group *k* will be dislocated ($\Pr Dis_{jk}$) is calculated by the following equations.

$$\Pr Dis_{jk} = 1/\{1 + EXP[-(b_0 + b_1 \times \%VLOSS_{jk} + b_2 \times D\_SF_{jk} + b_3 \times \%BLACK_{bg_k} + b_4 \times \%HISP_{bg_k})]\} \quad [16]$$

Where $\%VLOSS_{jk}$ represents the percent value loss of residential structure *j* in block group *k*. It uses the same logic employed in the DED measure calculated in section 5.1, but does not need to use economic values directly. It is calculated as follows.

$$\%VLOSS_{jk} = \sum_{i=1}^{n} p(DS_i) \times DF_i \times 100 \quad [17]$$

In addition, D_SF_{jk} is a qualitative dummy variable where 1 represents single-family structures and 0 represents multi-family structures. The variables $\%BLACK_{bg_k}$ and $\%HISP_{bg_k}$ are simply the percent Black and Hispanic sub-population in block group *k* respectively. The default coefficient values (b_1, b_2, b_3, and b_4) are listed in Table 5.5 and were developed from the empirical data.

Table 5.5 Default Values of Coefficients

Coefficients	Default Values
b_0	-0.42523
b_1	0.02480
b_2	-0.50166
b_3	-0.01826
b_4	-0.01198

The dislocation factor ($DisF_{jk}$) for the structure is then calculated from probability of dislocation ($\Pr Dis_{jk}$) by the following default operation: $DisF_{jk} = 1$ if $\Pr Dis_{jk} >= .5$; $DisF_{jk} = 0$ otherwise; where one (1) means the household is predicted to be dislocated. The default probability cutoff value of .5 can be adjusted based on different circumstances such as hazard characteristics, weather conditions, and infrastructure disruptions. The MAEviz implementation of this algorithm also allows users to aggregate household dislocation at block group, neighborhood, census tract, or other jurisdiction level for their specific planning purposes[3]. For example, the number of dislocated households for block group k ($DisHh_{bg_k}$) can be estimated as follows.

$$DisHh_{bg_k} = \sum_{j=1}^{m} \left(DisF_{jk}\right) \times \left(NO\_DU_{jk}\right) \times \left(AveHhDU_{bg_k}\right) \qquad [18]$$

[3] See APPENDIX B for example calculations using logistic regression algorithm.

5.4 Sensitivity of Algorithms

The estimation of population dislocation in MAEviz is conducted through the procedure as shown in Figure 5.1. The hazard data—created by inputting earthquake scenario information including location (longitude and latitude), magnitude, depth, spectrum method, attenuation and other site factors—is in the form of a raster grid containing the PGA values covering the study area. Then, the building structural damage map is created as a shape file by inputting the hazard and building inventory data. The building direct economic damage is estimated by inputting the building structural damage data as well as tables for nonstructural damage, inflation and occupancy damage multipliers. The population dislocation estimates, however, are not calculated from the building direct economic damage and census data as shown in the figure. In fact, when the two algorithms are estimating population dislocation, nonstructural damage is not included as one of the inputs. Instead, the modified HAZUS algorithm uses damage state probability, HAZUS dislocation factor, and average number of households per dwelling unit to estimate population dislocation. On the other hand, the logistic regression algorithm uses the building structural damage as calculated in equation [17], as well as building type, Black and Hispanic percentages, and average number of households per dwelling unit to estimate population dislocation. In this section, all three algorithms, including the two in MAEviz and one in HAZUS, use the same set of scenarios to produce population dislocation estimates for sensitivity analysis.

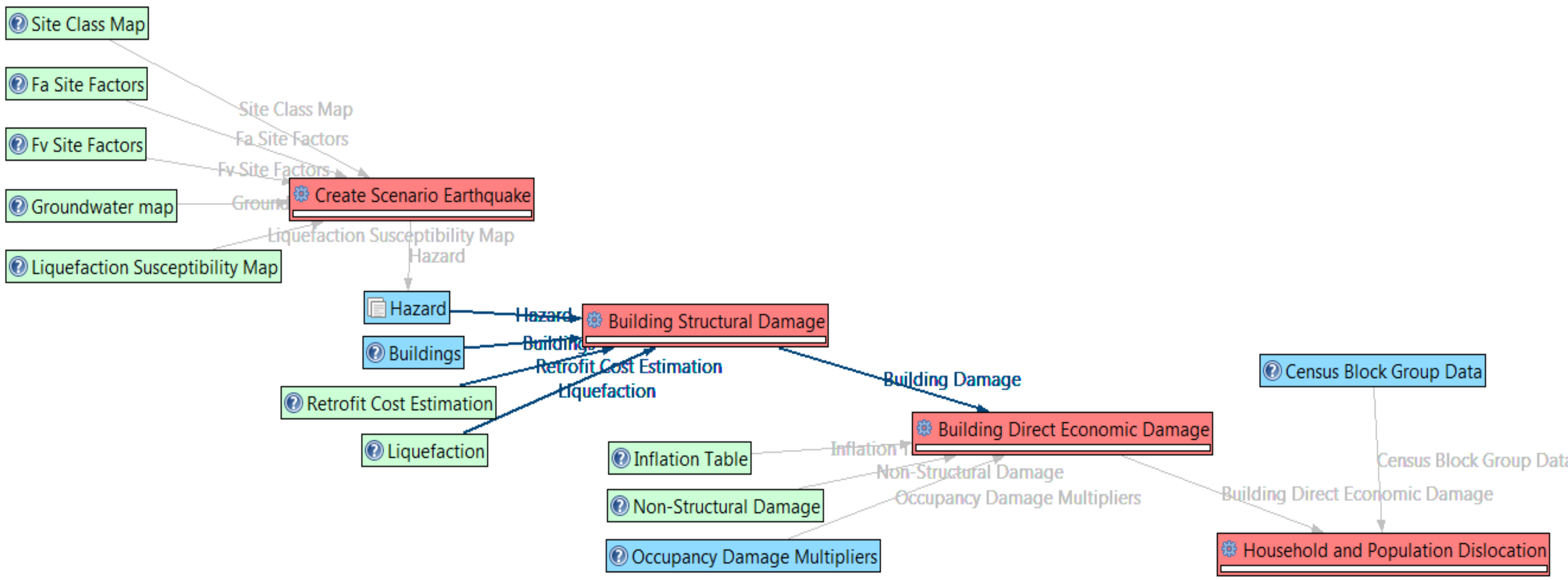

Figure 5.1 Population Dislocation Estimation Procedure in MAEviz

5.4.1 Earthquake Scenarios

This study employs 18 earthquake scenarios to examine the sensitivity of the two algorithms. These earthquake scenarios are also established in HAZUS to calculate population dislocation estimates to compare with the MAEviz results. As listed in Table 5.6, these 18 earthquake scenarios are created by combining three earthquake locations with six earthquake magnitudes. Blytheville and Marked Tree are both in the New Madrid seismic zone and located 55 miles north of and 34 miles northwest of downtown Memphis, respectively. Both locations have a history of high-magnitude earthquake events. The downtown Memphis location, where the probability of have a high magnitude event is extremely low, is intentionally created inside the study area to compare with the other two outside locations.

Table 5.6 Description of the Earthquake Scenario Locations

	Blytheville	Marked Tree	Downtown Memphis
Longitude	-89.919	-90.43	-90.078
Latitude	35.927	35.535	35.177
Depth (km)	10.0	10.0	10.0
Magnitude (Richter scale)	5.5; 6.0; 6.5; 7.0; 7.5; 8.0	5.5; 6.0; 6.5; 7.0; 7.5; 8.0	5.5; 6.0; 6.5; 7.0; 7.5; 8.0

Several factors are also required to create the hazard data in addition to the information described in Table 5.6. The National Earthquake Hazards Reduction Program (NEHRP) designed spectrum and Central and Eastern United States characteristic event are selected for the period spectrum method and attenuation relationship as the other two required inputs. As for optional inputs, site class D, NEHRP site factor and HAZUS liquefaction method are selected for site class, soil factor method, and liquefaction type, respectively. Population dislocation estimations in MAEviz and HAZUS both use the same set of parameters as described above.

5.4.2 Sensitivity Analysis of Estimation Results

The Shelby County population dislocation estimates calculated by the three algorithms using 18 earthquake scenarios are listed in Table 5.7. A preliminary examination of the estimates indicates some noticeable points. First, the modified HAZUS algorithm tends to produce the highest population dislocation estimates. It has the highest dislocation estimates in all earthquake scenarios except for the earthquake of magnitude 5.5 in Blytheville.

Second, the original HAZUS algorithm tends to produce lower estimate of population dislocation, especially in high-magnitude earthquakes. For example, an earthquake of magnitude 7.0 in downtown Memphis only results in dislocation of 32,566 households, or 9.62% of total households in Shelby County. The HAZUS dislocation numbers are not reasonable, especially because this same analysis shows an average of 52.46% building value loss for all residential structures in the area. Similar situations are found in high-magnitude earthquakes at all three scenario locations.

Table 5.7 Shelby County Population Dislocation Estimates Calculated by the Three Algorithms Using 18 Earthquake Scenarios

		Blytheville			Marked Tree			Downtown		
		Dislocated households	Percent of total households	Average percent of structural damage calculated by MAEviz	Dislocated households	Percent of total households	Average percent of structural damage calculated by MAEviz	Dislocated households	Percent of total households	Average percent of structural damage calculated by MAEviz
M=5.5	Original HAZUS	16.7	0.00%		34.7	0.01%		1,743.0	0.51%	
	Modified HAZUS	6.4	0.00%	0.51%	51.5	0.02%	0.54%	21,745.7	6.42%	9.19%
	Logistic	0	0.00%		0	0.00%		13,042.1	3.85%	
M=6.0	Original HAZUS	81.2	0.02%		191.2	0.06%		7,593.7	2.24%	
	Modified HAZUS	210.9	0.06%	0.79%	952.0	0.28%	1.44%	62,485.5	18.46%	24.87%
	Logistic	0	0.00%		0	0.00%		37,319.6	11.02%	
M=6.5	Original HAZUS	282.5	0.08%		608.7	0.18%		17,579.6	5.19%	
	Modified HAZUS	3,328.4	0.98%	2.65%	8,979.9	2.65%	5.28%	113,071.6	33.40%	38.77%
	Logistic	0	0.00%		0	0.00%		94,225.6	27.83%	
M=7.0	Original HAZUS	820.8	0.24%		1,962.5	0.58%		32,566.5	9.62%	
	Modified HAZUS	18,480.2	5.46%	8.17%	34,478.5	10.18%	13.45%	165,649.0	48.93%	52.46%
	Logistic	5,700.6	1.68%		15,377.8	4.54%		156,605.2	46.26%	
M=7.5	Original HAZUS	3,475.3	1.03%		9,731.0	2.87%		79,848.6	23.58%	
	Modified HAZUS	41,404.3	12.23%	16.17%	63,377.5	18.72%	23.15%	221,068.7	65.30%	64.90%
	Logistic	24,477.8	7.23%		54,486.4	16.09%		210,216.2	62.09%	
M=8.0	Original HAZUS	12,447.0	3.68%		21,872.8	6.46%		122,846.6	36.29%	
	Modified HAZUS	69,302.8	20.47%	25.56%	93,419.8	27.59%	32.89%	274,811.9	81.17%	74.98%
	Logistic	68,763.9	20.31%		82,911.3	24.49%		244,857.2	72.32%	

Note: Total households in Shelby County as of Census 2000: 338,560.

Figures 5.2, 5.3 and 5.4 show the sensitivity of the three algorithms with regard to six earthquake magnitudes at Blytheville, Marked Tree and downtown Memphis respectively, controlling for the other factors. As shown in Figure 5.2, the HAZUS algorithm is the least sensitive of the three to changes in magnitudes when earthquakes take place at Blytheville. All three algorithms produce very few dislocated households at magnitudes of 5.5 and 6.0. The modified HAZUS algorithm starts at magnitude of 6.5 to produce higher estimates than the other two algorithms. The logistic regression algorithm begins to increase significantly at M = 7.0 and catches up at magnitude of 8.0. The number of dislocated households calculated by the original HAZUS algorithm stays at very low level comparing to the other two algorithms.

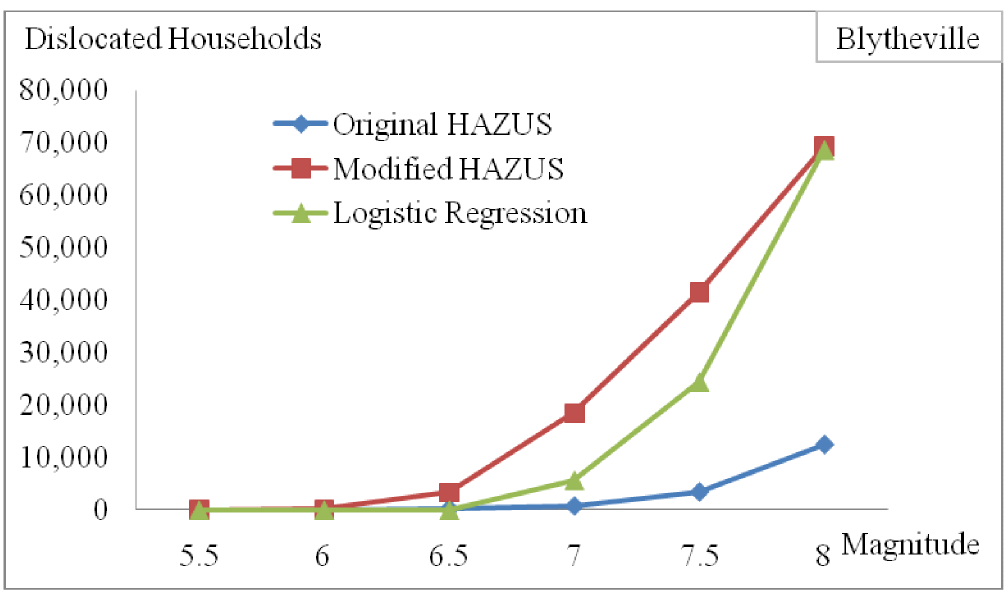

Figure 5.2 Sensitivity of the Three Algorithms in Blytheville Scenarios.

When the earthquakes are taking place at Marked Tree, the relationships between the numbers of dislocated households and earthquake magnitudes look similar to those found in the Blytheville scenarios. Both Figures 5.2 and 5.3 indicate that dislocation estimates produced by all three algorithms increase at a higher rate when the magnitude passes 6.5. This is particularly obvious in the estimates calculated by the logistic regression algorithm when the number of dislocated households starts to converge on the modified HAZUS estimate at M = 7.5. Unlike the Blytheville analysis, the Marked Tree analysis results do not converge at M = 8.0. However, the original HAZUS results are very low here, as well.

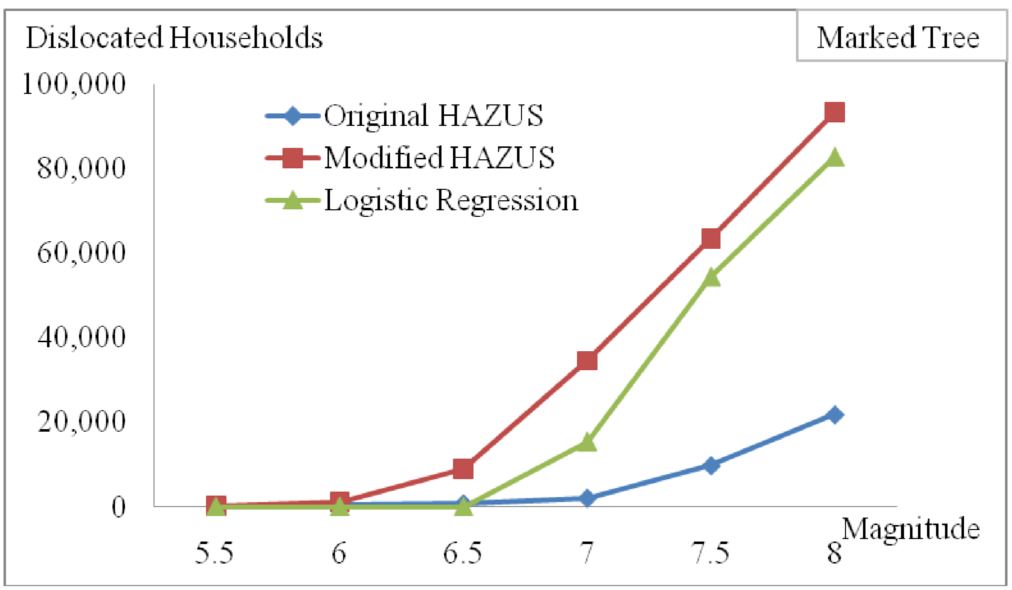

Figure 5.3 Sensitivity of the Three Algorithms in Marked Tree Scenarios.

When the earthquakes are taking place in the downtown Memphis, the relationships between the number of dislocated households and magnitudes are closer to linear for the three algorithms, compared with the other two scenario locations. An earthquake of magnitude 5.5 in downtown Memphis is sufficient to produce a damage level that forces people to leave because of the loss of building function and daily routines. Unlike the previous two cases, the modified HAZUS and logistic regression algorithms are extremely similar for all magnitudes. Original HAZUS is somewhat more similar to the other two algorithms in this case, but is still substantially lower at the higher magnitudes.

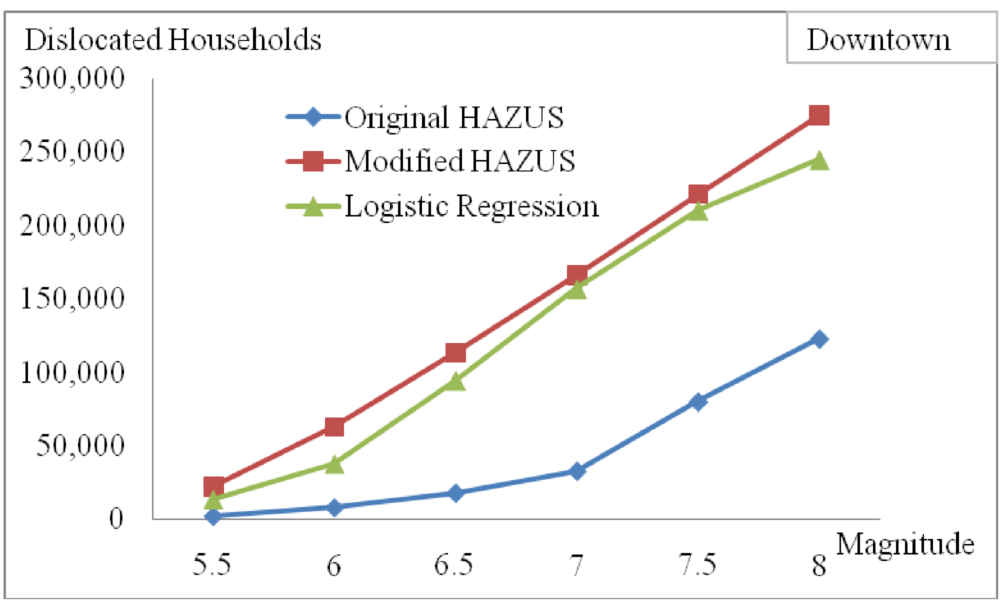

Figure 5.4 Sensitivity of the Three Algorithms in Downtown Memphis Scenarios.

Overall, the modified HAZUS and logistic regression algorithms produce similar dislocation estimates in most of the 18 earthquake scenarios. The estimates calculated by the two algorithms are obviously higher than those calculated by HAZUS especially in high-magnitude scenarios.

Finally, it is also important to address the uncertainties and the propagation of uncertainties in the estimation process that may influence the sensitivity of the algorithms and population dislocation estimates. Building structural damage is the major factor that influences the dislocation estimates. The uncertainties in modeling building structural damage include period spectrum method, attenuation relationship, site class, soil factor method and liquefaction method, all of which may propagate into the estimation process of population dislocation. It is therefore essential for users to be aware of the presence of these uncertainties when they are using these algorithms to estimate population dislocation under any circumstances.

6. DISCUSSION AND CONCLUSIONS

6.1 Discussion

This dissertation uses an empirical approach to develop algorithms to estimate population dislocation following a natural disaster. It starts with an empirical re-examination of the SDPIS data, integrated with the Miami-Dade County tax appraisal data and 1990 block group census data, to investigate the effects of household and neighborhood socioeconomic characteristics on household dislocation. Then one of the statistical models is selected from the empirical analysis and integrated into the algorithm that estimates the probability of household dislocation based on structural damage, housing type, and the percentages of Black and Hispanic population in block groups. This study also develops another population dislocation algorithm using a modified HAZUS approach that integrates the damage state probabilities proposed by Bai et al. (2007) and dislocation factors described in HAZUS to produce structural level estimates. Sensitivity analysis follows to examine the difference among the estimates produced by the two MAEviz algorithms and the HAZUS population dislocation algorithm. These analyses allow this dissertation to answer the following three research questions. First, how do household and neighborhood socioeconomic characteristics influence post-disaster household dislocation? Second, how can the population dislocation algorithm be specified to incorporate socioeconomic factors and produce structural level estimates that allows flexibility in aggregation to meet a user's specific planning purpose? Third, how does the dislocation algorithm developed in this study perform differently from the HAZUS model?

The empirical test of the seven research hypotheses answers the first research question. Hypothesis 1 is fully supported. Results in all statistical models indicate that building structural damage significantly increased the likelihood of household dislocation after Hurricane Andrew. Moreover, building structural damage has the strongest magnitude of effect among all the variables investigated in the study. This result is consistent with the earlier research finding that housing structural damage is the most dominant factor that affects post-disaster population dislocation (Comerio, 1998; FEMA, 2003; Harrald et al., 1992; Peacock & Girard, 1997; Quarantelli, 1982a; Smith & McCarty, 1996).

Hypothesis 2, that ethnic minority status of households will significantly decrease the likelihood of household dislocation following a disaster, is partially supported. The analysis indicates that Black ethnicity has a significantly negative effect on household dislocation. However, Hispanic ethnicity is found to have no significant effect on household dislocation. The difference between Cuban and non-Cuban Hispanic households suggested by the literature is not investigated because of the unavailability of information in the SDPIS data. Only one of the two ethnic minorities shows a significantly negative effect on household dislocation suggested by the literature.

The evidence for Hypothesis 3, that households living in single-family housing units will have a significantly lower level of household dislocation following a disaster, is mixed. Single-family detached housing does have a significantly negative effect on household dislocation when investigated together with neighborhood characteristics. However, the negative effect weakens and becomes insignificant when it is investigated with the other household level variables. This finding might be a result of the strong intercorrealtions among the household level variables. Nevertheless, results from the analysis show mixed evidence and do not fully support this hypothesis suggested by the literature.

Hypothesis 4, that neighborhood minority composition will significantly decrease the likelihood of household dislocation following a disaster, is partially supported. Black neighborhood composition consistently shows a significantly negative effect on household dislocation. When Hispanics are investigated as a group, the analysis has mixed results. Hispanic neighborhood composition has no significant effect on household dislocation when investigated with all neighborhood variables. However, the negative Hispanic neighborhood composition effect becomes significant when the renter composition is excluded from the analysis. This might be a result of the strong correlation between Hispanic and renter compositions. Furthermore, when Hispanics are divided into Cubans and non-Cubans, the non-Cuban composition consistently has a significantly negative effect on household dislocation. The results that predominant Black and non-Cuban Hispanic neighborhoods have significantly negative effects on household dislocation are consistent with the literature. However, the effects of Hispanic and Cuban compositions suggested by the literature are not fully supported by the analysis.

Hypothesis 5, that neighborhood income level will significantly increase the likelihood of household dislocation following a disaster, is not supported. The neighborhood median household income consistently shows no significant effect on household dislocation. Hypothesis 6, that neighborhood renter composition will significantly increase the likelihood of household dislocation following a disaster, is not supported. To the contrary, neighborhood renter composition consistently has a significantly negative effect on household dislocation. A further examination shows that renter composition has a strong correlation with Hispanic composition but is not correlated with household dislocation. Renter composition might therefore pick up the negative effect of Hispanic composition. Hypothesis 7, that neighborhood single-family housing composition will significantly decrease the likelihood of household dislocation following a disaster, is supported. The percentage of single-family housing units in block groups consistently shows a significantly negative effect on household dislocation, which is consistent with the finding suggested by the literature.

With regard to the second research question, this dissertation utilizes an empirical data to develop a logistic regression algorithm that includes the socioeconomic characteristics supported by the research literature and the empirical analysis conducted in this study. As illustrated in the earlier sections 3.2 and 5.3, the algorithm to predict the probability of household dislocation is actually the opposite form of the logistic regression model with the coefficients derived from the empirical data. As a result, this algorithm produces population dislocation estimates at the structure level, which is also the unit of analysis used in the empirical analysis. In the case of the modified HAZUS algorithm that has been discussed in section 5.2, it directly applies the HAZUS dislocation factor to the MAEviz damage state probability as the estimated proportion of households to be dislocated from the structure. MAEviz calculates damage state probabilities for each individual structure at its unique location, which is different from the HAZUS assumption that all structures in a census tract are located at the centroid of that census tract. Therefore, the modified HAZUS can also produce population dislocation estimates for individual structures. The MAEviz implementation of both algorithms allows aggregation of dislocation estimates at block group, neighborhood, census tract, or other jurisdiction level for a user's specific planning purposes.

As to the third research question, there are three ways in which the MAEviz and HAZUS algorithms perform differently. The first difference arises from the differing assumptions about the structure locations adopted by the MAEviz and HAZUS, as mentioned in the earlier paragraph. The HAZUS assumption substantially decreases the computational complexity and the time requirement for calculating the estimates. However, it ignores the variations in PGA and structural damage among buildings with respect to their locations in a census tract. MAEviz does provide estimates for each individual structure but requires a very large amount of time to perform the calculation. Second, MAEviz and HAZUS adopt different damage state schemes as noted in Table 5.1. HAZUS assumes that all households would leave completely damaged single- and multi-family structures and 90% of the affected households would leave extensively damaged multi-family structures. However, very few structures actually have 100% damage unless a catastrophic event happens. As a result the HAZUS algorithm consistently produces dislocation estimates that are much lower than those calculated by the other two algorithms. Finally, MAEviz allows later versions of building inventory data, period spectrum method, attenuation relationship, site class, soil factor method and liquefaction method to be imported for analysis while the HAZUS only allows updates of the building inventory data.

6.2 Limitations and Future Research

Like every other research, this dissertation has limitations. First, the SDPIS data was collected after a major disaster that damaged 135,446 housing units, and caused an estimated $15.9 billion housing-related loss in Miami-Dade County (Comerio, 1998). Therefore one should be cautious when applying the empirically based algorithm to events of minor to moderate severity. It is suggested that future studies attempting to develop population dislocation algorithms should include data collected after less severe events to increase the applicability of the algorithm to disasters having a wider range of intensities.

Second, the empirically based algorithm was developed by using data collected in Miami-Dade County that, in many respects, has unique social patterns. One also has to be cautious when applying the algorithm in a jurisdiction that has more variations in socioeconomic and/or socio-demographic patterns than Miami-Dade County. Future studies should include data from other areas with more variations in social patterns to enhance the applicability of the algorithm.

Finally, disaster research suggests that the pattern of post-disaster population dislocation is influenced by factors including housing structural damage, housing type, disaster type, weather, infrastructure disruption, job loss, and socioeconomic characteristics of households and their surrounding neighborhoods (Baker, 1991; Belcher & Bates, 1983; FEMA, 2003; Fried, 1966; Gladwin & Peacock, 1997; Haas et al., 1977; Heller, 1982; Lindell & Prater, 2003;Lindell et al., 2006; Morrow-Jones & Morrow-Jones, 1991; Peacock & Girard, 1997; Whitehead et al., 2000; Whitehead, 2005). This dissertation advances current algorithms by including socioeconomic characteristics in the estimation of population dislocation. However, the effects of disaster type, weather, infrastructure disruption and job loss have not been investigated and included in the modified algorithms. Thus, future studies should examine the effects of these factors and incorporate them into the population dislocation algorithm when supported by the empirical analysis.

6.3 Theoretical Contribution and Practical Implication

Despite its limitations, this dissertation has made theoretical contribution to population dislocation and housing recovery literatures. First, it provides quantitative evidence to support the previous anecdotal finding that households with higher socioeconomic status often possess greater mobility as a result of their favored accessibility to internal and external resources, transportation, and social networks, which allows better adjustment to forced movements due to natural disasters (Bolin, 1982; Drabek & Key, 1984; Hartman, 1964; Fried, 1966; Haas et al., 1977; Heller, 1982;

Morrow-Jones & Morrow-Jones, 1991). Second, the empirical findings in this dissertation echo Peacock and Girard's (1997) study, in which the marginalization of Blacks and Hispanics is found to have a negative effect on the mobility of households to leave disaster damaged homes. In addition, non-Cuban Hispanics experienced difficulties similar to Blacks in terms of leaving damaged homes after a natural disaster. Third, the findings in this study also have implications for housing recovery literature. Households of low socioeconomic status are less likely to leave damaged homes after a disaster. In addition, Morrow-Jones and Morrow-Jones's (1991) study noted that the most costless alternative for a homeowner may be to move back in the damaged house and repair it. In this context, these households are more likely stay after a disaster and experience all four phases of housing recovery, as proposed by Quarantelli (1982a). Contrarily, households of higher socioeconomic status may be freer to move or stay to rebuild as they choose. Therefore, they may not have to experience emergency shelter, temporary shelter, and/or even temporary housing in the recovery process.

This dissertation also has practical implications. First, disaster research indicates that Black and Hispanic households tend to suffer higher levels of housing damage in natural disasters because they tend to live in structures that were built according to outdated building codes, use inferior designs and construction materials, and were poorly maintained (Bolin, 1994; Bolin & Stanford, 1998; Peacock & Girard, 1997). In addition, this study found that Blacks and Hispanics, especially non-Cuban Hispanics, experienced more difficulties when trying to leave damaged homes after a natural disaster. In this context, Blacks and non-Cuban Hispanics tend to be those who most need shelter following the natural disasters. Therefore, it is particularly important to address the needs of these population segments in terms of locations, supplies and services in the provision of temporary shelter.

Second, this study establishes an example of transforming the results of quantitative empirical research into a practical planning tool, which is rarely found in disaster research. This research-based approach may also be used to extend other quantitative studies into useful tools for planning purposes, such as Zhang's (2006) study in single family housing recovery following Hurricane Andrew and Lu's (2007) comparative study of single family and multi-family housing recovery after Hurricane Andrew.

Finally, this dissertation successfully improves on the HAZUS population dislocation algorithm in two aspects as mentioned earlier. The finer spatial resolution of dislocation estimates increases the applicability of the algorithm for many planning purposes. In addition, the logistic regression algorithm is developed based on the empirical evidence, compared to HAZUS, which predicts the number of dislocated households based on inhabitable residential units under unreasonable dislocation factor assumptions.

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APPENDIX A

Example Calculations Using Modified HAZUS Algorithm:

Multi-family structures (OCC_TYPE = RES3)	Multi-family structure with 10 dwelling units (*NO_DU=10*)	Probability (P_{ilIM})	Dislocation Factor ($DisF_{mf}$)	P_{ilm} ***X*** $DisF_{mf}$	*AveHhDUbg* = .94
	Damage State	(S_a = 0.488g)			
	Insignificant (I)	0.063	0	0	
	Moderate (M)	0.094	0	0	
	Heavy (H)	0.256	0.9	0.2304	
	Complete (C)	0.587	1	0.587	
			$\sum_{i=1}^{4}\left(DisF_{mf_i} \times P_{ilM}\right) =$	.8174	$HhD_{mf_1} = .8174(10)(.94) = 7.68356$
	Multi-family structure with 30 dwelling units (*NO_DU=30*)				
	Damage State	(S_a = 0.277g)			
	Insignificant (I)	0.118	0	0	
	Moderate (M)	0.485	0	0	
	Heavy (H)	0.224	0.9	0.2016	
	Complete (C)	0.153	1	0.153	
			$\sum_{i=1}^{4}\left(DisF_{mf_i} \times P_{ilM}\right) =$	.3546	$HhD_{mf_1} = .3546(30)(.94) = 10.0$
single-family structures (OCC_TYPE = RES1)	Single-family 1 (*NO_DU=1*)	Probability (P_{ilIM})	Dislocation Factor ($DisF_{sf}$)	P_{ilm} ***X*** $DisF_{sf}$	
	Damage State	(S_a = 0.488g)			
	Insignificant (I)	0.063	0	0	
	Moderate (M)	0.094	0	0	
	Heavy (H)	0.256	0	0	
	Complete (C)	0.587	1	0.587	
			$\sum_{i=1}^{4}\left(DisF_{sf_i} \times P_{ilM}\right) =$	.587	$HhD_{sf_1} = .587(1)(.94) = .5578$
	Single-family 2 (*NO_DU = 1*)				
	Damage State	(S_a = 0.277g)			
	Insignificant (I)	0.118	0	0	
	Moderate (M)	0.485	0	0	
	Heavy (H)	0.224	0	0	
	Complete (C)	0.153	1	0.153	
			$\sum_{i=1}^{4}\left(DisF_{sf_2} \times P_{ilM}\right) =$	.153	$HhD_{sf_2} = .153(1)(.94) = .14382$

$$DisHh_{bg} = \sum_{m=1}^{M} HhD_{sf_m} + \sum_{n=1}^{N} HhD_{mf_n} = 17.68356 + .70162 = 18.38518 \cong 18.4$$

APPENDIX B

Example Calculations Using Logistic Regression Algorithm:

The following is the hypothetical damage and social characteristic for a block group containing 5 structures:

Structure	Direct Economic Damage to the Building	Pre-impact Building Value	$\%VLOSS_{jk}$	D_SF_{jk}	NO_DU	TOT_POP	TOT_HU	TOT_HH	$AveHhDU_{bg_k}$
1	30,000	50,000	60	1	1	54	24	18	0.75
2	350,000	500,000	70	0	20				
3	30,000	120,000	33.3	1	1				
4	30,000	50,000	60	1	1				
5	12,000	40,000	30	1	1				

1. Calculate number of dislocated households for block group k:

$$\Pr Dis_{jk} = 1 \Big/ \left\{1 + e^{-\left[b_0 + b_1 \times (\%VLOSS_{jk}) + b_2 \times (D\_SF_{jk}) + b_3 \times (\%BLACK_{bg_k}) + b_4 \times (\%HISP_{bg_k})\right]}\right\}$$

$$DisHh_{bg_k} = \sum_{j=1}^{m} \left(DisF_{jk}\right) \times \left(NO\_DU_{jk}\right) \times \left(AveHhDU_{bg_k}\right)$$

Structure	$\%VLOSS_{jk}$	D_SF_{jk}	$\%BLACK_{bg_k}$	$\%HISP_{bg_k}$	$\Pr Dis_{jk}$	$DisF_{jk}$	$AveHhDU_{bg_k}$	$(DisF_{jk}) \times (NO\_DU_{jk}) \times (AveHhDU_{bg_k})$	$DisHh_{bg}$
1	60	1	54.7743	25.911	0.320934	0	0.75	0 * 1 * 0.75 = 0	15
2	70	0			0.500044	1		**1 * 20 * 0.75 = 15**	
3	33.3	1			0.195975	0		0 * 1 * 0.75 = 0	
4	60	1			0.320934	0		0 * 1 * 0.75 = 0	
5	30	1			0.1834	0		0 * 1 * 0.75 = 0	

2. Calculating percent of dislocated households for block group k

$$PDisHh_{bg_k} = \frac{DisHh_{bg_k}}{TOT\_HH_{bg_k}} \times 100 = 15 / 24 * 100 = 62.5\%$$

3. Calculating total number of dislocated households for a jurisdiction covering p block groups:

$$TotDh = \sum_{k=1}^{p} DisHh_{bg_k}$$

APPENDIX C

Glossary of Symbols:

%SF: Percent of displacement for single-family residential occupancy class;

W_{SFM}: Weighting factor for moderate structural damage in the single-family residential occupancy class;

%SFM: Damage state percentage for moderate structural damage in the single-family residential occupancy class;

W_{SFE}: Weighting factor for extensive structural damage in the single-family residential occupancy class;

%SFE: Damage state percentage for extensive structural damage in the single-family residential occupancy class;

W_{SFC}: Weighting factor for complete structural damage in the single-family residential occupancy class;

%SFC: Damage state percentage for complete structural damage in the single-family residential occupancy class;

%MF: Percent of displacement for multi-family residential occupancy class;

W_{MFM}: Weighting factor for moderate structural damage in the multi-family residential occupancy class;

%MFM: Damage state percentage for moderate structural damage in the multi-family residential occupancy class;

W_{MFE}: Weighting factor for extensive structural damage in the multi-family residential occupancy class;

%MFE: Damage state percentage for extensive structural damage in the multi-family residential occupancy class;

W_{MFE}: Weighting factor for complete structural damage in the multi-family residential occupancy class;

%MFC: Damage state percentage for complete structural damage in the multi-family residential occupancy class;

#DH: Total number of displaced households in the census tract;

#SFU: Total number of single-family dwelling units in the census tract;

#MFU: Total number of multi-family dwelling units in the census tract;

#HH: Total Number of Households in the census tract;

DED_k : Direct economic damage to building *k*;

$p(DS_i)$: Probability of building *k* being in damage state *i*;

DF_i : Damage factor *i*, or percent of building value loss in damage state *i*;

$Bldg\_Val_k$: Value of building *k*;

HhD_{sf_m} : Displaced households for single-family structure *m*;

HhD_{mf_n} : Displaced households for multi-family structure *n*;

$AveHhDU_{bg_k}$: Average number of households per dwelling unit in block group *k*;

NO_DU_{jk} : Number of dwelling units of multi-family residential structure *j* in block group *k*;

$DisF_{sf}$: Dislocation factor for single-family structure;

$DisF_{mf}$: Dislocation factor for multi-family structure;

$\Pr Dis_{jk}$: Probability that residents of structure *j* in block group *k* will be dislocated;

$\%VLOSS_{jk}$: Percent value loss of residential structure *j* in block group *k*;

D_SF_{jk} : Qualitative dummy variable where 1 represents single-family structures and 0 represents multi-family structures;

$\%BLACK_{bg_k}$: Percent Black sub-population in block group *k*;

$\%HISP_{bg_k}$: Percent Hispanic sub-population in block group *k*;

$DisF_{jk}$: Logistic regression dislocation factor for structure *j* in block group *k*;

$DisHh_{bg_k}$: Number of dislocated households for block group *k*.

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