

## ABSTRACT

Title of Dissertation:       TRANSPORTATION RESILIENCE  
ARCHITECTURE: A FREMEWORK FOR  
ANALYSIS OF INFRASTRUCTURE,  
AGENCY AND USERS

*Nayel Urena Serulle, Doctor of Philosophy,  
2015*

Dissertation directed by:   Professor Cinzia Cirillo, Department of Civil &  
Environmental Engineering

How do some countries, or sectors of it, overcome potentially disastrous events while others fail at it? The answer lies on the concept of resilience, and its importance grows as our environment's deterioration escalates, limiting the access to economic, social, and natural resources. This study evaluates resilience from a transportation perspective and defines it as "the ability for the system to maintain its demonstrated level of service or to restore itself to that level of service in a specified timeframe" (Heaslip, Louisell, & Collura, 2009). The literature shows that previous evaluation approaches usually do not directly integrate all perspectives of a transportation system. In this manner, this study introduces the concept of *Transportation Resilience Architecture* (TRA) as a framework for evaluating resilience of a transportation system through the cumulative effect of a system's Infrastructure, Agency and User layer.

This research introduces three quantitative methodologies as a way to evaluate resilience through TRA. For Infrastructure, a practical tool for measuring the level of

accessibility to “safe zones” is presented, which takes advantage of the logsum measure resulting from Statewide Transportation Models. Results from the two locations analyzed (Frederick, MD and Anacostia, D.C.) suggest a positive correlation between income and accessibility. For Agency, metrics collected through a thorough literature review were combined with survey data to develop an evaluation framework based on Fuzzy Algorithms that yields to an index. The end product highlights the importance of interoperability as a disaster preparedness and response enhancing practice. Finally, for User, a dynamic discrete choice model was adapted to evaluate evacuation behavior, taking into account the disaster’s characteristics and the population’s expectations of them—a first from an evacuation perspective. The proposed framework is estimated using SP evacuation data collected on Louisiana residents. The result indicates that the dynamic discrete choice model excels in incorporating demographic information of respondents, a key input in policy evaluation, and yields significantly more accurate evacuation percentages per forecast.

TRANSPORTATION RESILIENCE ARCHITECTURE: A FRAMEWORK FOR  
ANALYSIS OF INFRASTRUCTURE, AGENCY AND USERS

by

Nayel Urena Serulle

Dissertation submitted to the Faculty of the Graduate School of the  
University of Maryland, College Park, in partial fulfillment  
of the requirements for the degree of  
Doctor of Philosophy  
2015

Advisory Committee:  
Professor Cinzia Cirillo, Chair/Advisor  
Professor Gang-Len Chang  
Professor Alexander Chen  
Professor Ali Haghani  
Professor Kevin Heaslip

© Copyright by  
Nayel Urena Serulle  
2015

## **Dedication**

To my daughter Mila Zoë, “I did it! You know?”

## **Acknowledgements**

First and foremost, I would like to express my unmeasurable gratitude to my dissertation advisor, Dr. Cinzia Cirillo, for her continuous support and faith in me. Without you, none of my achievements would have been possible. Second, I would like to thank my advisory committee members, DR. Gang-Len Chang, Dr. Alexander Chen, Dr. Ali Haghani and Dr. Kevin Heaslip for their valuable suggestions on this research. Third, I thank my friends and colleagues Jean-Michel Tremblay and Dr. Nikola Markovic for their help in this process.

I would like to extend my gratitude to the Center for Advanced Transportation Technology (CATT), especially to Mr. Thomas Jacobs, for their assistance in the data solicitation process to the Maryland State Highway Administration (MDSHA). Also, special thanks to Dr. Chester Wilmot and Dr. Ravindra Gudishala from LSU for providing essential information for this analysis.

To all my friends at the “Dirty Spring”, thank you for your support and making me feel like home in this country. To all my friends back in the D.R. and all who, in some way or another, has shaped me into the person that I am today, I thank you.

Last but not least, I thank my family, my beautiful wife and daughter, for their love and inspiration, my mother and father for always believing in me, and my brothers and sisters for rooting for me.

# Table of Contents

Dedication.....	ii
Acknowledgements.....	iii
Table of Contents.....	iv
List of Tables .....	vii
List of Figures .....	ix
Chapter 1: Introduction.....	1
1.1 Problem Statement.....	4
1.2 Research Objectives and Scope .....	5
1.3 Contributions.....	6
Chapter 2: Theoretical Framework .....	7
2.1 Review Methodology.....	7
2.3 The Concept of Resilience .....	9
2.4 Resilience Literature .....	11
2.4.1 Properties of Resilience.....	17
2.4.2 Practical Frameworks .....	18
2.5 Transportation Resilience Architecture .....	22
2.6 Conclusion .....	24
Chapter 3: Infrastructure Resilience .....	26
3.1 Background.....	27
3.2 Methodology.....	29
3.2.1 Consumer Surplus (CS).....	31
3.2.2 A Logsum Approach .....	32

3.2.3 Maryland Statewide Travel Model.....	33
3.3 Identifying Low Income Population in the MWCOG Region.....	35
3.4 A Real Case Study: Evacuation Due to Localized Floods.....	37
3.4.1 Case Study.....	38
3.4.2 Accessibility Analysis.....	42
3.5 Application of Results: Shelter Location Analysis.....	45
3.5.1 Model 1: Maximization of Minimum Accessibility (M1).....	46
3.5.2 Model 2: Maximization of Overall Accessibility (M2).....	47
3.5.3 Results from Location Models.....	48
3.6 Conclusions.....	52
Chapter 4: Agency Resilience.....	54
4.1 Background.....	55
4.2 Evaluation Framework: a Sustainable Livelihood Approach.....	59
4.2.1 Fuzzy Algorithms.....	62
4.2.2 Interaction of Variables.....	64
4.3 Data Collection and Analysis.....	66
4.4 Results Based on Simulated Data.....	70
4.4.1 Variables, Metrics and Measurement Range.....	70
4.4.2 Application of Fuzzy Algorithms: Simulated Results.....	74
4.5 Conclusion.....	80
Chapter 5: User Resilience.....	83
5.1 Background.....	83
5.1.1 Modelling Evacuation.....	83

5.1.2 Dynamic Discrete Choice Models.....	86
5.2 Evacuation Modeling Framework.....	90
5.2.1 General Evacuation Decision Problem.....	90
5.2.2 Dynamic Estimation Process.....	93
5.2.3 Experiment Using Simulated Data.....	95
5.3 Dataset Description.....	99
5.3.1 Socio-economic Characteristics of Low Income Population .....	101
5.3.2 Revealed Preference: Evacuation Behavior thru Hurricane Gustav ..	106
5.3.3 Stated Preference: Evacuation Behavior .....	107
5.3.4 Things to Note.....	114
5.4 Disaster Evolution and Model Estimation with Real Data .....	115
5.4.1 Perfect Knowledge .....	116
5.4.2 Stochastic Growth .....	116
5.4.3 Results Using Real Data.....	120
5.5 Conclusions.....	122
Chapter 6: Conclusion.....	124
6.1 Findings and Contributions.....	124
6.2 Future Research .....	126
Annex 1: Locations of New Shelters .....	128
Annex 2: Agency Resilience Survey .....	129
Annex 3: Fuzzy Inference System’s Rules .....	133
Glossary .....	137
Bibliography .....	138

## List of Tables

<b>Table 1.</b> Examples of major natural disasters impacting cities between 2000-2012. ....	2
<b>Table 2.</b> Definitions of resilience in different fields. ....	9
<b>Table 3.</b> Perspectives and methodologies in the resilience literature. ....	13
<b>Table 4.</b> Income Groups (in 1999 Dollars). ....	33
<b>Table 5.</b> 2010 Poverty Guidelines for the 48 Contiguous States and D.C. ....	35
<b>Table 6.</b> Case studies for accessibility analysis. ....	36
<b>Table 7.</b> Optimal Shelter Locations. ....	49
<b>Table 8.</b> Potential metrics to evaluate Agency Resilience. ....	68
<b>Table 9.</b> Summary of Metrics and Measurement Range. ....	74
<b>Table 10.</b> Rules for estimating Agency Resiliency. ....	78
<b>Table 11.</b> Agency Resilience Index for simulated base case and scenarios. ....	80
<b>Table 12.</b> Estimation with simulated data. ....	98
<b>Table 13.</b> Hypothetical storms presented to interviewed households. ....	100
<b>Table 14.</b> Household location and income distribution within each location. ....	103
<b>Table 15.</b> Evacuation decision distribution. ....	108
<b>Table 16.</b> Hurricanes that traversed through Louisiana between 1950 and 2010. ....	117
<b>Table 17.</b> Results of estimating dynamic discrete choice models. ....	121
<b>Table 18.</b> FIS rules for Initial Redundancy. ....	133
<b>Table 19.</b> FIS rules for Physical Capital. ....	133
<b>Table 20.</b> FIS rules for Human Capital. ....	134
<b>Table 21.</b> FIS rules for Response Index. ....	134
<b>Table 22.</b> FIS rules for Base Resilience. ....	135

**Table 23.** FIS rules for Agency Resilience. .... 136

## List of Figures

<b>Figure 1.</b> Average distribution of yearly fatalities and economic loss from tropical cyclones.....	3
<b>Figure 2.</b> Transportation Resilience Architecture.....	23
<b>Figure 3.</b> PUMA location for the Washington DC Metropolitan Region.....	37
<b>Figure 4.</b> Average weather-related fatalities from 1975 to 2004.....	38
<b>Figure 5.</b> a) MWCOG region; b) Effect of storm surge and 100-year flood on the MWCOG area.....	40
<b>Figure 6.</b> a) Hurricane storm surge effect on Frederick, MD; b) 100-year flood effect on Anacostia, Washington DC; c) Roads prone to flood.....	41
<b>Figure 7.</b> Accessibility to safe zones of Frederick City's population by income level. ...	44
<b>Figure 8.</b> Accessibility to safe zones of Anacostia's population by income level. ....	45
<b>Figure 9.</b> Optimal location of new shelters.....	51
<b>Figure 10.</b> Proposed framework for evaluating AR through sustainable livelihoods.....	61
<b>Figure 11.</b> A Comparison of fuzzy (left) and precise (right) sets. ....	63
<b>Figure 12.</b> Illustration of the geometric FIS computational method.....	64
<b>Figure 13.</b> Agency Resilience Triangle (based on Bruneau et al., 2003). ....	65
<b>Figure 14.</b> Dependency diagram as the basis for Fuzzy Inference. ....	66
<b>Figure 15.</b> Agency Resilience Index's Fuzzy Inference System. ....	75
<b>Figure 16.</b> Agency Resilience result-surface. ....	79
<b>Figure 17.</b> Scenario Tree.....	95
<b>Figure 18.</b> Louisiana's parishes. ....	102
<b>Figure 19.</b> Household size by income level. ....	104

<b>Figure 20.</b> Vehicle ownership by household income. ....	105
<b>Figure 21.</b> Education level by household income. ....	106
<b>Figure 22.</b> Response curve (of those who evacuate) during Hurricane Gustav. ....	107
<b>Figure 23.</b> Evacuation decision by hypothetical storm. ....	109
<b>Figure 24.</b> Distribution of time between forecast and evacuation. ....	110
<b>Figure 25.</b> Household evacuation decision by income. ....	111
<b>Figure 26.</b> Evacuation behavior of households based on their size. ....	111
<b>Figure 27.</b> Effect of pet ownership on evacuation decision. ....	113
<b>Figure 28.</b> a) Intended mode of evacuation; b) Intended number of vehicles used for evacuation. ....	114
<b>Figure 29.</b> First difference of hurricane category data. ....	118
<b>Figure 30.</b> Comparison of observed and estimated evacuation percentages. ....	122
<b>Figure 31.</b> Location of new shelters for $m=85$ (upper) and $m=100$ (lower). ....	128

## Chapter 1: Introduction

*At any moment, “the most vulnerable are those whose lives are the most constrained, such as the poor, who have the least access to coping resources” (Godschalk, 2003, p. 140).*

How do some countries, or sectors of it, overcome potentially disastrous events while others fail at it? The answer lies on the concept of resilience, and its importance grows as our environment’s deterioration escalates, limiting the access to economic, social, and natural resources. Resilience is an abstract measure that has been studied in an ample selection of fields, and it is commonly defined as the capacity to absorb shocks and maintain operations during disrupting events. This study evaluates resilience from a transportation perspective—particularly it provides quantitative methodologies to evaluate Transportation Resilience (TR henceforth) of low-income populations to disrupting events.

TR is defined as “the ability for the system to maintain its demonstrated level of service or to restore itself to that level of service in a specified timeframe” (Heaslip, Louisell, & Collura, 2009). It should be noted that disruptive events can be either planned (e.g., work-zone congestion), recurrent (e.g., rush hour) or non-recurrent (e.g., terrorist attack, natural disaster). This study focuses on non-recurrent (disastrous) events, which usually pose a major threat to communities, cities, countries, or regions—especially the disadvantaged ones—due to their randomness and magnitude.

In order to evaluate resilience to disasters, it is necessary to first clearly define what a disaster is (and its consequences). This research embraces the Centre for Research on the Epidemiology of Disasters’ (CRED) definition of disaster: “a situation or event, which overwhelms local capacity, necessitating a request to national or international level for external assistance.” The CRED states that in order for an event to be considered a disaster,

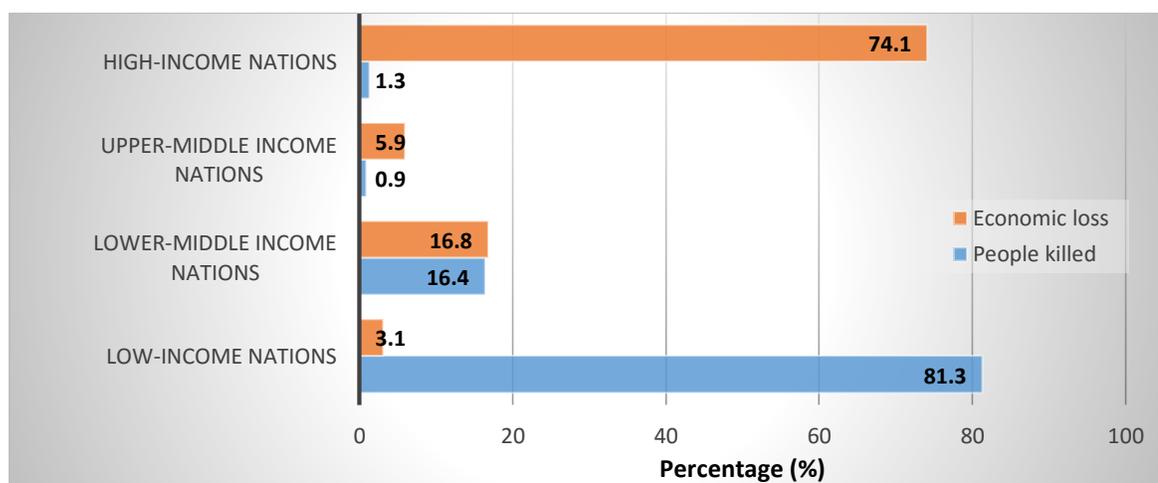
at least one of the following criteria must be fulfilled: a) ten or more people reported killed, b) 100 people or more reported affected, c) declaration of a state of emergency, and/or d) call for international assistance (CRED, 2009). In the first decade of the 21st century the world experienced a variety of unseen and unexpected man-made and natural disasters; some notable examples are the “9/11” attacks on 2001 with almost 3,000 casualties, the 2004 South Asian Tsunami, and Haiti’s earthquake in 2010— the latter two with over 220,000 casualties each. Table 1 presents examples of large natural disaster that occurred during the period of 2000-2012. In all these events, transportation played an important role, if not the most, in the process of preparing for, coping with, and recovering from them.

**Table 1.** Examples of major natural disasters impacting cities between years 2000-2012.

Popular Name	Countries Affected	Date of Event	Type of Hazard	Main Cities Affected	Total Death	Total Affected (millions)	Damages (US\$)
Hurricane Sandy	US, Bahamas, Dominican Republic, Canada	Oct-12	Hurricane	US East coast, New York	286	n.a.	68 billion
Haiti earthquake	Haiti	Jan-10	Earthquake	Port-au-Prince	222,570	3.4	n/a
Cyclone Nargis	Myanmar	May-08	Tropical cyclone	Yangon	138,366	2.42	4 billion
Hurricane Katrina	United States	Aug-05	Tropical cyclone	New Orleans	1,833	0.5	125 billion
Mumbai floods	India	Jul-05	Flood	Mumbai	1,200	20	3.3 billion
South Asian tsunami	Indonesia, Sri Lanka, India, Thailand, Malaysia, Maldives, Myanmar	Dec-04	Earthquake and tsunami	Banda Aceh, Chennai (some damages)	226,408	2.32	9.2 billion
Hurricane Ivan	Venezuela, Jamaica, Cuba, US	Sept-04	Hurricane	Grenada, Alabama, Florida, Louisiana	122	n.a.	1.2 billion

Partly extracted from: EM-DAT: The OFDA / CRED International Disaster Database ([www.emdat.net](http://www.emdat.net)), Université Catholique de Louvain – Brussels – Belgium. Modified from International Federation of Red Cross and Red Crescent Societies (2010).

A review of weather-events record shows that between 1970 and 2009, the average number of cyclones Category 1 and 2—following the Saffir-Simpson scale—decreased on an annual basis, cyclones Category 3 and 4 increased, and there was no significant change in the average number of Tropical Storms and cyclones Category 5 per year. Interestingly, even though the frequency of severe tropical cyclones has increased, overall worldwide mortality risk has decreased, whereas economic loss risk associated with these natural events has increased (UNISDR, 2011). Nevertheless, these endeavors have not been equally distributed across all income levels. On its 2009 disaster assessment report, the United Nations’ International Strategy for Disaster Reduction (UNISDR) found that for a given number of persons exposed to risk, and within the context of powerful Category 3 and 4 tropical cyclones, low-income countries are far more likely to suffer higher mortality rates and low economic loss than high-income countries, which, on the contrary, are more likely to suffer higher economic loss, and lower mortality (ISDR, 2009). Figure 1 illustrates the latter and highlights the necessity of studies of resilience that target low-income population.



**Figure 1.** Average distribution of yearly fatalities and economic loss from tropical cyclones. Source: International Federation of Red Cross and Red Crescent Societies, 2010

## 1.1 Problem Statement

Transportation resilience has proven to be important in securing economic stability and decreasing the number of casualties from a disruptive event, both desirable goals of many systems. In recent years, the demand for resilience evaluation models has grown significantly as a result of more frequent disastrous events and new policy concerns. For instance, in the United States on February 12th, 2013 the Presidential Policy Directive on Critical Infrastructure Security and Resilience advanced a national unity of efforts to strengthen and maintain critical infrastructure in order to improve their resilience (The White House Office of the Press Secretary, 2013). However, despite the interest in TR, consensus on how to measure it has not been reached (Madhusudan & Ganapathy, 2011; P. Murray-Tuite, 2006), which therefore limits policy evaluation.

A review of the literature shows that progress has been made on conceptualizing resilience; however, there is a lack of empirical work and development of an evaluation framework. For example, Bhamra, Dani, and Burnard (2011) reviewed 74 papers from a wide interdisciplinary selection that provided a direct link to the concept of ‘resilience’. They concluded that more real world-based research needs to be done in order to give value to theory. Particularly, work based on empirical methods can significantly add to and validate theoretical constructs around the resilience theme.

This dissertation will then focus on how to quantitatively and empirically evaluate TR of low-income populations while using, to the extent possible, existing and readily accessible information, therefore enhancing the flexibility and applicability of the proposed framework.

## 1.2 Research Objectives and Scope

Taking a step forward from previous studies that mostly focus on TR from a single perspective (e.g., network characteristics), the overall objective of this study is to provide an evaluation framework that could serve as the umbrella—common starting point—for future transportation resilience research, by proposing a multi-perspective real world-data based quantitative methodology to evaluate TR.

The study is divided into six main chapters:

1. *Introduction*. Introduces the research background, objectives, and the expected contributions from this research.
2. *Theoretical Framework*. Provides a comprehensive overview of relevant literature surrounding TR, identifying the different evaluation approaches previously used. Identifies shortcomings in the existing studies and proposes a research direction/conceptual framework for this dissertation.
3. *Infrastructure Resilience*. Provides a quantitative analysis of the physical environment as a component of TR, using accessibility as a proxy for it.
4. *Agency Resilience*. Presents an analysis of the institutional aspect of TR. Data is collected through a survey and a framework to develop an index is presented.
5. *User Resilience*. Suggests the use of a dynamic discrete choice estimation model approach of user behavior to evaluate users as a component of TR.
6. The final chapter presents the conclusion and suggests the way forward for future research.

### 1.3 Contributions

This study will contribute to the literature of TR by closing the existing knowledge gap with an innovative and quantitative real world-data driven evaluation framework that is flexible and transferable in nature, that is, one that can be easily applied across different types of disruptions and locations. To do so, the literature surrounding resilience of transportation networks and communities is explored and perspectives on the state of the practice in evaluating resilience is provided. The proposed approach could serve as a uniting conceptual framework of future research, facilitating the identification of voids within the literature. The tools developed in this research are evaluation frameworks for analyzing accessibility to safe zones, an agency preparedness and response capability, and user behavior during disasters, all through innovative approaches within the transportation field. These tools are useful for different transportation problems and most importantly, will help decision makers implement more effective policies by narrowing the alternatives of when, where, and how to invest available resources in order to increase resilience.

Furthermore, it is expected that the availability of a robust evaluation tool will increase the number of real case studies about TR. It is also expected that participants involved will increase awareness and promote the need of practical resilience evaluation tools, taking us one step closer to using resilience as a standard measure of performance and preparedness to disaster for transportation systems at all scales.

## Chapter 2: Theoretical Framework

This section provides a detailed literature review, helping identify gaps within the current state of practice – one being that research evaluating resilience of transportation systems focus on targeted aspects of resilience and specific perspectives or elements of the transportation system. For example, Madhusudan, and Ganapathy (2011) focused on resilience of ports, Reggiani (2013) on resilience from transport security perspective, Bhamra, Dani, and Burnard (2011) on organizational and enterprises resilience, Ortiz, Ecola, and Willis (2009) on freight TR, and Caplice, Rice, Ivanov, and Stratton (2008) proposed guidelines for developing state-wide freight resilience plans. This work provides a broader approach by linking the infrastructure, agency and user perspectives of a transportation system, under what this study designates as *Transportation Resilience Architecture*.

### 2.1 Review Methodology

The objective of this research is to bridge the knowledge gap that exists in TR. A literature review is a necessary step in constructing a research field and forms a fundamental part of any research conducted (Easterby-Smith, Thorpe, & Lowe, 2002), yielding a comprehensive view of the available literature. This study explores the literature surrounding resilience, providing perspectives on the state of the practice in its evaluation. This review follows an adapted version of Srivastava's (2007) literature evaluation framework. The steps are briefly explained below and the outcomes are presented in Tables 2 and 3.

- First, the unit of analysis is selected: in this study, the unit of analysis is a single research paper, book or report.
- Second, the process for collecting the material and delimiting the scope is defined: the literature review targeted journal articles, books, conference papers, theses, and reports. The materials were collected based on their availability on library databases and “Google Scholar”. Given the multidisciplinary nature of resiliency, researches in several fields were considered, although transportation remained as the main focus of the search. Keywords such as ‘transportation resilience’ and ‘evaluating resilience’ were used for the search. No time span or peer-reviewed limitations were considered in the sources collection process. Overall, 41 interdisciplinary research materials were selected for the analysis given their direct link to resilience.
- Finally, the classification context is defined: each material was analyzed and sorted based on two contexts –perspective and methodology– which led to the identification of relevant issues. While the perspective indicates the viewpoint of the material, the methodology indicates its approach – literature review, theoretical framework, and practical framework. In addition, information about whether the research contained a case study is presented.

To delimit the number of publications, when possible, methodological redundancies and highly descriptive papers (rather than analytical research) were disregarded. With this threshold the review process is optimized and diversity is ensured. Moreover, the objective of evaluating current state of practice is fulfilled.

### 2.3 The Concept of Resilience

Resilience is an abstract measure that has been studied in an ample selection of fields. Examples of these fields are economics (Briguglio, Cordina, Farrugia, & Vella, 2009), community disaster (Bruneau et al., 2003; Carreño, Cardona, & Barbat, 2007; S. E. Chang & Shinozuka, 2004; Godschalk, 2003; Mayunga, 2007), infrastructure (Omer, Mostashari, & Nilchiani, 2011), ecology (Cumming et al., 2005; Holling, 1973), and transportation (P. Murray-Tuite, 2006; Pitera, 2008; Ta, Goodchild, & Pitera, 2009; N Urena Serulle, Heaslip, Brady, Louisell, & Collura, 2011). There have been several definitions proposed for resilience, each slightly altered dependent on context (Bhamra et al., 2011). Although expressed differently, most definitions have common factors, such as “capacity to absorb shocks” and “maintain operation during disruptive events.” Table 2 presents a summary of definitions of resilience in several fields. This research follows Heaslip, Collura, and Louisell’s (2009) definition of TR as the ability for the system to maintain its demonstrated level of service or to restore itself to that level within a given timeframe.

**Table 2.** Definitions of resilience in different fields.

<b>Author(s)</b>	<b>Year</b>	<b>Perspective</b>	<b>Definition</b>
Holling	1973	Ecology	Persistence of systems and their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables.
Comfort	1999	Disaster Management	Capacity to adapt existing resources and skills to new situations and operating conditions.
Mileti	1999	Community	A locale is able to withstand an extreme natural event without suffering devastating losses, damage, diminished productivity, or quality of life and without a large amount of assistance from outside the community.
Bruneau et al.	2003	Community (Seismic)	Ability of social units (e.g., organizations, communities) to mitigate hazards, contain the effects of disasters when they occur, and carry out recovery activities in ways that minimize social disruption and mitigate the effects of future earthquakes.

Cumming et al.	2005	Social-Ecology	Ability of a system to maintain its identity (i.e., property of key components and relationships and their continuity through space and time).
Mohammad, Hutchison, & Sterbenz	2006	Communication	Network that has the ability to operate and maintain acceptable level of service under the presence of adverse conditions.
Falasca, Zobel, & Cook	2008	Freight Transportation/ Supply Chain	Ability of a supply chain system to reduce the probability of disruptions, to reduce the consequences of those disruptions, and to reduce the time to recover normal performance.
Briguglio et al.	2009	Economy	Ability to recover from or adjust to the negative impacts of external economic shocks.
Madni & Jackson	2009	System Eng.	Ability to anticipate and circumvent accidents, survive disruptions through appropriate learning and adaptation, and recover from disruptions by restoring the pre-disruption state as closely as possible.
Ta et al.	2009	Freight Transportation	Ability for the system to absorb the consequences of disruptions to reduce the impacts of disruptions and maintain freight mobility
Heaslip et al.	2009	Transportation	Ability for the system to maintain its demonstrated level of service or to restore itself to that level of service in specified timeframe.
National Research Council	2010	Climate Change	A capability to anticipate, prepare for, respond to, and recover from significant multi-hazard threats with minimum damage to social well-being, the economy, and the environment.
Leu, Abbass, & Curtis	2010	Transportation/ Network	System's ability to keep focusing on and meeting key objectives when faced with challenges in the surrounding operating environment.
U.S. Department of Transportation	2013	Transportation	A resilient transportation infrastructure will be able to function in the face of threats, and will be able to absorb shocks and adapt to changing conditions

The different definitions above raise the following questions: is resilience the ability to adapt to or prepare for? To recover or to maintain operation? All of the prior or a combination? A clear, universally accepted, and tailored to the unique characteristics of the transportation environment definition of resilience is needed. It is the belief of many researchers that the first step in measuring resilience is the understanding of it. In this context, the purpose of this study is not to present a new definition of resilience in the

context of transportation; instead, it is to fuel a discussion by highlighting the small but meaningful differences in the definition of resilience across and within fields of study.

#### 2.4 Resilience Literature

Given that transportation resilience is the main focus of this study, a higher weight was given to this perspective when selecting the reviewed literature. However, it should be noted that community resilience research presented high correlation with the field of transportation; therefore it was given a significant weight as well. From the 41 research pieces evaluated, 35 related to community and transportation. This sample highlights the strongest areas within the transportation and community resilience literatures. Around half of the material consists on theory building material –literature reviews and/or conceptual frameworks. The rest of the selected sources present some sort of practical framework, with only a few evaluating resilience by incorporating different aspects of its environment. Approximately half of the transportation literature evaluates resilience concentrating only on the network’s characteristics (e.g., topology, connectivity, capacity), with little to no consideration of the user and management’s effect on the overall resilience. In addition, only one research used survey as an approach to develop its framework, corroborating Bhamra et al.’s (2011) finding that survey and model development are the least preferred methods for evaluating resilience. One can only presume that the economic burden of surveys may be a reason for disregarding this method.

The next subsections describe relevant properties and evaluation techniques of resilience found in the literature. However, not all the papers are discussed in order to avoid redundancy and enhance the analysis. The reader is referred to Table 3, which summarizes the perspectives, methodologies, and approaches to conceptualize and measure resilience

of all reviewed literature; the Table is organized by perspectives. It should be noted that this is not meant to be an exhaustive list, but a comprehensive one instead. The purpose is to provide researchers with a sample of the different approaches that can be found in the TR literature.

**Table 3.** Perspectives and methodologies in the resilience literature.

Author(s)	Year	Perspective	Methodologies			Case Study	Approach
			Literature Review	Theoretical Framework	Practical Framework		
Mohammad, Hutchison, & Sterbenz	2006	Communication		X			Provides different network statuses depending on performance ranges.
Comfort & Haase	2006	Communication			X	X	Graph theory to evaluate robustness of communication network.
Tobin	1999	Community		X			Qualitative assessment of community resilience based on physical, social/cultural, economic, and political characteristics.
Bruneau et al.	2003	Community		X			Conceptualized resilience along interrelated dimensions (TOSE) and 4 properties (4R's).
Godschalk	2003	Community	X				Summarized properties of resilient systems suggested by previous literature.
Chang & Shinozuka	2004	Community			X	X	Probability of meeting goals.
Mayunga	2007	Community		X			Weighted sum of variables.
Carreño et al.	2007	Community			X	X	Fuzzy algorithms to combine different community-related attributes.
Cutter et al.	2008	Community	X	X			Propose measuring total impact of disasters as the cumulative effect of antecedent conditions, event characteristics, and coping responses.
Mayunga & Peacock	2010	Community			X	X	Average of 75 standardized capital livelihood indicators.
Global Adaptation Institute	2011	Community			X		Sum of standardized vulnerability and readiness related variables.
Tilio, Murgante, Trani, Vona, & Masi	2011	Community			X	X	Spatial multi-criteria approach using GIS to map standardized variables.
Briguglio et al.	2009	Economy			X		Sum of standardized averages of economic metrics.
Pitera	2008	Freight Transportation			X	X	Surveyed freight enterprises to identify state of practice in resilience enhancement strategies.

Author(s)	Year	Perspective	Methodologies			Case Study	Approach
			Literature Review	Theoretical Framework	Practical Framework		
Caplice et al.	2008	Freight Transportation		X		X	Propose a three-phase guideline (i.e., identification, assessment, and implementation) to develop state-wide freight resilience plans.
Falasca et al.	2008	Freight Transportation			X		Propose quantitative measures to evaluate the determinants of resilience within a supply chain (i.e., density, complexity, and node criticality) which enabled the simulation of resilience enhancing alternatives and their cost/benefit analysis.
Ta et al.	2009	Freight Transportation	X				Review of literature to define resilience of freight systems.
Ortiz, Ecola & Willis	2009	Freight Transportation	X	X			Defined actions and performance measures that affect freight resilience from a public agency (e.g., DOT, MPO) perspective.
Mansouri, Nilchiani, & Mostashari	2010	Freight Transportation		X		X	Combined Risk Management and Decision Analysis techniques to assess investments on resilience enhancing strategies of port infrastructure systems
Adams, Bekkem, & Toledo-Duran	2012	Freight Transportation			X	X	Plotted resilience triangles (first proposed by Bruneau et al., 2003) and show how to quantify two composite measures –reduction and recovery – based on the triangle’s geometry.
Chen & Miller-Hooks	2012	Freight Transportation/ Network			X		Formulated a stochastic mixed-integer program to measure resilience of multimodal freight networks. Resilience is defined as the ratio between the network’s capacity before and after a disruptive event.
Bhamra et al.	2011	Organizational	X				Multidisciplinary literature review.
Cumming et al.	2005	Social-Ecology	X	X			Qualitative assessment of the likelihood that a system will change.
Madni & Jackson	2009	System Eng.	X	X			Review of literature to define and understand resilience of systems.
Losada, Scaparra, & O’Hanley	2012	System Eng./ OR			X	X	Incorporated facility recovery time into a bilevel mixed integer linear program for protecting an uncapacitated

Author(s)	Year	Perspective	Methodologies			Case Study	Approach
			Literature Review	Theoretical Framework	Practical Framework		
							median type facility network against worst-case losses. In addition, they analyzed the tradeoff between added protection investments and possible efficiency gains.
Battelle	2007	Transportation		X			Proposed several indicators of redundancy as a proxy of resilience.
Heaslip et al.	2009	Transportation		X			Suggested individual, community, economic, and recovery metrics to evaluate TR.
Cox, Prager, & Rose	2011	Transportation			X	X	Measured resilience as the percentage avoidance of the maximum economic disruption that a particular shock could bring about (i.e., Direct Static Economic Resilience), focusing on changes in passenger journeys and passenger kilometers by mode in London after the terrorist attacks of 2005.
Urena Serulle et al.	2011	Transportation			X	X	Fuzzy algorithms to combine performance and management metrics.
Freckleton, Heaslip, Luoisell, & Collura	2012	Transportation			X	X	Weighted sum of individual, community, economic and recovery metrics.
Oswald, McNeil, Ames, & Gayley	2013	Transportation			X	X	Used GIS to map performance measures to infer resilience and analyze current and future (projected) status.
Croope, McNeil, Deliberty, & Nigg	2010	Transportation/ Infrastructure			X	X	Decision support framework for critical infrastructure policy evaluation.
Madhusudan & Ganapathy	2011	Transportation/ Infrastructure	X				Review of resilience literature from a transportation port infrastructure perspective.
Murray-Tuite & Mahmassani	2004	Transportation/ Network			X		Measured the reliability of all links within a network based on the availability of alternate paths, excess capacity, and travel time.
Murray-Tuite	2006	Transportation/ Network			X	X	Applied UE and SO traffic assignment techniques to obtain performance values.

Author(s)	Year	Perspective	Methodologies			Case Study	Approach
			Literature Review	Theoretical Framework	Practical Framework		
Berche, Ferber, Holoatch, & Holoatch	2009	Transportation/ Network			X	X	Evaluated resilience of public transportation to attacks using L-space and P-space representation of their network, and evaluating their properties (e.g., segmentation concentration, shortest path length, and Molly-Reed parameter) when important components were removed.
Ip & Wang	2009	Transportation/ Network			X		Node resilience: weighted average number of reliable independent paths between nodes. Network resilience: weighted sum of all node resilience.
Leu, Abbass, & Curtis	2010	Transportation/ Network			X	X	Graph theory to evaluate physical resilience, focusing on lost connectivity and cost of repair.
Omer et al.	2011	Transportation/ Network			X	X	Ratio between the network's travel time before and after a disruption.
Nagurney	2011	Transportation/ Network			X		Developed a Network Efficiency/Performance Measure, based on network's topology and demand.
Vugrin & Turnquist	2012	Transportation/ Network			X	X	Developed a stochastic optimization model that finds a set of pre- and post-event investment and operational decisions that result in smaller total impacts of disruptions.

### *2.4.1 Properties of Resilience*

Bruneau et al. (2003) suggested that resilience could be conceptualized along the following four interrelated dimensions: technical, organizational, social, and economic (TOSE). In addition, Bruneau et al. identified four properties of resilience: robustness, rapidity, redundancy, and resourcefulness (4 R's). The authors explained that robustness and rapidity could be viewed as the goal of resilience, and redundancy and resourcefulness as the way to achieve them. Godschalk (2003) compiled a set of suggested properties of resilient systems based on existing literature. He found that resilient systems tend to be redundant, diverse, efficient, autonomous, strong, interdependent, adaptable, and collaborative. Murray-Tuite (2006) summarized the properties of resilience found in the literature with ten indicators –diversity, efficiency, autonomous components, redundancy, strength, adaptability, collaboration, mobility, safety, and the ability to recover quickly. Similarly, Battelle (2007) related resilience to redundancy. According to Battelle, redundancy depends on excess capacity, level of intermodality, vulnerabilities (e.g., chokepoints), stochastic behavior of the network's users, and the effects of network management techniques. Mohammad et al. (2006) suggested different parameters for evaluating network resilience: density (e.g., number of nodes), mobility (e.g., speed), channel (e.g., capacity), node resources, network traffic, and derived properties (e.g., connectivity, delay). Ta et al. (2009) concluded that redundancy, autonomous components, collaboration, efficiency, adaptability, and interdependence were consistently mentioned as properties within evaluation frameworks in the literature of freight TR.

The definition of performance measures and standards for these properties is essential to the quantification of resilience. According to Cumming et al. (2005),

recognizing the resilient nature of a system's property is the key in identifying actions that alter the system's resilience or strategies that focus on enhancing or reducing particular concerns. Nevertheless, the multi-dimensional nature of resilience challenges the development of measures that are quantifiable, concise, and significant (S. E. Chang & Shinozuka, 2004). To the best of our knowledge, no single metric has been widely accepted as the measure of performance for most of the suggested resilient properties.

#### *2.4.2 Practical Frameworks*

The debate on how to measure resilience has become more attractive over the past two decades. Bhamra et al. (2011) reviewed 74 papers from a wide interdisciplinary selection that provided a direct link to the concept of resilience. They concluded that more real world-based research needed to be done in order to give value to theory. Particularly, work based on empirical methods can significantly add to and validate theoretical constructs around the resilience theme. Several practical approaches have been used in the literature, a subset of them are discussed next.

Following Bruneau et al.'s framework, Chang and Shinozuka (2004) established robustness and rapidity goals for each TOSE dimension (e.g., less than 5% of the community lose water) and proposed quantifying resilience as the probability of achieving those goals during the disastrous event. The probability indicates the percent of simulations for which outcomes meet these standards.

Briguglio et al. (2009), Mayunga and Peacock (2010), and the Global Adaptation Institute (2011) used the sum of and the average of standardized variables as part of their methodology to compute an index. On the one hand, Briguglio et al. (2009) suggested the use of macroeconomic stability, microeconomic market efficiency, good governance, and

social development as indicators of an economic resilience index (ERI). On the other hand, Mayunga and Peacock (2010) analyzed 75 different variables categorized by their relation to each livelihood capital (i.e., social, economic, physical, and human) and linked them to each disaster phase (i.e., preparedness, response, recovery, and mitigation). Lastly, the Global Adaptation Institute (2011), which uses adaptation as a synonym of resilience, developed an adaptation index by standardizing vulnerability based on water, food, health, and infrastructure factors, and readiness based on upper and lower thresholds of economic, governance, and social indicators. The final index is obtained by summing up the vulnerability and readiness sub-indexes and then adjusting for the country's per capita Gross Domestic Product.

Another methodology found in the literature is fuzzy sets. Fuzzy sets present a more flexible way of combining variables by allowing partial membership to a set. Carreño, Cardona, and Barbat (2007) used fuzzy algorithms to develop a risk management index. Their approach averaged four public policy indicators: risk identification, risk reduction, disaster management, and governance and financial protection.

Other authors have also used operational research and graph theory as a way to analyze resilience of networks; Comfort and Haase (2006) used graph theory to analyze the resilience of a communication network in disaster environments. Next, some of the practical frameworks found in the TR literature are presented.

#### *2.4.2.1 Practical Frameworks in Transportation*

In transportation, the term resilience has been associated to similar concepts like vulnerability, reliability, robustness, risk management, and redundancy, providing a starting point on how to measure resilience. These concepts have been quantitatively

evaluated in detail, mostly from the topological and operational aspect of a transportation network (Ip & Wang, 2009; Miller-Hooks, Zhang, & Faturechi, 2012; Murray-Tuite, 2006; Murray-Tuite & Mahmassani, 2004). Some of these evaluation frameworks are described next.

Murray-Tuite and Mahmassani (2004) measured the reliability of all links within a network based on the availability of alternate paths, excess capacity, and travel time between a given pair of nodes. Later on, Murray-Tuite (2006) proposed several metrics to analyze the network's properties of adaptability, mobility, safety, and ability to recover quickly. The metrics used were mainly based on the results of traffic assignment techniques (e.g., travel time of private and emergency vehicles, queue length and time, traffic volume) and physical characteristics of the network (e.g., available capacity of all modes and infrastructures).

Omer, et al. (2011) proposed a Network Infrastructure Resiliency Assessment (NIRA) framework which uses the ratio between the travel time prior to and after a disruption as an indicator of resilience. Similarly, Chen and Miller Hooks (2012) used a ratio to estimate resilience, this time between the network's capacity before and after a disruptive event. They formulated a stochastic mixed-integer program to obtain capacity measures of multimodal freight networks.

Adams, Bekkem, and Toledo-Duran (2012) plotted resilience triangles (first proposed by Bruneau et al., 2003) based on truck counts and travel time through a corridor before, during and after significant weather events. They quantified two composite measures –reduction and recovery – based on the triangle's geometry.

Oswald et al. (2013) proposed capturing resiliency of corridors through performance measures while adding spatial and temporal scales. For this, they suggested using GIS to map different indicators of performance (e.g., infrastructure age, travel time index, connectivity, commute time) and visually identify any current problem and trends. It should be noted that the methodology presented by Oswald et al. does not yield to a resilience index. Instead, it only highlights current and potential problems of the corridor and based on the findings, the planners and agencies can then develop and evaluate possible strategies that could improve the resilience of the corridor.

Urena Serulle et al. (2011) used fuzzy sets to develop a TR index; they posited that TR could be measured using nine metrics that indicate the availability, accessibility, cost of travel, performance and management of the transportation network. The resilience evaluation process estimates the pre-event level of resilience of the system and allows policy evaluation through sensitivity analysis.

While most research focus on defining resilience and proposing measures to achieve it, few focus on how resilience is perceived and what strategies are currently being implemented to achieve it (Pitera, 2008). Pitera explored and evaluated resiliency efforts being used in freight transportation. For this, the researcher interviewed 11 staff members responsible for transportation activities and operations of different enterprises. Discussions included the topics of resiliency, vulnerabilities, disruptions, and disruption procedures. Overall, 15 strategies were identified and the enterprises were ranked, among other things, based on the number of strategies implemented, the impact of these strategies on the entire supply chain process, the amount of resources spent on resiliency efforts, the cost saved due to resiliency efforts, and the types of disruptions accounted for.

In conclusion, two common aspects were found in the literature of TR: the dependence on performance measures and the focus on the topological and operational aspects of the network. As research on TR advances, so will the robustness of its variables, making it possible to achieve consensus on how to proxy them. However, the problem of being myopic in the evaluation approach still remains. The next subsection provides a framework for analysis which overcomes this limitation.

### 2.5 Transportation Resilience Architecture

The literature shows that most resilience evaluation frameworks rely on performance measures, even if indirectly. However, merely identifying the measures that affect or reflect resilience is not enough to assess it. These approaches usually do not directly integrate other perspectives of a transportation system, such as the human aspect, and the effects they have on the system's overall resilience level in their analyses. In this manner, this study introduces the concept of *Transportation Resilience Architecture* (TRA) as a framework for evaluating resilience of a transportation system, where it is proposed separating TR into infrastructure, agency and user layers, and evaluating the overall resilience as the cumulative effect of each layer. The assessment framework suggested here partly builds upon three studies: 1) Leu, Abbass, and Curtis' (2010) assumption that a transportation system can be laid out in linked layers; 2) Little's (2003) statement that complex systems have critical institutional and human elements that should be understood and integrated into the analytical framework; and 3) Cutter et al.'s (2008) notion that the overall impact of a disaster is a cumulative effect of the existing conditions, characteristics of the event, and coping responses of the community.

The TRA provides a framework comprised of three layers that allows a comprehensive evaluation of TR-enhancing strategies (see Figure 2). The Infrastructure Layer comprises the physical environment – including subsystems, their interfaces and underlying functionality that are required for each transportation and community service. The Infrastructure Layer is shown as the base because solid infrastructure are prerequisite to an effective resilient system. The Agency Layer includes the institutions, policies, processes and resources that are required for effective implementation, operation, and maintenance of resilient strategies. This is where the objectives and requirements for TR are established. Finally, the User Layer provides insight into the characteristics of the (potentially) affected population and their resilient capability.



**Figure 2.** Transportation Resilience Architecture.

An analytical framework should possess the resilient qualities of each layer because in order to achieve a specific objective (e.g., economic, social welfare, optimized service) one cannot separate the network from the people managing and using it; however, logic suggests that a hierarchy exists between these layers. This study suggests that infrastructure

resilience is the most important layer, followed by agency and then user resilience. The justification for this priority order is best illustrated by an example. Imagine a community living in a floodplain near a dam. Imagine also that hurricane-like heavy rain has been forecasted for the area. The ability of the dam, and the entire physical environment, to withstand the additional water and strong wind is of utmost importance since it will diminish overall damages, injuries and mortality while enabling response/recovery processes. Even if the infrastructure can withstand the rain, it is the responsibility of the agencies in charge of the dam and the community to be prepared to deal with the unpredictable consequences of drastic situations and provide guidance to the population, such as evacuation-related activities (if needed). Finally, the community is responsible for preparing themselves for the event by taking actions that could lower the probability of injuries and casualties (e.g., buying supplies, making sure their vehicles have gas, and evacuating within the suggested time, if applies).

The proposed assessment framework is flexible and transferable in nature, as it can be easily applied across different types of disruption and location. These characteristics were important objectives since not all disruptions have the same impact and not all data is available at all locations.

## 2.6 Conclusion

This review analyzed 41 studies in resilience, mostly related to transportation and community, and found that transportation and community resilience have been well investigated independently, but not together. In general, most studies have had a narrow perspective, excluding or giving very limited participation to other dimensions of the environment (e.g., social, economic, political, ecology, community) that affect resilience.

Based on the literature review, this chapter summarizes major studies related to this research and identifies promising research directions for this dissertation. In here, a summary of the research papers surrounding resilience of transportation and communities is provided, as well as a conceptual framework for analyzing TR. Transportation systems are complex by nature, as they overlap physical, technical, and human disciplines. In order to successfully and efficiently evaluate TR, the analysis framework must differentiate each components of the transportation system that affects its resilience. A review of the literature shows that progress has been made on measuring resilience, but there is a gap yet to be filled in evaluating resilience from the different components of a transportation environment –the infrastructure, the management agencies, and the users. This dissertation contributes to the literature by reducing this gap through the development of robust, yet flexible, quantitative methodologies to evaluate each component.

## Chapter 3: Infrastructure Resilience

*The key to a successful evacuation is being able to move people at risk to safer areas – (Levinson & Granot, 2002).*

Infrastructure resilience (IR) comprises the physical environment where all transportation-dependent activities (e.g., social, economic, leisure) take place. It should be noted that this layer of resilience is not limited to transportation infrastructure, as it can consider other service infrastructures (e.g., water and electricity) that could hinder transportation in the case of a disruptive event. This being said, this dissertation recognizes the difficult task of evaluating IR in its entirety and proposes to proxy it as the level of accessibility of a specific population. In more detail, this study evaluates the accessibility of low income population to safe zones using transportation models, specifically the Maryland Statewide Travel Model (MSTM). This approach allows for a more robust analysis of accessibility as it simultaneously take into account all available modes of transportation and the many other variables that influence their usage, such as in vehicle travel time, parking cost, walk time, toll cost, and transit fare.

The remaining of this chapter is organized as follows: Section 3.1 provides a background on accessibility analysis; Section 3.2 presents the methodology used to calculate network accessibility to recovery sites during evacuation; Section 3.3 defines low income households, in addition to methods and data available to locate them in the study areas; Section 3.4 explains the two real case studies developed in this study (evacuation due to localized floods of Frederick, MD and Anacostia, Washington DC); Section 3.5 provides a detailed accessibility analysis; and Section 3.6 summarizes the conclusions and suggestions for future investigations.

### 3.1 Background

Evacuations are more common than many people realize. While people along the Gulf and Atlantic coasts evacuate in the face of approaching hurricanes almost every year, these events are unusual in the Washington, DC region. Nevertheless, Agnes in 1972, Floyd in 1999, and Isabel in 2003 are examples of hurricanes-turned-tropical-storms that caused significant damages for the Washington, DC region in recent history. Furthermore, during the months of June and July, 2013, flash floods became a trend in the area, forcing people to leave their homes and causing damages as well. Such recent events make it clear that research is needed to develop evacuation-oriented evaluation frameworks that could complement existing robust traffic simulation techniques. For example, Chakraborty, Tobin, and Montz (2005) used a geographical information systems framework to determine the magnitude of evacuation assistance need of zones within the coastal area of Hillsborough County, Florida. For this, they combined various geophysical patterns (i.e., flood estimates) and social vulnerability indicators (i.e., population's demographics). However, socioeconomic demographics are not the only factors influencing the effectiveness of evacuation strategies (Dash & Gladwin, 2007). Murray-Tuite and Mahmassani (2003) modelled household evacuation behavior by incorporating people's desire to find relatives prior to leaving an area and then evacuate as an unit. The model yielded higher (and more realistic) evacuation time when compared to traditional evacuation models, which assume that people immediately move away from the danger.

Of the many factors influencing evacuation behavior, accessibility is of utmost importance, especially to the disadvantaged population (e.g., low income individuals and people with special needs). It is important to understand that the disadvantaged have a

different transportation network than the rest of the population, mainly because of their limited access to a full set of transport alternatives and resources, restrictions that are exacerbated in the midst of a disaster. Having access to transportation alternatives, even partially, provides individuals freedom from social, economic, and physical isolation (Sohail, 2005). Hence, transportation plays an important role, if not the most, in the process of preparing for and recovering from a disaster. This was evident in New Orleans with Hurricane Katrina and in Haiti with its earthquake.

In this study, disadvantaged individuals (DIs) are defined as those below the poverty line (as set by the 2010 National Poverty Guidelines) or those who may require special assistance. According to the Federal Transit Administration (2006), individuals who may require special assistance include: 1) individuals who cannot independently get to a pick up (evacuation) point; 2) individuals who live independently and require transportation from their location; 3) individuals who live in a group setting (e.g., group home, assisted living center) and require transportation directly from their location; 4) individuals in acute care/in-patient facilities; 5) individuals with disabilities; and 6) individuals with limited English proficiency.

The preliminary work of this research was performed as part of the “Regional Public Transportation Capacity Study for the Washington, DC Metropolitan Region” petitioned by the Metropolitan Washington Council of Government (MWCOG). This study builds upon this work and adds to it by using transportation models, such as the Maryland Statewide Travel Model (MSTM). The MSTM is a state of the practice model system developed to support policy analysis and decision making, and is currently used by MPOs and Maryland SHA. This study proposes to use an available planning tool to evaluate

accessibility in the case of emergency and presents a simple yet revealing practical method for measuring the level of accessibility to “safe zones.” For this study, safe zones are defined as locations that provide safe haven to evacuees or serve as transition points to such locations. Examples of these are pick-up/meeting points, shelters, hospitals, high altitude (flood-free) areas, and locations at least 5 miles away from the affected area. However, this definition can change as it depends on the magnitude, type and location of the event.

The tool allows for visual analysis of accessibility through GIS by superposing layers of information and identifying deficiencies. This provides practitioners, first responders, planners and other decision makers with insight into the mobility capabilities of different communities to take the necessary steps to ensure the efficient and optimal distribution of resources. The tool is flexible in its application and easily transferable to any location for which the necessary data is available.

### 3.2 Methodology

Transport modeling measures what would people do based on existing behavior. On the other hand, accessibility measures what could people do (Abley, 2010). Being able to measure accessibility enables comprehensive policy evaluation by taking into account all potential alternatives of transportation linked with demographic data. Usually, accessibility is reported as the amount of people or percentage of a population that can access a destination within a specified threshold, generally time-, distance- or cost-related, or a combination of them. Apparicio, Abdelmajid, Riva, and Shearmur (2008) measured geographical accessibility of residential areas (i.e. census tracts) to selected health care services using different distance types (i.e., Cartesian and network) and aggregation

methods (e.g., population weighted mean). Abley (2010) developed a methodology to assess the accessibility of a neighborhood, as commissioned by the New Zealand Transport Agency. Their methodology yielded color-coded maps indicating the accessibility level of a given neighborhood based on a desired time, distance or cost bound. In their 2011 report, “Missed Opportunity,” Tomer, Kneebone, Puentes, and Berube (2011) measured how effectively transportation networks in metropolitan areas connect workers to jobs. For this, they measured how many people, grouped by skill sets, were covered by transit and how many jobs they can reach within a reasonable amount of time, usually 90 minutes. Yigitcanlar, Sipe, Evans, and Pitot (2007) measured accessibility to basic community’s services through public transportation based on walking distance and travel time. Nicholls (2001) measured accessibility to recreation locations (i.e., parks) through a 0.5 mile coverage-radius and walking-distance threshold. In addition, authors have measured accessibility between locations by using a distance-based gravity calculation approach (i.e., sum of attraction measure –such as number of doctors or jobs– divided by distance-based attribute –such as travel time or area), see Kockelman (1997) and Thouez, Bodson, and Joseph (1988).

Although practical, these approaches lack in simultaneously taking into account all available modes of transportation and the many other variables that influence their usage, such as in vehicle travel time, parking cost, walk time, toll cost, and transit fare. Kwan and Weber (2003) stated the need to go beyond conventional spatial and temporal frameworks to measure accessibility. Geurs and Wee (2004) and Litman (2003) suggested that more advanced, yet easy to interpret, utility- and activity-based accessibility measures are needed to improve current practice in measuring accessibility. Hence, this research attempts to fill

such void and bypass the stated limitations by taking advantage of the logsum measure resulting from transportation models.

### 3.2.1 Consumer Surplus (CS)

CS is the utility a person receives from a choice situation. A researcher is often interested in measuring the change in CS that is associated with a particular policy (e.g., building a new metro line or applying a new parking policy) since it is important to measure the benefits of the project and compare them to the costs. Similarly, a change in the attributes of an alternative can have an impact on CS that is important to assess. Consumer surplus is  $CS_n = (1/\alpha_n) \max_j(U_{nj})$  where  $U_{nj}$  is the utility of alternative  $j$  for person  $n$  and  $\alpha_n$  is the marginal utility of income:  $dU_n/dY_n = \alpha_n$ , with  $Y_n$  the income of person  $n$ . The division by  $\alpha_n$  translates utility into dollars, since  $1/\alpha_n = dY_n/dU_n$ . The researcher only observes  $V_{nj}$  instead of  $U_{nj}$ , where  $V_{nj}$  is the known part of the utility  $U_{nj}$ . Furthermore, the researcher is able to calculate the expected CS as  $E(CS_n) = \frac{1}{\alpha_n} E[\max_j(V_{nj} + \varepsilon_{nj}) \forall j]$ . If each  $\varepsilon_{nj}$ , the unknown part of the utility of alternative  $j$  for person  $n$ , is iid extreme value and the utility is linear in income (so that  $\alpha_n$  is constant with respect to income), then:  $E(CS_n) = \frac{1}{\alpha_n} \ln(\sum_{j=1}^J e^{V_{nj}}) + C$ , where  $C$  is an unknown constant that represents the fact that the absolute level of utility cannot be measured. Note that the argument in parentheses in the previous expression is the denominator of the logit choice probability. The expected consumer surplus in a logit model is simply the log of the denominator of the choice probability, and can be estimated for any population that has the same representative utility. This is often called the logsum term. The reader is referred to Train (2003) for more details on discrete choice models and their application.

### *3.2.2 A Logsum Approach*

Logit models are frequently used in transportation. They provide the basis for consumer surplus, measured by the logsum (LS). In practice, logsums are rarely used in project assessments. Instead, the benefits of a project are based on changes in cost and time to travelers. This study applies the concept of CS to evaluate the accessibility within the Metropolitan Washington Council of Government (MWCOG) region. The computation of CSs are made based on a disaggregate logsum accessibility measure using the Maryland Statewide Transportation Model (MSTM). The logsum provides a robust solution to measure the full accessibility benefits from land-use and transport policies, taking advantage of the availability of discrete choice travel-demand models. The MSTM accounts for changes in generalized transportation costs and destination utility; moreover, it is a multi-layer model working at a regional, statewide and urban level. Key input data to the MSTM include population and employment, by income category, for each traffic zone, in addition to highway and transit networks, including the Washington Metropolitan Area Transit Authority (WMATA), the Maryland Transit Administration (MTA), and MARC Train commuter rail system and all local transit systems within the Baltimore-Washington area.

Due to limitations in the data, this study uses income as the only discerning factor between disadvantaged and non-disadvantaged population. The accessibility analysis was divided by income level. Income data was available in 1999 dollars (see Table 4). Furthermore, information on several combinations of transportations was available for the calculation of utility. Such combinations include all transportation modes – drive alone, share ride/carpooling, and if the person walked or drove to the different transit alternatives

available (e.g., bus, express bus, metro, commuter rail). The analysis was performed using all modes of transportation available to the population of the selected zones. Ideally, the analysis would separate also by vehicle ownership, but such disaggregation was not available in the data and approximation through drive alone or carpooling information is ill-advised due to Washington, DC’s high attraction of transit users who own or have access to a vehicle.

**Table 4.** Income Groups (in 1999 Dollars).

<b>Income Group</b>	<b>Income Range</b>	<b>Median Income</b>
Lower Quartile	< \$20,000	\$10,720
Lower-Middle Quartile	\$20,000 to \$39,999	\$29,840
Middle Quartile	\$40,000 to \$59,999	\$49,240
Upper-Middle Quartile	\$60,000 to \$99,999	\$76,350
Upper Quartile	> \$100,000	\$161,330

The end result of this approach is a measure of accessibility that can be mapped from one origin zone to all the possible destinations in the MWCOG region. It represents accessibility benefited by population groups making the same trip – segmentation is based on income. In addition, historical and estimated weather information is used to locate vulnerable locations. By applying the LS framework to the vulnerable location, it is possible to evaluate their accessibility level to “safe zones” (i.e., shelters, hospitals, and unaffected areas) and evacuation routes.

### *3.2.3 Maryland Statewide Travel Model*

The MSTM relies on a four-step model, in which the parameters obtained from the model outputs are used for this accessibility analysis. Some assumptions were made in the analysis, as applied by the MTSM: 1) only MWCOG statewide modeling zones (SMZs) are considered in the analysis; 2) the coefficients calibrated for the work trip purpose was

used in the analysis; 3) accessibility is considered by 5 income groups; 4) a total of 11 mode choices were available; 5) utility was specified considering a nested logit structure and with predefined specification and parameters. This research recognizes that choices and behavior under distress situations are different from normal condition. Therefore, only considering commuter's trips allow us to better proxy accessibility during evacuation by assuming that in the event of a disaster evacuees will use the modes and routes that they are most familiar with. Furthermore, using travel models allow us to modify mode and route alternatives (e.g., eliminating access to links or transit stations) in order to better represent choices under evacuation situation.

The four steps model is structured as follow: a) 866 SMZs where used as input for the MSTM, each zone contained the aggregated information necessary for estimating the generation of trips (e.g, number of households, workers, employment, schools, and whether the zone is a CBD or not); b) MSTM trip distribution was based on a gravity model formulation that employs composite travel time functions by purpose, a function of highway and transit time, as well as roadway tolls, and value of time; c) Mode choice is a nested logit choice model. The model divides the options into transit and auto. Transit consists of nests that groups transit alternatives, such as "Rail" (light rail and Metro), "Commuter Rail" (AMTRAK and MARC), and "Bus" (all bus services). Auto is disaggregated into drive-alone and share-ride alternatives. Information on in vehicle time, operating cost, waiting time, parking cost, among other, was used in the utility function; and d) Travel demand forecasts from both the MSTM statewide model components are assigned to a network through factors of the respective daily trip matrices, deriving peak and off-peak trip matrices for network assignment.

For a complete explanation of the MSTM model the reader is referred the ‘MSTM Users Guide’, which is available from Maryland State Highway Administration upon request.

### 3.3 Identifying Low Income Population in the MWCOG Region

The first part of this study consists on locating the areas with highest percentage of low-income population. In this study, low income population consists of households whose total income is below 1.5 times the 2010 National Poverty Guidelines for the respective household size. These guidelines are updated each year and issued in the *Federal Register* by the Department of Health and Human Services (HHS), see Table 5.

For this task, the American Community Survey (ACS) 2006-2010 5-year estimates were used. The information is aggregated at the Public Use Microdata Areas (PUMAs) level. This data set has proven to be a valid source of information because of its wide-ranging sample size and reputation of its collector, the U.S. Census Bureau. Figure 3 illustrates the location of the PUMAs that characterize the scope of this study. However, it should be noted that PUMAs vary in shape and size, hence encompassing different communities. In addition, household and individual weights provided by the ACS were used to reduce sampling bias and error of over- and under-represented subpopulations.

**Table 5.** 2010 Poverty Guidelines for the 48 Contiguous States and D.C. Source: U.S. Department of Human Health Services.

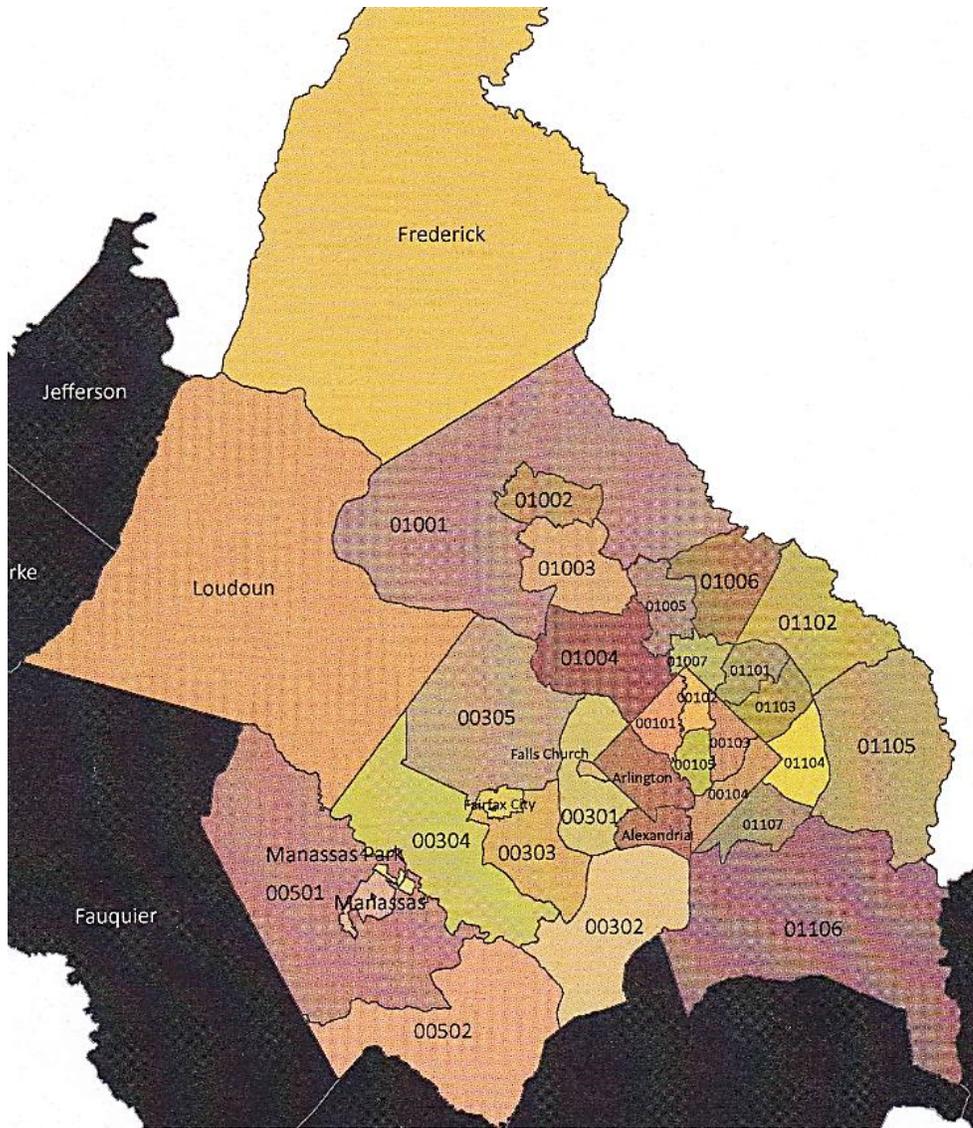
Persons in family/ household	Poverty guideline
1	\$10,830
2	\$14,570
3	\$18,310
4	\$22,050
5	\$25,790
6	\$29,530
7	\$33,270

8	\$37,010
For families with more than 8 persons, add \$3,740 for each additional person.	

Overall, nearly 10% of Maryland’s households fall within the low income criteria, with PUMAs 00300 and 01005, part of Frederick and Prince George’s County, having the highest percentage of low income households with 1% and 0.8%, respectively. Astoundingly, nearly 45% of all low income households are located in Prince George’s County. Finally, 18% of the households within PUMA 01101 (i.e., College Park-Hyattsville area) are low income. As for Washington, DC, approximately 19% of its households are low income. The center and south-east DC regions, PUMAs 00105 and 00104 respectively, have the overall highest percentage of low income households, with 6.8% and 4.3% low income households, respectively. Also startlingly, 30.8% of the households within the south-east region are low income. For contrast, this study will focus on two subareas, Anacostia, DC, and Frederick City, MD. The locations were selected for analysis based on their different concentration of low income population, the variety of available transportation modes, and difference in proximity to a metropolitan area, which helps in demonstrating the range of the LS approach, see Table 6.

**Table 6.** Case studies for accessibility analysis.

<b>Location</b>	<b>PUMA</b>	<b>SMZ</b>	<b>Reference City</b>	<b>Median HH Income</b>
Washington DC	00104	1268	Anacostia	\$19,238
Frederick County	00300	956	Frederick City	\$42,529

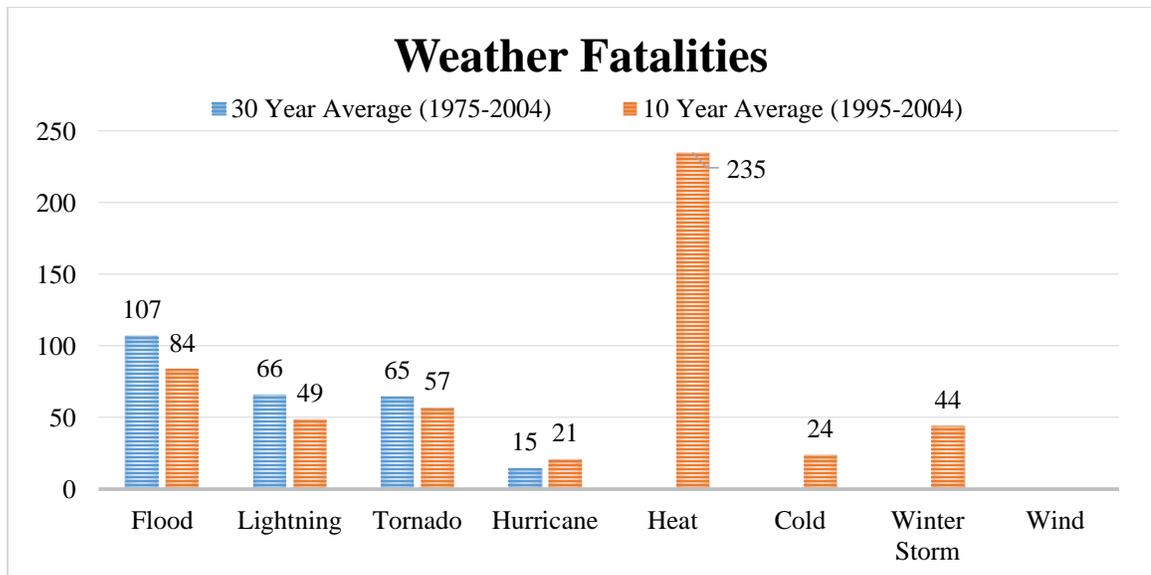


**Figure 3.** PUMA location for the Washington DC Metropolitan Region.

### 3.4 A Real Case Study: Evacuation Due to Localized Floods

Every year, on average, hundreds of lives and billions of dollars are lost across the United States due to extreme weather events. According to National Weather Service (NWS, 2012), floods and flash floods are the second deadliest weather phenomenon in the United States, taking more lives than hurricanes and tornados combined (see Figure 4). A flash flood is defined by the NWS as a flood that develops in under six hours; however,

sometimes they form in a matter of minutes, hence their danger. They tend to occur in low-lying areas with poor drainage, with urban areas particularly at risk. A significant percentage of the people who die due to floods make the mistake of attempting to drive or walk through flooded areas and are swept away by the rapid water. Some causes of flash flooding include heavy rain, ice jams, and dam or levee break.



**Figure 4.** Average weather-related fatalities from 1975 to 2004. Source: NOAA (2006).

### 3.4.1 Case Study

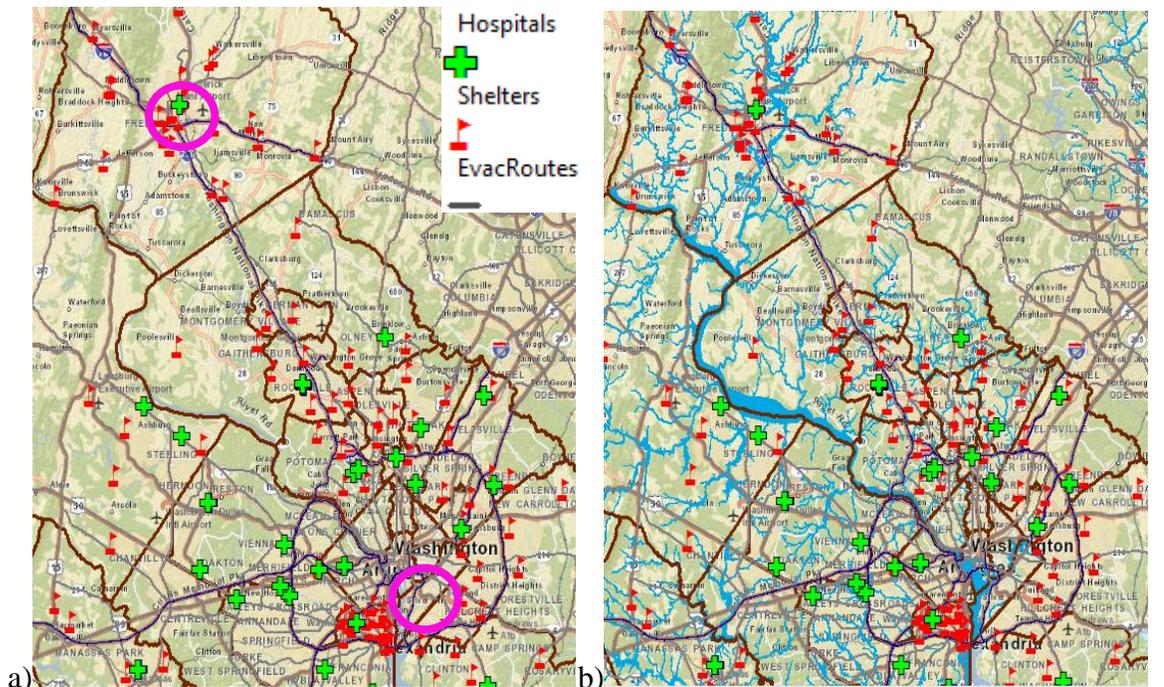
In this study two case scenarios will be evaluated: 1) an evacuation of Frederick, MD and 2) an evacuation of Anacostia, Washington DC due to localized floods. The case scenarios were developed as realistically as possible using available information from several official sources. Each case is based on information about ‘Storm Surge’ and ‘100-year flood’, which were extracted from Maryland’s OSPREY imap, developed by the Maryland Emergency Management Agency (MEMA). The ‘Storm Surge’ map shows potential flood heights resulting from historical, hypothetical, or predicted hurricanes by assessing pressure, size, forward speed, track, and wind data. The calculations are applied

to an area's shoreline, analyzing its physical features (e.g., bay and river configurations, water depths, bridges, and roads) and presenting the worst-case scenario for the entire basin. 'Storm Surge' has been developed for category 1-4 hurricanes represented by the Saffir-Simpson Scale. On the other hand, the '100-year Flood' shows hazard areas corresponding to floods that have a one-percent chance of being equaled or exceeded on an annual basis. Official information on shelter and hospital locations, as well as evacuation routes, were provided by the Maryland State Highway Administration (MDSHA); this list includes 170 locations approved to serve as shelters (including schools, recreational centers, and fire stations) and 175 hospitals. While the totality of these locations is spread across Maryland, Virginia, and Washington, DC, only 109 shelters and 36 hospitals are located within the MWCOG region and therefore incorporated into the analysis. Finally, the evacuation routes used in this study are the ones served out by the MEMA and the MDSHA in events such as hurricanes to get people away from high risk areas; these routes were complemented with information on "routes prone to flood" also extracted from Maryland's OSPREY map, which are identified as routes that present recurrent and occasional floods problems.

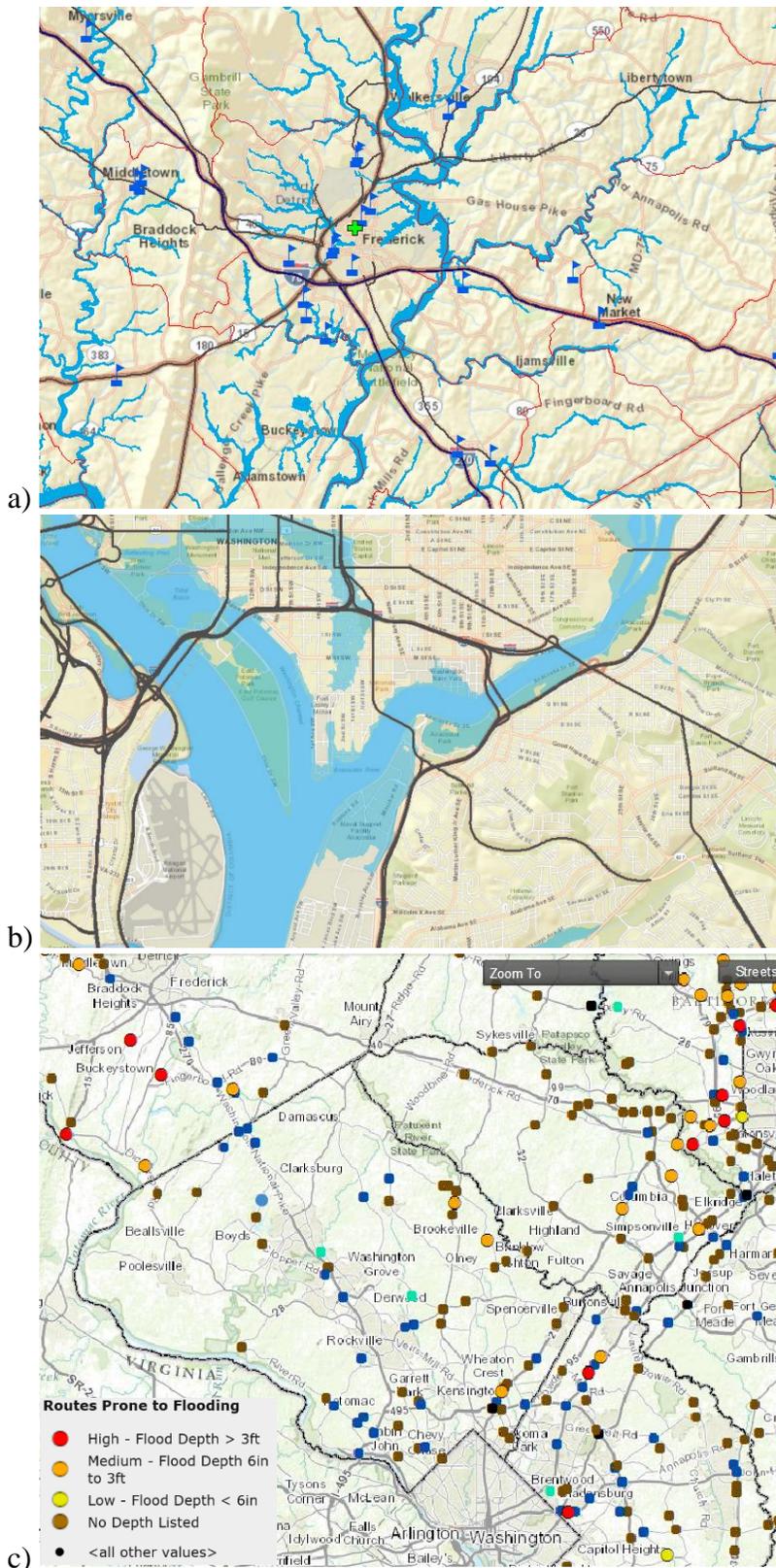
The MWCOG region is peculiar in that it comprises two states, Maryland and Virginia, and the District of Columbia (DC), with the Potomac River and Anacostia River (a branch of Potomac) passing through all three locations. Communities close to these rivers tend to be at high risk during hurricane and flood events. Figure 5 compares the MWCOG region at a normal state and under the effect of extreme water events, represented by the light blue color. It should be noted that data about the effect of the '100-year Flood' was not available for all counties, hence the missing information to the east of DC. Figure

5 also illustrate the location of hospitals, shelters and evacuation routes as provided by official agencies. The subareas to be analyzed are highlighted with a purple circle.

Figure 6 presents the affected zones in more detail. In Figure 6a it is visible how the high water levels covers part of downtown Frederick and its municipal airport – roughly 0.75 square miles. The effects of the ‘100-year Flood’ are also noticeable in Figure 6b, where the flood covers around 0.6 square miles of the Anacostia’s rivershore, in addition to the flooding in central DC. Finally, Figure 6c highlights the roads that are prone to flooding (the dots mark location and data availability on the OSPREY map, although not all dots contain information). In the event of a major flood, these roads should be expected to be unreliable, or chokepoints, based on their flooding history.



**Figure 5.** a) MDCOG region; b) Effect of storm surge and 100-year flood on the MDCOG area.



**Figure 6.** a) Hurricane storm surge effect on Frederick, MD; b) 100-year flood effect on Anacostia, Washington DC; c) Roads prone to flood.

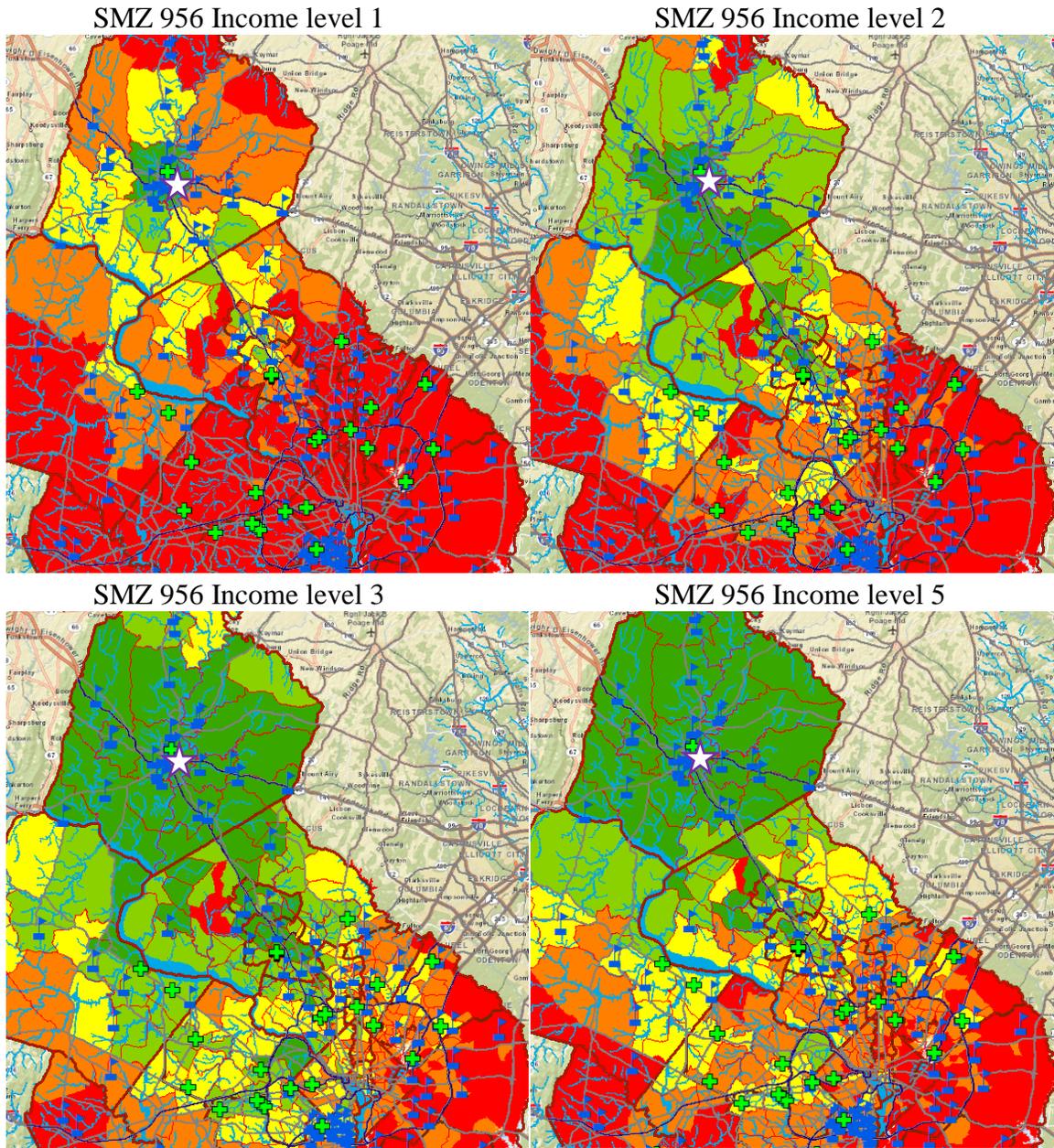
### *3.4.2 Accessibility Analysis*

The proposed methodology allows for a sketch-level assessment of the accessibility of targeted communities to safe zones by income level. The following are the major findings from the analysis conducted for Frederick City and Anacostia's (marked with the white star on Figure 7 and Figure 8):

- The visual result suggests that income and accessibility are positively correlated.
  - In both locations, Frederick City and Anacostia, there is a clear inequality in accessibility to safe zones between the different income levels (see Figure 7 and Figure 8).
- Income, or an overall lack of resources, may not be the sole limitation of accessibility.
  - Location, the privation of access to a vehicle, dependency on transit services, and longer travel times, among other factors, also play a role in inducing accessibility inequality. This is evident when each location's income levels are compared, making it clear that Frederick's residents can reach more locations than Anacostia's.
    - According to the American Community Survey (ACS) 2006-2010 5-year estimates, only 23% of households within Frederick County do not own a vehicle whereas in Southeast DC almost 70% of households do not own a vehicle. In addition, it should be noted that Southeast DC residents have access to a more developed transit network (e.g., DC metro), which may affect vehicle ownership decision.
- Safe zone availability is correlated to how much the population can travel.

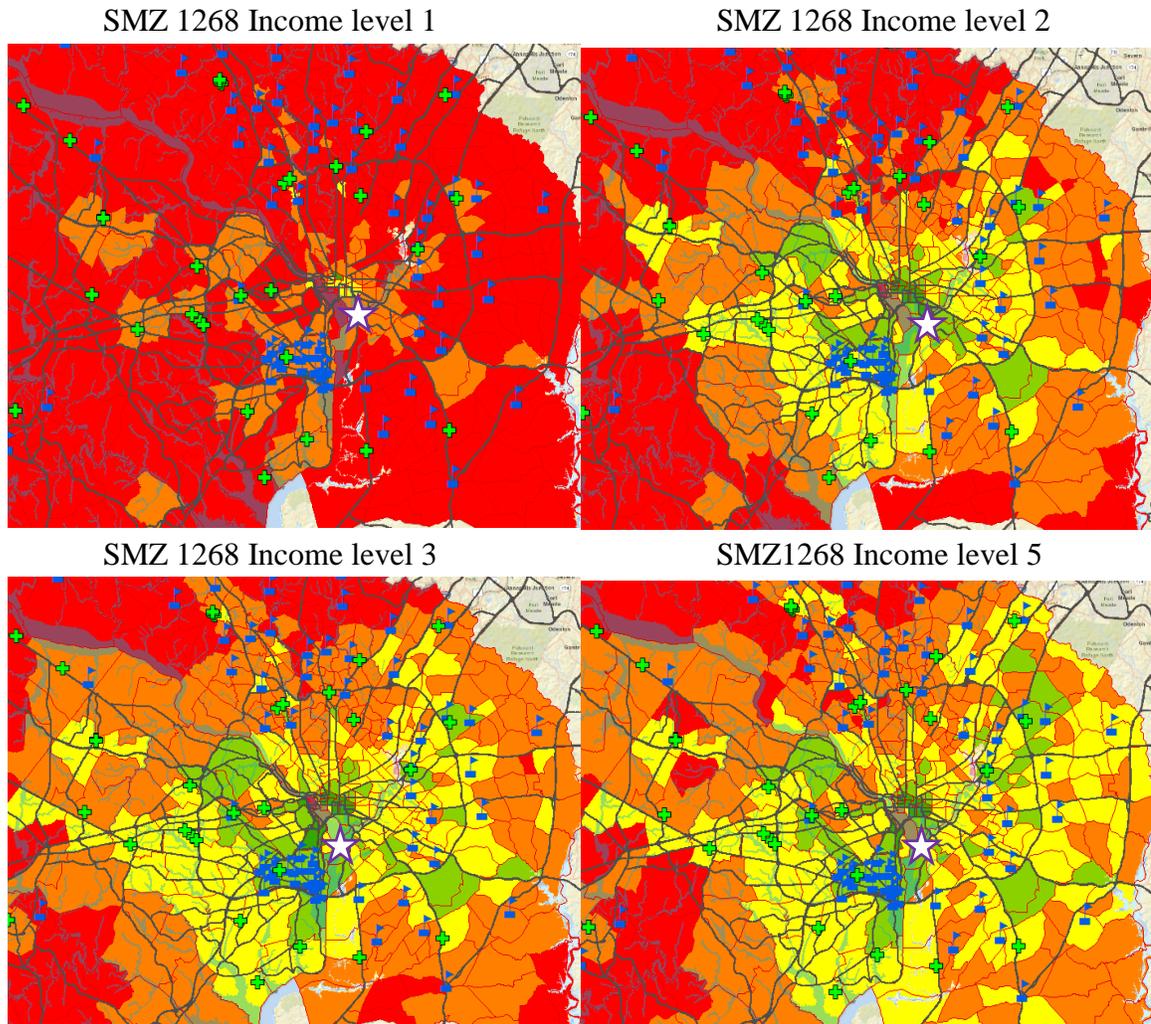
- Frederick's low income population have a moderate amount of shelters they can get to in the case of a flood, and options increases as income increases. However, the county lacks in hospitals, having only one in the center of the city, which also puts residents on high risk if a flood occurs. It is not until income level 3 that a significant amount of hospitals become accessible.
- Anacostia's lower income population has very limited access to shelters and hospitals. However, a significant improvement in accessibility can be perceived starting on income level 2, making available to the population a significant amount of alternatives in the event of an evacuation due to their proximity to DC.
- Potential floods on major roads could diminish accessibility within the MWCOG region.
  - Roads connecting Frederick to hospitals located to the south (closer to DC and Leesburg) and Anacostia to northern located shelters are prone to flood (see
  - Figure 6c), further increasing the probability of casualties of the disadvantaged.
  - Road and rail transit could also be affected by excessive surface water, partially or completely interrupting services to different locations.
- The spatial distribution of shelters does not adequately cover the MWCOG region.
  - A large cluster of shelters is located south of DC, making them more accessible to DC's low income population – recall that the highest percentage of low income households is located in the southern areas of DC. Nonetheless, there is a striking lack of shelters west and, to a lesser degree, east of DC. In both

directions, the population outside the beltway may be at the highest risk because of the lack of shelters, having little to none alternatives to stay at.



**Figure 7.** Accessibility to safe zones of Frederick City's population by income level.

Accessibility levels: ■ = High; ■ = Medium-High; ■ = Medium; ■ = Medium-Low; ■ = Low.



**Figure 8.** Accessibility to safe zones of Anacostia's population by income level.  
 Accessibility levels: ■ = High; ■ = Medium-High; ■ = Medium; ■ = Medium-Low; ■ = Low.

3.5 Application of Results: Shelter Location Analysis

In order to showcase potential application of the proposed accessibility measuring framework, this research considers the problem of building shelters in the optimal location based on the accessibility of all Origin-Destination (O-D) pairs. Here, the Logsum accessibility value is used as the base of obtaining two objective alternatives: (i) one that

maximizes the minimum accessibility and (ii) another that maximizes overall accessibility. Given the nature of the Logsum values obtained from the MSTM, within-zone accessibility may not be the highest of a SMZ. For the location problem, this research assumes that the accessibility within a given zone is 20% higher than the maximum of such zone, allowing the model to yield more realistic results.

The results are obtained through binary integer programs that optimally locates shelters at the regional level. The analysis is limited to the MWCOG region, which is composed of 525 SMZs, with 67 of them having at least one shelter. For this location analysis it is assumed that this number can be increased to 100 zones—thus 33 new shelters could be built if necessary, with the limitation that only one shelter will be placed per selected zone.

### *3.5.1 Model 1: Maximization of Minimum Accessibility (M1)*

This model ensures that a relatively accessible shelter is provided to all the zones (i.e., remote zones would still have access to a shelter). Let  $I$  denote a set of zones indexed by  $i$  and  $j$ . Define  $y_j$  as a binary variable which equals 1 if a shelter is located within zone  $j \in I$  and 0 otherwise. Let  $a_{ij}$  be the Logsum accessibility value of zone  $i \in I$  to zone  $j \in I$ . Define a binary variable  $x_{ij}$  which equals 1 if the most accessible shelter to zone  $i \in I$  is located in zone  $j \in I$  (note that  $i$  may equal  $j$ ). Using this variable, it is possible to compute the accessibility from zone  $i \in I$  to the most accessible shelter as  $d_i = \sum_{j \in I} x_{ij} a_{ij}$ . Also let  $\psi = \min_{i \in I} d_i$  be the minimum of all the previously computed accessibility factors.

The objective is to open at most  $m$  shelters in a way that would maximize the minimum accessibility to a shelter. This optimization problem is formulated as a binary integer program:

$$\max_{x_{ij}, y_i \in \{0,1\}} \psi \quad (3.1)$$

$$s. t. \quad \sum_{j \in I} y_j \leq m \quad (3.2)$$

$$x_{ij} \leq y_j \quad \forall i, j \in I \quad (3.3)$$

$$\sum_{j \in I} x_{ij} = 1 \quad \forall i \in I \quad (3.4)$$

$$d_i = \sum_{j \in I} x_{ij} a_{ij} \quad \forall i \in I \quad (3.5)$$

$$\psi \leq d_i \quad \forall i \in I \quad (3.6)$$

The objective function (3.1) maximizes the minimum accessibility  $\psi$ . The constraint (3.2) ensures that at most  $m$  shelters are opened. The constraints (3.3) ensure that  $x_{ij} = 0$  if there is no shelter located at  $j \in I$  (i.e., if  $y_j = 0$ ). Equations (3.4) and (3.5) compute the minimum accessibility for each zone. The last set of constraints (3.6) ensures that  $\psi$  indeed denotes the smallest accessibility of all the zones. Note that  $x_{ij}$  can be linearly relaxed without altering the problem (i.e., if  $x_{ij} \geq 0$ ). Finally, note that M1 can account for existing shelters by letting  $y_i = 1$  for the corresponding zones and by increasing  $m$  by the number of existing shelters.

### 3.5.2 Model 2: Maximization of Overall Accessibility (M2)

Model 1 targets a justifiable objective because it ensures that a relatively accessible shelter is provided to each zone. In contrast with M1, this alternate model (M2) maximizes the average accessibility which may leave some zones without easily accessible shelters, but would likely yield an increased accessibility for most other zones. Using the same notation as before, this problem is formulated as a binary integer program.

$$\max_{x_{ij}, y_i \in \{0,1\}} \frac{1}{|I|} \sum_{i \in I} d_i \quad (3.7)$$

$$s. t. \quad \sum_{j \in I} y_j \leq m \quad (3.8)$$

$$x_{ij} \leq y_j \quad \forall i, j \in I \quad (3.9)$$

$$\sum_{j \in I} x_{ij} = 1 \quad \forall i \in I \quad (3.10)$$

$$d_i = \sum_{j \in I} x_{ij} a_{ij} \quad \forall i \in I \quad (3.11)$$

The objective function (3.7) maximizes the average accessibility from a zone to its most accessible shelter, while constraints (3.8)-(3.11) model the same relations as in the previous formulation. Note that dropping  $1/|I|$  from the objective function does not change the optimal allocation of shelters, which implies that maximizing average accessibility is equivalent to maximizing overall accessibility (i.e.,  $\sum_{i \in I} d_i$ ).

### 3.5.3 Results from Location Models

As formulated, both model seek to maximize their respective objective function, based on the accessibility level between all O-D pairs. This value of accessibility is defined by the Logsum measure, which for the selected zones range from 0.639 to 3.40 units of utility. The models are limited by a maximum number of potential shelters  $m$ . This limitation should not be confused with the number of shelters that would be built—notice that the constraint is  $\sum_{j \in I} y_j \leq m$  instead of  $\sum_{j \in I} y_j = m$ . Hence,  $m$  should be viewed as the maximum number of shelters that could be built if demand, from an accessibility point of view, is sufficiently high. In a real case,  $m$  would be limited by available resources, both economic and non-economic, affecting the number of shelters to be built. Given this,

several iterations were performed of both models to discern accessibility gain with relation to *m*. Table 7 details the results of these iterations and their resulting locations.

**Table 7.** Optimal Shelter Locations.

Model	<i>m</i> *	Logsum**	New Locations
1	100	2.216	i624, i631, i632, i657, i678, i683, i692, i706, i740, i743, i744, i756, i758, i759, i761, i762, i764, i771, i780, i782, i783, i797, i805, i806, i878, i895, i896, i902, i924, i953, i962, i965, i1353
	85	2.215	i624, i631, i632, i678, i683, i692, i740, i743, i744, i756, i764, i771, i780, i782, i797, i896, i902, i1353
	70	2.215	i624, i908, i1319
	69	2.215	i902, i1353
	68	2.106	i905
2	100	2.385	i611, i614, i659, i661, i680, i682, i687, i694, i709, i731, i907, i946, i1189, i1192, i1193, i1194, i1195, i1196, i1197, i1201, i1202, i1203, i1205, i1213, i1216, i1224, i1225, i1237, i1240, i1242, i1243, i1258, i1320
	85	2.371	i611, i659, i661, i680, i682, i694, i709, i731, i907, i946, i1192, i1193, i1196, i1197, i1201, i1216, i1237, i1320
	70	2.356	i907, i1192, i1320
	69	2.355	i907, i1320
	68	2.352	i907

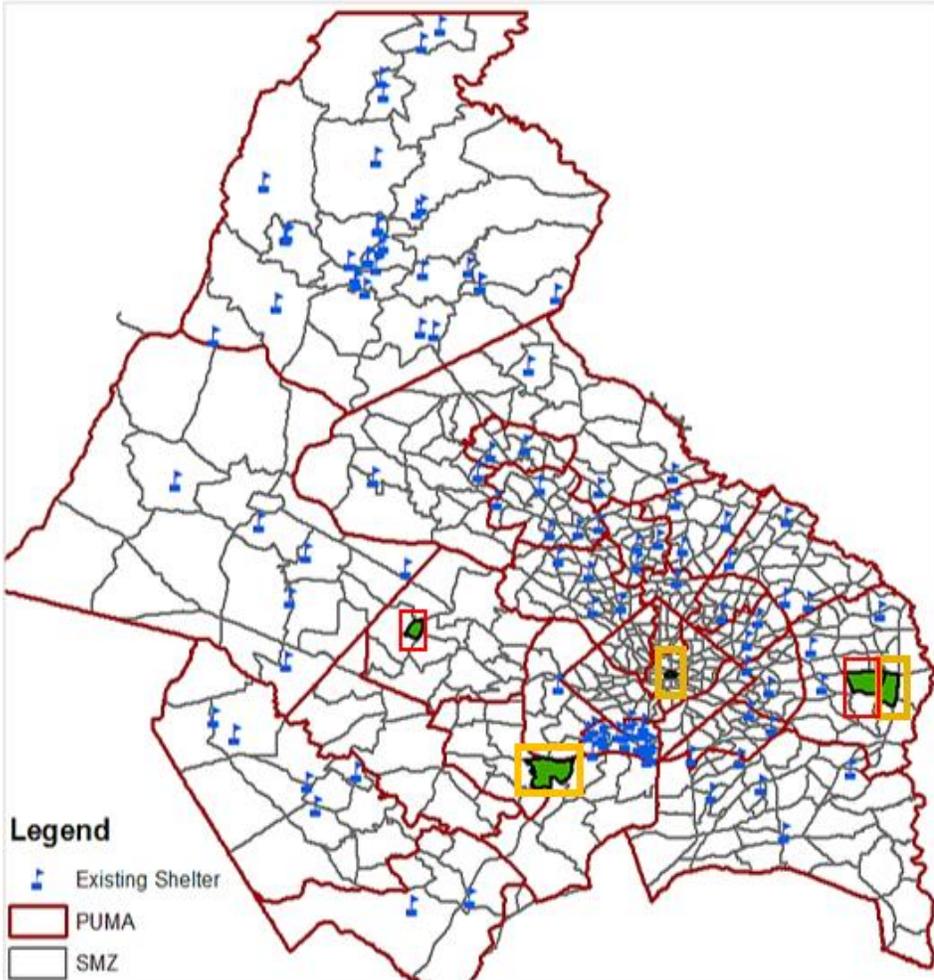
\*Includes 67 existing shelters    \*\*Base accessibility of 2.015 for M1 and 2.298 for M2

Results of M1 indicate that with the addition of two shelters, one in Prince George’s, MD (i902) and another in Fairfax, VA (i1353), accessibility is increased to a similar level as if 33 new shelters were added across the MWCOG region. In other words, adding shelters in other locations beyond these two will marginally influence regional accessibility to shelters given other zones limitations. Conversely, results from M2 indicate a more significant increase of accessibility as more shelters are added. This is an expected result as M2 locates the shelter in zones that serve as destinations with highest overall accessibility.

Figure 9 illustrates the two locations identified by M1 (highlighted within the red squares) as the best alternatives for locating new shelters, and after which adding new

shelters provides limited improvement of accessibility. The results could be viewed as low, but recall that there are 67 zones with existing shelters in the area, which significantly simplifies the optimization problem given the vast covered area. Additionally, Figure 9 also shows the first three locations suggested by M2 (highlighted within the orange squares) that should be considered to improve overall accessibility. Notice that one of the suggested SMZ is in the heart of D.C. Mapped results from both models when  $m$  equals 85 and 100 can be viewed in Annex 1.

Finally, the same analysis was performed relaxing the existing shelters constraint on M1 and with the objective of locating 10 and 100 shelters. Surprisingly, the results indicate that an accessibility of 2.215 and 2.216 can be reached with 10 and 100 shelters, respectively. These findings corroborate the findings of M1, indicating that, although not necessarily economically feasible, building shelters with sufficient capacity within a limited number zones would be enough to ensure that a reasonable level of accessibility to shelters is obtained from any location within MWCOCG region.



**Figure 9.** Optimal location of new shelters.

It should be noted that the proposed models do not account for the capacities of shelters and population size at each zone, as well as other significant variables that may affect the selection of the optimal location and the amount of shelters to be built, such as sociodemographic data (e.g., income, household sizes and number of vehicles) and available budget. Therefore, the results obtained here should not be taken as final. Instead, the goal is to showcase the type of analysis that could be performed if one were to introduce the Logsum accessibility measure into location problems. Once more robust information is acquired, it will be possible to extend these models to also account for more contributing factors.

### 3.6 Conclusions

The approach proposed in this study, which is based on the logsum measure for accessibility, accounts for many other factors influencing population's accessibility level (e.g., transit frequency, waiting time, number of transfer, transfer time, parking cost) when compared to more traditional measuring approaches – which proxy accessibility through travel time, travel cost, or trip distance. Furthermore, this method allows us to perform a disaggregated analysis by income level (and potentially by any other population characteristic), overcoming a limitation of traditional approaches. Finally, the logsum approach utilizes coefficients from the transportation model which captures behavioral responses to changes in trip attributes, making it possible to capture trips within the study area regardless of travel times.

The visual results suggest that there is a positive correlation between accessibility and income level; however, it can be affected by the attributes of the location. Logistics problems were also found in the location of shelters, leaving some areas without nearby alternatives to go to. It is clear that low income population need careful attention and that a great deal of resources should be dedicated to enhance their mobility in the event of an evacuation. Furthermore, results from the optimal shelter location problem indicate that two more shelters are needed to increase accessibility, one in Prince George's, MD and another in Fairfax, VA.

This approach is the first iteration in the development of a comprehensive and practical assessment tool that evaluates IR through an accessibility analysis. The main goal is to highlight the areas that are lacking, and could potentially hinder the evacuation processes, in a simple and presentable manner. Future iterations could address the present

limitations, among which are the incomplete information on disadvantaged population, the need for more accurate weather data, and the lack of non-commuter trips. In addition, statistical analysis is needed to increase reliability of the results. Future research is also needed to identify other factors impeding evacuation mobility and to incorporate temporal constraints (e.g., departure time) into the accessibility analysis. Finally, the limitations of the proposed location optimization models should be addressed in parallel with the ones stated for the accessibility analysis.

## **Chapter 4: Agency Resilience**

Agency Resilience (AR) refers to the institutions, policies, processes and resources that are required for effective implementation, operation, and maintenance of resilient strategies. It is at this layer where the objectives and requirements for TR are established. At a higher level, AR provides the basis for understanding who the implementers are and the roles these implementers could take within an architecture-based resilient system. At a lower level, AR improves preparedness and response capability of agencies by taking into account more operational, rather than only managerial, characteristics of an agency. This study focuses on such lower level and presents a comprehensive set of easily measurable metrics, based on previously and newly proposed indicators, allowing for a broader assessment of AR. These variables are classified based on their contribution to the agency's "sustainable livelihood" and combined using fuzzy algorithm, yielding to an AR index. This research recognizes that in reality no one agency is fully responsible for all disaster management processes. Therefore, whenever a reference is made about agency it should be understood as a network of institutions that influence preparedness and response capability to disasters.

The rest of the chapter is organized as follows: Section 4.1 provides a background on evaluating an agency's risk management capability; Section 4.2 describes the evaluation framework proposed in this study; Section 4.3 describes the data collection process; Section 4.4 summarizes and analyzes the data; and Section 4.5 presents results from simulated data.

### 4.1 Background

The role of agency before, during, and after a disaster is of extreme significance, especially nowadays when technological advances in warning and communication systems facilitate coordination and quicker response across and within different levels of organization (i.e., community, city, state, national and international). Measuring agency preparedness and agency response to different kinds of disasters has been at the center of American public policy after 9/11, the anthrax attacks, and hurricane Katrina; but the absence of clear metrics to evaluate preparedness and response is still problematic (Elliott, 2010). Specifically, Hurricane Katrina in 2005 exposed a failure of policy and leadership at the federal level which paralyzed managerial and administrative capacity at the local level, resulting in a lack of coordination and an effective command system (Cigler, 2006; Farazmand, 2005).

Formal (rigorous) theories establishing the assessment process are still absent from the literature. Most recent efforts have focused on assessing preparedness with “yes/no” surveys and checklists that allow each agency to evaluate their preparedness levels, as well as to conduct cross-sectional comparisons across organizations, states or regions. Jackson (2008) suggests that efforts have been concentrated not only on inputs (e.g., response personnel, existence of an evacuation plan), but also on capabilities—an agency’s capacity to deliver on such inputs. However, too much emphasis is put on quantity (whether an input or capability is in place or not, or how much of a given input exists), rather than in the quality or time stability/adaptability—highlighting an important shortcoming of the checklist approach. Jackson explains that the latter might be more important when responding to a disaster. Variations of surveys and checklists are many, examples follow.

The Target Capabilities List (TCL), developed by the U.S. Department of Homeland Security (DHS), encompasses four areas related to DHS's mission: prevention, protection, response, and recovery. Including 37 core capabilities, this list provides a basis for the assessment of preparedness and establishes a standard for national agency's preparation for major disasters (DHS, 2007). "Each capability includes a definition; outcome; preparedness and performance activities, tasks, and measures. The TCL also identifies the role of governmental and non-governmental organizations, the private sector, and citizens in building and maintaining capabilities." (DHS, 2007, p. 1). FEMA understands this list as a dynamic document that must be refined as lessons are learned over time.

Another example is the United Nations' Disaster Preparedness for Effective Response guidance and indicators package from the Hyogo Framework for Action (HFA). The HFA has a holistic approach in the measuring of objectives, outputs and activities that strengthen disaster preparedness capabilities for disaster reduction of a nation. Their approach includes indicators regarding "early warning systems, ongoing risk and vulnerability assessment, capacity building, the creation and maintenance of stand-by capacities and the stockpiling of humanitarian supplies" (UNISDR & UNOCHA, 2008, p. 25). Specifically, they divide their assessment tool in three areas and several subareas.

- 1) Holistic Approaches, Strategies and Institutional Frameworks: (a) Holistic Approaches and Preparedness, (b) National Institutional and Legislative Frameworks, and (c) Coordination at the Local, National, Regional and International Level.
- 2) Preparedness Planning: (a) Contingency Planning, (b) Capacity Analysis and

Capacity-building, (c) Hazard Monitoring, Forecasting and Early Warning, and (d) Information Management and Communication.

- 3) Readiness for Response: (a) Emergency Services and Stand-by Arrangements, (b) Incorporation of Early Recovery into Preparedness Planning, and (c) Resource Allocation and Funding.

For each sub-area, the HFA looks at specific qualitative indicators for governments, civil society, regional organization and international actors, following customized yes/no checklists per sub-area. No details in regard to quantification and aggregation of responses are provided; expected outcomes, however, are presented for each sub-area.

Another case of usage of surveys and checklist is presented on Sutton and Tierney (2006). The authors identify common metrics (which stem from qualitative questions) used by different organizations/agencies for public sector preparedness assessment. Specifically they look at the data archives at the UCLA Center for Public Health and Disasters, FEMA, DHS, the Infrastructure Security Partnership, the Environmental Monitoring and Assessment Program and The Joint Commission on the Accreditation of Healthcare, regarding earthquakes. Such common metrics belong to the following five areas: 1) hazard knowledge, 2) management, direction and coordination, 3) formal and informal response plans and agreements, 4) life safety protection, and 5) initiation of recovery.

Public opinion data has also been looked at as an approach to evaluate agency. For example, when evaluating agency preparedness in Hawaii, Prizzia (2007) asked three questions to survey senior managers about their opinions on the appropriateness of current coordination efforts to response to disasters, the way in which improvements can be achieved, and the way in which the media can assist in increasing preparedness and

coordination. Kirschenbaum (2004) made an interesting use of opinion data for assessing an organization effectiveness in this regard. He starts from the statement that “what the organization claims to be its client oriented stated goals and its constituents’ perception of actual delivery of these relevant service-goals, form the basis for a measure of organizational effectiveness”, assuming the agencies do want to deliver on their promises (p. 77). The author obtained stated goals from public documents, among which were: “(1) informing the civilian population of potential emergencies; (2) providing instructions to emergency organizations how to deal with civilian populations; (3) control and management of Hazmat materials and coordinating organizations to maximize civilian safety; (4) providing, maintaining and informing the population about warning systems; (5) preparation for, and response to, biochemical and atomic threats through the distribution of gas mask kits, shelters and their maintenance; (6) authority over the civilian population, including evacuations and post disaster rehabilitation; (7) the recruitment of civilian manpower during emergencies; (8) coordinating civilian logistic and supply organizations; (9) preparing civilian emergency health and medical facilities; and (10) having the authority over the requisition of all civilian emergency types of equipment.” (p.86). For measuring these metrics, and as described for other studies/tools above, Kirschenbaum relied on “yes/no” questions only that were based on respondents’ perceptions of whether the organization has delivered on a particular goal or not.

Finally, an interesting approach to assessing agency’s risk management capabilities is that of Cardona (2005) and Cardona (2007). He developed an index based on a composite of qualitative indicators modeled with fuzzy theory. With their selected indicators for the index, Cardona sought to have a set of “transparent, robust, representative and easily

understood” measures for policymakers (p.79). Moreover, the author wanted to build an index that allowed for cross-city, region, country and other territorial levels comparisons, and with a methodology of evaluation easy to carry across time. The index consists of six public policy areas which receive a performance score ranging from 1 to 5, where 1 is low and 5 is optimal. They included indicators within the four areas of: 1) risk identification, 2) risk reduction, 3) disaster management, and 4) governance and financial protection. Each indicator within each public policy area was weighted depending on its relative importance, which was established based on experts’ inputs.

Given the limitations of the approaches presented, and the stated need for complementing current assessment tools, this chapter presents a new attempt at measuring an agency’s preparedness and response capability of an agency with quantitative indicators (without disregarding quality).

#### *4.2 Evaluation Framework: a Sustainable Livelihood Approach*

This study proposes an approach that recognizes the necessity of classifying each variable based on its contribution to the agency layer. For this, the well-known sustainable livelihood approach, also known as the capital-based approach, is combined with the notion of AR. The Institute of Development Studies defines sustainable livelihoods as capabilities, assets, and activities required for a means of living, which in hand can cope with and recover from stresses and shocks, while not undermining the natural resource base (Scoones, 1998). The Department for International Development (1999) defines these capitals as follows:

- Human capital refers to the skills, knowledge, good health and physical capability, which are important for the successful pursuit of different livelihood strategies.

- Physical capital comprises the basic infrastructure and producer goods (e.g., tools, equipment, shelter, and energy) needed to support livelihoods.
- Economic capital (also known as financial capital) refers to the available stock (e.g., cash, credit/debt, and savings) and regular inflows (e.g., income and remittances), which are essential for the pursuit of any livelihood strategy.
- Natural capital encompasses the natural resource stocks (e.g., soil, water, air, and genetic resources) and environmental services, such as hydrological cycle and available land, from which resource flows and services useful for livelihoods are derived.
- Social capital refers to the social resources (e.g., networks, affiliations, associations) upon which people draw when pursuing different livelihood strategies requiring coordinated actions.

These capitals relate to AR as follows: 1) Physical capital entails the physical environment that makes an agency capable to efficiently maintain and harden the transportation network; 2) Human capital entails the personnel, from both private and public organizations, needed to competently manage a transportation network before, during and after a disaster, and recover it in the latter situation; 3) Economic capital entails the financial stability of a transportation agency, which enables the implementation of proactive and reactive disaster management strategies; and 4) Social capital entails the agency's ability to efficiently support, coordinate and implement preparedness and response activities, procedures, methods, and tools. Natural capital will not be considered as it does not relate to an agency structure. The final framework is presented in Figure 10.



**Figure 10.** Proposed framework for evaluating AR through sustainable livelihoods.

Fouracre (2001) explains that roads and transport are a key element of a country's infrastructure (physical capital), as they improve livelihood outcomes through better access to natural assets and management of forest resources (natural capital). Transport is also the means of access to other facilities and services (which may be uneconomic to provide locally), and a means to social bonding and development (social capital). The development of rural transport infrastructure and services improves access to human assets such as health and education (human capital), and stimulates improved agricultural production and marketing potential, therefore increasing income generation and surplus capital which can be expended on essential services (economic capital).

The capital-based approach allows for easier identification of deficiencies, since it first separates AR into the capitals that affect it, leading to more thorough and tailored recommendations and proving to be a suitable tool for assessing one-dimensional systems.

The sustainable livelihood approach and its application have been well documented in many studies. The reader is referred to Scoones (1998), DFID (1999), Davis (2000), Sohail (2005), Alexander, Chan-Halbrendt, and Salim (2006), and Mayunga (2007) for more details.

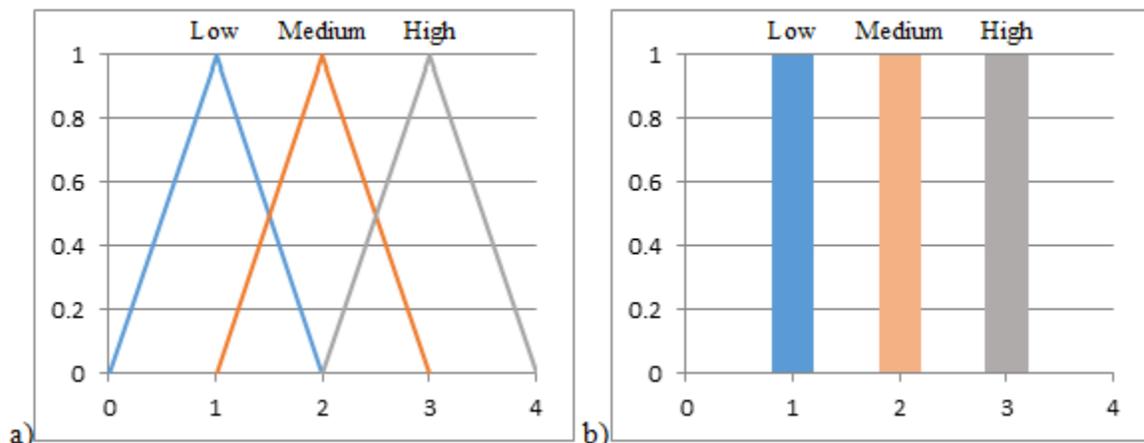
The decision to use sustainable livelihood capitals highlights an inherent problem when dealing with different perspectives: how to evaluate and combine the certainly different types of data (i.e., qualitative and quantitative) that could be used to explain each capital. In order to overcome this challenge, this study suggests the use of Fuzzy Algorithms, as explained in the Subsections 4.2.1 and 4.2.2 that follow.

#### *4.2.1 Fuzzy Algorithms*

Classical set theory reaches its limits when the property that determines the membership of an element to a set is defined in such a way that a clear distinction between membership and exclusion is no longer possible (Hanss, 2005). Fuzzy Sets fill this gap by working with undefined limits, allowing elements of a universal set to gradually belong or not to a specific set. Fuzzy Sets allow for mathematical processes to recognize different types of values, allowing the analyst to represent a wider range of values than conventional numbers. The final objective of the Fuzzy Set is the mathematical representation of linguistic or qualitative responses, such as *strongly agree/disagree*, *significant influence*, *little effort*, *moderate satisfaction*.

Figure 11 presents a comparison between a Fuzzy Set and a Regular Set. In this comparison, Fuzzy Sets are represented using triangular shaped membership functions; however, several types of membership functions can be used to explain the interaction between the different levels of a variable and diverse degrees of ‘softness’. The most

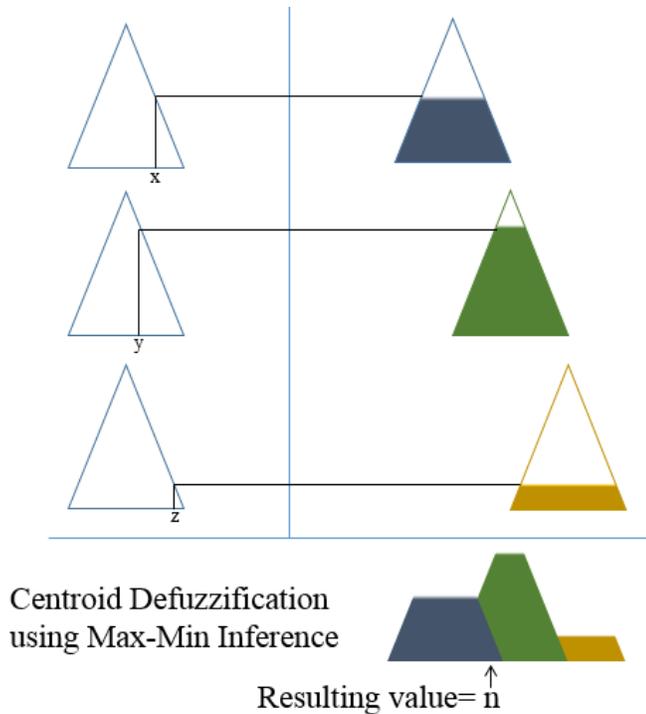
common types are triangle, trapezoidal, exponential, type S, and bell shape. In general, the base of the membership function and the degree of overlap represent the degree of ‘fuzziness’ when evaluating the values to be used in the Fuzzy Inference System (FIS) computational environment.



**Figure 11.** A Comparison of fuzzy (left) and precise (right) sets.

FIS translate the variable’s raw measure (input) into a fuzzy number and effectively combines measured quantitative data with operational experience and with qualitative and imprecise information (Babuska, Verbruggen, & Hellendoorn, 1999). Urena Serulle (2010) explains the benefits of this approach when evaluating TR given the uncertainty about the event that will affect the system and the variety of variables needed to evaluate the different aspects of TR. Within a FIS, all rules that apply are called on simultaneously and a result for each applicable rule is determined. The output from each partially fulfilled rule is a contribution to the aggregate output, which is represented in a shape with a measurable area, yielding a final “crisp” value through a process known as *defuzzification*. For a set of rules such as “if Input 1 is X and Input 2 is Y and Input 3 is Z ... then, the output is n,” the resulting value  $n$  is obtained by combining a *defuzzification* technique with an inference method. Figure 12 illustrates an example that applies a centroid *defuzzification*, where the

center of mass of the result provides the crisp value, and a min-max inference method, where the output membership function is given the value generated by the rule that apply to each input. It should be noted that there is a variety of *defuzzification* and inference methods. The reader is referred to Hanss (2005) for a detailed description of Fuzzy Arithmetic.

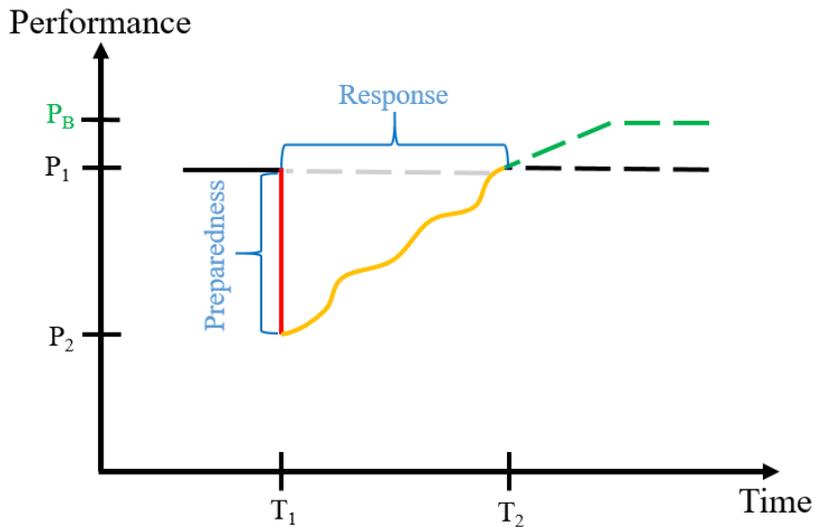


**Figure 12.** Illustration of the geometric FIS computational method.

#### 4.2.2 Interaction of Variables

The main objectives of any agency that seeks to be resilient are to increase its level of preparedness and improve its response capability. The interaction of these objectives can be presented through a resilience triangle, which was first introduced by Bruneau et al. (2003) within an earthquake disaster resilience context. The resilience triangle shows the loss of operation performance of an agency over time due to a disruption, as well as the pattern of recovery (see Figure 13). The higher the level of preparedness of the agency, the

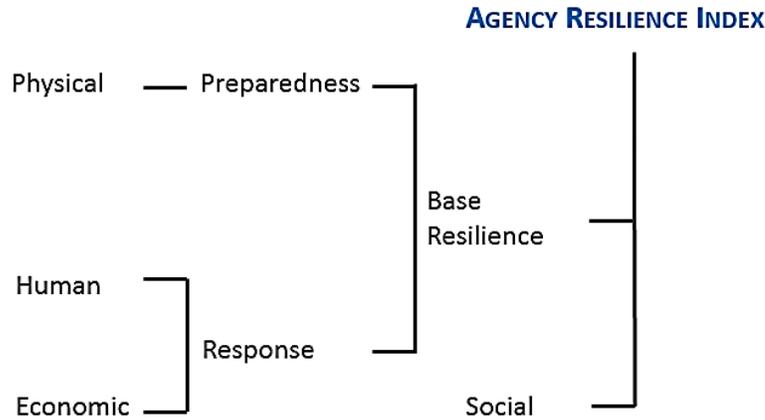
lower the effect of the disruption ( $P_1-P_2$ ). Similarly, the higher the response capability of the agency, the shorter the time of recovery ( $T_2-T_1$ ). As can be seen, after a disaster, an agency has the opportunity to go back to its original state ( $P_1$ ) or “build back better” ( $P_B$ ).



**Figure 13.** Agency Resilience Triangle (based on Bruneau et al., 2003).

The proposed methodology for generating a measure of AR is based on a dependency relationship between the sustainable livelihood capitals. Figure 14 illustrates the hierarchical structure that serves as the basis of the FIS method used in this study. Each node in the system, which is the point where two or more variables combine, is represented by a FIS. This study assumes that physical capital directly influences an agency’s preparedness to disasters. Similarly, human and economic capitals relate to an agency’s response capability, as they represent the available resources in the case of a disaster. Recall that preparedness and response grasp the main activities pursued by a resilient agency. Therefore these two values are combined in order to obtain a Base Resilience value—the agency’s risk management capability without any kind of coordination technique applied for optimization of resources. Finally, the social capital is defined as a leveraging variable, as it represents the agency’s ability to efficiently coordinate and implement preparedness

and response activities, procedures, methods, and tools. Increased social capital provides real time shifting of resources and demands within the agency, which could minimize recovery activities. This variable is used as a leverage of the agency’s Base Resiliency value because of its secondary contribution to performance optimization, and consequently the overall agency’s resiliency.



**Figure 14.** Dependency diagram as the basis for Fuzzy Inference.

Each of the capitals can be characterized according to the availability of quality data to support valuation within the process. Sections 4.3 and 4.4 explain the process of data collection and application within the dependency diagram to obtain an index.

### 4.3 Data Collection and Analysis

The next step of this study is to refine the proposed methodology through the collection of real-life data, enabling the development of the Agency Resilience Index. This research attempts to provide a comprehensive analysis of AR by including as many quantitative variables as possible in order to robustly describe each capital. To the extent possible, this research will follow Chang and Shinozuka (2004) suggestion that metrics’ selection, definition and weights should be developed in consultation with decision-makers, the public, experts in the affected fields, and other potential end-users. However,

it should be noted that including a vast number of indicators introduces complexity in the evaluation framework as it broadens the concept of resilience—in the past this complexity has obstructed the creation and empirical test of broad models of resilience (Cumming et al., 2005). While Carreño (2007) suggested the use of a limited amount of indicators in order to decrease redundancy and weighting complexity, mixed approaches were found in the literature in terms of the amount and type (qualitative or quantitative) of metrics to use, with no consensus on which one is best—as much as 75 variables have been used to evaluate resilience as a whole. Therefore, this research also considers the applicability of the model when selecting the data to be used (recall that the objective is to develop a robust, yet flexible methodology).

A total of 130 practitioners within U.S. transportation-related agencies (e.g., state DOT, SHA and MPOs) were contacted to participate in an online survey regarding the agency's and/or their perspective on resilience and what metrics could be used to evaluate AR. More than one person within each agency was contacted in order to increase the probability of an agency participating. The survey can be viewed in Annex 2. Three survey invitation emails were sent. The first invitation was sent between July 10<sup>th</sup> and 13<sup>th</sup>, 2015, and two subsequent reminders on August 21<sup>st</sup> and October 5<sup>th</sup>, 2015. Despite the different attempts to contact practitioners across the US, and obtain their perspective on agency resilience, 54 surveys were initiated (i.e., opened the webpage), out of which 10 completed the survey, with only 5 of them actually providing metrics. Of the ones who did not answer, one expressed unwillingness to participate due to data security concerns, and others simply stated the lack of information regarding resilience-oriented plans within their agency to complete the survey—providing an indication of the (deficient) state-of-knowledge of AR.

Regarding the latter, some agencies conveyed that they are about to start or recently started efforts to measure resilience of their agency. From the agencies that provided reasons for non-participation, all workers were excluded from subsequent attempts of contact.

As an effort to initiate a consensus-seeking discussion, and to complement the information obtained through the survey, this research identifies other candidate variables from the literature review process that could be used to proxy each capital, as well as other newly suggested (to the best of our knowledge) or adapted by this research. Table 8 summarizes these variables, as well as the ones from the survey. Following the proposed conceptual framework, each variable is linked to a specific Agency Resilience sustainable livelihood capital and a brief definition and at least one possible metric for valuation are also provided. It should be noted that this is not meant to be an exhaustive list. The objective here is to provide a list of metrics to which academics and practitioners could turn for guidance in the (type of) information needed when assessing AR, helping close the gap related to assessment metrics highlighted by Elliot (2010). In general, the selected variables are consistently used in transportation, community, and disaster management analyses. Most of them are normally available through metropolitan planning organizations and national studies, or are relatively easy to estimate. However, this research’s findings suggest that several variables would be better explained by a range or qualitative measures, instead of precise values.

**Table 8.** Potential metrics to evaluate Agency Resilience.

<b>Variable</b>	<b>Definition</b>	<b>Reference(s)</b>	<b>Possible Metric(s)</b>	<b>Capital</b>
Disaster Reserve Funds	Availability of a special fund reserved for disasters.	M. Carreño et al., 2007; Survey	(i) % of GDP or millions of dollars per 100,000 people dedicated to disaster management; (ii) % of funds allocated for system disasters (emergencies) per budget year; (iii) Qualitative measure based	Economic

<b>Variable</b>	<b>Definition</b>	<b>Reference(s)</b>	<b>Possible Metric(s)</b>	<b>Capital</b>
			on the existence and optimal expenditure of the fund.	
Disaster Management Personnel	Available professionals in disaster and transportation management in the area.	Survey	(i) Number of registered/employed transport and disaster management professionals in the area or per 100,000 people; (ii) % of employees trained in disruption relief activities.	Human
Experienced Staff	Available experienced staff.	Survey	Percentage of staff members with 10+ yrs of experience	Human
Scalability (Alternate relief personnel)	Capability to increase personnel before, during and after emergencies.	Survey	Percentage change in personnel size.	Human
Structural Recovery Personnel	Presence of construction personnel that could help with reconstruction after a disaster.		Number of civil engineers and construction workers in the area or per 100,000 people.	Human
Disaster Response Personnel	Available response personnel.	Carreño, Cardona, & Barbat, 2006; Mayunga & Peacock, 2010	Number of registered/employed response staff (e.g., firefighters, doctors, nurses, and law enforcement) in the area or per 100,000 people.	Human
Structural Preparedness Personnel	Presence of construction evaluation staff.	Mayunga & Peacock, 2010	Number of construction/building inspectors in the area or per 100,000 people.	Human
Management Redundancy	Availability of alternate private and public transportation related agencies.	Survey	(i) Number of Transportation Management Centers within the area; (ii) Number of private and public transport related agencies in the area or per 100,000 people.	Human/ Physical
Infrastructure's Health Monitoring Systems	Observation and evaluation of structural damage of key infrastructure.	C. Chang & Mehta, 2009; A. M. Madni & Jackson, 2009; Omer et al., 2011; Survey	(i) Percentage of key infrastructure that is monitored for structural damage; (ii) Percentage of road covered.	Physical
Power Redundancy	Availability of back-up generators.	Survey	Number of back-up generators available.	Physical
Data Redundancy	Availability of back-up servers.	Survey	Number of back-up servers available.	Physical
Alternative Infrastructure Proximity	Distance between original and alternate infrastructure.	Survey	Distance in miles between main location of servers, generators, or office space and their respective back-ups.	Physical

<b>Variable</b>	<b>Definition</b>	<b>Reference(s)</b>	<b>Possible Metric(s)</b>	<b>Capital</b>
Infrastructure Resistance	Level of seismic resistance of the infrastructure.		Percentage of agency infrastructure that is seismic resistance or has been retrofitted.	Physical
Age of Equipment	Age of supervision and response equipment.	Survey	Average age (in years) of equipment.	Physical
Structural Preparedness	Presence of construction evaluation policies that help prepare for and mitigate the effects of disasters.		Qualitative measure (low to high). Percentage of construction/building inspected within a reasonable timeframe	Physical
Information Dissemination Capability	Ability to broadcast information to the public and officials.	Comfort & Haase, 2006; Charnkol & Tanaboriboon, 2006	Percentage of roads covered by VMS, AM radio station, and 511 telephones, as well as presence in social media and any other warning method.	Physical/ Social
Interoperability	Accurate and timely communication within and across agencies.	Carreño et al.'s (2007); Survey	Qualitative measure (low to high).	Social

#### 4.4 Results Based on Simulated Data

Insightful information regarding potential metrics to evaluate AR was gathered by combining the information from the survey with the one from the review of existing literature. Subsequently, synthetic information of a hypothetical agency was developed in order to validate the proposed “Sustainable Livelihood–Fuzzy Algorithm” approach by showcasing its expected results and analysis capability.

##### *4.4.1 Variables, Metrics and Measurement Range*

For this study, seven variables of interest were selected from Table 8 for AR assessment based on their representation of an agency’s important preparedness and response attributes that contribute to resiliency. Furthermore, they allow for the assignment of a quantitative (or qualitative) performance measurement(s). Next is an explanation of each

variable, the selected metric for assessment and the respective measurement range necessary for the FIS. It should be noted that value ranges for the following variables are subject to size and other characteristics of the agency, as well as to the level of analysis. So these are just proposed values for the current case study, but should not be blindly generalized for other cases.

#### Power Redundancy (PR)

This variable refers to how vulnerable an agency is to power outage. Lack of energy can limit the performance of critical functions of an agency in the eve of a disaster. The presence of auxiliary generator(s) will drastically decrease the risk of losing power. Therefore, this research assumes that if no generators are being used, then the agency has a low PR; whereas if one or two or more are available, then the agency has medium and high PR, respectively.

#### Data Redundancy (DR)

This variable refers to how vulnerable an agency is to data/server outage. Similar to PR, lack of access to necessary data and/or operating systems can limit the performance of critical functions of an agency in the eve of a disaster. The presence of a back-up server will significantly lower this risk. In this manner, if no server is available, then the agency has a low DR; if one exists, then the agency has a medium DR; and finally, if 2 or more back-up servers are available, then the agency has high DR.

#### Alternate Infrastructure Proximity (AIP)

In extreme cases, the possibility still exists of losing access to both the main and alternate system. Therefore, the geographical location of the back-up with reference to the original should be taken into account to truly guarantee redundancy. This research suggest that if the distance between both systems is 5 miles or less, then the agency has low AIP;

if the distance is 15 miles, then AIP is Medium; and if the distance is 25 miles or more, then AIP is high.

#### Disaster Management Personnel (DMP)

This variable refers to the available professionals with training and/or experience in disaster management. Having a significant number of trained personnel will increase the strength of the agency's vertical and horizontal structure, and its execution of disaster response plans. In this sense, if an agency has no personnel with specific training and/or experience in disaster management, then it has a low DMP; if 20% of its personnel is trained, then DMP is medium; and if 40% or more is trained then DMP is high.

#### Scalability (SC)

It is inefficient, from budget perspective, for an agency to keep the amount of staff necessary to prepare for and respond to a disaster on active duty all year around. Therefore, a key resilient characteristic of an agency is its ability to change its personnel size in order to satisfy the new, and many time spontaneously increased, demand. For this research, this variable is estimated by a percentage increase in size, where 0% is low, 25% is medium and 50% or more is high SC.

#### Emergency Funds (EF)

An agency's ability to respond during distress is fueled by its available economic solvency and funds reserve. Many planning approaches exist in which agencies estimate the losses attached to the different types and amount of events that could occur throughout a year, along with the economic funds necessary to diminish them. Assuming that a "plan for the worse, hope for the best" strategy is commonly applied by agencies, if an agency

reserves at most 1% of its yearly budget for emergency response, then it has low EF; if it reserves 2%, it has medium EF; and if it reserved 3% or more it has high EF.

#### Interoperability (IN)

By the time of completion of this research, no quantitative value could be obtained to measure how well coordination happens within and across transportation agencies. To date, qualitative information is necessary to evaluate this variable, under its specific condition. This research follows Carreño et al.'s (2007) qualitative scale for “organization and coordination of emergency operations,” as presented below, to measure IN:

1. Different organizations attend emergencies but lack resources and various operate with only voluntary personnel.
2. Specific legislation defines an institutional structure; roles for operational entities and coordination of emergency commissions throughout the country.
3. Considerable coordination exists in some cities, between organizations in preparedness, communications, search and rescue, emergency networks, and management of temporary shelters.
4. Permanent coordination for response between operational organizations, public services, local authorities and civil society organizations in the majority of cities.
5. Advance levels of interinstitutional organization between public, private and community based bodies. Adequate protocols exist for horizontal and vertical coordination at all territorial levels.

These metrics represent characterizations at the lower level of operation, which is the focus of this research. Table 9 provides a summary of the metrics and measurements range of each variable used in this study. Recall that the objective of this research is to

develop a flexible yet robust tool for evaluating AR, and therefore the proposed ranges should be revised on a case by case basis.

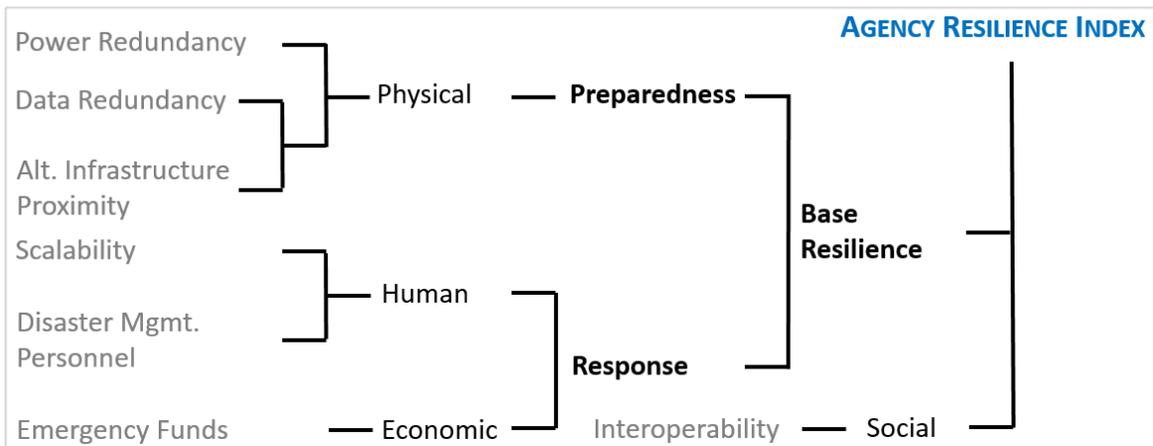
**Table 9.** Summary of Metrics and Measurement Range.

<b>Variable</b>	<b>Metric</b>	<b>Low</b>	<b>Medium</b>	<b>High</b>
Power redundancy	Availability of back-up generators	0	1	2
Data redundancy	Availability of back-up servers	0	1	2
Alternate Infrastructure Proximity	Distance between main and back-up systems	5 mi	15 mi	25 mi
Disaster Management Personnel	% of employees trained or experienced in disruption relief activities	0%	20%	40%
Scalability	Capability to increase personnel before, during and after emergencies	0%	25%	50%
Emergency Funds	Percentage of funds allocated for disasters (emergencies) per budget year	1%	2%	3%
Interoperability	Accurate and timely communication within and across agencies.	1	3	5

#### *4.4.2 Application of Fuzzy Algorithms: Simulated Results*

An updated dependency diagram was developed based on the selected variables. Figure 15 shows the interaction of the input variables used to assess each capital, which are characterized as first level metrics. The membership functions for each variable are continuous functions derived from the input rule sets that were created specifically for this research. Different types of membership functions (e.g., triangular, trapezoidal, etc.) were used to best describe each relationship and to account for any changeability within the variables. The membership functions along with the relative weights of influence specified for each variable provided the output to the following variable. That is, the combination of the first level metrics will determine the value of the second level metrics (i.e., capital

indexes). The second level metrics determine the third level (i.e., preparedness and response indexes) and so forth. Therefore, changes in the input (first level) metrics, along with the leveraging Social Capital, will extend through the fuzzy structure to the final AR Index. In summary, the estimation of the AR Index is derived from applying the “if-then” rules that enable each FIS, and the interaction between membership functions, which in hand determines the value of the next level variable.



**Figure 15.** Agency Resilience Index’s Fuzzy Inference System.

In general, all rules necessary for evaluating the different FIS (i.e., each node on the system) were developed through a two-step process that combines numerical calculation and engineering judgment. In the first step input metrics were standardized and the output was estimated based on the suggested weight of each metric. Here, all outputs are normalized into a 5-level scale membership function, where 1 is ‘Low’ and 5 is ‘High’. Any output within a specific range can then be categorized based on the scale—that is, any value below 1 is Low, between 1 and 2 is Medium-Low, between 2 and 3 is Medium, between 3 and 4 is Medium-High, and above 4 is High. However, given the different scales of first level inputs, not all results might be consistent with logic (e.g., two Low values yielding a Medium-Low). In the second step engineering judgment was used to validate

such outputs and make any necessary changes. This research uses MATLAB's Fuzzy Logic Toolbox for the development and evaluation of all FIS. Details about the logic behind the different FIS at each level are provided next.

- Capital Indexes: The Physical Index is evaluated in two parts. First, Data Redundancy (DR) and Alternate Infrastructure Proximity (AIP) are combined. In order to obtain real data redundancy it is necessary to not only have a back-up, but also for it to be located in a safe location outside of the potential disaster zone. This is not the case with power (PR), as it is inefficient from a budget perspective, to locate generators far from the users (e.g., buildings and management centers). This research assumes that DR is more important than AIP, explaining 70%, under the logic that it is necessary to have a back-up in order to locate it. Furthermore, the output from this sub-FIS is assumed to always be Low when no alternate system is available (i.e., DR is equal to 0). The second part uses the resulting value from combining DR and AIP as input with PR to estimate the Physical Index, both with equal weight. From a human capital perspective, both the presence of experienced/trained personnel and the ability to increase the workforce to satisfy increasing demand are of utmost importance for disaster response. Therefore, Scalability and Disaster Management Personnel are assumed to have equal weight when estimating the Human Index. Finally, the Economic and Social Indexes are only influenced by one variable each, Emergency Funds and Interoperability, respectively. Hence, no weight assignment is needed; instead, ranges are incorporated in the membership functions to accommodate the different values each variable may have.

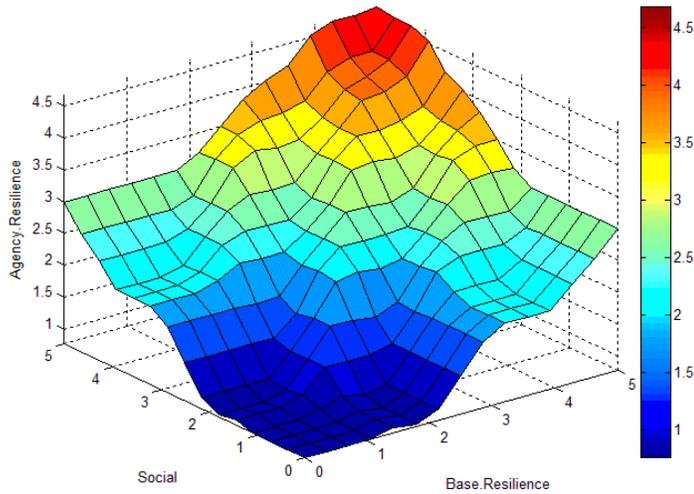
- Preparedness and Response: The Preparedness Index explains how able an agency is to withstand a disastrous event and it's estimated directly from the Physical Index. On the other hand, the Response Index combines Human and Economic Indexes to estimate the agency's capability to respond to such event. This study assumes that the economic component explains 65% of the Response Index, based on the logic that response strategies are more significantly limited by the lack of (access to) economic resources than human resources. In simple terms, it is easier to obtain extra personnel (e.g., volunteers) than it is to obtain extra monetary funds.
- Base Resilience and Agency Resilience Index: The final steps of the methodology consists of combining Preparedness and Response into a Base Resiliency Index (BR) for the agency and merging it with the leveraging variable, Social Index, into the Agency Resiliency Index (ARI). Preparedness and Response are assumed to equally impact BR, since their interaction can be viewed as reciprocal. Base Resilience represents the resilience level of an agency based only on its basic properties. However, given the common distribution of responsibilities across agencies, communication and coordination between them is key to reach an optimal resilience level. Therefore, Interoperability and Base Resilience are assumed to have equal weight when evaluating the final Agency Resilience Index.

The tool provides useful visual outputs, such as a result-surface plot of all possible combinations of inputs and their respective output and 2D plot of a selected input variable the output. As an example, the rules used to obtain the AR Index are presented in Table 10. All rules used in this research can be seen in Annex 3.

**Table 10.** Rules for estimating Agency Resiliency.

IF	Base Resilience	AND	Social	THEN	Agency Resilience
If	Low	and	1	then	Low
If	Low	and	2	then	Low
If	Low	and	3	then	Medium-Low
If	Low	and	4	then	Medium-Low
If	Low	and	5	then	Medium
If	Medium-Low	and	1	then	Low
If	Medium-Low	and	2	then	Medium-Low
If	Medium-Low	and	3	then	Medium-Low
If	Medium-Low	and	4	then	Medium
If	Medium-Low	and	5	then	Medium
If	Medium	and	1	then	Medium-Low
If	Medium	and	2	then	Medium-Low
If	Medium	and	3	then	Medium
If	Medium	and	4	then	Medium
If	Medium	and	5	then	Medium-High
If	Medium-High	and	1	then	Medium-Low
If	Medium-High	and	2	then	Medium
If	Medium-High	and	3	then	Medium
If	Medium-High	and	4	then	Medium-High
If	Medium-High	and	5	then	High
If	High	and	1	then	Medium
If	High	and	2	then	Medium
If	High	and	3	then	Medium-High
If	High	and	4	then	High
If	High	and	5	then	High

The result of “fuzzifying” inputs and applying the “if-then” rules presented in Table 10 is the 3D surface shown in Figure 16. As can be seen, at their maximum level, both Base Resilience and Social Capital yield an AR value of 3 (i.e., Medium). In other words, if one of the variables has a value of zero, the other would help the agency obtain a medium level of resilience. Additionally, in-between values follow identical slopes, indicating that, under these set of rules, investing in Social Capital could returns the same benefits as attempting to improve Base Resilience.



**Figure 16.** Agency Resilience result-surface.

A synthetic agency was simulated to showcase the application and analysis capability of the proposed framework. This example was perceived as a medium-level transportation office, where the agency,  $MPO_x$ , is responsible for carrying out the transportation planning process of a metropolitan area with a population of 500,000. Table 11 summarizes the characteristics of the agency under the base case and improvement scenarios and their respective AR Index. As can be seen, under its current condition,  $MPO_x$  has an AR Index value of 2—a Medium-Low level of resilience that indicates that the agency is somewhat able to withstand a disaster. An analysis of the input variables for the base case provides insight of why such value of resilience. In detail: (i) data redundancy is significantly narrowed by the small distance between the original and back-up servers, having a cascade-effect into Physical Capital and forth; (ii) limited funds and capacitated personnel could hinder the capacity of  $MPO_x$  to apply and manage different response processes; and (iii) the low level of Base Resilience is compensated to some degree by the average interoperability level, improving its overall resilience level.

The effect of improving each capital is evaluated in scenarios one through four (the change in each variable is highlighted in red font). Of the different improvements possible,

enhancing coordination and communication with other agencies provides the biggest benefit, increasing the AR Index by 50%. This provides a cost-effective alternative for MPO<sub>x</sub> to improve its overall ability to prepare and respond to disasters, although not necessarily the easiest to implement due to political and geographical constraints. The second most beneficial improvement comes from ensuring accessibility to information and operating systems during disasters. Having servers located in a location with low probability of being included in the disaster diameter will increase Base Resilience by around 70%. Finally, increasing MPO<sub>x</sub>'s disaster management capability (e.g., capacitating existing personnel or hiring experienced ones) and increasing its funds available for disaster response will yield the same AR Index.

**Table 11.** Agency Resilience Index for simulated base case and scenarios.

Variable	Base Case	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Power redundancy	1	1	1	1	1
Data redundancy	1	1	1	1	1
Alternate Infrastructure Proximity	10 mi	30	10 mi	10 mi	10 mi
<b>Physical Index</b>	<b>2.5</b>	<b>4</b>	<b>2.5</b>	<b>2.5</b>	<b>2.5</b>
Disaster Management Personnel	15%	15%	40%	15%	15%
Scalability	25%	25%	25%	25%	25%
<b>Human Index</b>	<b>2.3</b>	<b>2.3</b>	<b>4</b>	<b>2.3</b>	<b>2.3</b>
Emergency Funds	1.5%	1.5%	1.5%	2.5%	1.5%
<b>Economic Index</b>	<b>1.84</b>	<b>1.84</b>	<b>1.84</b>	<b>3.55</b>	<b>1.84</b>
Interoperability	3	3	3	3	5
<b>Social Index</b>	<b>3</b>	<b>3</b>	<b>3</b>	<b>3</b>	<b>5</b>
<b>Base Resilience</b>	<b>1.62</b>	<b>2.73</b>	<b>2.5</b>	<b>2.5</b>	<b>1.62</b>
<b>Agency Resilience Index</b>	<b>2</b>	<b>2.7</b>	<b>2.5</b>	<b>2.5</b>	<b>3</b>

#### 4.5 Conclusion

Urena Serulle et al. (2011) states that a measure of resilience could be used to substitute other performance indexes since resilience can be viewed as the collection of key performance indicators. This research supports this notion and in this chapter

introduces an alternate quantitative approach to measure resilience of transportation agencies as a way to fill the existing void in the academic literature regarding AR. The framework for analysis combines two well-known and used approaches, Sustainable Capitals and Fuzzy Algorithms. The first decomposes agency resilience into groups of related metrics, whereas the latter enables a flexible multi-criteria analysis. The framework is flexible in the sense that it can deal with different type of data (i.e., scales and units) and makes it possible to evaluate intermediate values as well as defined values.

To the best of the author's knowledge, the first nationwide survey regarding AR was conducted here, where transportation professionals within different agencies were asked about their perspective on agency resilience specifically and how it could be characterized with quantitative data. Despite the low response rate, this research still contributes to the discussion on how to evaluate AR. The information collected was merged with the one found in or derived from the multidisciplinary literature review (Sections '2.4 Resilience Literature' and '4.1 Background') to compile a set of potential quantitative metrics that could serve as a starting point for future research in this area. Seven variables were selected from this list to evaluate AR. The results of the simulated example indicates that, under the specified set of rules, improving coordination and developing joint efforts across agencies provides a (potentially) cost-effective way to significantly increase an agency's resilience level.

A noteworthy detail found through the survey is the apparent lack of information regarding resilience, specifically of agencies, and the recent attempt to fill this gap—some agencies stated they are about to or recently starting research on this topic. Therefore, this research recommends that another nationwide survey be conducted in one or two years to

collect this information, preferably with stronger support in order to guarantee higher participation rate. Future research should focus not only on identifying metrics for evaluation but also on their weights.

## Chapter 5: User Resilience

The layer User Resilience (UR) provides insight into the characteristics of the (potentially) affected population and their resilient capability, making it more economically and socially driven than the rest. Similar to previous layers, UR comprises a vast number of variables that inform the resilience level of a given population. As a result, this study proposes that UR be evaluated through an analysis of the evacuation behavior of a given population. Understanding what affects the decision process of a population potentially at risk from a disaster is of utmost importance when developing and implementing resilience-enhancing policies. For this, a dynamic discrete choice model is suggested, taking into account the disaster's and population's characteristics.

The rest of the chapter is organized as follows: Section 5.1 provides a background into the problem of evacuation demand estimation and dynamic modelling; Section 5.2 describes the approach to develop a dynamic model; Section 5.3 describes the data to be used for model estimation; Section 5.4 explains the estimated results using SP data; and Section 5.5 concludes.

### 5.1 Background

#### *5.1.1 Modelling Evacuation*

In the event of a disaster, the affected population goes through four stages of reaction: collection, evaluation, decision, and implementation (Williams, 1964). In the first stage, the population collects information on the disaster, mainly through disaster warning messages. Then, the information is evaluated, generally based on the perceived relevance. Finally, a decision is made and implemented within a selected timeframe. The transition

through these stages makes travel demand for evacuation different from ordinary travel needs. In order to understand travel needs in disastrous situations, it is necessary to gather knowledge on evacuation behavior. For this, research to comprehend evacuation must move beyond estimating the amount of evacuees, towards an understanding of what factors are crucial in determining the forces behind evacuation travel demand (Dash & Gladwin, 2007; Lindell, Lu, & Prater, 2005).

In their research, Dash and Gladwin (2007) found that, historically, factors such as age of the decision maker (Mileti, Drabek, & Haas, 1975; Grunfest, Downing, & White, 1978; Perry R. W., 1979), presence of kids or seniors in the household (Carter, Kendall, & Clark, 1983; Gladwin & Peacock, 1997), gender (Bolin, Jackson, & Crist, 1996; Fothergill, 1996; Bateman & Edwards, 2002), disability (Van Willigen, Edwards, Edwards, & Hesse, 2002), ethnicity (Drabek & Boggs, 1968; Perry & Greene, 1982; Perry & Mushkatel, 1986), and income (Schaffer & Cook, 1972; Sorensen, Vogt, & Mileti, 1987; Bolin, 1986) have all been shown to influence evacuation outcomes. Additionally, previous experience (Hutton, 1976; Baker, 1979; Perry, Lindell, & Greene, 1982; Sorensen, Vogt, & Mileti, 1987) and geographic location (Simpson & Riehl, 1981; Gladwin & Peacock, 1997) affect the evacuation decision-making process. Similarly, Charnkol and Tanaboriboon (2006) found that, as expected, permanent residents, larger families, people living further away from the seashore, people that haven't directly or indirectly experienced a disaster event, and people without disaster knowledge are less likely to have a faster response time (i.e., time required to physically travel to safer area) than their counterparts—same results are found when other types of disasters are evaluated. The reader is referred to Carnegie and

Deka (2010) for a more comprehensive review of the array of factors that have been reported to influence evacuation decision.

The suggestion of incorporating time into evacuation modeling is found throughout the literature (Pel, Bliemer, & Hoogendoorn, 2011a). Identifying what will get people to evacuate in a timely manner would enable more robust traffic-clearing models during disasters. A common practice in hurricane evacuation travel demand estimation is to estimate the total evacuation demand and departure time through simple relationships such as means, rates, and distributions rather than the more sophisticated mathematical relationships observed in urban transportation planning (Mei, 2002). These estimates are generally determined by applying an exogenous response curve stating the percentage of departures in each time interval (Pel, Bliemer, & Hoogendoorn, 2011b). Response curves have been vastly studied; however there is still a debate about the distribution it should follow—instantaneous departure (Chen & Zhang, 2004; Chiu, Villalobos, Gautam, & Zheng, 2006), a Uniform distribution (Liu, Lai, & Chang, 2006; Yuan, Han, Chin, & Hwang, 2006), a Poisson distribution (Cova & Johnson, 2002), a Weibull distribution (Lindell, Prater, Perry, & Wu, 2002) or sigmoid curve (Kalafatas & Peeta, 2009; Xie, Lin, & Waller, 2010), to mention a few. The drawback of the response curve approach is that there is no clear behavioral basis to justify the method (Pel et al., 2011a).

An area that requires much additional effort is the translation of the considerable amount of knowledge on evacuees' behavior during the time of crisis into reliable quantitative measures of the timing of evacuee mobilization (Southworth, 1991). Discrete choice analysis has been used to address this issue. This research introduces the use of dynamic discrete choice models to estimate such evacuation demand as they are gaining

significance in the state of practice due to their robust results. Subsection 5.1.2 provides a review of the literature surrounding dynamic modelling.

### *5.1.2 Dynamic Discrete Choice Models*

Dynamic models estimate decisions as a sequence of discrete choices where at each time period the decision maker chooses the utility-maximizing alternative. In his seminal work, Rust (1987) developed a regenerative optimal stopping model of bus engine replacement based on accumulated mileage, in which at each time period the decision-maker is faced with the decision of whether to replace the engine of a public transportation bus or to wait one more period, risking unexpected engine failure. The model allows for recurrent participation of the buses by resetting their mileage to zero after their engine is replaced—hence the term regenerative. Rust estimates the utility based on the expected cost of operation of each alternative, where expected accumulated mileage is given by a draw from an exponential distribution. Other influential papers include Wolpin (1984) on fertility and child mortality, Miller (1984) on job matching and occupational choice, and Pakes (1986) on patent renewal.

Since these seminal papers, dynamic discrete choice models (DDCM) has been applied in many different scenarios, including labor economics, industrial organization, economic demography, health economics, development economics, political economy, and marketing. Keane and Wolpin (1997) studied the career choices of young men based on the reward of each occupation alternative (i.e., to study or to work) over the life cycle. Their model optimize such reward by taking into account the individual's evolution of education (and its related cost), income and skill-sets through a given age range. Similarly, Ge (2013) focused on the decision of whether to attend college, work or a combination of

both of women with a high school degree. Furthermore, Heckman and Navarro (2007) evaluated associated earnings outcomes for different levels of education while considering anticipations about potential future outcomes associated with the various choices. For this, they provide a semiparametric non-regenerative formulation of dynamic discrete choice models of treatment times and the consequences of choice.

From an employment perspective, Rust and Phelan (1997) and Karlstrom, Palme and Svensson (2004) used dynamic discrete choice models to estimate retirement from the labor force based on time-dependent retirement benefits (e.g., pension and healthcare). On the other hand, Gurmu, Ihlanfeldt and Smith (2008) estimate the participation on full-time employment of families that receive welfare through a dynamic probit model which incorporates residential location and time-varying variable, such as employment status. More broadly, Keane and Wolpin (2002a, 2002b) evaluated the impact of welfare benefits on economic and demographic behavior—employment status, household size and education to mention a few.

In market share analysis, Gönül (1998) assesses the effect of time-varying cost and preferences (purchase history) on the sales of different over-the-counter medicine brands. Whereas Hetrakul (2012) evaluated ticket cancellations and exchanges within railway service in response to varying trip schedule, cost, and refund/exchange policy.

Many other examples of the application of dynamic models exist in the literature. The reader is referred to Keane, Todd and Wolpin (2011), Aguirregabiria and Mira (2010) and Keane and Wolpin (2009) for a comprehensive survey of the literature surrounding the different structures and applications of DDCM.

### 5.1.2.1 Dynamic Discrete Choice Models in Transportation

Despite the vast application of DDCM, its use within the field of transportation has been limited when compared to other fields. Gao, Frejinger and Ben-Akiva (2010) proposed a policy routing choice model with a cumulative prospect theory utility function (a non-expected utility framework) to measure choice under risk. Their model is adaptive since information is updated as the traveler traverses through a stochastic network (*en route*). Alternatively, Fosgerau, Frejinger, and Karlstrom (2013) developed a dynamic route choice model where the path choice problem is formulated as a sequence of link choices. At each stage (i.e., node), the traveler chooses the link that maximizes the sum of instantaneous utility and the expected downstream utility. On the other hand, dynamic models have also been used to estimate car ownership and its related decisions (e.g., type of vehicle, tenure and usage), where variables such as income, fuel prices and cumulated mileage are treated as stochastic state variables—see de Lapparent and Cernicchiaro (2012), Cirillo, Xu, and Bastin (2013), and Glerum et al. (2015).

In evacuation analysis, dynamic travel demand is usually modelled through repeated binary logit models where the share of people who decide to evacuate and depart presently, or postpone the decision to evacuate, are estimated at each time period. Fu and Wilmot (2004) developed a sequential binary logit model to estimate the decision to evacuate when threatened by a hurricane at several time intervals before landfall. For this, information from 320 households in Southwest Louisiana was collected following hurricane Andrew. In their model, travelling speed of the hurricane, time of day, and distance from the hurricane were treated as dynamic variables. They concluded that sequential binary logit is capable of estimating the decision of whether to evacuate or not.

Later, Fu, Wilmot and Zhang (2006) improved the model by including hurricane wind speed and time-to-landfall data from hurricane Floyd in South Carolina and tested the calibrated model on the hurricane Andrew data. The predicted dynamic travel demand yielded similar results to the observed travel demand, indicating that there is potential in transferring weights to different location and hurricane scenarios. Similarly, Wilmot and Gudishala (2013) developed a sequential logit model following a conventional model structure and based on newly collected hurricane data from a State Preference (SP) survey in Louisiana.

The current state-of-practice is to estimate the dynamic utility of evacuating (or not evacuating) using prevailing conditions. However, it is logical to assume that people not only consider current conditions, but are also capable of predicting future conditions and base their decision on this information as well (Pel et al., 2011a). For example, Wilmot and Gudishala (2013) developed a sequential nested logit that combines the decision of whether to evacuate or stay into time period nests. The nested model linked the utility of a lower nest to an upper nest, that is linking time period  $i+1$  to  $i$ , by using the Logsum of the utilities.

The purpose of this research is to contribute to the literature of DDCM by applying demand estimation during hurricane evacuation by proposing a new approach, founded on Cirillo, Xu and Bastin's (2013) work on dynamic modelling of car ownership and Hetrakul's (2012) work on dynamic modelling of train user's ticket cancellation/exchange behavior. Here, the previous models will be adapted to develop a hurricane evacuation model using a dynamic discrete choice regression model capable of combining prevailing and expected hurricane conditions, resulting in a more robust estimation of the evacuation

response and factors affecting it. The model is then applied using SP data collected from Louisiana residents.

## 5.2 Evacuation Modeling Framework

As previously stated, this research builds upon Cirillo, Xu and Bastin (2013) and Cirillo and Hetrakul (2012), modifying and updating them to reflect the behavior of evacuees in the midst of a disaster, which for this study is a hurricane. This subsection provides background on dynamic discrete choice models and explains how it is applied in this study.

### *5.2.1 General Evacuation Decision Problem*

Consider a population set  $E = \{1, \dots, M\}$  and time periods  $t = 0, 1, \dots, T$ . In each time period  $t$ , consumer  $i$  has two options:

- 1) to evacuate and obtain a terminal period payoff  $u_{it}$ ;
- 2) to postpone and obtain a one-period payoff  $c_{it}$ , which is a function of individual  $i$ 's attributes and the current characteristics of the disaster, i.e.  $c(x_{it}, q_{it}; \theta_i \alpha_i)$ .  $x_{it}$  is a vector of attributes for individual  $i$  at time  $t$  (e.g., sex, education, income, age) and  $q_{it}$  is the vector of characteristics of the disaster (e.g., category, time to landfall, time of day).  $\theta_i$  and  $\alpha_i$  are parameters vectors for  $x_{it}$  and  $q_{it}$  respectively.

Using bold font for random variables and normal font for their realizations, the payoff  $\mathbf{b}_{it}$  (i.e., to evacuate at time  $t$ ) is expressed as a random utility function:

$$\mathbf{b}_{it} = u(x_{it}, \mathbf{y}_t, \theta_{it}, \lambda_i, \epsilon_{it}) \quad (5.1)$$

where

- $x_{it}, \theta_i \in \mathfrak{R}^Q$  are defined a above;

- $\mathbf{y}_t \in \mathfrak{R}^H$  is a random vector of dynamic attributes at time  $t$ , which represents the evolution of a disaster over time.  $\lambda_i$  is a vector of parameters related to  $\mathbf{y}_t$ .
- $\epsilon_{it}$  is an individual-specific random term, whose components are independently and identically GEV distributed amongst individuals and periods. It is assumed that  $\epsilon_{it}$  is independent from  $\mathbf{y}_t$ .

Although this formulation can be extended to mixed GEV kernel (Bastin, Cirillo, & Toint, 2006), the parameters are here assumed to be the same over individuals, i.e.  $\theta_i = \theta$ ,  $\alpha_i = \alpha$ , and  $\lambda_i = \lambda$ ,  $i = 1, \dots, M$ . A one-step decision process is assumed, in which, at each time period  $t$ , the individual decides whether to evacuate or to postpone the evacuation until the optimal time period  $\tau$ , time when the consumer decides to evacuate instead of postponing. The individual deciding to evacuate or postpone is the optimal stopping problem at time  $t$ :

$$D_t(\mathbf{b}_{it}, c_{it}) = \max_{\tau} \left\{ \sum_{k=t}^{\tau-1} \beta^{k-t} c_{it} + \beta^{\tau-t} E_{\mathbf{y}_{\tau}}[\mathbf{b}_{it\tau} | \mathbf{y}_t] \right\} \quad (5.2)$$

where

- $\beta$  is a discount factor in  $[0,1)$ ;
- $c_{it}$  is the payoff function of individual  $i$ 's attributes and the characteristics of the disaster when choosing to postpone the evacuation, as defined before.

It is important to note that the expectation in (5.2) is taken with respect to the disaster evolution  $\mathbf{y}_t$ .  $D_t$  remains a random function due to the terms  $\epsilon_{it}$  present in the random utility functions. According to the previously described assumption about  $\epsilon_{it}$ ,  $b_{it}$  is Gumbel distributed with a scale factor equals to 1 and  $\gamma_{it}$  is the mode of the distribution

of  $b_t$ . It is also stressed that if  $\tau = t$ , the right-hand term in (5.2) reduces to  $b_{it}$ . It is then easy to see the individual's decision can be transformed from (5.2) into:

$$D_t(b_{it}, c_{it}) = \max\{b_{it}, c_{it} + \beta E_{y_{t+1}}[D_{t+1}(b_{i,t+1}, c_{i,t+1})|y_t]\} \quad (5.3)$$

Equation 5.3 indicates that the decision process consists on evacuating at time  $t$  or delaying it over one period, taking the payoff  $c_{it}$  plus the discounted future return. This is a standard optimal stopping problem, with a stopping set given by

$$\Gamma(y_t) = \{b_{it} | b_{it} \geq W_{it}\} \quad (5.4)$$

where  $W_{it}$  is the reservation utility level for individual  $i$  and its defined as:

$$W_{it} = c_{it} + \beta E_{y_{t+1}}[D_{t+1}(b_{i,t+1}, c_{i,t+1})|y_t] \quad (5.5)$$

Using (5.5), (5.3) can be simplified to:

$$D_t(\mathbf{b}_t) = \max\{b_{it}, W_{it}\} \quad (5.6)$$

It is assumed that the random terms  $\epsilon_{it}$  take specific realizations when selecting an individual  $i$ , meaning that the individual  $i$  has access to all values of his/her utility function—the vectors  $\epsilon_{it}$  are simply the unobserved factors. Simply put, individual  $i$  will choose to evacuate at time  $t$  only when  $b_{it} > W_{it}$ . If  $i$  is randomly drawn from the population, the analyst can compute the probability of postponing the evacuation until the next period as:

$$\begin{aligned} \pi_{it}(y_t) &\stackrel{\text{def}}{=} P_{it}[D_t(b_{it}) = W_{it}|y_t] \\ &= P_{it}[b_{it} \leq W_{it}] \\ &= F_v(W_{it}, y_t) = e^{-e^{-(W_{it}-y_{it})}} \end{aligned} \quad (5.7)$$

Note the probability is taken with the set of random variables  $\epsilon_{il}$ , for  $l = t, t + 1, \dots$ , i.e. the variables unobserved by the analyst but with known values for individual  $i$ .

### 5.2.2 Dynamic Estimation Process

The parameter estimation process is done by applying the maximum likelihood estimation method to:

$$\mathcal{L}(\theta, \lambda, \beta) = \prod_{i=1}^M \prod_{t=1}^H P_{it}[D_t(b_{it})|\theta, \lambda, \beta] \quad (5.8)$$

where

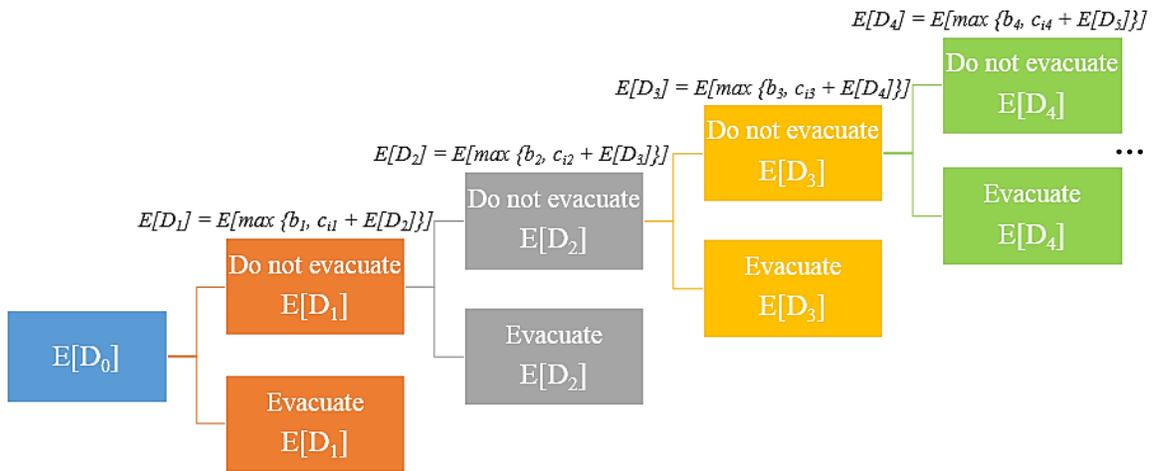
- $\theta$  is a vector of stationary preference parameters related to individual attributes  $x_{it}$ .
- $\lambda$  is a vector of parameters related to the dynamic attributes of the disaster,  $y_t$ .
- $\beta$  is the discount factor, set to 1 for simplicity.

The probabilities of (5.8) are taken with respect to the distribution of the variable  $\epsilon_{it}$ , as in (5.7), given the values of the parameters.  $H$  represents the number of time periods where observations were collected, which in this case is limited by the number of forecast – therefore  $H$  is equal to four.

As explained before, the probability of  $\pi_{it}$  depends on  $W_{it}$ , which can be calculated as is (5.5).  $W_{it}$  is composed of two parts: the utility of the current disaster attributes  $c_{it}$  and the expected utility in the next time period  $\beta E_{y_{t+1}}[D_{t+1}(\mathbf{b}_{i,t+1}, c_{i,t+1} | y_t)]$ . The key step during the estimation process is to identify how to calculate the expected utility. At each time period, the individual is assumed to be forward-looking (i.e., they have a perception about the future scenarios), which are characterized by the disaster's attributes changing over time. This research uses a finite horizon scenario tree providing a reasonable behavioral rooting since individuals can only perceive future attributes for a limited number of time periods (see Shapiro, Dentcheva, and Ruszczyński (2009), Hetrakul (2012) and Cirillo et al. (2013) for examples). Therefore, at time period  $t$ , the individual faces two

alternatives, to evacuate or to postpone evacuation. The individual will continue the decision process into the period  $t + 1$  only if he/she had decided to postpone evacuation in time period  $t$ . Therefore, the decision process can be characterized by a scenario tree (see Figure 17), which is the base for the expected utility calculation. The following steps describe the procedure to calculate  $\pi_{i1}$  based on the expectation  $E_{y_1}[D(\mathbf{b}_{i1}, c_{i1})|i]$ , which will be indicated by  $E[D_1]$  because all the expectations in the example are for individual  $i$ :

- Assumption: It is assumed that the individual has the expectation over a limited number of future periods. Given that we are dealing with disaster with usually limited forecasts, here it is assumed that individuals can only predict one period ahead. Therefore, at time period  $t = 1$ , the individual can anticipate the future characteristics of a disaster (e.g., category and evacuation order) at time period  $t = 2$ . Whereas  $E[D_3] = 0$  since the individual knows nothing of time period 3 when faced with the decision at time period 1, same for any time period beyond  $t+1$ .
- Evaluation of  $E[D_2]$ : To obtain the probability of  $\pi_{i1}$  it is necessary to estimate  $W_{i1}$  (using 5.5), which in hand depends on  $E[D_2]$ . At time 1, the individual has two alternatives for successive time 2, to evacuate or not to evacuate (see Figure 17). The right side of the utility function  $E[D_1] = E[\max \{b_1, c_1 + \beta E[D_2]\}]$  represents the utility of the "do not evacuate" alternative. Based on the above assumption,  $E[D_3]$  is zero when calculating  $E[D_2]$  at time  $t=1$ .
- These steps are then repeated to calculate  $\pi_{i2}$  with the assumption that respondent can anticipate the characteristics of the disaster at time period 3 and  $E[D_4]$  is zero, and so on for the rest of the estimations.



**Figure 17.** Scenario Tree.

### 5.2.3 Experiment Using Simulated Data

A synthetic sample of 1,000 households' choices over four potential time periods have been simulated to validate the proposed dynamic discrete choice formulation. The hypothetical scenario is a hurricane in route to make landfall for which five forecasts are provided,  $t \in \{1, \dots, 5\}$ . In order to comply with the one period look ahead assumption, choices are estimated for the first four periods. At each observation period, there are two alternatives in the choice set that mimic respectively the decision to evacuate or do not evacuate. It should be noted that this model is not regenerative, therefore, any household that decides to evacuate is out of the sample.

Two types of variables were generated in the simulated dataset, static and dynamic. Static variables relate to household characteristics, specifically household's income, size, presence of kids, and previous experience with evacuation; whereas dynamic variables provide time-varying information of the disaster, namely hurricane category, time to expected landfall, and whether they are at the last forecast. These variables were selected based on the information found in the literature review regarding the factors that influence

evacuation decisions. The variables in the simulated dataset have been generated using the following criteria:

- Household income varies on 7 levels of variation: (1) Less than \$15,000; (2) = \$15,000 to \$24,999; (3) \$25,000 to \$39,999; (4) \$40,000 to \$79,999; (5) \$80,000 to \$119,000; (6) \$120,000 to \$149,000; and (7) Over \$150,000. It was assumed that 10% of the population had income level 1, 20% had level 2, 50% were uniformly distributed between levels 3 and 4, and the remaining 20% were uniformly distributed between levels 5 through 7.
- It was assumed that 70% of households have between 1 and 3 family members and that the remaining 30% have between 4 and 6.
- Assumption of presence of kids (i.e., under 17 years of age) were made based on the size of the household. Single-member households were assumed to contain no kids. If the household were composed of 2 members, there were a 5% chance of one of them being a kid. Households with 3 or 4 members were given a 50% probability of having a kid, whereas families with 5 or more members were given an 80% probability of having at least one kid.
- It was assumed that 50% of households have had previous experience with evacuation (either directly or indirectly).
- For the first forecast, hurricane category was uniformly distributed in the range of 1-5 following the Saffir-Simpson scale. After this initial forecast, it was assumed that hurricanes could only increase or decrease (within the 1 to 5 scale limit) at most two categories between forecasts. For example, if in Forecast 2 the category is 2, then in Forecast 3 the category was uniformly distributed between 1 and 4.

- Time to expected landfall was uniformly distributed within each forecast following these ranges: (1) 67-77 hrs, (2) 44-52 hrs, (3) 21-27 hrs, (4) 10-14 hrs, and (5) 4-8 hrs away.
- The communication of the last forecast is a dummy variable with 0-1 values that takes the value of 1 if the period of observation is forecast 4 and 0 otherwise.

Respondents are supposed to choose between two alternatives: evacuate and not evacuate. Utility of evacuation of household  $i$  on time  $t$  can then be specified as:

$$U_{evac,it} = \beta_{income}HHinc + \beta_{size}HHsize + \beta_{kids}HHkids + \beta_{exp}HHexp + \beta_{category}HC + \beta_{time}TTEL + \beta_{Last\ FC}FC4 + \varepsilon_i$$

where  $HHinc$  is household income,  $HHsize$  is household size,  $HHkids$  is the presence of at least one kid in the family,  $HHexp$  is the experience of the household with evacuation,  $HC$  is the hurricane category,  $TTEL$  is the time to expected landfall and  $FC4$  is the last forecast. The random term  $\varepsilon_i$  is iid extreme-value distributed at a given time period. Three models were estimated using the simulated data and the specification defined above: (i) a model where decisions are generated following a logit distribution and estimated with a dynamic model, LogDyn; (ii) a model where decisions are generated following a dynamic distribution and estimated with a logit model, DynLog; and (iii) a model where both generation and estimation are done dynamically, DynDyn. In the logit model (DynLog), respondents are not considering future disaster evolution when making decisions at each time period. The model is simply formulated as a traditional MNL with two alternatives; utilities include both static and dynamic variables, for consistency with the dynamic model formulation. All models are coded in R language.

In order to validate which model better recovers the true values, Root Mean Square Deviation (RMSD) is adopted as it aggregates individual differences between the true and predicted values into a single measure of predictive power. The bigger the RMSD, the poorer the model's ability to reproduce the true phenomenon. The RMSD is defined as

$$RMSD(\hat{\theta}) = \sqrt{E((\hat{\theta} - \theta)^2)} = \sqrt{\frac{\sum_{i=1}^n (\hat{\theta}_i - \theta_i)^2}{n}}$$

where  $\hat{\theta}$  is the observed (true) value,  $\theta$  is the modelled value at time  $i$ , and  $n$  is the number of parameters. Results of the estimations are presented in Table 12. The last part of the table reports the RMSD. Overall, models with dynamic estimation obtained lower RMSD, indicating lower bias in its coefficients, with DynDyn model yielding the lowest value of all.

**Table 12.** Estimation with simulated data.

Var	True Value	Model	Average	SD	CI 95%	Min	Max
Hurricane Category	0.2	LogDyn	0.1465	0.0258	0.0051	0.0932	0.2119
		DynLog	0.2635	0.0287	0.0057	0.2004	0.3365
		DynDyn	0.1971	0.0275	0.0055	0.1305	0.2752
Time to Expected Landfall	-0.03	LogDyn	-0.0280	0.0021	0.0004	-0.0341	-0.0235
		DynLog	-0.0337	0.0022	0.0004	-0.0402	-0.0289
		DynDyn	-0.0302	0.0019	0.0004	-0.0352	-0.0264
Last Forecast (FC4)	-3.3	LogDyn	-3.1601	0.3534	0.0701	-4.3564	-2.4143
		DynLog	-3.5930	0.1910	0.0379	-4.2687	-3.2495
		DynDyn	-3.2767	0.3395	0.0674	-4.1807	-2.5989
Previous Experience	0.9	LogDyn	0.7650	0.1009	0.0200	0.5055	1.0276
		DynLog	1.0805	0.0971	0.0193	0.8290	1.3691
		DynDyn	0.9001	0.0959	0.0190	0.6623	1.1650
Household Size	-0.3	LogDyn	-0.2829	0.0460	0.0091	-0.3959	-0.1744
		DynLog	-0.3139	0.0436	0.0086	-0.4223	-0.2226
		DynDyn	-0.2981	0.0388	0.0077	-0.3852	-0.1719
Presence of Kids	0.3	LogDyn	0.2592	0.1456	0.0289	-0.0632	0.5928
		DynLog	0.3024	0.1385	0.0275	0.0272	0.6166
		DynDyn	0.2943	0.1247	0.0248	0.0124	0.5575
Household Income	-0.15	LogDyn	-0.1550	0.0260	0.0052	-0.2291	-0.0887
		DynLog	-0.1402	0.0257	0.0051	-0.2039	-0.0841

		DynDyn	-0.1474	0.0242	0.0048	-0.2195	-0.0874
	<b>RMSD</b>	LogDyn	<b>0.0780</b>				
		DynLog	<b>0.1324</b>				
		DynDyn	<b>0.0092</b>				

### 5.3 Dataset Description

Hurricane Katrina came in contact with the city of New Orleans in 2005. Later on September 1, 2008, Hurricane Gustav made landfall near Cocodrie, Louisiana as a Category 2 hurricane. Gustav originated as a tropical storm southeast of Port-au-Prince, Haiti, on August 25, 2008 and developed into a hurricane on August 26. These two experiences combined with the closeness between events, highlighted the need of a practical and more reliable framework for evacuation behavior analysis.

On 2010, the Public Policy Research at Louisiana State University conducted a survey that collected information on the evacuation behavior of resident of New Orleans. The survey had two main parts: 1) a Revealed Preference (RP) section that gathered information of the respondent's evacuation decision during the threat of hurricane Gustav, and 2) a Stated Preference (SP) section that registered the respondent's evacuation behavior based on hypothetical hurricane scenarios. The survey used the RP data and adapted it to collect dynamic information and enhance the realism of each scenario by presenting it in audio-visual form on a DVD. Each household was presented 3 hypothetical storms, where each storm contained 4 forecasts. At each forecast the respondent made the decision of whether to evacuate or not. A total of nine hypothetical storms were developed, each one with time-dependent information on hurricane category (HC), evacuation order (EO), time (TOD) of day, time to expected landfall (TTEL) and day of the week (DOW), see Table 13. The reader is referenced to Wilmot and Gudishala (2013) for a more detailed explanation of the survey design and data collection process.

**Table 13.** Hypothetical storms presented to interviewed households.

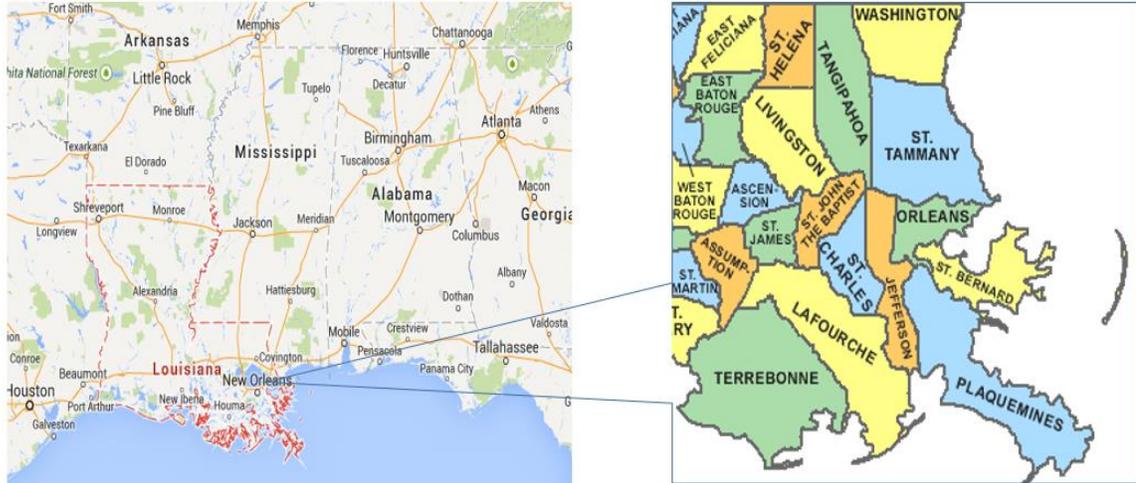
Storm	Characteristics	Forecast1	Forecast2	Forecast3	Forecast4
1	HC1	4	4	4	3
	EO1	None	Voluntary	Mandatory	Mandatory
	TOD1	10.25	6.25	0.25	14.25
	TTEL1	70	50	32	18
	DOW1	3	4	5	5
2	HC2	5	4	3	2
	EO2	Voluntary	Mandatory	Mandatory	Voluntary
	TOD2	12.50	14.50	16.00	1.00
	TTEL2	72	45	19	8
	DOW2	1	2	3	4
3	HC3	3	4	3	3
	EO3	None	Voluntary	Mandatory	Mandatory
	TOD3	6.50	6.50	8.50	15.50
	TTEL3	68	44	18	11
	DOW3	6	7	1	1
4	HC4	5	3	2	2
	EO4	None	Voluntary	Voluntary	Voluntary
	TOD4	12.50	13.50	12.50	1.50
	TTEL4	69	44	21	8
	DOW4	3	4	5	6
5	HC5	3	5	2	1
	EO5	None	Voluntary	None	None
	TOD5	9.50	12.50	11.50	23.50
	TTEL5	76	49	26	14
	DOW5	2	3	4	4
6	HC6	5	3	2	1
	EO6	None	Voluntary	Voluntary	Voluntary
	TOD6	9.50	15.50	16.50	3.50
	TTEL6	75	45	20	9
	DOW6	3	4	5	6
7	HC7	1	3	2	2
	EO7	None	Voluntary	Mandatory	Mandatory
	TOD7	11.50	9.50	9.50	0.50
	TTEL7	74	52	28	13
	DOW7	5	6	7	1
8	HC8	4	3	3	3
	EO8	None	Voluntary	Mandatory	Mandatory
	TOD8	12.50	9.50	8.50	20.50
	TTEL8	67	46	23	11
	DOW8	7	1	2	2
9	HC9	5	3	2	1
	EO9	None	Voluntary	Voluntary	Voluntary
	TOD9	6.50	10.50	6.50	22.50
	TTEL9	75	47	27	11
	DOW9	6	7	1	1

A total of 310 households responded to the survey, including 22 households that were part of the pilot survey. This study only considered information gathered from the main survey – 288 households, which translate into 864 potential observations. However, not all data points were could be used. A data cleaning process was undertaken to eliminate incoherent answers, such as evacuating before the first forecast. After cleaning the data, 281 households remained– yielding 250 observations on Storm 1, 253 on Storm 2, and 260 on Storm 3, for a total of 763 observations.

### *5.3.1 Socio-economic Characteristics of Low Income Population*

As previously stated, the final sample size used in this study was 281 households (and 763 independent observations). This subsection describes the sampled population based on the gathered information, with special interested in “low income households” (LIHH). Continuous household income information was not available, instead income ranges are provided, making it impossible to follow the US National Poverty Guideline provided by the Department of Health and Human Services (2014). Given this, it is assumed that LIHH is any household with an income less than USD\$25,000, which are households that fall within the ranges “Less than \$15k” or “\$15k-24.9K”.

It should be noted that all descriptive statistics presented here are based on weighted data. The surveyed households are distributed across 10 neighborhoods, all of them highly vulnerable to extreme weather events given their low altitude and proximity to the coast. Figure 18 illustrates the location of these parishes.



**Figure 18.** Louisiana’s parishes. Sources: [www.maps.google.com](http://www.maps.google.com) and <http://www.digital-topo-maps.com>

The sampled households present demographic distributions parallel to Louisiana’s 2010 National Census data in many of the different characteristics, indicating that a random sample was successfully collected. For instance, 64.5% of the sample was white, 20% African-american, and 6% other – 9.5% did not respond – whereas the census data yields 63.9%, 32.8%, and 3.3% for the same races.

Table 14 shows the income characteristics of the households across the parishes. As can be seen, a third of them are located in the Jefferson parish, followed by St. Tammany, Orleans and Terrebonne. Saint Bernard and Plaquemines are the parishes with the least households, accounting for only 1.5% of the sample combined. Furthermore, around 31% of the households earns less than US\$25,000, meaning that a significant percentage could be considered as low income. Approximately 68% of households in St. John the Baptist and 47% in Terrebonne are low income. In contrast, 12% of households could be considered as high income (HIHH) as they earn US\$120,000 or more, with Plaquemines and St. Charles having the highest percentage of high income households, 27% and 23% respectively.

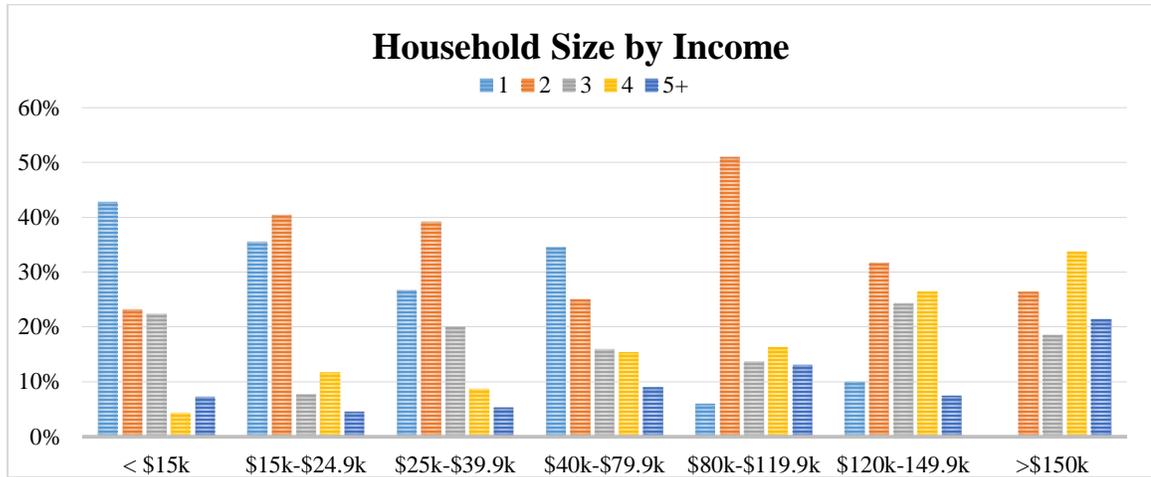
Furthermore, the data shows that income has no effect on the type of house residents live in. The majority (85%) of the sampled population live in a permanent house, with 8% living in an apartment/condo and only 5% live in a mobile home, the rest live in other type of housing.

**Table 14.** Household location and income distribution within each location.

		Parish Household Income Distribution						
Parish Name	% of HH	Less than \$15k	\$15k-\$24.9k	\$25k-\$39.9k	\$40k-\$79.9k	\$80k-\$119.9k	\$120k-150k	More than \$150k
Jefferson	33.1%	5.5%	23.2%	17.8%	26.6%	16.3%	4.7%	5.9%
St. Tammany	18.5%	20.7%	7.4%	6.2%	39.1%	13.6%	3.3%	9.7%
Orleans	15.0%	16.8%	13.9%	8.7%	43.1%	8.4%	4.0%	5.1%
Terrebonne	13.4%	36.6%	10.6%	13.7%	10.5%	14.9%	8.6%	5.2%
Tangipahoa	6.9%	8.0%	10.7%	19.9%	28.7%	14.3%	11.0%	7.4%
Lafourche	5.0%	0.0%	24.4%	15.0%	21.1%	31.2%	4.1%	4.1%
St. John the Baptist	3.9%	12.5%	55.3%	11.9%	20.2%	0.0%	0.0%	0.0%
St. Charles	2.6%	0.0%	7.9%	7.9%	45.9%	15.3%	15.3%	7.8%
St. Bernard	0.8%	0.0%	23.8%	0.0%	0.0%	76.2%	0.0%	0.0%
Plaquemines	0.7%	0.0%	0.0%	0.0%	27.4%	46.0%	26.6%	0.0%
<b>Overall</b>		14.10%	17.10%	13.00%	29.10%	15.10%	5.50%	6.10%

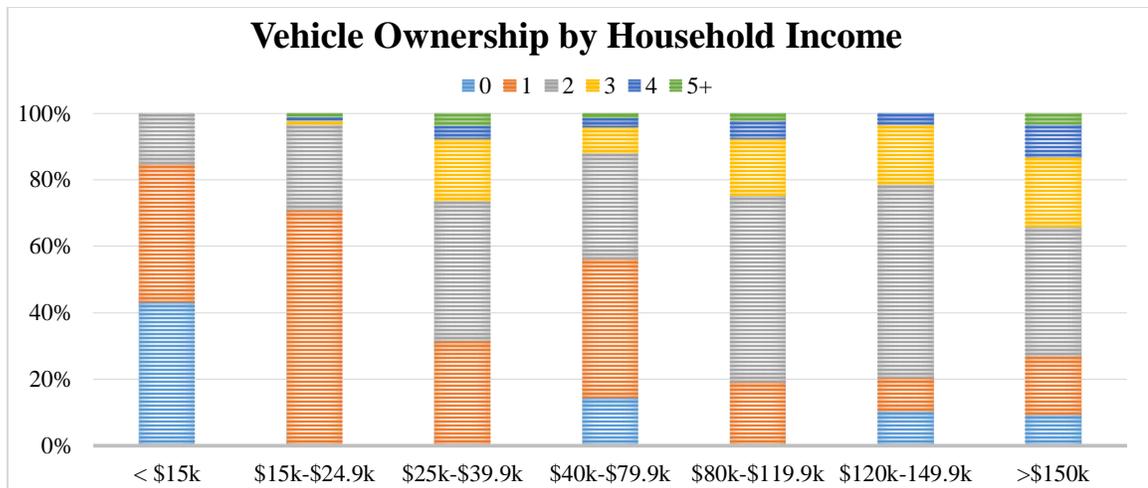
An analysis of the household size shows that the majority of households (61%) have at most 2 members, while 16% have 3 members, 14% have 4, and the remaining 9% have 5 or more members. This distribution results in a sample's average household size is 2.44 members. As expected, as household income increases so does the size of the household, see Figure 19. Interestingly, around 50% of the households with an income between \$80k and \$119.9k have only 2 members. In addition, around 25% of households have at least one member that is at most 17 years old and 67% of households have no member under 17 years of age – 8% of households did not answer this age related question. Moreover, 95%

of the 2-member households and 41% of 3-member households do not have any young member.



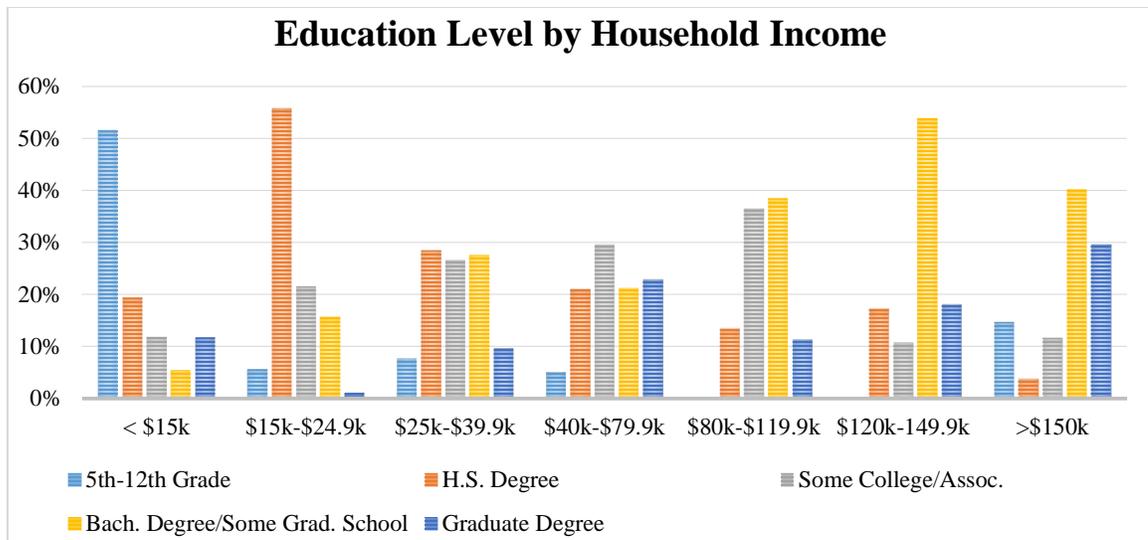
**Figure 19.** Household size by income level.

The majority of households (75%) have one or two vehicles, whereas 14 % has three or more vehicles. The remainders of the households do not own any vehicle. The average number of vehicles owned per household is 1.65. As can be seen in Figure 20, over 40% of households with an income below \$15,000 do not own a vehicle. Surprisingly, around 10% of high income households do not own vehicle. One could speculate that this might be because those households are well located and therefore do not need a vehicle.



**Figure 20.** Vehicle ownership by household income.

In general, approximately 37% of households achieved at most a high school degree. In contrast, 38% of households have at least one member with a bachelor degree or higher. The rest of the household attend some college or obtained an associate degree. As one would expect, 65% of high income households have obtained at least a bachelor degree, whereas 26.4% of low income households did not finished high school and 39.3% have at most a high school diploma. This supports the well-known notion that income and education are highly correlated. Figure 21 presents the distribution of household education by its income.



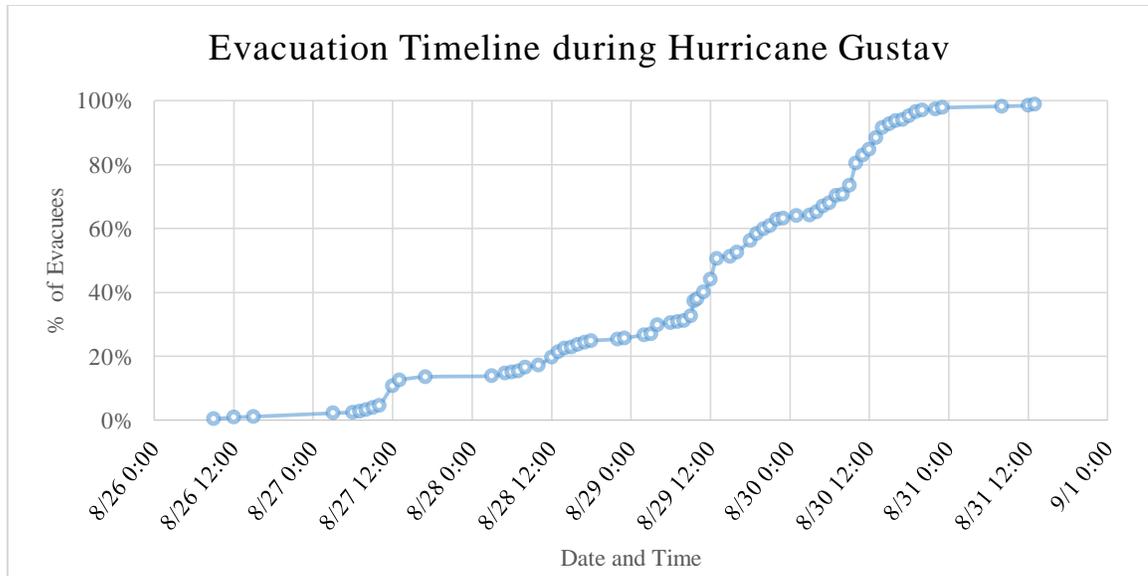
**Figure 21.** Education level by household income.

### 5.3.2 Revealed Preference: Evacuation Behavior thru Hurricane

#### *Gustav*

This subsection provides a brief summary of the respondent’s evacuation decision during Hurricane Gustav, based on the 281 households. Around 74% of the sampled population evacuated during Gustav, with most of the evacuation happening within 3 days of landfall. Their response curve (i.e., departure time distribution) is shown in Figure 22.

As expected, 97% evacuated on a private vehicle (4% would get a ride) and a significant percentage (around 30%) of evacuees stayed within the State of Louisiana. In addition, 20% looked for refuge in Mississippi, 10% travelled to Alabama, 16% were equally distributed between Tennessee and Florida, 7% went to Georgia, 6% to Texas, and 3% to Arkansas – the remainder evacuated to other states. Friends or relative and hotels/motels appear to be the go-to refuge for most evacuees, accounting for roughly 52% and 36% of the refuge selection, respectively. Surprisingly, only 1.7% went to public shelters looking for safe haven.



**Figure 22.** Response curve (of those who evacuate) during Hurricane Gustav.

Finally, of those who evacuated, nearly 60% stated that they did not feel safe. Conversely, of the 26% that did not evacuate, around half (45%) did not do so because they believed their house was adequate and/or the storm was not severe. The latter follows a cognitive dissonance logic, meaning that households perceive safety yet information on a possible threat is received, then these conflicting beliefs are resolved by denying or ignoring the warning information. Examples of this behavior were collected by Leach and Campling (1982).

### *5.3.3 Stated Preference: Evacuation Behavior*

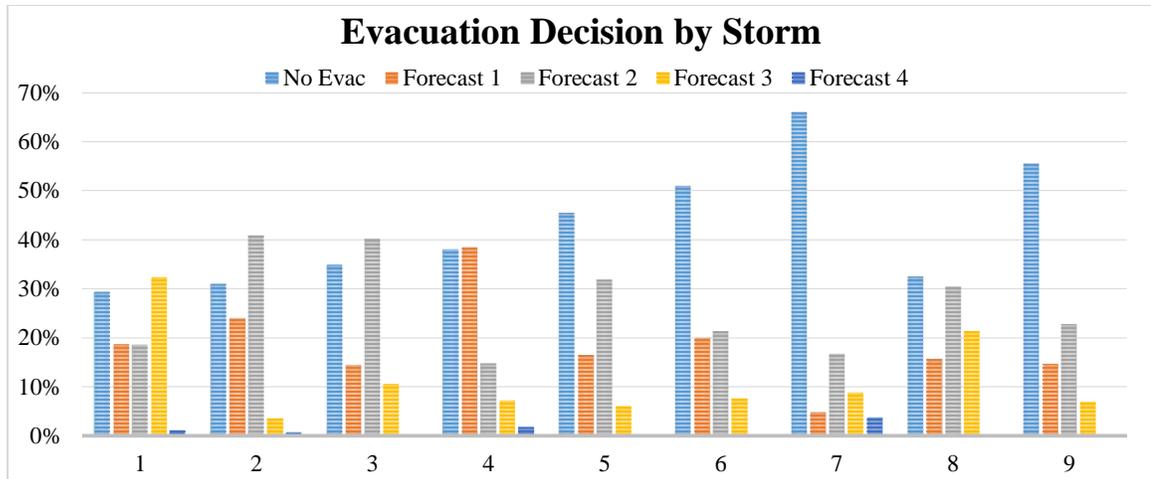
This subsection provides information regarding the evacuation behavior of the respondents, based on the 763 observations (each storm is considered an independent observation). Table 15 shows the distribution of the households' evacuation decision, that is whether they evacuated or not, and if so, at what point in time. Households decided not to evacuate in 43% of the hypothetical scenarios, a low percentage given that 84% of the households are located in a flood zone. Also, there is a clear unwillingness to wait until the

last moment to evacuate, as indicated by the low percentage of households (0.8%) that would evacuate after Forecast 4.

**Table 15.** Evacuation decision distribution.

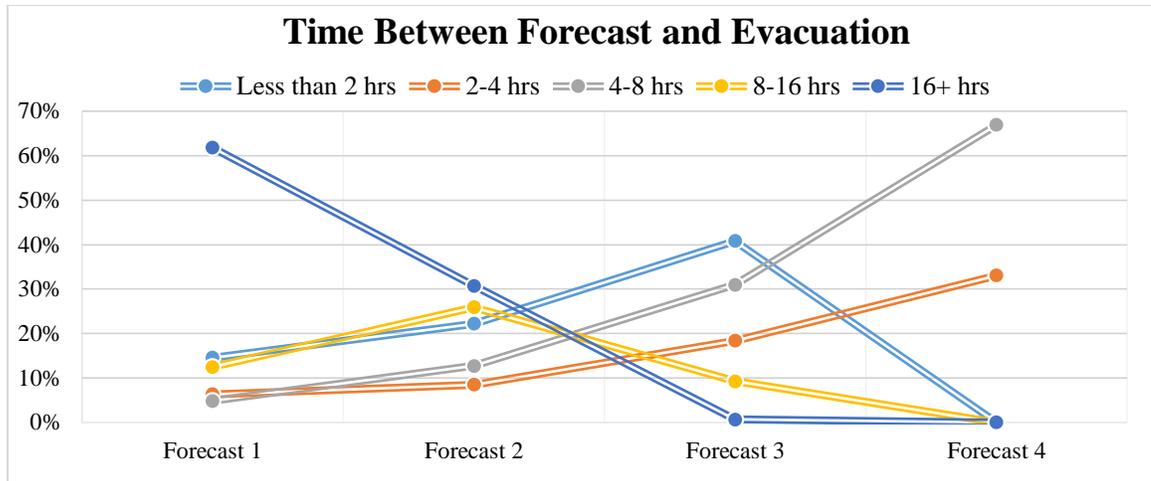
<b>Evacuation Decision</b>	<b>% of Observations</b>	<b>% of Evacuees</b>
Do not evacuate	43.1%	-
Forecast 1	18.3%	32.2%
Forecast 2	26.3%	46.2%
Forecast 3	11.5%	20.2%
Forecast 4	0.8%	1.4%
<b>Total</b>	<b>100%</b>	<b>100%</b>

The evacuation behavior is explained in more detail in Figure 23, where the distribution of evacuation decision for each storm is illustrated. As can be seen, Storms 7 and 9 have the lowest percentage of evacuees, which might be explained by the low hurricane category in the case of Storm 7 and by the lack of a mandatory evacuation order in Storm 9. It should be noted that Storm 7 follows the actual characteristics of Hurricane Gustav. Furthermore, approximately 66% of the households that were presented with Storm 7 evacuated – resembling the 74% evacuation rate of the total sampled population during Gustav. Interestingly, 74% of those who evacuated during Gustav would not evacuate under the presented scenarios, whereas 32% of those who did evacuate would not evacuate now.



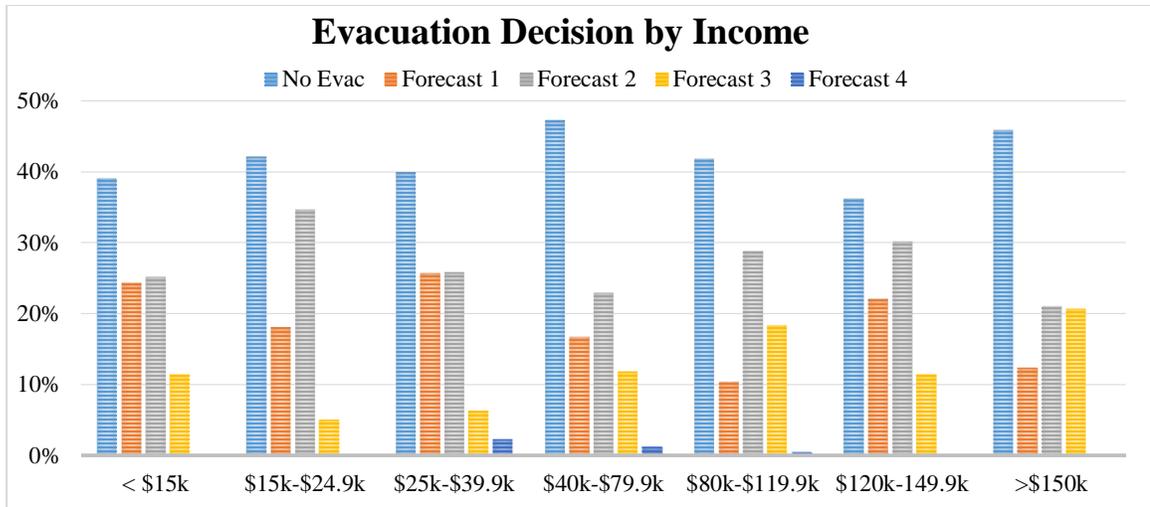
**Figure 23.** Evacuation decision by hypothetical storm.

Generally, households prefer to evacuate sooner rather than later. Now, the decision of how much time to wait after a forecast depends, amongst many factors, on the time of that forecast. For instance, over 60% of households that would evacuate after the first forecast do so 16 hours or more after the forecast, see Figure 24. However, this percentage halves on Forecast 2 and drops to almost zero on Forecast 3, indicating that the longer a household waits for future forecasts the faster they tend to evacuate after it – which is an expected behavior. Overall, 23.2% of households that decided to evacuate do so within the first two hours, 10.1% between two and four hours, 14.6% between four and eight hours, 17.9% between 8 and 16 hours, and 34.2% would wait at least 16 hours to evacuate.



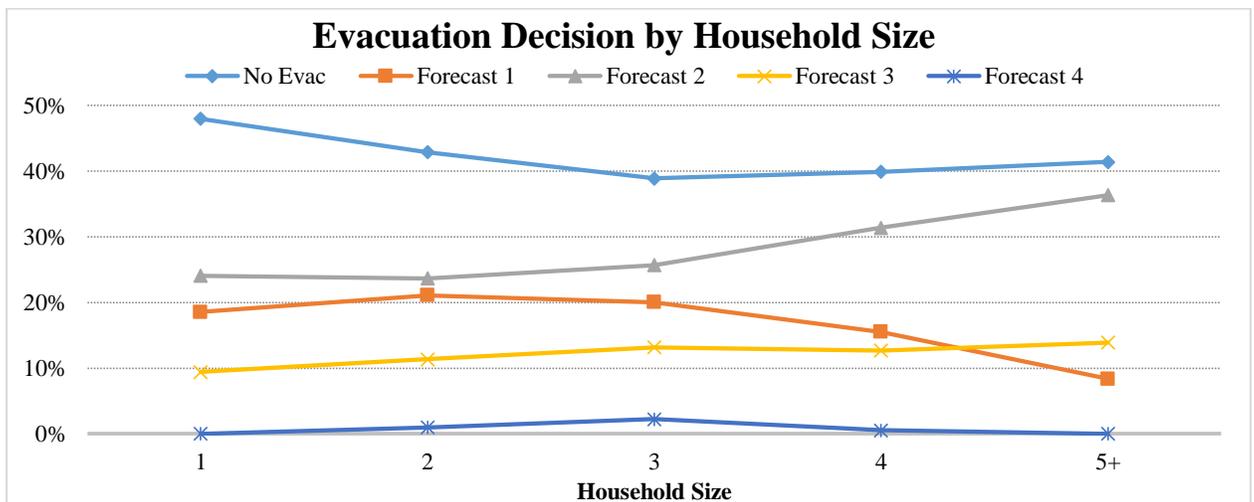
**Figure 24.** Distribution of time between forecast and evacuation.

Figure 25 shows that there is a positive relationship between income level and the decision to wait longer to evacuate. The same results are obtained if education level is analyzed, following the well-known notion that income and education are strongly correlated. It is also evident that regardless of income the majority of households that evacuate do so after the first two forecasts (comprising approximately 79% of the evacuees). No reliable information can be inferred from households that would evacuate after Forecast 4 because of its low percentage; however, the data (weakly) suggests that those who wait until after Forecast 4 are middle income households.



**Figure 25.** Household evacuation decision by income.

It is sound to assume that households with a high number of members experience a more troublesome task of evacuation, and therefore would prefer to wait and see if such task could be avoided. The data shows that bigger households prefer to wait for the second or third forecast before evacuating (see Figure 26). However, households with 3 or more members tend to evacuate more when compared to those that have 1 or 2 members. As a side note, 39% of low income households only have one member.

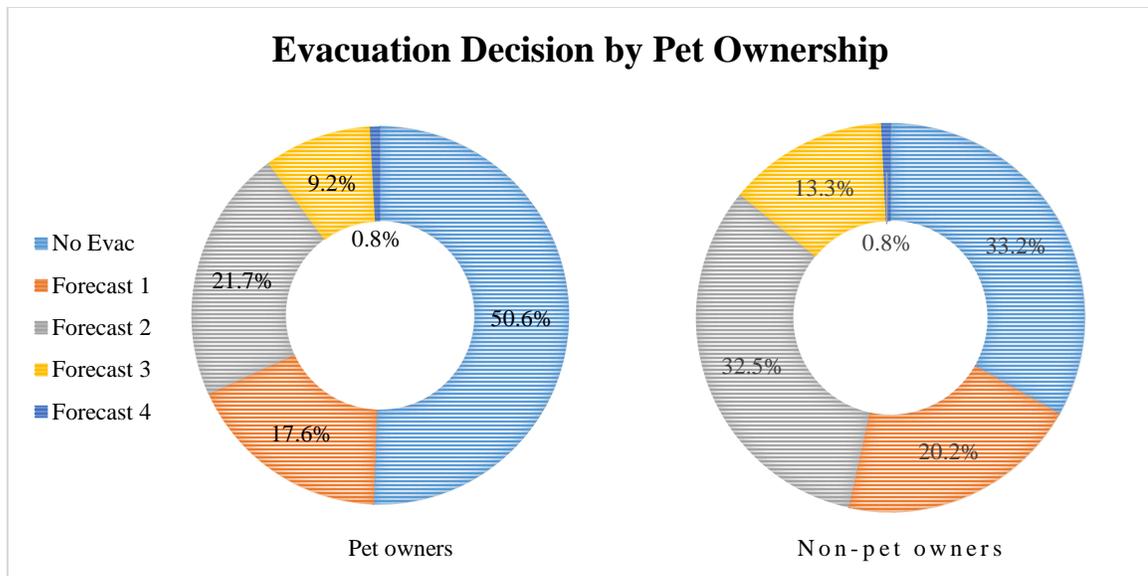


**Figure 26.** Evacuation behavior of households based on their size.

Vehicle ownership is a key factor that affects the decision of whether to evacuate or not, since it has a direct connection to the evacuee's mobility level and time flexibility. An analysis of the sampled population yields that household that own either none or at least 4 vehicles have the lowest percentage of evacuees, with around 46% and 30% respectively. Low mobility might explain the non-owners' evacuation behavior, whereas one can assume that the high multi-vehicle owners' unwillingness to evacuate is explained by their (most likely) high household size – 43% of households with 4 or more vehicles have 4 or more members. Households that own between 1 and 3 vehicles have a fairly similar behavior, with an evacuation rate of approximately 40% and a tendency to evacuate during the first and second forecast.

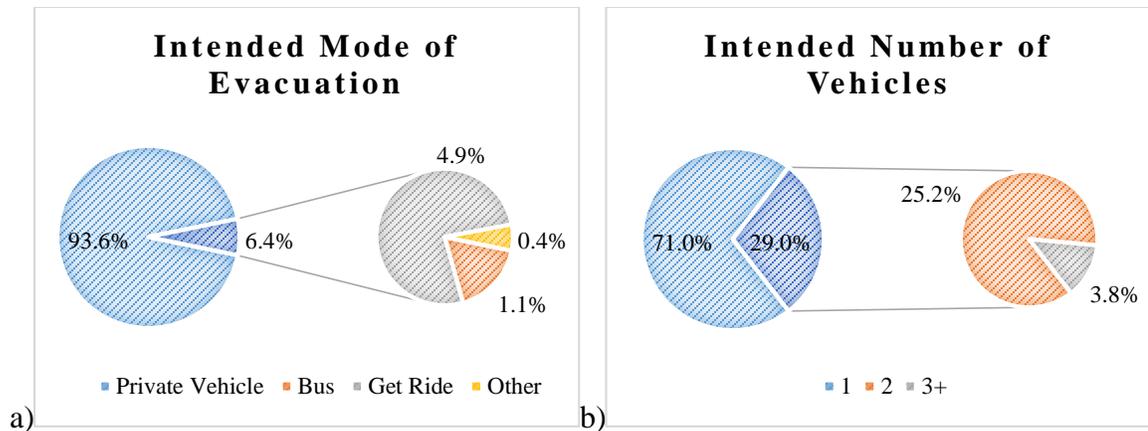
Physical characteristics of the house, such as type and location, also play an important role on the decision to evacuate – if the house provides reliable shelter (or it is thought that it can), people might be less prone to evacuate. Around 80% of the population lives in a permanent home; however, 84% of all households are located in a flood zone, highlighting their vulnerability to water-related threats. One can assume that this was a significant factor when the population was faced with the decision to evacuate or not during Hurricane Gustav – recall that 73% of the sampled population evacuated during Gustav.

Households also have secondary traits that can be significant risk factors for evacuation failure, one of which is pet ownership (Hunt, Bogue, & Rohrbaugh, 2012). Within the sampled population pet ownership is fairly similar with 45% having pets and 51% not having pets – 4% did not answer. Nevertheless, Figure 27 shows that there is a significantly different evacuation behavior, with 17% less evacuees, between pet owners and households that do not own a pet.



**Figure 27.** Effect of pet ownership on evacuation decision.

As previously stated, approximately 57% of the sampled population would attempt to evacuate under the presented scenarios. Around 94% of this sub-population would evacuate by private vehicle, 5% would get a ride with someone else and 1% would use the bus (see Figure 28a). Those who evacuate with the assistance of another (i.e., take a ride) tend to wait more until Forecasts 3 to do so. One reason for this might be that they would like to avoid the distress of moving from their location to the departure point so they wait to confirm whether it is necessary or not to evacuate. Furthermore, as can be seen in Figure 28b, approximately 71% of the evacuees would do so using only one vehicle, 25% would use two vehicles, and 4% would use three or more vehicles. Recall that 51% of the population had two vehicles or more, meaning that a significant percentage would leave at least one vehicle behind.



**Figure 28.** a) Intended mode of evacuation; b) Intended number of vehicles used for evacuation.

### 5.3.4 Things to Note

There are many factors that affect the decision of a household on whether to evacuate or not. This section portrays some of these factors and provides insight into the characteristics of the sample, from which the following conclusions can be drawn:

- There is a clear income-based segregation of the population within the surveyed area.
- One could infer that there are very few single-parent households and a significant presence of adult couples with no kids (i.e., members less than 17 years of age), given the low percentages of kids within 2- and 3-member households.
- Although the high dependency on private vehicles is evident, a significant percentage of LIHH and HIHH do not own vehicle. As a whole, 11% of HHs have no vehicle, so they need to evacuate through another means of transportation, such as public transportation, take a ride with someone or government assistance.
- Households with fewer members evacuate less but do so faster than their counterpart. Evacuation might be easier for such households, which might explain why they prefer evacuating early (before Forecast 3).
- Based on the socioeconomic data from 5.3.1 Socio-economic Characteristics of Low Income Population, a significant percentage (45%) of high income houses

have 4 or more members. This could explain why high-income households evacuate in advance.

- Around 8% of the population's job does required them to stay at home, indicating that they are forced to wait until as late as possible before evacuating, which puts them in more risk.
- Even though pet-ownership was not mentioned as a significant reason for not evacuating during Gustav, the data shows that it does has some effect on evacuation behavior.
- There is a strikingly high percentage of households located on flood zones. Concerning agencies should invest in educating the residents on their risks and how to efficiently evacuate. This could increase the evacuation rate and reduce the effects of a disaster.
- In general, there was a negative variation on households' willingness to evacuate when compared to their behavior during Gustav. A detailed study is needed to see what changed for these households that might be hindering them to evacuate.

#### 5.4 Disaster Evolution and Model Estimation with Real Data

As previously stated,  $\mathbf{y}_t$  represents the evolution of the disaster's attribute over time, a key element in the estimation of expected utility. Since the future appears uncertain to the individual affected, this (expectation of) evolution needs to be represented in some sort. Here, it is proposed to estimate expectation from the respondent's perspective instead of using market (equilibrium) values, as it is commonly used in the literature (Keane & Wolpin, 1997; Rust, 1987). In this sense, this research experiments with two different disaster evolution assessment methodologies:

1. Perfect Knowledge: Respondents have perfect knowledge of the future value of the dynamic variable. For example, if we consider hurricane category as the dynamic variable, at time  $t$  respondent  $i$  knows the category of the hurricane at time  $t+1$ .

2. Stochastic Growth: Respondents expectation follows a stochastic growth model where dynamic variables change according to a random walk with a drift.

#### *5.4.1 Perfect Knowledge*

With approximately 75% of households in the US having access to internet (United States Census Bureau, 2014), accessibility to historic and real-time information is higher than ever, allowing households (and individuals) to make more educated decision. Therefore, it is sound to assume that, within reason, they can successfully estimate future trends and/or behaviors. With this in mind, the dynamic model was estimated assuming a “perfect knowledge” approach for estimating the expected utility of respondents (i.e., expectations and future scenarios are an exact match). Given that we only have four forecasts, a new forecast scenario (Forecast 5) was developed using a static approach for the estimation of the final expected utility with a 6 hours difference from FC4. In here, it is assumed that respondent believed that the hurricane category and evacuation order would not change between Forecasts 4 and 5. Finally, the sequential model previously presented was estimated twice for comparison purposes, one in search of the best model possible and another to adapt the dynamic model.

#### *5.4.2 Stochastic Growth*

As a way to mathematically model disaster evolution, this study proposes an assessment methodology where past observations can be used to predict future conditions. The first step to do so is obtaining data of past hurricanes. This study uses the dataset “Best Track Data” known as Atlantic HURDAT2 collected by the National Hurricane Center (NHC). The NHC conducts an analysis of all storms in its area of responsibility to

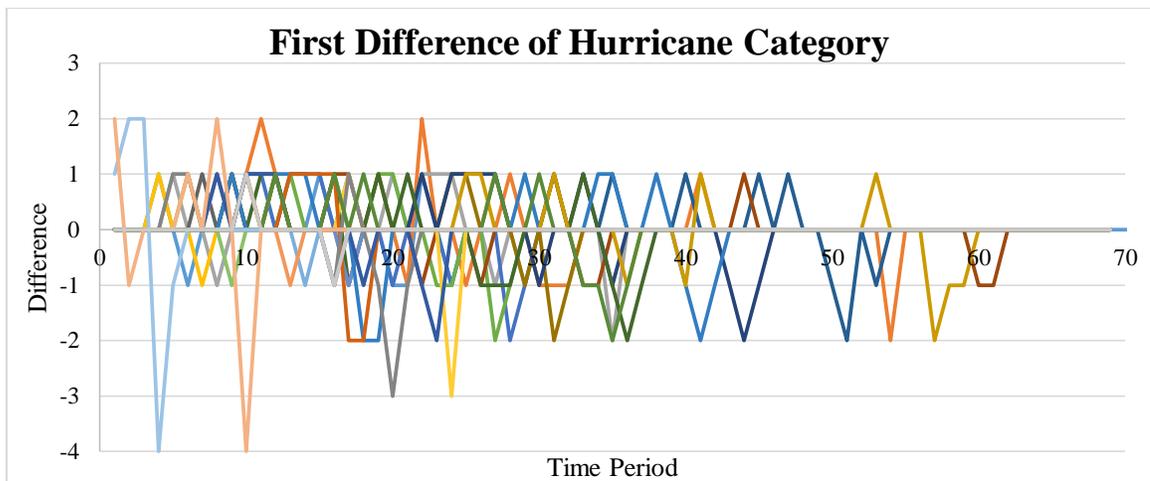
determine the official assessment of the cyclone's history. Additionally, they perform ongoing retrospective investigation of any tropical cyclone brought to their attention, and update the historical record to reflect any changes found through their analysis. The end product is a rich dataset that provides detailed information for every six hours interval on location, speed and landfall, to mention a few, of all storms that traversed the Atlantic region between the years 1851 and 2014 (Landsea, Franklin, & Beven, 2015). For this study, all events prior to 1950 and those which did not reach a hurricane level within the area of study (i.e., Louisiana), following the Saffir-Simpson scale, were filtered out. At the end, 27 storms remained (see Table 16) yielding a total of 1,065 data points.

**Table 16.** Hurricanes that traversed through Louisiana between 1950 and 2010.

Name	Date	Name	Date
IDA	Nov. 10, 2009	JUAN	Oct. 27-31, 1985
IKE	Sept. 13, 2008	ELENA	Sept. 2, 1985
GUSTAV	Aug. 31, 2008	DANNY	Aug. 16, 1985
HUMBERTO	Sept. 13, 2007	BOB	July 11, 1979
RITA	Sept. 24, 2005	CARMEN	Sept. 7-8, 1974
KATRINA	Aug. 29, 2005	EDITH	Sept. 16, 1971
LILI	Oct. 3, 2002	CAMILLE	Aug. 17-18, 1969
GEORGES	Sept. 27-28, 1998	BETSY	Sept. 9-10, 1965
DANNY	July 18, 1997	HILDA	Oct. 2-3, 1964
OPAL	Oct. 4, 1995	CARLA	Sept. 10-12, 1961
ANDREW	Aug. 26, 1992	ETHEL	Sept. 15, 1960
GILBERT	Sept. 15-19, 1988	AUDREY	June 27, 1957
FLORENCE	Sept. 9, 1988	FLOSSY	Sept. 24, 1956
BONNIE	June 26, 1986		

Now that historical data is ready for analysis, the next step is to discern how to model hurricane's characteristics. An important aspect to take into account is that the dynamic nature of a variable does not guaranty that the variable is independently dynamic (i.e., their change is not correlated with other variables). For example, variables such as time of day and day of week are continuous variables that progress linearly as time passes

by. Similarly, evacuation order might appear to be random, but in reality it is a subjective decision made by officials based on the storm's severity and distance. On the other hand, the latter two characteristics can change independently and randomly from time and each other. Of the information available in both the historical and surveyed datasets, hurricane category is the only one that truly behaves independently (and randomly), all the rest are (to some degree) dependent on time, location and/or the category of the hurricane. Therefore, in order to understand the random behavior of a hurricane, the first difference is taken with relation to each hurricane's category. The result resembles a pure noise (i.i.d. variations), demonstrating a stochastic behavior which could be characterized as a random walk (a sequence of random steps), see Figure 29.



**Figure 29.** First difference of hurricane category data.

Autoregressive models are a suitable approach to describe time-varying processes based on a linear relation to past values and an error term. This method has been used in the past for different purposes. For instance, Melnikov (2013) evaluated the impact of technological change on the dynamics of consumer demand based on the consumer's expectations of future product quality and consumers, while illustrating various ways of implementing random walks.

Several autoregressive models are available, however this study proposes the use of an AR(1) model, which depends only on one previous value, with a drift:

$$r_t = \alpha r_{t-1} + \gamma + \varepsilon_t \quad (5.9)$$

where

- $\alpha$  is the dependence factor.
- $\gamma$  is the drift.
- $\varepsilon_t$  is a normally distributed error term with mean zero and variance  $\sigma^2$ .

In order to compute the choice probability  $P$ , the dynamic model compares the reservation utility  $W$  and the mode of  $\mu$ , the maximum of the alternative's utility (in this case only one, to evacuate). These two quantities depend on the predictors used in the model, which this study assumes to follow an AR(1) model. Therefore different realizations for these predictors will produce different values of  $W$  and  $\mu$ . Therefore, the procedure implemented here calculates the expected value of  $W$  and  $\mu$  through simulation. The simulation generates  $B$  realizations of the AR(1) series of the predictors and compute the corresponding  $W$  and  $\mu$  values. Then, the mean is taken of these simulated  $W$  and  $\mu$  to compute the choice probability. This simulation is only used to compute the probability of doing nothing (i.e., not evacuating,  $P_{NotEvac}$ ). In the case where the decision is to opt for one of the alternatives, then choice probability will be  $(1 - P_{NotEvac}) * P_{alt}$ , where  $P_{alt}$  is just a regular static choice probability, hence no requirement to perform a simulation for it. However, the value  $P_{NotEvac}$  always needs to be computed.

Using Louisiana's historical hurricane data to estimate the coefficients in 5.9, it is found that the dependence factor ( $\alpha$ ) is equal to 0.931926, the drift ( $\gamma$ ) is equal to 0.072533,

and the standard deviation ( $\sigma$ ) of the error term is 0.533634. The dynamic logit model can now be estimated using these values as input.

#### 5.4.3 Results Using Real Data

For this study, Fu and Wilmot (2004)'s sequential logit model is used as the base for comparison. The suggested method allows the use of all observations (i.e., binary choices) simultaneously, therefore reducing computational efforts and avoiding small data sample size for later time intervals. Their proposed model is as follows:

$$L = \prod_{n=1}^N P_n(i) = \prod_{n=1}^N P_n(i)_{s/c} \prod_{j=1}^{i-1} [1 - P_n(j)_{s/c}] \quad (5.10)$$

where  $P_n(i)$  denotes the probability that household  $n$  evacuates in time interval  $i$ ,  $N$  is the total number of households and  $P_n(\bullet)_{s/c}$  is the probability that the utility of a household to evacuate is greater than the utility of the household to not evacuate in time interval  $i$ , provided that the household has not already evacuated. The reader is referred to the source paper for in depth explanation of the methodology.

Table 17 shows the models that were considered the best. It should be noted that both dynamic model approaches (Perfect Knowledge and Stochastic Growth) yield strikingly similar results. In general, all models estimated significant coefficients with expected signs. The models indicate that as hurricane category and evacuation order increase, so does the willingness to evacuate and that if the household waits until the last forecast, they are less likely to evacuate—recall from Figure 22 that around 98% of Gustav's evacuees did so by at least 24hrs before landfall, highlighting household's willingness to evacuate early. One can assume that latter is due to the fact that households may prefer to avoid congestion and the risk of experiencing the hurricane out in the open.

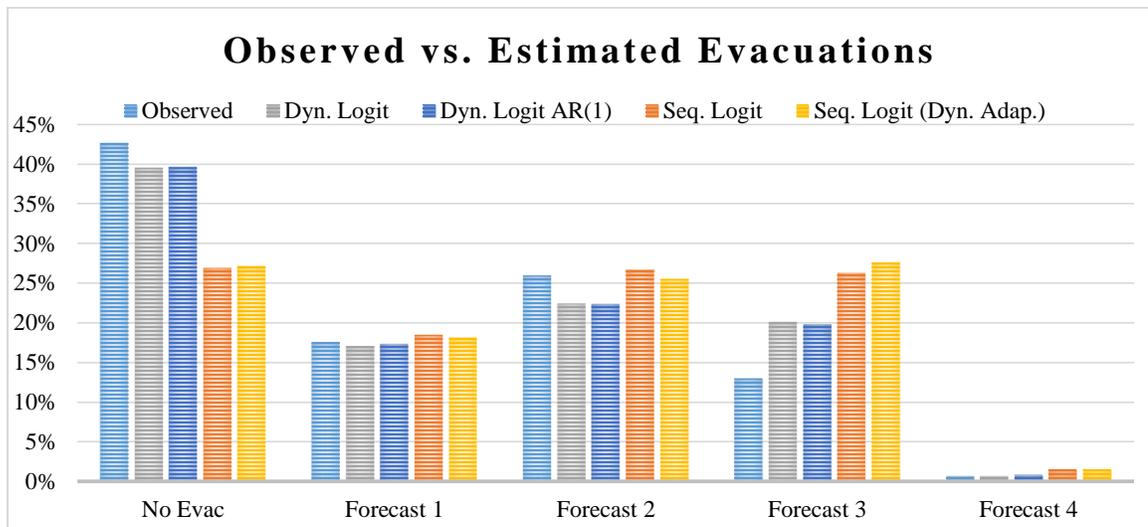
However, if the hurricane is too far away, this would lower the probability of evacuating. Additionally, having past experience with evacuation (i.e., if the household evacuated during Hurricane Gustav) has a significant positive effect on the decision to evacuate. Finally, based on the results from the dynamic model, it is clear that households are less willing to evacuate during the evening and that household size and income have negative effect on evacuation, whereas the presence of kids has a positive influence on the decision to evacuate.

**Table 17.** Results of estimating dynamic discrete choice models.

Variable Name	Dynamic Logit with PK	Dynamic Logit with AR(1)	Sequential Logit	Seq. Logit (Dyn. Adaptation)
Hurricane Category	0.2256*** ( $<0.01$ )	0.2020*** ( $<0.01$ )	0.4776*** ( $<0.01$ )	0.5790*** ( $<0.01$ )
Evacuation Order			0.4730*** ( $<0.01$ )	
TOD4 (6PM-12AM)	-1.0564 (0.105)	-1.2288* (0.082)		-0.969 (0.205)
Time to Expected Landfall	-0.0294*** ( $<0.01$ )	-0.0277*** ( $<0.01$ )	-0.0150** (0.02)	-0.0330*** ( $<0.01$ )
Last Forecast (FC4)	-3.3004*** ( $<0.01$ )	-3.1979*** ( $<0.01$ )	-2.8623*** ( $<0.01$ )	-2.9444*** ( $<0.01$ )
Evacuation Experience (Gustav)	0.8890*** ( $<0.01$ )	0.8751*** ( $<0.01$ )	1.5740*** ( $<0.01$ )	1.5520*** ( $<0.01$ )
Household Size	-0.2733*** ( $<0.01$ )	-0.2813*** ( $<0.01$ )		0.0006 (0.96)
Number of Kids (Less than 17yrs old)	0.2907*** ( $<0.01$ )	0.3020*** ( $<0.01$ )		0.0071 (0.91)
Household Income	-0.1561*** ( $<0.01$ )	-0.1505*** ( $<0.01$ )		-0.0286 (0.44)
Constant			-3.6673*** ( $<0.01$ )	-2.5797*** ( $<0.01$ )
Number of Observations:	763	763	2155	2155
L(0):			-1086.63	-1086.63
LL:	-968.51	-970.20	-909.04	-913.83
LR $\chi^2$ (4):			355.19	345.6
Prob > $\chi^2$ :			$<0.0001$	$<0.0001$

Pseudo R <sup>2</sup> :			0.1634	0.1590
***Significant at the 1% level	**Significant at the 5% level		*Significant at the 10% level	

Figure 30 compares the observed evacuation versus the estimated ones. The sequential models seem to provide good estimations for earlier periods, but loose prediction power on the latter ones. However, the dynamic models yields good estimation in all periods with significantly less error per period and cumulative (as can be seen in the estimation of Non-Evacuees).



**Figure 30.** Comparison of observed and estimated evacuation percentages.

### 5.5 Conclusions

Modeling approaches within evacuation behavior analysis generally do not incorporate dynamic variables. This chapter presents the result of introducing dynamic variables and respondent’s expectations into discrete choice estimation in the context of hurricane evacuation. Although Dynamic Discrete Choice Models (DDCM) have been (scarcely) used in the past within the field of transportation, to the best of the author’s knowledge, this is the first time such model is presented from an evacuation perspective.

The resulting model is compared to existing discrete choice methods, namely Logit and Sequential Logit. Simpler approaches may yield predictions sufficient for analysis of a hurricane evacuation event, but fail in incorporating demographic information, limiting its policy evaluation capability. In this sense, it is evident that DDCM are more beneficial and insightful, and can serve as a tool for evaluating new policies that could improve the efficiency of evacuations and emergency planning.

This is just the first step in the development of a robust model that allows stochastic variables. Further research is needed to better represent the evolution of the disaster's attribute over time ( $\mathbf{y}_t$  in this research), a key element in the estimation of expected utility. This research experiments with two representation of evolution, however more detailed and robust approaches are needed in order to improve estimation accuracy. Future research could include a random behavior where respondents have no knowledge of the future and therefore dynamic variables change randomly over time, selecting a new value at each time  $t$  from a given array of possible values. For instance, at each evaluation period  $t$  a value is randomly selected for hurricane category from the 5 potential categories following the Saffir-Simpson scale. Additionally, future research could include other formulations of random walks and a random behavior of expectations. It would also be interesting to extend the dynamic model to include departure time, mode of evacuation and destination to further improve the policies regarding shelters location, demand management and distribution of resources. Finally, more rigorous datasets are needed to include more socioeconomic information, but most importantly, datasets that provide more detailed time periods of analysis from a forecast perspective. This will allow to better understand the many different (dynamic) factors that influence the evacuation decision

## Chapter 6: Conclusion

This chapter concludes the dissertation by summarizing its important findings and contributions. We then discuss future avenues for this research and possible improvements to the evaluation framework.

### 6.1 Findings and Contributions

This dissertation focuses on improving the analysis of resilience of transportation systems. The primary contributions of this research are:

- Finding 1: literature on transportation resilience is still limited when compared to other fields of knowledge. Furthermore, most of the research seems to focus more on the operational side of transportation, instead of providing a more general view within the field.
- Contribution 1: This dissertation presents four thorough multidisciplinary literature reviews (Chapters 2 through 5) that highlight the voids in the existing academic and technical literature on transportation resilience. These reviews serve not only as support to the proposed framework, but for any future research in the field.
- Finding 2: There is a clear need for a guideline or unifying framework of analysis of transportation resilience.
- Contribution 2: One of the main contributions of this research is the proposed novel framework of evaluation, *Transportation Resilience Architecture*, which links the three components of a transportation system: Infrastructure (Chapter 3), Agency (Chapter 4) and User (Chapter 5). A first of its kind within the transportation resilience field, this framework could serve as an umbrella for all future research.

- Finding 3: Accessibility measures commonly used in transportation are extremely limited by fixed thresholds that do not consider other potential factors that affect accessibility levels of a targeted population.
- Contribution 3: A comprehensive and practical assessment tool that evaluates Infrastructure Resilience through a Logsum-based accessibility analysis—a new framework from a transportation perspective. This analysis showcase how to collect and use readily available official information, such as the one inside travel models and geographical weather data, to obtain more robust accessibility measures. Furthermore, this method allows us to perform a disaggregated analysis by income level (and potentially by any other population characteristic), overcoming a limitation of more traditional approaches
- Finding 4: Most analysis of an agency’s resilience level, or performance proxy, found in the literature are based on qualitative information, with little consensus on how and/or what to measure.
- Contribution 4: A flexible, yet robust, quantitative framework to analyze Agency Resilience that combines the Sustainable Livelihood analysis framework with Fuzzy Algorithms. Furthermore, this research contributes by providing newly proposed metrics and others suggested by previous literature and several experts in the field of transportation (related to different agencies across the nation) that serve as a starting point for future research in this area.
- Finding 5: Modeling approaches within evacuation behavior analysis do not incorporate dynamic variables and expected values of such variables.

- Contribution 5: An adaptation of dynamic discrete choice models with respondent's expectations as a proxy for User Resilience. Although these models have been (scarcely) used in the past within the field of transportation, this dissertation study is the first to do so from an evacuation perspective. Additionally, this research proposes two methods for incorporating respondent's expectation into the modelling framework.

## 6.2 Future Research

This research presents an innovative analysis framework for transportation resilience (TR) that combines the three most important component of a transportation system, its infrastructure, agencies and users. The *Transportation Resilience Architecture* (TRA) is able to incorporate a broad cross-section of the resilience-enhancing strategies, allowing for better definition, planning and evaluation of alternatives. However, being the first time such framework is introduced, future research is needed to better define the utilities (i.e., specific information on infrastructure, agency and user) that are required for TR analysis and the flow of information between its components. In general, this research evaluate resilience through proxies. Future research is needed to develop robust quantitative frameworks to identify and evaluate more factors that characterize resilience within the architecture's different perspectives.

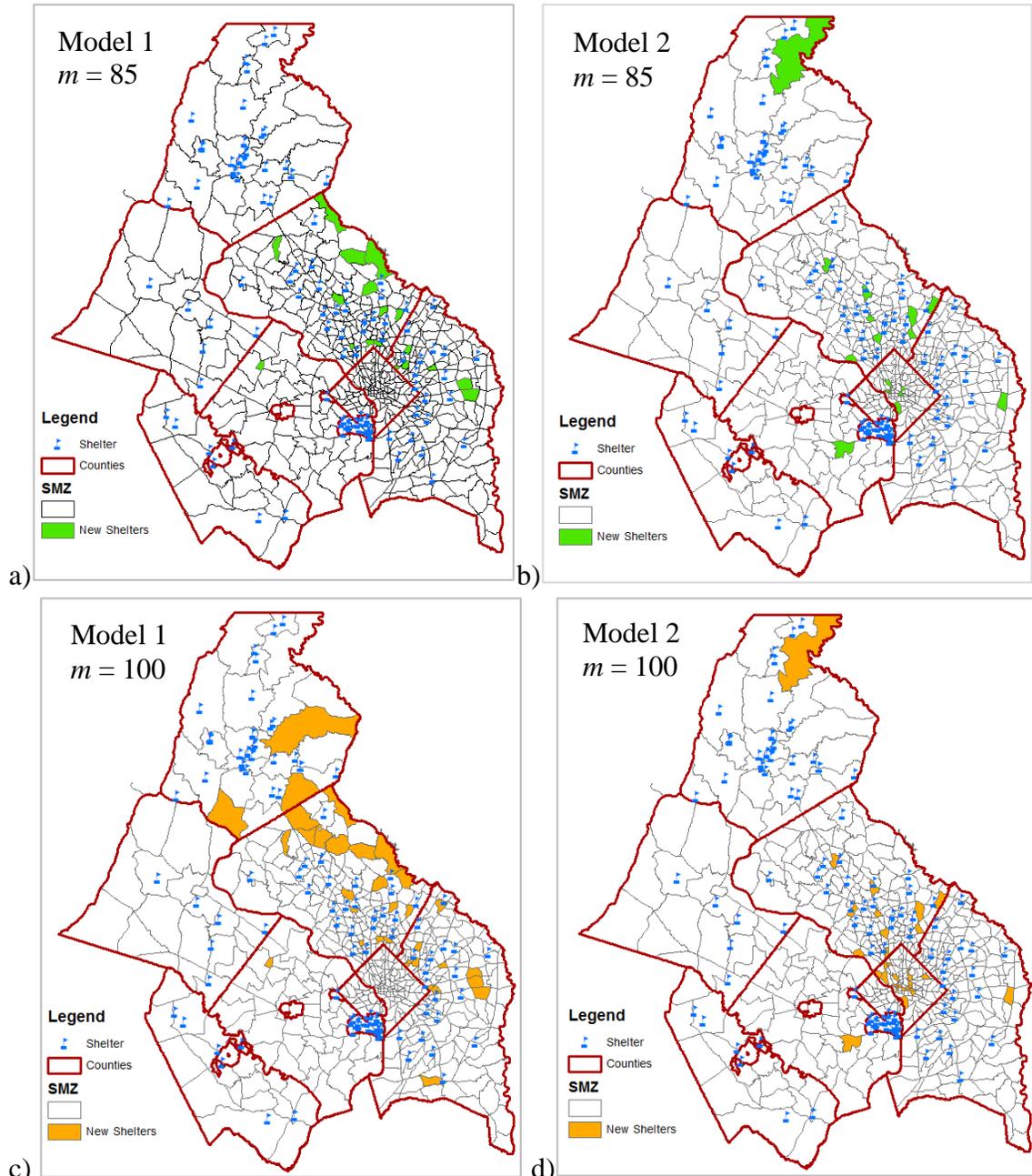
For the accessibility analysis, in terms of data quality, it would be desirable to obtain more detail information about disadvantaged population, incorporate more accurate weather data, and add non-commuter trips to the analysis. In addition, statistical analysis is needed to increase reliability of the results. It would be also interesting to identify and integrate other factors impeding evacuation mobility and temporal constraints (e.g.,

departure time) into the accessibility analysis. Finally, for the location analysis, more (official) information on construction budget, shelter's capacity, actual/expected demand, and other variables is needed to fully evaluate the best location of shelters.

From the agency perspective, this research highly recommends that a strongly supported nationwide survey is conducted to assess current state-of-knowledge, including recently started and future research, on agency resilience. A second survey is also needed to reach consensus not only on quantitative metrics for evaluation, but also on their weight and appropriate method of combination.

For the dynamic model of evacuation, in terms of the evolution of the disaster's attribute(s) over time ( $\mathbf{y}_t$  in this research), more detailed and robust approaches are needed in order to improve estimation accuracy. Future research could include other formulations of random walks and a random behavior of expectations. It would also be interesting to extend the dynamic model to include departure time, mode of evacuation and destination to further improve the policies regarding of shelters location, demand management and distribution of resources. Finally, more rigorous datasets are needed to include more socioeconomic information, but most importantly, datasets that provide more detailed time periods of analysis from a forecast perspective. This will allow to better understand the many different (dynamic) factors that influence the evacuation decision.

## Annex 1: Locations of New Shelters



**Figure 31.** Location of new shelters for  $m=85$  (upper) and  $m=100$  (lower).

## **Annex 2: Agency Resilience Survey**

### **Introduction**

The objective of this survey is to collect information about your agency's transportation resilience. Transportation resilience refers to the ability of a network to maintain its demonstrated level of service or to restore itself to such level of service in a given period. While a transportation network's resilience involves different levels (namely, users, institutions and infrastructure), this study centers on the resilience of transportation agencies/institutions. At a higher level, agency resilience provides the basis for understanding who the implementers are and the roles that these implementers could take within a resilient system. At a lower level, agency resilience improves preparedness and response capability of agencies by taking into account more operational, rather than only managerial, characteristics of an agency. With this survey, I am hoping to identify a comprehensive set of easily measurable metrics to assess agency resilience at such lower level.

Thank you in advanced for your time.

Nayel Urena Serulle  
PhD Candidate, University of Maryland

### **Disclaimer**

There are no known risks associated with participating in this research project. Participants will be asked to provide their name, agency, position and contact information. This information will be available to the investigator and any member of the research team. Responses will not be shared with other employees or supervisors at your company. Any potential loss of confidentiality will be minimized by storing data in a secure location (i.e.,

password protected computer). If a report or article is written about this research project, your identity will be protected to the maximum extent possible. Your information may be shared with representatives of the University of Maryland, College Park or governmental authorities if you or someone else is in danger or if we are required to do so by law. Your participation in this research is completely voluntary. You may choose not to take part at all. If you decide to participate in this research, you may stop participating at any time. If you decide not to participate in this study or if you stop participating at any time, you will not be penalized. By clicking next, you agree to these conditions and provide consent to use any information that is provided in this survey. If you decide to stop taking part in the study, if you have questions, concerns, or complaints, or if you need to report an injury related to the research, please contact the investigator:

Nayel Urena Serulle  
8750 Georgia Ave., Unit 817A,  
Silver Spring, MD 20910  
(650)-387-9117 [nus@umd.edu](mailto:nus@umd.edu)

**(Survey begins)**

*Please state your:*

Name

Agency

Position

Email

Phone number

*Recall that the objective of this survey is to identify a comprehensive set of easily measurable metrics to assess agency resilience. In this sense, please provide quantifiable metrics for the following capitals.*

Q1 Physical capital refers to the physical environment that makes an agency capable to efficiently maintain and harden the transportation network. Name (at least three) metrics you believe affect the physical resilience of an agency.

Q2 Human capital refers to the personnel, from both private and public organizations, needed to competently manage a transportation network before, during and after a disaster, and recover it in the latter situation. Name (at least three) metrics you believe affect the human resilience of an agency.

Q3 Economic capital refers to the financial stability of a transportation agency, which enables the implementation of proactive and reactive disaster management strategies. Name (at least three) metrics you believe affect the economic resilience of an agency.

Q4 Social capital refers to the agency's ability to efficiently support, coordinate and implement preparedness and response activities, procedures, methods, and tools. Name (at least three) metrics you believe affect the social resilience of an agency.

*The following are questions to better understand the agency's and/or your perspective and work on resilience.*

Q5 What are your agency's transportation priorities?

Q6 Have these changed in the last few years?

Q7 If resilience is not included in the priorities, why do you think this is?

Q8 Please define resiliency as understood in your agency

Q9 How does your agency measure resilience?

Q10 What makes your transportation agency unreliable or vulnerable?

Q11 Are you taking any specific actions to reduce these vulnerabilities? Why or why not?

Q11 Do you want to do more to reduce vulnerabilities? If so, what steps are being envisioned?

Q12 Is there anything about your agency (profile, structure, culture) that you feel leads to natural resiliency?

Q13 How are disruptions currently being handled?

Q14 Do you have a plan to address high impact, low probability disruptions (e.g., hurricanes, flash floods, tornados)? What is it? How specific is it?

Q15 Do you think the current state of our transportation infrastructure impacts the resiliency or reliability of your agency (e.g., the amount of roads, quality of roads, and potential for failure)?

Q16 Do you think that improvements to the resiliency of the transportation infrastructure network would improve the resiliency of your agency? How so?

Q17 Do you think that improvements to the resiliency of the population (i.e., users or community) improve the resiliency of your agency? How so?

Q18 What transportation challenges do you foresee for the next years?

### Annex 3: Fuzzy Inference System's Rules

All rules used for the development of the different Fuzzy Inference Systems are presented here. It should be noted that given the structure of the dependency diagram, Economic Capital and Preparedness Index are only influenced by one input and therefore do not need rules.

**Table 18.** FIS rules for Initial Redundancy.

IF	Data Red.	AND	Alt. Inf. Prox.	THEN	Initial Redundancy
If	0	and	5	then	Low
If	0	and	15	then	Low
If	0	and	25	then	Low
If	1	and	5	then	Medium-Low
If	1	and	15	then	Medium
If	1	and	25	then	Medium-High
If	2	and	5	then	Medium-High
If	2	and	15	then	High
If	2	and	25	then	High

**Table 19.** FIS rules for Physical Capital.

IF	Initial Red.	AND	Power Red.	THEN	Physical Capital
If	Low	and	0	then	Low
If	Medium-Low	and	0	then	Low
If	Medium	and	0	then	Medium-Low
If	Medium-High	and	0	then	Medium-Low
If	High	and	0	then	Medium
If	Low	and	1	then	Medium-Low
If	Medium-Low	and	1	then	Medium-Low
If	Medium	and	1	then	Medium
If	Medium-High	and	1	then	Medium-High
If	High	and	1	then	High
If	Low	and	2	then	Medium-Low
If	Medium-Low	and	2	then	Medium
If	Medium	and	2	then	Medium-High
If	Medium-High	and	2	then	High
If	High	and	2	then	High

**Table 20.** FIS rules for Human Capital.

<b>IF</b>	<b>Scalability</b>	<b>AND</b>	<b>Dis. Mgmt. Per.</b>	<b>THEN</b>	<b>Human Capital</b>
If	0	and	0	then	Low
If	0	and	20	then	Low
If	0	and	40	then	Medium-Low
If	25	and	0	then	Low
If	25	and	20	then	Medium
If	25	and	40	then	Medium-High
If	50	and	0	then	Medium
If	50	and	20	then	Medium-High
If	50	and	40	then	High

**Table 21.** FIS rules for Response Index.

<b>IF</b>	<b>Human</b>	<b>AND</b>	<b>Economic</b>	<b>THEN</b>	<b>Response</b>
If	Low	and	Low	then	Low
If	Medium-Low	and	Low	then	Low
If	Medium	and	Low	then	Medium-Low
If	Medium-High	and	Low	then	Medium-Low
If	High	and	Low	then	Medium-Low
If	Low	and	Medium-Low	then	Low
If	Medium-Low	and	Medium-Low	then	Medium-Low
If	Medium	and	Medium-Low	then	Medium-Low
If	Medium-High	and	Medium-Low	then	Medium
If	High	and	Medium-Low	then	Medium
If	Low	and	Medium	then	Medium-Low
If	Medium-Low	and	Medium	then	Medium
If	Medium	and	Medium	then	Medium
If	Medium-High	and	Medium	then	Medium
If	High	and	Medium	then	Medium-High
If	Low	and	Medium-High	then	Medium
If	Medium-Low	and	Medium-High	then	Medium
If	Medium	and	Medium-High	then	Medium-High
If	Medium-High	and	Medium-High	then	Medium-High
If	High	and	Medium-High	then	Medium-High
If	Low	and	High	then	Medium
If	Medium-Low	and	High	then	Medium-High
If	Medium	and	High	then	Medium-High
If	Medium-High	and	High	then	High
If	High	and	High	then	High

**Table 22.** FIS rules for Base Resilience.

<b>IF</b>	<b>Preparedness</b>	<b>AND</b>	<b>Response</b>	<b>THEN</b>	<b>Base Resilience</b>
If	Low	and	Low	then	Low
If	Medium-Low	and	Low	then	Low
If	Medium	and	Low	then	Medium-Low
If	Medium-High	and	Low	then	Medium-Low
If	High	and	Low	then	Medium
If	Low	and	Medium-Low	then	Low
If	Medium-Low	and	Medium-Low	then	Medium-Low
If	Medium	and	Medium-Low	then	Medium-Low
If	Medium-High	and	Medium-Low	then	Medium
If	High	and	Medium-Low	then	Medium
If	Low	and	Medium	then	Medium-Low
If	Medium-Low	and	Medium	then	Medium-Low
If	Medium	and	Medium	then	Medium
If	Medium-High	and	Medium	then	Medium
If	High	and	Medium	then	Medium-High
If	Low	and	Medium-High	then	Medium-Low
If	Medium-Low	and	Medium-High	then	Medium
If	Medium	and	Medium-High	then	Medium
If	Medium-High	and	Medium-High	then	Medium-High
If	High	and	Medium-High	then	High
If	Low	and	High	then	Medium
If	Medium-Low	and	High	then	Medium
If	Medium	and	High	then	Medium-High
If	Medium-High	and	High	then	High
If	High	and	High	then	High

**Table 23.** FIS rules for Agency Resilience.

<b>IF</b>	<b>Base Resilience</b>	<b>AND</b>	<b>Social Capital</b>	<b>THEN</b>	<b>Agency Resilience</b>
If	Low	and	Low	then	Low
If	Medium-Low	and	Low	then	Low
If	Medium	and	Low	then	Medium-Low
If	Medium-High	and	Low	then	Medium-Low
If	High	and	Low	then	Medium
If	Low	and	Medium-Low	then	Low
If	Medium-Low	and	Medium-Low	then	Medium-Low
If	Medium	and	Medium-Low	then	Medium-Low
If	Medium-High	and	Medium-Low	then	Medium
If	High	and	Medium-Low	then	Medium
If	Low	and	Medium	then	Medium-Low
If	Medium-Low	and	Medium	then	Medium-Low
If	Medium	and	Medium	then	Medium
If	Medium-High	and	Medium	then	Medium
If	High	and	Medium	then	Medium-High
If	Low	and	Medium-High	then	Medium-Low
If	Medium-Low	and	Medium-High	then	Medium
If	Medium	and	Medium-High	then	Medium
If	Medium-High	and	Medium-High	then	Medium-High
If	High	and	Medium-High	then	High
If	Low	and	High	then	Medium
If	Medium-Low	and	High	then	Medium
If	Medium	and	High	then	Medium-High
If	Medium-High	and	High	then	High
If	High	and	High	then	High

## Glossary

ACS	American Community Survey
AR	Agency Resilience
CRED	Centre for Research on the Epidemiology of Disasters
CS	Consumer Surplus
DDCM	Dynamic Discrete Choice Models
FIS	Fuzzy Inference System
HIHH	High Income Household
IR	Infrastructure Resilience
LIHH	Low Income Household
LS	Logsum
MEMA	Maryland Emergency Management Agency
MSTM	Maryland Statewide Travel Model
MWCOG	Metropolitan Washington Council of Government
PUMA	Public Use Microdata Areas
RP	Revealed Preference
SMZ	Statewide Modeling Zones
SP	Stated Preference
TR	Transportation Resilience
TRA	Transportation Resilience Architecture
UR	User Resilience

## Bibliography

- Abley, S. (2010). Measuring accessibility and providing transport choice, (July), 1–15.
- Adams, T., Bekkem, K., & Toledo-Duran, E. (2012). Freight Resilience Measures. *Journal of Transportation Engineering*, 138(11), 1403–1409. doi:10.1061/(ASCE)TE.1943-5436.0000415.
- Aguirregabiria, V., & Mira, P. (2010). Dynamic discrete choice structural models: A survey. *Journal of Econometrics*, 156(1), 38–67. doi:10.1016/j.jeconom.2009.09.007
- Alexander, B., Chan-Halbrendt, C., & Salim, W. (2006). Sustainable likelihood considerations for disaster risk management: Implications for implementation of the government of Indonesia tsunami recovery plan. *Disaster Prevention and Management*, 15(1), 31–50.
- Apparicio, P., Abdelmajid, M., Riva, M., & Shearmur, R. (2008). Comparing alternative approaches to measuring the geographical accessibility of urban health services: Distance types and aggregation-error issues. *International Journal of Health Geographics*, 7, 7. doi:10.1186/1476-072X-7-7
- Babuska, R., Verbruggen, H. B., & Hellendoorn, H. (1999). *Promising fuzzy modeling and control methodologies*. Netherlands.: Delft University of Technology.
- Baker, E. J. (1979). Predicting response to hurricane warnings: A reanalysis of data from four studies. *Mass Emergencies and Disasters*, 9-24.
- Bastin, F., Cirillo, C., & Toint, P. (2006). Application of an adaptive monte-carlo algorithm for mixed logit estimation. *Transportation Research Part B*, 577–593.
- Bateman, J. M., & Edwards, B. (2002). Gender and evacuation: A closer look at why women are more likely to evacuate for hurricanes. *Natural Hazards Review*, 107-117.
- Battelle. (2007). *Evaluation of the Systems ' Available Redundancy to Compensate for Loss of Transportation Assets Resulting from Natural Disasters or Terrorist Attacks*.
- Berche, B., Ferber, C. Von, Holovatch, T., & Holovatch, Y. (2009). Resilience of public transport networks against attacks. *The European Physical Journal*. Retrieved from <http://link.springer.com/article/10.1140/epjb/e2009-00291-3>
- Bhamra, R., Dani, S., & Burnard, K. (2011). Resilience: the concept, a literature review and future directions. *International Journal of Production Research*, 49(18), 5375–5393. doi:10.1080/00207543.2011.563826

- Bolin, R. (1986). *The 1986 California floods: Quick Response Research Rep. No. 02*. Boulder, Colorado: University of Colorado.
- Bolin, R., Jackson, M., & Crist, A. (1996). Gender inequality, vulnerability, and disasters: Theoretical and empirical considerations. En E. Enarson, & B. Morrow, *The gendered terrain of disasters*. Westport, Connecticut.
- Briguglio, L., Cordina, G., Farrugia, N., & Vella, S. (2009). Economic Vulnerability and Resilience: Concepts and Measurements. *Oxford Development Studies*, 37(3), 229–247. doi:10.1080/13600810903089893
- Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., ... von Winterfeldt, D. (2003). A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities. *Earthquake Spectra*, 19(4), 733–752. doi:10.1193/1.1623497
- Caplice, C., Rice, J., Ivanov, B., & Stratton, E. (2008). *Development of a State Wide Freight System Resiliency Plan* (Vol. 7931). Cambridge, MA. Retrieved from [http://ctl-test1.mit.edu/sites/default/files/library/public/paper\\_freight\\_system\\_resilience.pdf](http://ctl-test1.mit.edu/sites/default/files/library/public/paper_freight_system_resilience.pdf)
- Cardona, O. D. (2005). *System of Indicators for disaster risk management*. Washington, DC. Retrieved from <http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:SYSTEM+OF+INDICATORS+FOR+DISASTER+RISK+MANAGEMENT#3>
- Cardona, O. D. (2007). Indicators for Disaster Risk Management: Disaster Risk Communication Tools from a Holistic Perspective. In *20 ANNI DI SVILUPPO E PROTEZIONE DEL TERRITORIO* (pp. 1–15). Morbegno, Regione Lombardia. Retrieved from [http://understandrisk.org/sites/default/files/01CardonaSystemofIndicators\\_0.pdf](http://understandrisk.org/sites/default/files/01CardonaSystemofIndicators_0.pdf)
- Carnegie, J. A., & Deka, D. (2010). Using hypothetical disaster scenarios to predict evacuation behavioral response. *89th Annual Meeting of the Transportation Research Board*. Washington, DC: TRB.
- Carreño, M., Cardona, O., & Barbat, A. (2007). A disaster risk management performance index. *Natural Hazards*, (64), 1–20. doi:10.1007/s11069-006-9008-y
- Carter, M. T., Kendall, S., & Clark, J. P. (1983). Household response to warnings. *Mass Emergencies and Disasters*, 95-104.
- Chakraborty, J., Tobin, G., & Montz, B. (2005). Population evacuation: assessing spatial variability in geophysical risk and social vulnerability to natural hazards. *Natural Hazards Review*, (February), 23–33. Retrieved from [http://ascelibrary.org/doi/pdf/10.1061/\(ASCE\)1527-6988\(2005\)6%3A1\(23\)](http://ascelibrary.org/doi/pdf/10.1061/(ASCE)1527-6988(2005)6%3A1(23))

- Chang, C., & Mehta, R. (2009). Fiber optic sensors for transportation infrastructural health monitoring. *Control in Transportation Systems*, 3(1), 214–221. Retrieved from <http://www.ifac-papersonline.net/Detailed/40432.html>
- Chang, S. E., & Shinozuka, M. (2004). Measuring improvements in the disaster resilience of communities. *Earthquake Spectra*, 20(3), 739–755. doi:10.1193/1.1775796
- Charnkol, T., & Tanaboriboon, Y. (2006). Tsunami Evacuation Behavior Analysis: One Step of Transportation Disaster Response. *IATSS RESEARCH*, 30(2), 83–96.
- Chen, L., & Miller-Hooks, E. (2012). Resilience: An Indicator of Recovery Capability in Intermodal Freight Transport. *Transportation Science*, 46(1), 109–123. doi:10.1287/trsc.1110.0376
- Chen, X., & Zhang, F. B. (2004). Agent-Based Modeling and Simulation of Urban Evacuation: Relative Effectiveness of Simultaneous and Staged Evacuation Strategies. *83rd Transportation Research Board Annual Meeting*. Washington DC, United States: TRB.
- Chiu, Y., Villalobos, J., Gautam, B., & Zheng, H. (2006). Modeling and Solving the Optimal Evacuation-Route-Flow-Staging Problem for No-Notice Extreme Events. *85th Transportation Research Board Annual Meeting*. Washington DC, United States: TRB.
- Cigler, B. A. (2006). Who's in charge: The paradox of emergency management. *PA Times*, 28(5), 7-10.
- Cirillo, C., & Hetrakul, P. (2012). *An Integrated Analysis of the Social and Transportation Needs of Low Income Populations for the Washington D.C. Metropolitan Region: Task 3*.
- Cirillo, C., Xu, R., & Bastin, F. (2013). *A Dynamic Formulation for Car Ownership Modeling*. *European Transport Conference*. College Park, MD. Retrieved from <http://www.tinbergen.nl/wp-content/uploads/2014/01/A-Dynamic-Formulation-for-Car-Ownership-Modeling1.pdf>
- Comfort, L. K., & Haase, T. (2006). Communication, Coherence, and Collective Action: The Impact of Hurricane Katrina on Communications Infrastructure. *Public Works Management & Policy*, 11(1), 1–16. doi:10.1177/1087724X06289052
- Cova, T., & Johnson, J. (2002). Microsimulation of Neighborhood Evacuations in the Urban-Wildlife Interface. *Environment and Planning A*, 2211-2229.
- Cox, A., Prager, F., & Rose, A. (2011). Transportation security and the role of resilience: A foundation for operational metrics. *Transport Policy*, 18(2), 307–317. doi:10.1016/j.tranpol.2010.09.004

- CRED. (2009). Criteria and Definition. Retrieved from <http://www.emdat.be/criteria-and-definition>
- Croope, S., McNeil, S., Deliberty, T., & Nigg, J. (2010). *Resiliency of Transportation Corridors Before, During, and After Catastrophic Natural Hazards*. Retrieved from <http://trid.trb.org/view.aspx?id=1117583>
- Cumming, G. S., Barnes, G., Perz, S., Schmink, M., Sieving, K. E., Southworth, J., ... Holt, T. (2005). An Exploratory Framework for the Empirical Measurement of Resilience. *Ecosystems*, 8(8), 975–987. doi:10.1007/s10021-005-0129-z
- Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., & Webb, J. (2008). A place-based model for understanding community resilience to natural disasters. *Global Environmental Change*, 18(4), 598–606. doi:10.1016/j.gloenvcha.2008.07.013
- Dash, N., & Gladwin, H. (2007). Evacuation decision making and behavioral responses: Individual and household. *Natural Hazards Review*, 3(August), 69–77. Retrieved from [http://ascelibrary.org/doi/abs/10.1061/\(ASCE\)1527-6988\(2007\)8:3\(69\)](http://ascelibrary.org/doi/abs/10.1061/(ASCE)1527-6988(2007)8:3(69))
- Davis, A. (2000). Transport and Sustainable Rural Livelihoods in Zambia: Case Study. In *Egypt Social Fund for Development* (pp. 1–15). Transport Research Laboratory.
- De Lapparent, M., & Cernicchiaro, G. (2012). How long to own and how much to use a car? A dynamic discrete choice model to explain holding duration and driven mileage. *Economic Modelling*, 29(5), 1737–1744. doi:10.1016/j.econmod.2012.05.018
- DFID. (1999). *Sustainable livelihoods guidance sheets*. ... *Development: London*.) Available at: [www.livelihoods.org](http://www.livelihoods.org). ... Retrieved from <http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:SUSTAINABLE+LIVELIHOODS+GUIDANCE+SHEETS#1>
- DHS. (2007). *Target Capabilities List: A Companion to the National Preparedness Guidelines*. Obtenido de FEMA: <http://www.fema.gov/pdf/government/training/tcl.pdf>
- Drabek, T. E., & Boggs, K. (1968). Families in disaster: Reactions and relatives. *Marriage Family*, 443–451.
- Easterby-Smith, M., Thorpe, R., & Lowe, A. (2002). *Management Research – An Introduction*. London: Sage Publications.
- Elliott, R. (2010). *Measuring disaster preparedness of local emergency medical services agencies*. NAVAL POSTGRADUATE SCHOOL. Retrieved from

<http://oai.dtic.mil/oai/oai?verb=getRecord&metadataPrefix=html&identifier=ADA531808>

- Falasca, M., Zobel, C., & Cook, D. (2008). A decision support framework to assess supply chain resilience. *Proceedings of the 5th International ISCRAM Conference*, (May 2008), 596–605. Retrieved from [http://www.iscramlive.org/dmdocuments/ISCRAM2008/papers/ISCRAM2008\\_Falasca\\_et.al.pdf](http://www.iscramlive.org/dmdocuments/ISCRAM2008/papers/ISCRAM2008_Falasca_et.al.pdf)
- Farazmand, A. (2005). Crisis management or management crisis? *PA Times*, 28(10), 6-10.
- Federal Transit Administration. (2006). *Disaster Response and Recovery Resource for Transit Agencies*.
- Fosgerau, M., Frejinger, E., & Karlstrom, A. (2013). A link based network route choice model with unrestricted choice set. *Transportation Research Part B: Methodological*, 56, 70–80. doi:10.1016/j.trb.2013.07.012
- Fothergill, A. (1996). Gender, risk and disaster. *Mass Emergencies and Disasters*, 33-56.
- Fouracre, P. (2001). *Transport and sustainable rural livelihoods. Rural Travel and Transport Program*. East Kilbride, UK. Retrieved from <http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Transport+and+sustainable+rural+livelihoods#1>
- Freckleton, D., Heaslip, K., Luoisell, W., & Collura, J. (2012). Evaluation of Transportation Network Resiliency with Consideration for Disaster Magnitude. In *91st Annual Meeting of the Transportation Research Board* (Vol. 5). Retrieved from <http://docs.trb.org/prp/12-0491.pdf>
- Fu, H., & Wilmot, C. G. (2004). A Sequential Logit Dynamic Travel Demand Model For Hurricane Evacuation. *Transportation Research Record: Journal of the Transportation Research Board*, 1882, 19–26.
- Fu, H., Wilmot, C., & Zhang, H. (2006). Modeling the hurricane evacuation response curve. *Transportation Research Record* 2022, 94-102.
- Gao, S., Frejinger, E., & Ben-Akiva, M. (2010). Adaptive route choices in risky traffic networks: A prospect theory approach. *Transportation Research Part C: Emerging Technologies*, 18(5), 727–740. doi:10.1016/j.trc.2009.08.001
- Ge, S. (2013). Estimating the returns to schooling: Implications from a dynamic discrete choice model. *Labour Economics*, 20, 92–105. doi:10.1016/j.labeco.2012.11.004

- Geurs, K., & Wee, B. (2004). Accessibility evaluation of land-use and transport strategies: review and research directions. *Journal of Transport Geography*, 127-140.
- Gladwin, H., & Peacock, W. G. (1997). Warning and evacuation: A night for hard houses. En W. Peacock, B. Morrow, & H. Gladwin, *Hurricane Andrew: Gender, ethnicity and the sociology of disasters* (págs. 52-74). Routledge, New York.
- Glasserman, P. (2004). *Monte Carlo Methods in Financial Engineering*. New York, NY: Springer.
- Glerum, A., Vastberg, O. B., Frejinger, E., Karlström, A., Hugosson, M. B., & Bierlaire, M. (2015). A dynamic discrete-continuous choice model of car ownership, usage and fuel type. *Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation (CIRRELT)*.
- Global Adaptation Institute. (2011). *Global Adaptation Index: Measuring What Matters*. Washington, DC.
- Godschalk, D. R. (2003). Urban Hazard Mitigation: Creating Resilient Cities. *Natural Hazards Review*, 4(3), 136–143. doi:10.1061/(ASCE)1527-6988(2003)4:3(136)
- Gönül, F. F. (1998). Estimating price expectations in the OTC medicine market: An application of dynamic stochastic discrete choice models to scanner panel data. *Journal of Econometrics*, 89(1-2), 41–56. doi:10.1016/S0304-4076(98)00054-2
- Gruntfest, E., Downing, T., & White, G. F. (1978). *Big Thompson Flood*. Boulder, Colorado: Institute of Behavioral Science, Univ. of Colorado.
- Gurmu, S., Ihlantfeldt, K. R., & Smith, W. J. (2008). Does residential location matter to the employment of TANF recipients? Evidence from a dynamic discrete choice model with unobserved effects. *Journal of Urban Economics*, 63(1), 325–351. doi:10.1016/j.jue.2007.02.002
- Hanss, M. (2005). *Applied fuzzy arithmetic: An introduction with engineering applications*, . New York: Springer.
- Heaslip, K., Louisell, W., & Collura, J. (2009). A Methodology to Evaluate Transportation Resiliency for Regional Network. *88th Transportation Research Board Annual Meeting*. Washington, D.C.: TRB.
- Heaslip, K., Louisell, W., & Collura, J. (2009). Quantitative Evaluation of Transportation Resiliency for Regional Networks. *88th Transportation Research Board Annual Meeting*. Washington, DC.

- Heckman, J. J., & Navarro, S. (2007). Dynamic discrete choice and dynamic treatment effects. *Journal of Econometrics*, 136(2), 341–396. doi:10.1016/j.jeconom.2005.11.002
- Herve, M. (2011). *Role du signal prix du carbone sur les dcisions d'investissement des entreprises. Ph.D. thesis*. Paris, France: Universite Paris-Dauphine.
- Hetrakul, P. (2012). *Discrete Choice Models for Revenue Management*. University of Maryland. Retrieved from <http://drum.lib.umd.edu/handle/1903/13498>
- Holling, C. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics*, 4, 1–23. Retrieved from <http://www.jstor.org/stable/10.2307/2096802>
- Hunt, M. G., Bogue, K., & Rohrbaugh, N. (2012). Pet Ownership and Evacuation Prior to Hurricane Irene. *Animals*, 2(4), 529–539. doi:10.3390/ani2040529
- Hutton, J. (1976). The differential distribution of death in disaster: Atest of theoretical propositions. *Mass Emergencies and Disasters*, 261-266.
- International Federation of Red Cross and Red Crescent Societies. (2010). *World disaster report - focus on urban risk*. Retrieved from <http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:World+Disaste+R Eport#0>
- Ip, W. H., & Wang, D. (2009). Resilience Evaluation Approach of Transportation Networks. *2009 International Joint Conference on Computational Sciences and Optimization*, 618–622. doi:10.1109/CSO.2009.294
- ISDR. (2009). *Global assessment report on disaster risk reduction*. Geneva, Switzerland.
- Jackson, B. (2008). *The Problem of Measuring Emergency Preparedness*. Santa Monica, CA. Retrieved from [http://www.rand.org/pubs/occasional\\_papers/OP234/](http://www.rand.org/pubs/occasional_papers/OP234/)
- Kalafatas, G., & Peeta, S. (2009). Planning for Evacuation: Insights from an Efficient Network Design Model. *Journal of Infrastructure Systems*, 21-30.
- Karlstrom, A., Palme, M., & Svensson, I. (2004). A dynamic programming approach to model the retirement behaviour of blue-collar workers in Sweden. *Journal of Applied Econometrics*, 19(6), 795–807. doi:10.1002/jae.798
- Kaufmann, A., & Gupta, M. (1988). *Fuzzy mathematical models in engineering and management science*. North-Holland: Elsevier Science.
- Keane, M. P., Todd, P. E., & Wolpin, K. I. (2011). *The Structural Estimation of Behavioral Models: Discrete Choice Dynamic Programming Methods and*

*Applications. Handbook of Labor Economics* (Vol. 4). Elsevier Inc.  
doi:10.1016/S0169-7218(11)00410-2

- Keane, M. P., & Wolpin, K. I. (1997). The Career Decisions of Young Men. *Journal of Political Economy*, 105(3), 473–522. doi:10.1086/262080
- Keane, M. P., & Wolpin, K. I. (2002a). Estimating Welfare Effects Consistent with Forward-Looking Behavior. Part I: Lessons from a Simulation Exercise. *The Journal of Human Resources*, 37(3), 570–599.
- Keane, M. P., & Wolpin, K. I. (2002b). Estimating Welfare Effects Consistent with Forward-Looking Behavior. Part II: Empirical Results. *The Journal of Human Resources*, 37(3), pp. 570–599. doi:10.2307/3069682
- Keane, M. P., & Wolpin, K. I. (2009). Empirical applications of discrete choice dynamic programming models. *Review of Economic Dynamics*, 12(1), 1–22.  
doi:10.1016/j.red.2008.07.001
- Kirschenbaum, A. (2004). Measuring the effectiveness of disaster management Organizations. *Journal of Mass Emergencies and Disasters*, 22(1), 75–102.  
Retrieved from  
[http://www.safetylit.org/citations/index.php?fuseaction=citations.viewdetails&citationIds%5B%5D=citjournalarticle\\_55960\\_4](http://www.safetylit.org/citations/index.php?fuseaction=citations.viewdetails&citationIds%5B%5D=citjournalarticle_55960_4)
- Kockelman, M. (1997). Travel behavior as function of accessibility, land use mixing, and land use balance: Evidence from San Francisco Bay area. *Transportation Research Record*, 116-125.
- Kwan, M., & Weber, J. (2003). Individual Accessibility Revisited: Implications for Geographical Analysis in the Twenty-first Century. *Geographical Analysis*.
- Landsea, C., Franklin, J., & Beven, J. (2015). *The Revised Atlantic Hurricane Database (HURDAT2)*. Retrieved from <http://www.nhc.noaa.gov/data/?text#annual>
- Leu, G., Abbass, H., & Curtis, N. (2010). Resilience of ground transportation networks: a case study on Melbourne. In *33rd Australasian Transport Research Forum Conference*. Retrieved from <http://www.worldtransitresearch.info/research/3825/>
- Levinson, J., & Granot, H. (2002). *Transportation Disaster Response Handbook*. Academic Press.
- Lindell, M., Prater, C., Perry, R., & Wu, J. (2002). *EMBLEM: an Empirically based Large-scale Evacuation Time Estimate Model*. College Station, TX: Hazard Reduction and Recovery Center (Texas A&M).

- Lindell, M., Lu, J., & Prater, C. (2005). Household decision making and evacuation in response to Hurricane Lili. *Natural Hazards Review*, (November), 171–179. Retrieved from [http://ascelibrary.org/doi/abs/10.1061/\(ASCE\)1527-6988\(2005\)6:4\(171\)](http://ascelibrary.org/doi/abs/10.1061/(ASCE)1527-6988(2005)6:4(171))
- Litman, T. (2003). Measuring Transportation: Traffic, Mobility and Accessibility. *ITE Journal*, 28-32.
- Little, R. (2003). Toward more robust infrastructure: observations on improving the resilience and reliability of critical systems. In *Proceedings of the 36th Hawaii International Conference on System Sciences* (p. 9). Hawaii. Retrieved from [http://ieeexplore.ieee.org/xpls/abs\\_all.jsp?arnumber=1173880](http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1173880)
- Losada, C., Scaparra, M. P., & O’Hanley, J. R. (2012). Optimizing system resilience: A facility protection model with recovery time. *European Journal of Operational Research*, 217(3), 519–530. doi:10.1016/j.ejor.2011.09.044
- Liu, Y., Lai, X., & Chang, G. (2006). Two-level Integrated Optimization System for Planning of Emergency Evacuation. *Journal of Transportation Engineering*, 800-807.
- Madhusudan, C., & Ganapathy, G. (2011). Disaster resilience of transportation infrastructure and ports—An overview. *International Journal of Geomatics and Geosciences*, 2(2), 443–456. Retrieved from <http://www.indianjournals.com/ijor.aspx?target=ijor:ijggs&volume=2&issue=2&article=009>
- Madni, a. M., & Jackson, S. (2009). Towards a Conceptual Framework for Resilience Engineering. *IEEE Systems Journal*, 3(2), 181–191. doi:10.1109/JSYST.2009.2017397
- Madni, A. M., & Jackson, S. (2009). Towards a Conceptual Framework for Resilience Engineering. *IEEE Systems Journal*, 3(2), 181–191. doi:10.1109/JSYST.2009.2017397
- Mansouri, M., Nilchiani, R., & Mostashari, A. (2010). A policy making framework for resilient port infrastructure systems. *Marine Policy*, 34(6), 1125–1134. doi:10.1016/j.marpol.2010.03.012
- Mayunga, J. (2007). Understanding and Applying the Concept of Community Disaster Resilience: A capital-based approach. *Academy for Social Vulnerability and Resilience Building*, (July), 22–28. Retrieved from <https://www.ihdp.unu.edu/file/download/3761.pdf>
- Mayunga, J., & Peacock, G. W. (2010). The Development of a Community Disaster Resilience Framework and Index. In G. W. Peacock (Ed.), *Advancing the Resilience*

- of Coastal Localities: Developing, Implementing and Sustaining the Use of Coastal Resilience Indicators: A Final Report* (pp. 2–57). College Station, TX: NOAA.
- Mei, B. (2002). *Development of Trip Generation Models of Hurricane Evacuation*. Baton Rouge, Louisiana: Louisiana State University.
- Melnikov, O. (2013). Demand for differentiated durable products: The case of the u.s. computer printer market. *Economic Inquiry*, *51*(2), 1277–1298. doi:10.1111/j.1465-7295.2012.00501.x
- Mileti, D., Drabek, T., & Haas, E. (1975). *Human systems in extreme environments: A sociological perspective*. Boulder, Colorado: Institute of Behavioral Science, Univ. of Colorado.
- Miller, R. a. (1984). Job Matching and Occupational Choice. *Journal of Political Economy*, *92*(6), 1086. doi:10.1086/261276
- Miller-Hooks, E., Zhang, X., & Faturechi, R. (2012). Measuring and maximizing resilience of freight transportation networks. *Computers & Operations Research*, *39*(7), 1633–1643. doi:10.1016/j.cor.2011.09.017
- Mohammad, A. A. J., Hutchison, D., & Sterbenz, J. J. P. G. (2006). Towards quantifying metrics for resilient and survivable networks. In *14th IEEE International Conference on Network Protocols* (pp. 2–4). Santa Barbara, CA. Retrieved from [https://wiki.ittc.ku.edu/resilinetts\\_wiki/images/ICNP\\_poster\\_v3.pdf](https://wiki.ittc.ku.edu/resilinetts_wiki/images/ICNP_poster_v3.pdf)
- Murray-Tuite, P. (2006). A comparison of transportation network resilience under simulated system optimum and user equilibrium conditions. In *2006 Winter Simulation Conference* (pp. 1398–1405). Retrieved from [http://ieeexplore.ieee.org/xpls/abs\\_all.jsp?arnumber=4117764](http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=4117764)
- Murray-Tuite, P., & Mahmassani, H. (2003). Model of household trip-chain sequencing in emergency evacuation. *Transportation Research Record: Journal of Transportation Research Board*, *1831*(January 2003), 21–29. Retrieved from <http://trb.metapress.com/index/C196482M075N570Q.pdf>
- Murray-Tuite, P., & Mahmassani, H. (2004). Methodology for Determining Vulnerable Links in a Transportation Network. *Transportation Research Record*, *1882*(1), 88–96. doi:10.3141/1882-11
- Nagurney, A. (2011). Building Resilience into Fragile Transportation Networks in an Era of Increasing Disasters. In *90th Annual Transportation Research Board Meeting*. Washington, DC.
- Nicholls, S. (2001). Measuring the accessibility and equity of public parks: a case study using GIS. *Managing Leisure*, 201-219.

- NOAA. (29 de March de 2006). *Floods cost lives and billions of dollars in property damage each year around the United States*. Recuperado el 23 de July de 2013, de <http://www.noaanews.noaa.gov/stories2006/s2601.htm>
- NWS. (4 de March de 2012). *Floods & Flash Floods: Introduction*. Recuperado el 24 de July de 2013, de <http://www.crh.noaa.gov/dmx/?n=preparefloodintro>
- Omer, M., Mostashari, A., & Nilchiani, R. (2011). Measuring the Resiliency of the Manhattan Points of Entry in the Face of Severe Disruption. *American Journal of Engineering and Applied Sciences*, 4(1), 153–161. Retrieved from <http://www.thescipub.com/abstract/10.3844/ajeassp.2011.153.161>
- Ortiz, D., Ecola, L., & Willis, H. (2009). *Adding resilience to the freight system in statewide and metropolitan transportation plans: developing a conceptual approach*. AASHTO Standing Committee on Planning. Retrieved from <http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:ADDING+RESILIENCE+TO+THE+FREIGHT+SYSTEM+IN+STATEWIDE+AND+METROPOLITAN+TRANSPORTATION+PLANS+:+DEVELOPING+A+CONCEPTUAL+APPROACH#0>
- Oswald, M., McNeil, S., Ames, D., & Gayley, R. (2013). Identifying Resiliency Performance Measures for MegaRegional Planning: A Case Study of the BosWash Transportation Corridor. *Transportation Research Record Practice-Ready Papers*. Retrieved from <http://docs.trb.org/prp/13-1198.pdf>
- Pakes, A. (1986). Patents as Options: Some Estimates of the Value of Holding European Patent Stocks. *Econometrica*, 54(4), 755–784. doi:10.2307/1912835
- Pel, A. J., Bliemer, M. C. J., & Hoogendoorn, S. P. (2011a). A review on travel behaviour modelling in dynamic traffic simulation models for evacuations. *Transportation*, 39(1), 97–123. doi:10.1007/s11116-011-9320-6
- Pel, A. J., Bliemer, M. C. J., & Hoogendoorn, S. P. (2011b). Modelling traveller behaviour under emergency evacuation conditions. *EJTIR*, 11(11), 166–193. Retrieved from [http://www.ejtir.tbm.tudelft.nl/issues/2011\\_02/pdf/2011\\_02\\_03.pdf](http://www.ejtir.tbm.tudelft.nl/issues/2011_02/pdf/2011_02_03.pdf)
- Perry, R. W. (1979). Evacuation decision making in natural disasters. *Mass Emergencies and Disasters*, 25-38.
- Perry, R. W., & Greene, M. R. (1982). *The role of ethnicity in the emergency decision-making process*. National Emergency Training Center.
- Perry, R. W., Lindell, M. K., & Greene, M. (1982). Threat perception and public response to volcano hazards. *Journal of Social Psychology*, 199-204.

- Perry, R., & Mushkatel, A. H. (1986). *Minority citizens in disasters*. Athens: University of Georgia Press.
- Pitera, K. (2008). *Interpreting Resiliency: An Examination of the Use of Resiliency Strategies within the Supply Chain and Consequences for the Freight Transportation System*. University of Washington. Retrieved from [http://courses.washington.edu/cee500/pitera\\_final\\_thesis.pdf](http://courses.washington.edu/cee500/pitera_final_thesis.pdf)
- Prizzia, R. (2007). The Role of Coordination in Disaster Management. In J. Pinkowski (Ed.), *Disaster Management Handbook* (pp. 75–98). CRC Press. Retrieved from [http://scele.ui.ac.id/berkas\\_kolaborasi/konten/bencana2014genap/bencana25-28/Disaster\\_Management\\_Handbook.pdf#page=106](http://scele.ui.ac.id/berkas_kolaborasi/konten/bencana2014genap/bencana25-28/Disaster_Management_Handbook.pdf#page=106)
- Reggiani, A. (2013). Network resilience for transport security: Some methodological considerations. *Transport Policy*, 28, 63–68. doi:10.1016/j.tranpol.2012.09.007
- Rust, J. (1987). Optimal Replacement of GMC Bus Engines : An Empirical Model of Harold Zurcher. *Econometrica*, 55(5), 999–1033.
- Rust, J., & Phelan, C. (1997). How Social Security and Medicare Affect Retirement Behavior In a World of Incomplete Markets. *Econometrica*, 65(4), 781–831.
- Schaffer, R., & Cook, E. (1972). *Human response to Hurricane Celia*. College Station, Texas: Texas A&M University.
- Scoones, I. (1998). *Sustainable rural livelihoods: a framework for analysis*. Brighton, England: Institute of Development Studies. Retrieved from [http://200.17.236.243/pevs/Agroecologia/Sustainable Rural Livelihoods-Scoones.pdf](http://200.17.236.243/pevs/Agroecologia/Sustainable_Rural_Livelihoods-Scoones.pdf)
- Shapiro, A., Dentcheva, D., & Ruszczyński, A. (2009). *Lectures on Stochastic Programming: Modeling and Theory*. Philadelphia, PA: SIAM.
- Simpson, R. H., & Riehl, H. (1981). *The hurricane and its impact*. Baton Rouge, Louisiana : LSU Press.
- Sohail, M. (2005). Sustaining livelihoods by improving urban public transport. *Proceedings of the ICE - Engineering Sustainability*, 158(1), 9–15. doi:10.1680/ensu.2005.158.1.9
- Sorensen, J. H., Vogt, B. M., & Mileti, D. S. (1987). *Evacuation: An assessment of Planning and Research*. Oak Ridge, Tennessee: Oak Ridge National Laboratory.
- Southworth, F. (1991). *Regional Evacuation Modeling: A State of the Art Review*. Oak Ridge, U.S.A.: Oak Ridge National Laboratory.

- Srivastava, S. K. (2007). Green supply-chain management: A state-of-the-art literature review. *International Journal of Management Reviews*, 9(1), 53–80. doi:10.1111/j.1468-2370.2007.00202.x
- Sutton, J., & Tierney, K. (2006). Disaster preparedness: concepts, guidance, and research. In *Fritz Institute Assessing Disaster Preparedness Conference*. Sebastopol, CA: Fritz Institute. Retrieved from <http://www.fritzinstitute.org/pdfs/whitepaper/disasterpreparedness-concepts.pdf>
- Ta, C., Goodchild, A. V., & Pitera, K. (2009). Structuring a Definition of Resilience for the Freight Transportation System. *Transportation Research Record: Journal of the Transportation Research Board*, 2097, 19–25. doi:10.3141/2097-03
- The White House Office of the Press Secretary. (2013). Presidential Policy Directive: Critical Infrastructure Security and Resilience. Retrieved from <http://www.whitehouse.gov/the-press-office/2013/02/12/presidential-policy-directive-critical-infrastructure-security-and-resil>
- Thouez, J., Bodson, P., & Joseph, A. (1988). Some methods for measuring the geographic accessibility of medical services in rural regions. *Medical Care*, 34-44.
- Tilio, L., Murgante, B., Trani, F. Di, Vona, M., & Masi, A. (2011). Resilient city and seismic risk: a spatial multicriteria approach. In *International Conference on Computational Science and Its Applications* (pp. 410–422). Retrieved from <http://www.springerlink.com/index/E83M354Q59003U32.pdf>
- Tobin, G. (1999). Sustainability and community resilience: the holy grail of hazards planning? *Global Environmental Change Part B: Environmental Hazards*, 1(1), 13–25. doi:10.1016/S1464-2867(99)00002-9
- Tomer, A., Kneebone, E., Puentes, R., & Berube, A. (2011). Missed Opportunity : Background, (May).
- Train, K. (2003). *Discrete Choice Methods with Simulation*. Cambridge: Cambridge University Press.
- UNISDR. (2011). *Global assessment report on disaster risk reduction*. Geneva, Switzerland.
- UNISDR, & UNOCHA. (2008). *Disaster Preparedness for Effective Response: Guidance and Indicator Package for Implementing Priority Five of the Hyogo Framework*. Geneva, Switzerland.
- United States Census Bureau. (2014). *Measuring America: Computer and Internet Trends in America*. Washington, DC: U.S. Department of Commerce.

- Urena Serulle, N. (2010). *Transportation Network Resiliency : A Fuzzy Systems Approach*. Utah State University.
- Urena Serulle, N., Heaslip, K., Brady, B., Louisell, W., & Collura, J. (2011). Resiliency of Transportation Network of Santo Domingo, Dominican Republic. *Transportation Research Record: Journal of the Transportation Research Board*, 2234, 22–30. Retrieved from <http://trb.metapress.com/index/J1326N4285305247.pdf>
- Van Willigen, M., Edwards, T., Edwards, B., & Hesse, S. (2002). Riding out the storm: Experiences of the physically disabled during Hurricanes Bonnie, Dennis, and Floyd. *Natural Hazards Review*, 98-106.
- Vugrin, E., & Turnquist, M. (2012). *Design for Resilience in Infrastructure Distribution Networks*. Retrieved from [http://www.sandia.gov/CasosEngineering/docs/Vugrin\\_resilient\\_design\\_2012\\_6050.pdf](http://www.sandia.gov/CasosEngineering/docs/Vugrin_resilient_design_2012_6050.pdf)
- Williams, H. (1964). Human factors in warning and response systems. En G. H. Grosser, H. Wechsler, & M. Greenblatt, *The Threat of Impending Disaster: Contributions to the Psychology of Stress* (pág. 335). Cambridge, MA: M.I.T. Press.
- Wilmot, C., & Gudishala, R. (2013). *Development of a Time-Dependent Hurricane Evacuation Model for the New Orleans Area*. Baton Rouge, Louisiana. Retrieved from <http://trid.trb.org/view.aspx?id=1246733>
- Wolpin, K. I. (1984). An Estimable Dynamic Stochastic Model of Fertility and Child Mortality. *Journal of Political Economy*, 92(5), 852. doi:10.1086/261262
- Xie, C., Lin, D.-Y., & Waller, S. (2010). A Dynamic Evacuation Network Optimization Problem with Lane Reversal and Crossing Elimination Strategies. *Transportation Research Part E: Logistics and Transportation Review*, 295-316.
- Yigitcanlar, T., Sipe, N., Evans, R., & Pitot, M. (2007). A GIS-based land use and public transport accessibility indexing model. *Australian Planner*, 30-37.
- Yuan, F., Han, L., Chin, S., & Hwang, H. (2006). Proposed Framework for Simultaneous Optimization of Evacuation Traffic Destination and Route Assignment. *Transportation Research Record*, 50-58.