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Modeling Mass Care Resource Provision Post Hurricane

Tammy Marie Muhs
University of Central Florida

MODELING MASS CARE RESOURCE PROVISION POST HURRICANE

by

TAMMY MARIE POITRAS MUHS
B.S. University of North Florida, 1998
M.S. University of North Florida, 2001

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Major Professor: John P. Kincaid

ABSTRACT

Determining the amount of resources needed, specifically food and water, following a hurricane is not a straightforward task. Through this research effort, an estimating tool was developed that takes into account key demographic and evacuation behavioral effects, as well as hurricane storm specifics to estimate the number of meals required for the first fourteen days following a hurricane making landfall in the State of Florida.

The Excel based estimating tool was created using data collected from four hurricanes making landfall in Florida during 2004-2005. The underlying model used in the tool is a Regression Decision Tree with predictor variables including direct impact, poverty level, and hurricane impact score. The hurricane impact score is a hurricane classification system resulting from this research that includes hurricane category, intensity, wind field size, and landfall location.

The direct path of a hurricane, a higher than average proportion of residents below the poverty level, and the hurricane impact score were all found to have an effect on the number of meals required during the first fourteen days following a hurricane making landfall in the State of Florida.

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LIST OF ACROYMNS AND ABBREVIATIONS

AOML – The Atlantic Oceanographic and Meteorological Laboratory

ARC – American Red Cross

ARC/TSA – American Red Cross/The Salvation Army

ATCF – Automated Tropical Cyclone Forecast

CGIS – Canada Geographic Information System

DHS – US Department of Homeland Security

E – East

E – early hurricane mode

EOC – Emergency Operations Center

ESRI – Environmental Systems Research Institute, Inc.

ERV – emergency response vehicle

FDPBR– Florida Department of Professional and Business Regulation

FDEM – Florida Division of Emergency Management

FDOT – Florida Department of Transportation

FEMA – Federal Emergency Management Agency

GIS – Geographic Information System

HAZUS-MH – Hazards United States-Multi-Hazard

HSI – Hurricane Severity Index

HMTAP – Hazard Mitigation Technical Assistance Program

NSPH – Harvard School of Public Health

in – inch

int – hurricane intensity

kt – knot

L – late hurricane model

mph – miles per hour

MSW – Master of Social Work

N – North

NCDC – National Climatic Data Center

NEMIS – National Emergency Management Information System

NEMA – National Emergency Management Association

NHC – National Hurricane Center

NSGIC – National States Geographic Information Council

NOAA – National Oceanic and Atmospheric Administration

NVOAD – National Voluntary Organizations Active in Disaster

PAD6716 – Information Systems for Public Managers and Planners

POD – Point of Distribution

POP90_SQMI – Population per 90 square miles

PS – partner services

R_e– effective radius

S – South

SQMI – square mile

TSA–The Salvation Army

Trk – hurricane track

URISA – Urban and Regional Information Systems Association

V_{max}– maximum velocity

W – West

CHAPTER 1: INTRODUCTION

1.1 Background

Among all the natural disasters, hurricanes are the most damaging to the United States and its territories, causing an average of 14 deaths and five billion in property damage each year (National Windstorm Impact Reduction, 2004). Blake, Rappaport, and Landsea (2007) looked at hurricane landfalls and found that there was an average 1.8 major hurricanes (category 3 or above) yearly for the 156 years spanning 1851–2006.

In recent years, there have been several major hurricanes make landfall in the United States. The years 2004 and 2005 each had six major hurricanes make landfall. "In 2004, the State of Florida was affected by an unprecedented four hurricanes in 2 months, causing widespread damage and destruction" (U.S. Department of Homeland Security, 2005 p. 3). The year 2008 was considered one of the most active seasons in the past 64 years with sixteen named storms, including a total of eight hurricanes, of which five were considered major hurricanes (NOAA, 2008). Gary Bell, lead seasonal hurricane forecaster at the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center, referred to the 2008 hurricane season as part of the "active hurricane era" stating that it was the tenth season to produce above-normal activity in the past fourteen years (NOAA, 2008). According to hurricane forecasters at NOAA, the increase in hurricane activity since 1995 can be attributed to lingering La Nina effects, warmer tropical Atlantic Ocean temperatures, and atmospheric conditions (NOAA, 2008). In the following table, the average number of tropical cyclones that reached storm, hurricane, and major hurricane status for specific time periods is provided (Blake et al., 2007). The data seem to support the claims of an "active hurricane era."

Table 1: Average tropical storms, hurricanes, and major hurricanes

The average number of tropical cyclones, including subtropical storms after 1967, that reached storm, hurricane, and major hurricane status are listed for the period of 1851-2006 with different time increments provided for comparison purposes.				
Period	Number of years	Average number of Tropical Storms	Average number of Hurricanes	Average number of Major Hurricanes
1851-2006	156	8.7	5.3	1.8
1944-2006 Note: This period marks the start of aircraft reconnaissance	63	10.6	6.1	2.7
1957-2006	50	10.7	6.0	2.4
1966-2006 Note: This period marks the start of geostationary satellite coverage	41	11.1	6.2	2.3
1977-2006	30	11.4	6.3	2.5
1987-2006	20	12.6	6.8	2.9
1997-2006	10	14.5	7.8	3.6

Blake et al., 2007

In the following figures, the number of named storms, hurricanes, and major hurricanes spanning the years 1980 through 2010 are provided (NOAA Miami Regional Library, 1872-2004; National Hurricane Center, 1998-2010). A linear trend line is imposed on each of the graphs, however it is not meant to show a linear relationship between time and the number of named storms, hurricanes, and major hurricanes, but instead to show an overall increasing trend in the number of named storms, the number of hurricanes, and the number of major hurricanes over the past thirty years.

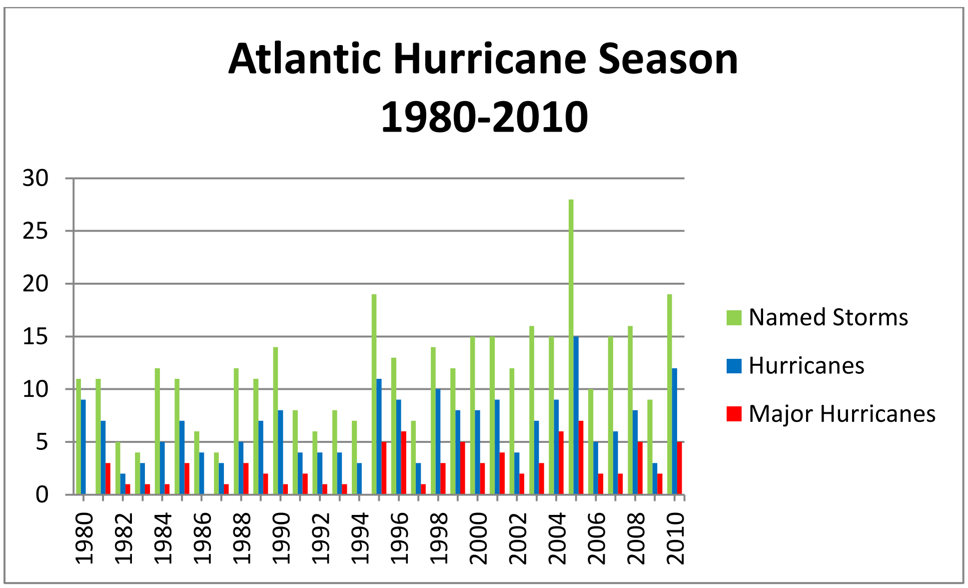


Figure 1: Summary of the Atlantic Hurricane Seasons 1980-2010

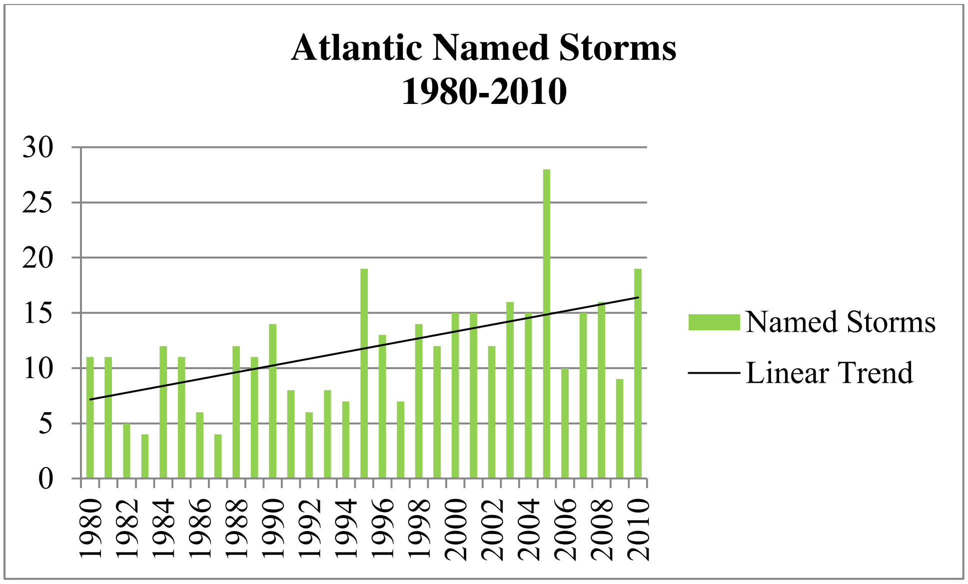


Figure 2: Number of named storms of the Atlantic Hurricane Season 1980-2010

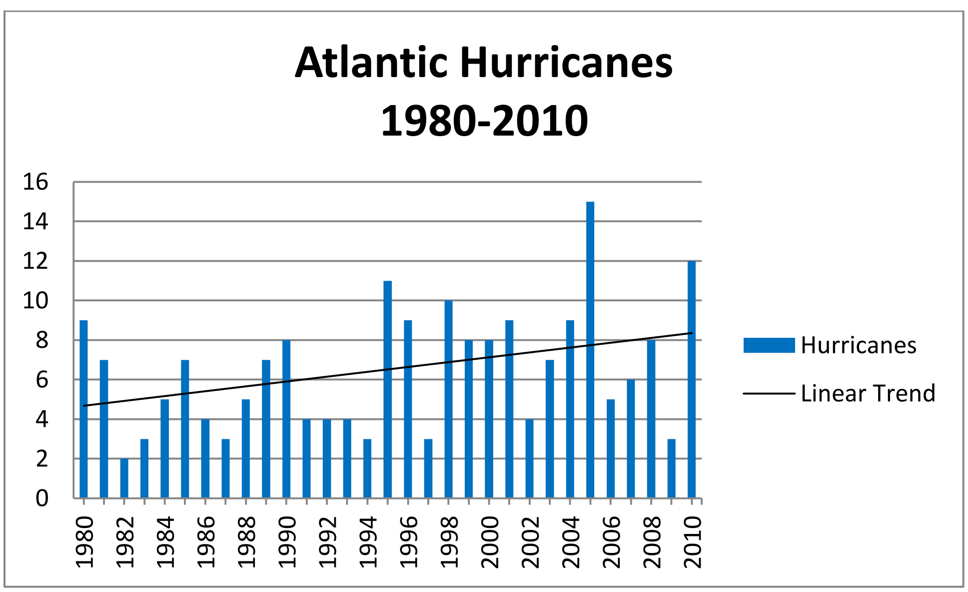


Figure 3: Number of hurricanes of the Atlantic Hurricane Season 1980-2010

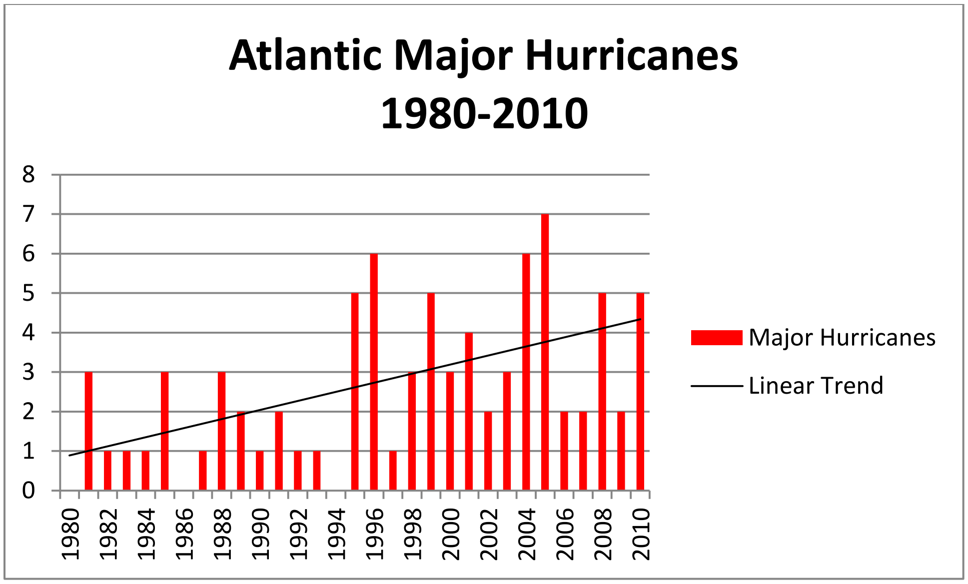


Figure 4: Number of major hurricanes of the Atlantic Hurricane Season 1980-2010

In addition to high winds, hurricane hazards also include storm surge, flooding, and tornadoes, all which put both people and property at risk. According to a 2003 NOAA/U.S. Census report, fifty-three percent of the U.S. population lives within 50 miles of the coast, which implies that hurricanes making landfall on the coast are likely to impact a lot of people, especially when one considers the effects of flooding well into the mainland areas in the path of the storm (National Oceanic and Atmospheric Association (NOAA) Magazine, 2007). As such, hurricanes originating in the Atlantic Ocean typically impact lives and properties along the US Gulf Coast, East coast, and Caribbean Islands (NOAA Magazine, 2007).

One of the major hurricanes during 2005 that impacted the U.S. Gulf Coast was Hurricane Katrina, which made landfall on August 29, 2005 as a powerful Category 3 hurricane. Katrina ravished the shores of the Gulf Coast resulting in $96 billion in estimated damages, an estimated 1,330 deaths, and 770,000 people being displaced (U. S. Executive Office of the President, 2006). According to data provided by the Federal Emergency Management Agency (FEMA), over 1.2 million people along the northern Gulf Coast were under evacuation orders but the number that evacuated is unknown (Knabb, Rhome, & Brown, 2005).

As seen in the aftermath of Hurricane Katrina, the provision of mass care was certainly an area that warranted additional attention. Local, state, and federal agencies were besieged in response to the demands placed on them by Hurricane Katrina. As a result,

> …there was widespread dissatisfaction with the level of preparedness and the collective response. As events unfolded in the immediate aftermath and ensuing days after Hurricane Katrina's final landfall, responders at all levels of government—many victims themselves—encountered significant breakdowns in vital areas such as emergency communications as well as obtaining essential supplies and equipment. The causes of these breakdowns must be well understood and addressed in order to strengthen the nation's ability to prepare for, respond to, and recover from major catastrophic events in the future (U. S. Government Accountability Office, 2006, p. 3).

Although Katrina's landfall in Florida on August 25, 2005 is not the landfall most people associate with Katrina, it still had a profound effect on Florida as well as the country as a whole. The following year, Florida included disaster preparedness as one of the top State concerns (Emergency Preparedness News, 2006). Even without the effects of Katrina, this is understandable considering the fact that forty percent of all land-falling U.S. hurricanes hit Florida and eighty-three percent of category four or higher hurricane strikes have hit either

Florida or Texas (NOAA, 2010). In a paper by Leatherman & Defraene (2006), four Florida locations, Lake Okeechobee, Florida Keys, Miami/Ft. Lauderdale, and Tampa/St. Petersburg, were included in the list of the U.S. mainland's ten most vulnerable areas to hurricane.

"Statistics show that the largest loss of life and property occur in locations experiencing the core of a category 3 or stronger hurricane" (Blake et al., 2007, p. 3). Using several models, hurricane paths are projected well in advance of their actual landfall. By evacuating areas that are likely to be impacted, the costs caused by hurricanes, including loss of lives, can be reduced. This approach is especially important given the increased accuracy of forecasters to predict the track of a hurricane resulting in fewer unnecessary evacuations. (U.S. Department of Transportation Federal Highway Administration, 2003).

When evacuation efforts are not successful, there are complications in the relief efforts including a need for additional shelters, supplies, and rescue missions. Even with a successful evacuation effort, resources are needed for those that did not evacuate, those who evacuated but stayed in the same area, and those responding to the disaster.

1.2 Problem Statement

The distribution of resources, specifically food and water, following a hurricane falls under the category of mass care. "Mass care includes sheltering, feeding operations, emergency first aid, bulk distribution of emergency items, and collecting and providing information on victims to family members" (Florida Division of Emergency Management, 2009b, p. 1). Mass care resources from Local, State, and Federal governmental and non-governmental agencies are deployed in a coordinated manner to meet specific, phased mass care goals and objectives (Florida Division of Emergency Management, 2009b). Determining the amount of resources needed following a hurricane is not a straightforward task. The governmental and non-governmental agencies are constrained by budgets as well as resource availability. If the estimated amount of resources is higher than what is actually required, it is not fiscally efficient, however if the estimate is too low the end consequence could be that hurricane survivors would not have access to much needed mass care resources. The projection of needed commodities post hurricane, specifically food and water, would benefit from research and evaluation to be able to provide better estimates of the amounts required.

1.3 Research Contribution

"Minimizing delay in providing priority commodities and healthcare to the survivors can greatly improve the survival rate" (Ozdamar & Yi, 2008, p. 14). In addition to concerns regarding delivery of resources following a hurricane, there is a need to be able to estimate the amount of resources needed. A modeling tool that uses demographics, behavioral studies, and storm specifics to assist in estimating the resources necessary to sustain hurricane disaster survivors has not been developed.

Through this research effort, an estimating tool was developed that takes into account key demographic and evacuation behavioral effects as well as storm specifics to estimate the number of meals needed for residents post hurricane. Specifically, this tool estimates the number of meals required following a hurricane for the area population at the State level. This datum is then used as input into an integrated Excel spreadsheet developed over a period of several years by Michael Whitehead, Mass Care Coordinator in the State of Florida, to determine the amount of resources (e.g., distribution trucks, kitchens, and fuel) required for the provision of the meals.

The tool is an improvement over the current State estimation system as it includes key demographics, evacuation behavioral effects, all counties reporting meals served for four hurricanes making landfall in Florida resulting in 135 observations, and additional storm specifics in the estimation process, whereas the previous estimating system considered only limited counties reporting meals served for the four hurricanes resulting in 41 observations, only used the category of the storm, and was limited to the linear regression capabilities of Excel.

This research combines Excel, census data, ArcGIS (version 9.3), Hurrevac 2010 (version 1.0.492), and DTREG (version 10.3.3) in the creation of the estimating tool. The State of Florida can use this tool to aid in decisions when estimating the amount of mass care resources necessary following a hurricane. Although it is created specifically for emergency response in Florida, it could be adapted to serve other geographic areas.

1.4 Dissertation Outline

The remaining chapters of this dissertation include the following: Chapter 2 provides a literature review of work to date in the areas of hurricane models, evacuation behavior, modeling tools used in emergency response, and command, control, and operations. The methodology employed is discussed in Chapter 3, which is broken down into selection of the area of interest, census attribute selection, geospatial data, meal preparation and delivery, and initial model assumptions. Chapter 4 is a discussion of the findings of this research. Chapter 5 is a presentation of the conclusions and future research.

CHAPTER 2: LITERATURE REVIEW

In order to develop a more robust model of post-hurricane mass care, it is first necessary to understand the variables that affect the severity of hurricane damage, likelihood of non-evacuation, and types of post-hurricane needs. Research was conducted to investigate hurricane models, evacuation behavior, and post-hurricane emergency response.

2.1 Hurricane Models

A hurricane is a tropical cyclone with winds greater than 74 miles per hour. First published in 1974, the Saffir-Simpson scale measures the present intensity of a hurricane to categorize it as a category 1 to a category 5 hurricane based on wind speed. As hurricane intensity changes, the current intensity is used to categorize the storm. The scale has been used to estimate the potential property damage and flooding expected in the landfall region. (See Appendix A) Recently, the Saffir-Simpson Hurricane Scale was revised to remove the surge and flood descriptions and update the wind-impact and was consequently renamed the Saffir-Simpson Hurricane Wind Scale. (See Appendix B)

Emergency preparations begin prior to the hurricane making landfall. The expected landfall region, based on center track of a tropical cyclone, is identified in an effort to begin the emergency preparations. A variety of forecast models are used to predict hurricane center track and intensity. Although all the forecast models are used to predict hurricane track and intensity, the different types of models, dynamical, statistical, statistical-dynamical, trajectory, and consensus vary quite a bit. Dynamical models use the physics of the atmosphere in the prediction whereas statistical models use only historical relationships. A statistical-dynamical model blends the dynamical and statistical techniques. Trajectory models use a separate dynamical model and consensus models incorporate the forecasts of several of the models. Typically, multiple models are typically used to predict center track and intensity. According to the National Hurricane Center (2009) there is an accepted list of the most commonly used track and intensity models used by the forecasters at the National Hurricane Center (NHC). (See Appendix C)

For this dissertation the actual storm specific information, including the recorded path, from the NHC is used to determine the directly impacted counties and storm specifics. When using the estimating tool, emergency managers can use the NHC Forecast Advisories and Hurricane Evacuation (HURREVAC), which is a storm tracking and assistance software tool, to predict the counties that will be directly impacted.

2.2 Hurricane Severity Index

Although the Saffir-Simpson Hurricane Wind Scale is widely used to estimate expected damage from a hurricane, a major limitation of the scale is that it only uses the present intensity of a hurricane to categorize it as a category 1 to a category 5 hurricane based on wind speed, which can result in a lower category storm producing more damage than a higher category storm or two storms of the same category producing two very different levels of damage. An example of the first instance would be Katrina, a category 3 storm that had a higher damage value compared to Camille, which was a category 5 storm. An example for the second instance would be Dennis and Ivan, both category 3 storms producing very different amounts of damage. Hebert, Weinzapfel, and Chambers (2010), of ImpactWeather, introduced the Hurricane Severity Index (HSI) which uses the wind field size in addition to the maximum sustained winds in their intensity/strength scale. The HSI is a 50 point scale with 25 points determined by the intensity and 25 points determined by the size of the wind field. The 25 points determined by the intensity of the storm results in a 30 kt. tropical depression receiving 1 intensity point and 25 points being assigned for a hurricane that is 150 kt. The exponential scale results in values being assigned based on the relationship of wind speed to the force exerted on an object where the intensity points fall into one of three cases.

Table 2: HSI Intensity Points Based on Wind Speed

Maximum Velocity (V_{max})	HSI Intensity Points Assigned
$V_{max} < 30$	0
$30 \leq V_{max} \leq 150$	$\left(\frac{V_{max}}{30}\right)^2$
$150 < V_{max}$	25

(Hebert et al., 2010)

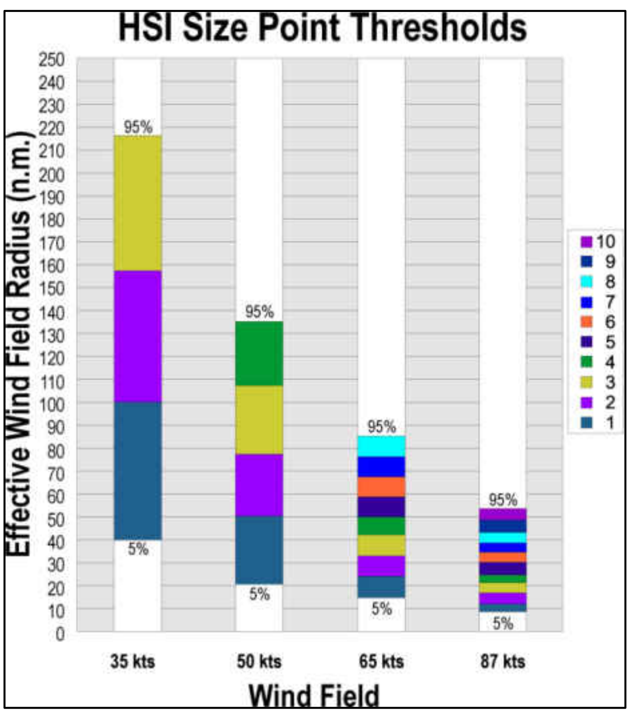
To determine the number of points to assign based on wind field size, Hebert et al. (2010) researched the three standard wind radii, 35, 50, and 65 kt. in the NHC database, and the 87 kt radii, which were not included in the NHC database, were estimated using a multiple regression equation

$$Re_{87estimated} = 0.5683Re_{65} + 0.0792V_{max} - 9.5383 \quad (1)$$

where Re_{65} is the known effective radius of the 65 knot wind field and V_{max} is the maximum sustained wind speed. For each storm from 1988 through 2005, the average coverage of the 35, 50, 65, and 87 kt. winds was calculated, which provided the baseline to classify each wind field as below average, average, or above average. The size point range for each of the four wind radii was determined with the minimum value for each wind radius being 1 point. The maximum size points were not linearly assigned as doubling the wind speed results in a wind force four times the initial force, so the stronger 65 and 87 kt. wind radii had a maximum size point range of 8 and 10 respectively whereas the 35 and 50 kt. wind radii had a maximum size point of 3 and 4 respectively. Next, the researchers standardized the wind radii of all the cyclones in the dataset by calculating an effective radius for each wind threshold. "The effective radius defines the radius of a circle that has the same areal coverage as the tropical cyclone's wind field" (Hebert et al., 2010, p. 2). To calculate the effective radius they used

$$Re = \frac{1}{2}\sqrt{RNE^2 + RSE^2 + RSW^2 + RNW^2} \quad (2)$$

where RNE represents the number of nautical miles that the wind radius of interest extends in the northeast quadrant, likewise RSE, RSW, RNW represents the wind radius of interest in the southeast, southwest, and northwest quadrants respectively. For example, when calculating the 65 kt. effective radius, if 65 kt. winds were only present in the northeast quadrant extending out 20 nautical miles then the values for RSE, RSW, and RNW would be 0 and RNE would be 20 for the effective radius calculation for the 65 kt. wind radius. The effective radius is calculated for each of the four wind radii. The HSI size points for each of the four wind radii are then assigned according to the following figure with the sum equaling the number of size points assigned.



(Hebert et al., 2010)

Figure 5: Hurricane Severity Index Size Point Thresholds

The total HSI is calculated by summing the points assigned for intensity and the points assigned for wind field size. The HSI utilizes wind field size in addition to the maximum sustained winds in their intensity/strength scale which results in a more complete measure when compared to the Saffir-Simpson Hurricane Scale that uses only maximum wind speed to quantify the hurricane. Hebert et al. (2010) claim that since the HSI uses the wind field size, it can be used to estimate a tropical cyclone's true destructive potential both at sea and at landfall.

2.3 Evacuation Studies

"The Federal Emergency Management Agency (FEMA) defines an evacuation as an organized, phased, and supervised dispersal of people from dangerous or potentially dangerous areas" (Federal Emergency Management Agency, 1996, p. 261). Evacuation has also been defined as "the mass physical movement of people, of a temporary nature, that collectively emerges in coping with community threats, damages, or disruptions (Quarantelli, 1980, p. 10)." The later definition requires the evacuation to involve a large number of people who are making a round-trip, and indicates that the behavior is complex and interactive as opposed to simple and individualistic (Quarantelli, 1980).

The evacuation outcome is dependent on the public response to the evacuation, with the number of households that evacuate, how promptly evacuees leave, the number of evacuees who seek refuge in public shelters, the number of evacuees who leave or attempt to leave the local area and where they go, and the number of vehicles used having the greatest impact on the evacuation

(Baker, 2006). It is important to note that during a mandatory evacuation, one cannot expect compliance from the entire populace.

Researching variations in evacuation response is a relatively recent interest dating back to the mid-1950s when Killian investigated evacuation response of residents after hurricane Florence made landfall in Panama City, Florida (Baker, 1991; Senkbeil, Brommer, Dixon, Brown & Sherman-Morris, 2010). Consistent with Perry's research, which found evacuation "literature was fairly small and widely scattered" (Perry, 1979, p. 26), when Quarantelli (1980) completed a review of the published evacuation studies, the study by Killian, a 1974 study by Hans and Sell, and a study completed by Strope et al. in 1977, were the only English language published studies on peacetime evacuation response. A first effort analytic model of evacuation behavior is presented in Quarantelli's (1980) paper with community context, defined as the area's resources and ability to deal with the emergency, threat conditions, social processes, defined as attempts at communication, decision making, and task manifestation, patterns of behavior, and consequences for preparedness being the major components included in the model.

Baker (1991) also completed a study involving the patterns of behavior, which involved analyzing principle studies documenting coastal resident's response during hurricane threats from twelve different hurricanes between 1961 and 1989. He found that "evacuation rates vary from place to place in the same hurricane and from storm to storm in the same place" (Baker, 1991, p. 66). Most of the studies Baker analyzed asked residents why they left or why they stayed. Common reasons cited for staying were respondents felt safe in their location, they wanted to protect their property from the storm and looters, or they needed to fulfill obligations to their employer, whereas those that evacuated said they did so because they felt the storm would or could strike their area or they evacuated based on the severity of the storm (Baker, 1991).

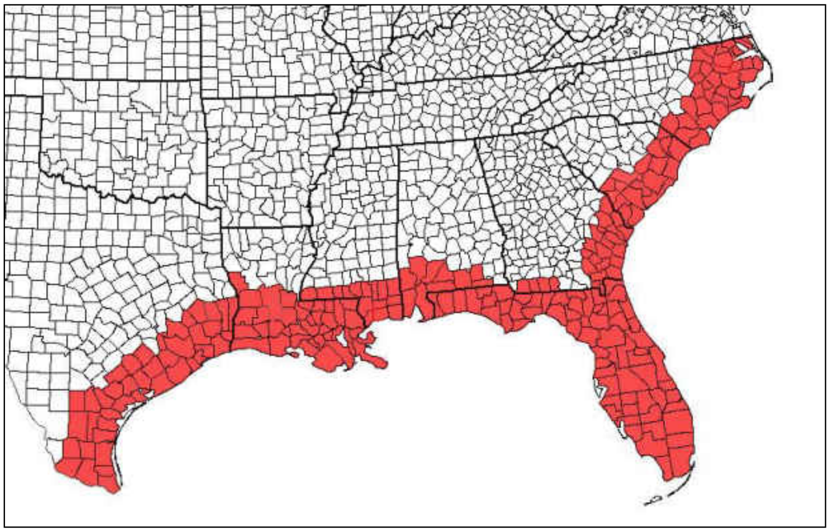
In the last 35 years, there have been numerous models and theories put forth to describe how evacuees approach a hurricane evacuation. For the purposes of this research, case studies and existing post-storm assessment surveys on some of the most recent hurricanes were used in an attempt to understand the evacuee decision-making process.

In the FEMA-Army Corps of Engineers post-storm assessments of hurricanes Charlie, Jeanne, and Frances, the sample populace interviewed was asked what made them decide to evacuate. The most frequent response was evacuation notices from public safety officials, with severity of the storm being the other most common response (U.S. Army Corps of Engineers, 2005a; U.S. Army Corps of Engineers, 2005b).

Evacuation orders as well as other official notices such as warnings and watches are related to evacuation (Gladwin & Peacock, 1997, Whitehead, Edwards, Van Willigen, Maiolo, & Wilson, 2001, Baker, 2006, Burnside, Miller, & Rivera, 2007, U.S. Army Corps of Engineers, 2005a, U.S. Army Corps of Engineers, 2005b). In addition to the decision to evacuate, residents must also decide when to evacuate, what to take with them, means of travel, what route they will take, and their destination (Ozbay & Yazici, 2006). Of the three types of possible evacuation orders (voluntary, recommended, and mandatory), a mandatory evacuation is most significant when determining resource needs as mandatory evacuations are given in areas where the most predicted devastation will occur (Wolshon, Urbina, & Levitan, 2001).

The Solis, Thomas, and Letson (2010) study involved a final dataset of 1,135 households from the southeast and northwest regions of Florida who completed an internet-based survey with a focus on the 2005 hurricane seasons direct impact on Florida. The study found the parameters experience, mobile homes, flood zones, home ownership, children, owning a pet, expenses, major storm, and geographical region were statistically different from zero at the .01 level of significance with experience, mobile homes, flood zones, children, and major storm all having a positive association with evacuation (Solis et al., 2010). Solis et al. also found that home ownership, owning a pet, expenses including storm preparation costs, and living in the southeast region of Florida all had significant negative associations with evacuation.

The Harvard School of Public Health (HSPH) *Project on the Public and Biological Security* study of high-risk hurricane areas included interview surveys, completed between July 5 and 11, 2006, by 2,029 non-institutionalized adults living in hurricane risk counties within 50 miles of the coast in Alabama, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, and Texas (Blendon, Benson, Buhr, Weldon, & Herrmann, 2006).



(Blendon et al., 2006)

Figure 6: Geographic area of the high-risk hurricane areas study

The surveys were conducted in an effort to determine the percentage of the populace that would not evacuate given an evacuation order for an impending hurricane. The weighted survey results were used to represent the total adult population in the region as a whole, with the margin of error for the total sample being plus or minus 4.4 percentage points (Blendon et al., 2006).

According to the study, the primary reason residents did not evacuate was their concern over safety and security (Blendon et al., 2006). Blendon et al. found that of the respondents that did not evacuate, 68% indicated that their home was well-built and they felt it was safer to remain in their homes, with 54% indicating that travel along congested roads was a factor in their decision, and the worries that their possessions would be stolen or damaged was stated as a reason to not evacuate by 31% of the respondents.

Based on results of the non-orthogonal regression study, the key demographic attributes associated with those who did not evacuate were age, race, and income (Blendon et al., 2006). A summary of findings for the study is listed in the following table.

Table 3: Attribute and Criteria Summary of the high-risk hurricane areas study

Attribute/ Measure	Did not Evacuate
Age	Majority of the elderly, greater than or equal to 65 years of age, were unable to evacuate; reasons cited include disabilities and required medical care.
Race	Contrary to images from Hurricane Katrina, 41% of whites were likely to stay in their home during a hurricane as opposed to 23% of African Americans with the top reason for not evacuating for both groups stated was they felt their homes would be safe. In addition, African Americans were more likely than whites to also cite lack of resources.
Income	Low income households cited lack of resources and transportation as a reason for not evacuating.

(Blendon et al., 2006)

Many studies have found the residents' previous evacuation experiences can also be linked to evacuation order compliance (Moore, Daniel, Linnan, Campbell, Benedict, & Meier, 2004; Aguirre, 1994; Dash & Gladwin, 2005; Riad, Norris, & Ruback, 1999). In a study, which involved residents who experienced two hurricanes in close succession, of those residents who evacuated for the first hurricane, 79.9% also evacuated for the second hurricane leaving 20.1% that did not evacuate for the second hurricane even though they chose to evacuate for the first one, interestingly, of those that did not evacuate for the first hurricane, only 9.3% decided to evacuate for the second one (Smith & McCarty, 2007).

The strength or category of the hurricane also affects evacuation decisions. In the studies involving hurricanes Frances and Jeanne, the strength of the storm was the principal reason given for not evacuating (U.S. Army Corps of Engineers, 2005a, U.S. Army Corps of Engineers, 2005b). The effect of the strength of the storm on evacuation rates was one of the factors considered in the evacuation rate planning assumptions for the hurricane evacuation behavioral analysis for the Maryland Western Shore study (Baker, 2006). As shown in Table 4, with an increase in the strength of the storm, evacuation rate planning assumptions for the study also increased.

Table 4: Evacuation rate planning assumptions for the study

Percentage of residents who live in other than a mobile home who will evacuate given the specific category of storm			
Residents home is located in the following Storm Surge Risk Zone	Cat 1 Storm is predicted to make landfall in the region	Cat 2 Storm is predicted to make landfall in the region	Cat 3 Storm is predicted to make landfall in the region
Non-surge Risk Zone	20%	25%	30%
Cat 2-4 Storm Surge Risk Zone	30%	40%	60%
Cat 1 Storm Surge Risk Zone	50%	55%	70%
Percentage of residents who live in a mobile home who will evacuate given the specific category of storm			
Residents mobile home is located in the following Storm Surge Risk Zone	Cat 1 Storm is predicted to make landfall in the region	Cat 2 Storm is predicted to make landfall in the region	Cat 3 Storm is predicted to make landfall in the region
Non-surge Risk Zone	50%	60%	65%
Cat 2-4 Storm Surge Risk Zone	60%	65%	75%
Cat 1 Storm Surge Risk Zone	65%	70%	80%

(Baker, 2006)

During a 1999 telephone survey of 895 North Carolina residents affected by Hurricane Bonnie in the previous year, participants were told that Bonnie was a category 3 hurricane and then asked questions concerning a hypothetical future hurricane with a randomly assigned hurricane storm intensity based on the Saffir-Simpson Hurricane Scale (Whitehead, Edwards, Van Willigen, Maiolo, Wilson, & Smith, 2000). (See Appendix E) The calculated probabilities of evacuation given each of the scenarios presented in the survey are included in the following table.

Table 5: Evacuation probabilities based on hurricane intensity and official notices

Saffir-Simpson Scale	Probability: Would evacuate given hurricane watch	Standard Error	Probability: Would evacuate given voluntary evacuation order	Standard Error	Probability: Would evacuate given mandatory evacuation order	Standard Error
1	0.03	0.012	0.03	0.013	0.38	0.068
2	0.04	0.016	0.05	0.018	0.45	0.070
3	0.10	0.016	0.11	0.019	0.64	0.036
4	0.18	0.046	0.20	0.051	0.76	0.057
5	0.48	0.072	0.51	0.074	0.94	0.022

(Whitehead et al., 2000)

When comparing the probability of evacuation given a hurricane watch versus a voluntary evacuation order, the greatest difference in probabilities was 0.03. However, when comparing evacuation probabilities between a voluntary and a mandatory evacuation order, the difference ranged between 0.35 for a category 1 and 0.56 for a category 4 hurricane. This would imply that the likelihood of residents evacuating is increased when a mandatory evacuation order is given.

2.3.1 Vulnerable and Special Needs Population

During a disaster, everyone is “at risk” however the degree of risk or vulnerability is not consistent across the population. For example, Gray-Graves, Turner, & Swan (2010) indicate that age does not necessarily make a person more vulnerable, instead it increases the likelihood of having special needs that can lead to increased frailty.

“Due to a number of reasons, including lack of financial resources for staying in a hotel or traveling great distances, low income evacuees are more likely to seek public shelter (Florida Division of Emergency Management, 2008, p. 11).” In a 1991 Florida Hurricane Evacuation Study, it was assumed that thirty-five percent of low income populations would seek public shelter if a serious hurricane was imminent (NOAA, 1991). “In fact, the Hurricane Andrew study found that lower income households are three times more likely to seek shelter within the area than persons from upper income households (Peacock & Gladwin, 1993).”

Although some studies have found age to be insignificant for evacuation (Zhang, Prater, & Lindell, 2004), those over age 60 may be less likely to evacuate according to Gladwin et al. (1997) , whereas Blendon and others (2006) use 65 years of age and older for a group of residents less likely to evacuate, and Van Willigen, Edwards, Lormand, and Wilson (2005) found that for each one year decrease in age, the odds of evacuation increased by two percent after Hurricane Floyd.

2.3.2 Tourists

Visitors to the area could be considered a special needs population. Based on interviews following five major disasters, Drabek (1999) found that most visitors or migrants (71%) prepared to leave immediately after receiving initial warnings through the media. Baker found no evidence that visitors are reluctant to leave when the area that they are staying is issued an evacuation order and stated that "it is reasonable to assume that 90% to 95% of vacationers will evacuate their accommodations if evacuation orders are issued (Florida Division of Emergency Management, n.d., p. 21)."

2.3.3 Animal Issues

When making an evacuation decision, household pets are often a contributing factor in the decision process with pet ownership resulting in a lower probability of evacuation (Whitehead 2003, Whitehead et al., 2000). The majority of United States households have pets with 37.2% of households owning at least one dog and 32.4% of households owning at least one cat, with an overall approximation of 57.4% of households having at least one pet (American Veterinary Medical Association, 2007). The inclusion of pets in any State or local government emergency evacuation plan is required by The Pets Evacuation and Transportation Standards Act (2006). This Act authorizes use of funds to "procure, construct, or renovate emergency shelter facilities and materials that will temporarily accommodate people with pets and service animals." In addition to the consideration of people seeking emergency shelter with their accompanying pets, there are issues involved with sheltering said pets including health and safety concerns of the occupants of the shelter, which should be addressed when creating a shelter plan.

2.4 Modeling Tools Used in Emergency Response

The use of modeling tools has been shown to be an effective method of preparing for an emergency response. Simulations and forecasting models are two examples of modeling tools often used for emergency response planning and preparation.

Simulations provide invaluable training for emergency responders of critical and dangerous incidents as they allow emergency responders to choreograph response efforts prior to being faced with the actual event resulting in the potential to save lives, resources, and property (Degnan, Jacobs, Tarr, & Gibbs, 1996). In general, simulator training is more beneficial than other forms of training in the areas of cost savings, safety, and instructional effectiveness (Kincaid, Donovan, & Pettit, 2003).

FEMA started the catastrophic planning initiative in an effort to improve response capabilities following a catastrophic event. Harvey Johnson testified before a congressional subcommittee stating "A well-constructed State catastrophic plan provides the critical foundation for development of an effective, integrated Federal-State response. Localized catastrophic planning provides essential knowledge for the development of the most effective preparedness and response efforts." Johnson's testimony is found on page 87 in Preparing for all Hazards: Are We Ready (2007).

The FEMA Catastrophic Disaster Planning Initiative utilizes capability analysis and quantitative requirements at State and local levels to identify shortfalls that must be filled with Federal resources. The three geographic areas for the initiative include the State of California, the New Madrid Seismic Zone, which includes eight states, and the State of Florida. The State of California and the New Madrid Seismic Zone both involve earthquake disasters, whereas the Florida Catastrophic Planning Initiative involves hurricane disaster. The focus of the initiative is to identify risk areas, response capabilities, evaluate loss estimates, and complete comprehensive planning strategies for dealing with shortfalls.

The Florida Catastrophic Planning Initiative utilizes a worst case scenario simulation known as "Hurricane Ono", which was developed by Subject Matter Experts (Florida Division of Emergency Management, 2008). Scenario-based resource planning uses a project scenario to establish the necessary common framework for defining required resources in context of a modeled or actual event, evaluation of capabilities across a region as well as throughout multiple levels of emergency management, and identification of potential resource shortfalls (Florida Division of Emergency Management, 2009a, p. 2).

The hypothetical catastrophic scenario involves Hurricane Ono, a Category 5 hurricane that makes landfall just north of Fort Lauderdale at approximately 11 a.m. on a Monday, September

10. The northwestwardly direction across the state causes tornadoes and storm surge on Lake Okeechobee, which results in a breaches of the Herbert Hoover Dike. Ono leaves land after 36 hours, entering the Gulf of Mexico where it regains strength and makes landfall a second time as a Category 4 hurricane in the Florida panhandle. The consequence projections that follow were derived from the scenario using scientific methods based on extensive research (Florida Division of Emergency Management, 2008).

Table 6 Hurricane Ono Consequence Projections

Identifiers	Number or percentage (First landfall N. of Fort Lauderdale)	Number or percentage (2nd landfall in panhandle)
Total Population	6,808,926	4,360,133
Percentage of population that are 65 or older	17.1%	20.4%
Percentage of population considered at or below poverty level	12.9%	12.6%
Number of households (Two different projections are used for the same identifier in the first landfall N. of Fort Lauderdale)	2,581,978 in table 12 and 2,569,572 in table 15	1,786,246
Number of households without a car	248,065, or 9.6%	126,311 or 7.1%
Renter occupied units	29.1%	24.4%
Number of homeless	14,346	25,047
Total number of evacuees	2,897,404 or 42.6%	1,166,247 or 26.7%
Evacuees remaining in county	1,513,625 or 52.2% of evacuees	659,875 or 56.6% of evacuees
Seeking public shelter	283,851 or 9.8%	174,937 or 4.0%
Non-evacuating population	3,911,522 or 57.4%	3,193,886 or 73.3%
Population remaining in the area (includes non-evacuating population and all evacuees who evacuate to a shelter in the area)	5,426,147 or 79.7%	3,853,761 or 88.4%
Amount of debris	75,852,149 cubic yards	1,291,665 cubic yards

Customers without electricity	88%	31%

(Florida Division of Emergency Management, 2008)

These projections are for a hypothetical catastrophic category 5 hurricane. They project 9.8% of the population evacuating to shelters and only 21.3% of the population leaving the area for the first landfall North of Fort Lauderdale. Based on the American Veterinary Medical Association's U.S. Pet Ownership and Demographics Sourcebook (2007), the projected percentage of households with pets should be around 57.4% but the Florida Division of Emergency Management (2008) state that 60-70% of U.S. households have pets and survey results from the 2004 storms showed 50-60% of residents in the evacuated areas had pets. The projection used in the scenario gives 1,002,133 households having dogs and 873,654 households owning cats but does not provide an unduplicated household count to determine the projected percentage of households being used in the scenario. The noted discrepancies are included to remind the reader of the intrinsic variability in these types of projections.

2.5 Command, Control, and Operation

Inherent in every emergency response is one or more emergency response plans that are monitored by a command, control, and operation center. At the center, a commander at the scene receives information, analyzes the data, often with the assistance of a support staff, and makes decisions. Motivated by the observation that emergency response organizations must be prepared to improvise during response activities, Mendonca, Beroggi, and Wallace (2001) proposed that new models must be developed and the traditional command and control structure of decision making must be revised to accommodate greater flexibility and creativity by teams.

> Improvisation is an essential element of the emergency response team as no two disasters are the same. Without improvisation, emergency management loses flexibility in the face of changing conditions. Without preparedness, emergency management loses clarity and efficiency in meeting essential disaster-related demands. Equally importantly, improvisation and preparedness go hand in hand. One need not worry that preparedness will decrease the ability to improvise. On the contrary, even a modest effort to prepare enhances the ability to improvise (Kreps, 1991, p. 33).

In an emergency response plan, the role of service organizations, as well as local, state, and federal responders cannot be overstated. "It is critical to note that nonprofit and faith-based organizations have an important role to play in planning for and responding to disasters. To reach their full potential, however, they must be able to access financial, physical, and human resources. This requires assistance from other nongovernmental organizations and governmental agencies" (Green, Kleiner, & Montgomery, 2007, p. 42).

2.5.1 Service Organizations: American Red Cross and Salvation Army

Founded in 1881, the American Red Cross offers humanitarian care to victims of natural disasters, guided by its Congressional Charter and led by the more than half a million volunteers and 35,000 employees working at the almost 700 locally supported chapters (American Red Cross, n.d.). "The relationship between the American Red Cross and the federal government is unique in that it is an independent entity that is organized and exists as a nonprofit, tax-exempt, charitable institution pursuant to a charter granted to it by the United States Congress" (American Red Cross Federal Charter, n.d.). The Federal Charter of the American Red Cross gives the organization a legal status of "a federal instrumentality", which requires it "to fulfill the provisions of the Geneva Conventions, provide family communications and other support to the U.S. military, and maintain a system of domestic and international disaster relief under the National Response Plan coordinated by FEMA" (American Red Cross Federal Charter, n.d.). .

During the 2008 hurricane season, eight named storms struck the U.S. coast. In response, the Red Cross provided relief by opening more than 1,000 shelters, serving more than 16 million meals and snacks to first responders and residents, offered 54,000 mental health contacts, distributed more than 232,000 clean-up and comfort kits, and partnered with more than 100 government representatives at the local, state, and federal emergency operation centers (American Red Cross, 2009).

Red Cross disaster relief focuses on meeting people's immediate emergency disaster-caused needs. When a disaster threatens or strikes, the Red Cross provides health and mental health services, shelter, and food to address basic human needs. In addition to these services, the core of Red Cross disaster relief is the assistance given to individuals and families affected by disaster to enable them to resume their normal daily activities independently (American Red Cross, n.d.). According to the American Red Cross, immediate physical needs people might have as a result of a disaster include a place to sleep, blankets to keep warm, food, water, first aid/medical supplies, clean-up supplies, toiletries, and baby supplies (American Red Cross of Central Florida, 2005).

Another service organization, the Salvation Army was formed in 1865 and participated in its first major disaster response on September 5, 1900 following a major hurricane in Galveston Texas (Salvation Army, n.d.). They are officially recognized across the country as a sanctioned disaster relief and assistance organization within the National Voluntary Organizations Active in Disaster (NVOAD). They work with federal, state and local authorities to provide assistance following a disaster and are included in the FEMA National Response Framework.

The Salvation Army's contributions include emergency preparedness, immediate emergency response, and long-term disaster recovery. Emergency preparedness includes disaster training and education as well as maintaining the internal infrastructure necessary to respond quickly in response to a disaster (Salvation Army, n.d.). To this end, they maintain a fleet of emergency response vehicles, which include mobile canteens and kitchen units as well as warehouse facilities used to stockpile food, water, and medical supplies.

Immediate emergency response services of the Salvation Army are coordinated with federal, state, and local governments in an effort to provide food and hydration services, emergency shelters, cleanup supplies, and emergency communications. During Hurricane Katrina, the Salvation Army served 5.6 million meals and assisted 2.5 million people (Salvation Army, n.d.).

Long-term disaster recovery is also part of the Salvation Army's mission through a coordinated effort with local, state, and federal entities, with activities including restoration and rebuilding, social services, and in-kind donations management.

As the Salvation Army is a faith based organization, they also provide spiritual and emotional support services for victims and emergency support workers upon request. (Salvation Army, n.d.).

2.5.2 Local and State Organizations

Local and state emergency responders include law enforcement, fire service, emergency medical services, emergency management, public works, and the National Guard. These organizations play a major role in any emergency response plan. Often referred to as first responders, the individuals in these organizations provide protection and preservation of life and property. They work together following applicable operational, resource, and communication policies.

2.5.3 Federal: Federal Emergency Management Agency (FEMA)

The Federal Emergency Management Agency (FEMA) became part of the US Department of Homeland Security (DHS) on March 1, 2003. "FEMA's mission is to support our citizens and first responders to ensure that as a nation we work together to build, sustain, and improve our capability to prepare for, protect against, respond to, recover from, and mitigate all hazards

(FEMA, 2010)." FEMA employs over 3,700 full time employees working at the headquarters in Washington D.C., regional and area offices, the Mount Weather Emergency Operations Center, and the National Emergency Training Center. FEMA partners with the American Red Cross, state emergency management offices, national emergency management organizations, federal level partners including the Federal Communications Commission, Commerce Department's National Weather Service, Department of Health and Human Services, the Department of Defense, and Veterans Administration, as well as public and private hospitals and the private sector.

FEMA has a recovery directorate that provides individual support, including emergency housing, financial assistance, and unemployment assistance, as well as assistance that helps states and communities with debris removal, restoration of public systems and facilities, and emergency protective measures. The Response Division provides the coordinated federal operational and logistical response capability in an effort to save lives, minimize suffering, and protect property (FEMA, 2010).

CHAPTER 3: METHODOLOGY

In this chapter, we select our area of interest and look at the census attributes identified in the literature review. We use the geospatial data for a visual representation of the demographic and geographic attributes. A description of the meal preparation and delivery process as well as initial assumptions necessary for the model are included.

3.1 Selection of Area of Interest

In general, the area of interest for this project is the State of Florida as the estimating tool is designed to be used at the state level. However, as the tool could be adapted for use at the county level, we identify a specific county to be used as an example.

If a hurricane makes landfall in Florida, the greatest impact will most likely occur in a coastal area given that Florida has 1,800 miles of coastlines (State of Florida, 2009). Daytona Beach, located in Volusia County, is a Central Florida coastal community that was selected as the area of interest at the county level. According to the 2000 Census, Daytona Beach was listed as one of the most populous metro areas with 493,000 rounded to the nearest thousand (State of Florida, 2009), with the city of Daytona Beach having an estimated population of 64,183 in 2006 (U.S. Census Bureau, n.d.).

3.2 Census Attribute Selection

After an exhaustive literature review was completed, the census attributes that were found to affect evacuation in the different studies were considered. The studies by Blendon et al. (2006) and Solis et al. (2010) were given strong consideration in our census attribute selection as these studies were both completed recently and both included Florida with the latter considering Florida exclusively. Additionally, the Florida Division of Emergency Management (2008) Hurricane Ono projections are considered a major source of information as the scenario is geographically located in Florida and involves category 4 and 5 hurricanes for which there is little actual data.

3.3 Geospatial Data

In 1962, Dr. Roger Tomlinson, known as the "father of GIS" developed the Canada Geographic Information System (CGIS), which was the world's first operational geographic information system (GIS) (Urban and Regional Information Systems Association, n.d.). A GIS can be used to store, analyze, and display land-related data by using geographic location to relate disparate data as well as collect and manage location-based information (O'Looney, 2000).

The "effectiveness of geospatial systems in support of public safety, emergency preparedness, and disaster response has, by now, been well established and well documented through its use following the 9/11 terrorist attack, the Shuttle disaster, hurricanes, western wildfires, and countless other regional and local disaster operations. Disaster management experts almost universally agree that robust information assets – especially those that are geospatially oriented and integrated – are essential for adequate disaster and emergency planning, mitigation, response, and recovery. In short, geospatial systems help save lives." (Public Technology Institute, 2006, p. 2)

> Currently, applications in the field of GIS that may be helpful in disaster response include spatial analysis to generate statistics on user-defined geographic regions, network analysis to calculate distances, routes, and network flow rates, automated mapping and facilities mapping to translate numerical data regarding locations and facilities into a visual display, geocoding and global positioning systems to identify a particular location given coordinates, database management systems to perform standard database manipulation capabilities, spatial decision support systems to analyze geographic data to support decisions, expert systems to apply rule based criteria to data for decision making, and automated spatial modeling to model how a process interacts with geographic constraints over time (O'Looney, 2000).

3.3.1 Geographic Visualization

In the following map, you will see the state of Florida divided into its 67 counties with the Emergency Operations Centers (EOC) displayed. These EOCs are the communications and command centers that agencies around the state would use in the event of a disaster.

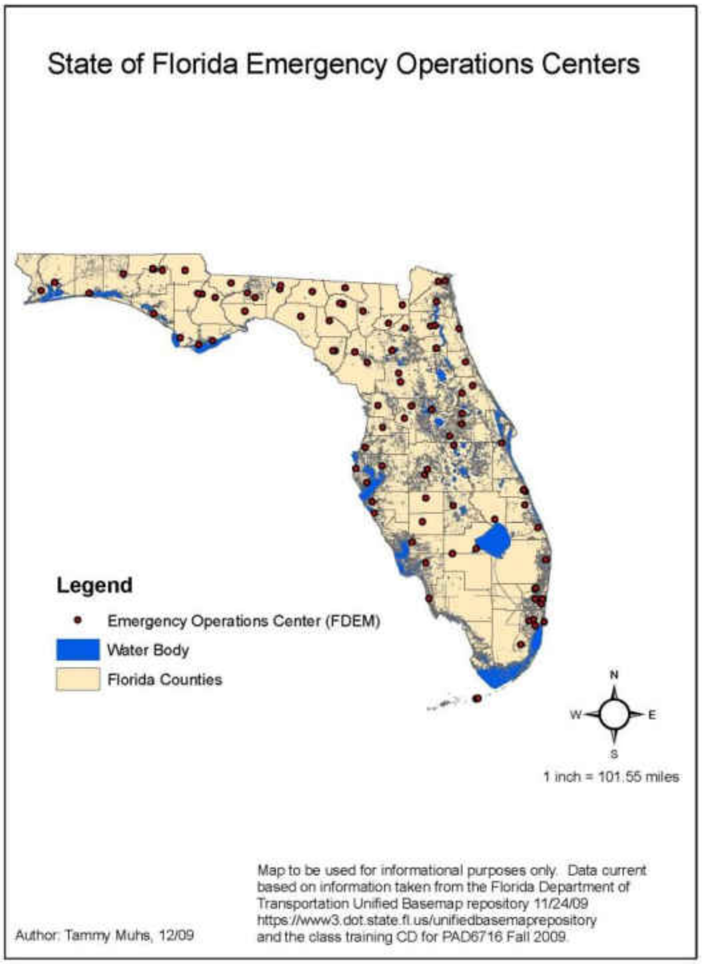


Figure 7: State of Florida Emergency Operations Centers

As our region of interest at the county level is Daytona Beach, the next map provides the reader with a visual display of its geographical location in regards to the state. The Central Florida region is represented in green.

Figure 8: Specific region of interest

3.3.2 Density Maps

In addition to showing where things are geographically located, it is often helpful to be able to represent the quantity associated with a particular feature within a specific geographic region.

For a single value, a graduated color scheme is effective. If the goal is to display multiple values of data for a given area, dot density maps should be considered. Dot density maps are created by selecting a value field, dot size, and number of units that the dot will represent. ArcMap reads the value, calculates the number of dots to display in the corresponding polygon, and then places them randomly within the polygon (Allen, 2009). When a mandatory evacuation is ordered for an area, dot density maps can be created to display the projected number of residents who will remain in the area based on key demographic attributes. A limitation of this feature is the random placement of the dots. The displayed dots should only be used as a general view of density, not as a data grouping, as the distribution is randomly generated. An advantage of this feature is that one set of data can be displayed on top of another symbolized layer.

According to Blendon et al. (2006), one of the key demographic attributes associated with those who did not evacuate when a mandatory evacuation was ordered was age, with residents greater than or equal to 65 years of age being less likely to evacuate and a second attribute was race with 41% of whites not evacuating compared to 23% of African Americans. ArcGIS 9.3 was used to create a map with a graduated color scheme representing the number of white residents per 90 square miles with a dot density layer overlay representing the number of residents who are 65 years or older in each county. This type of map allows the reader to quickly identify counties in which there is a high number of residents likely to remain in the area after a mandatory evacuation order is given based on residents age and race.

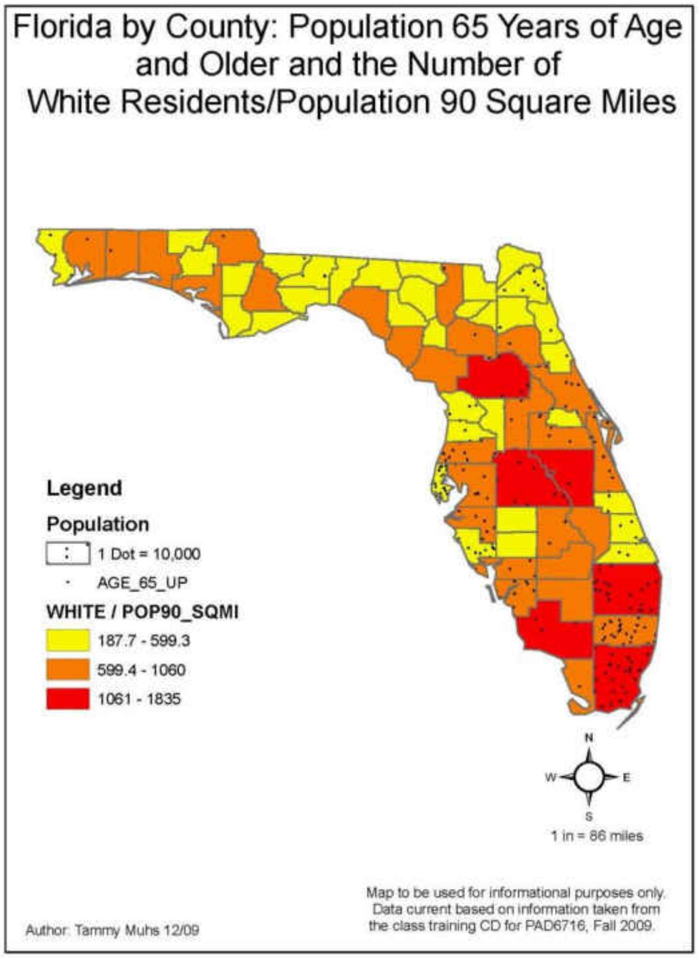


Figure 9: Population of at least 65 years of age and number of white residents

3.3.3 Network Analysis

When you have residents that do not follow a mandatory evacuation order, they often require some mass care assistance. In order to facilitate the delivery of mass care resources following a hurricane, network analysis can be completed to assist with the routing of Emergency Response Vehicles (ERV) and placement of food preparation kitchens.

A network is a collection of vertices and edges where there exists at least one weight for every edge. If the network is a transportation network, the weight is often the distance traveled to arrive at the next vertex. The distance traveled when traversing the network is referred to as the network distance. GIS procedures consider explicit and intrinsic attributes of the network when calculating the network distance. As such, results could differ in regard to network distance depending on the problem being considered.

In the following map, designated emergency shelters and roads, including streets and highways, are displayed for Volusia County. This map provides a visual display of the designated shelters throughout the county. The shelters are designed to provide mass care to evacuees who remain in the county or those who travel from another county seeking shelter. Any mass care resource distribution must consider the evacuees at the shelters as well as those residents who did not comply with the mandatory evacuation order by choosing to stay in their home.

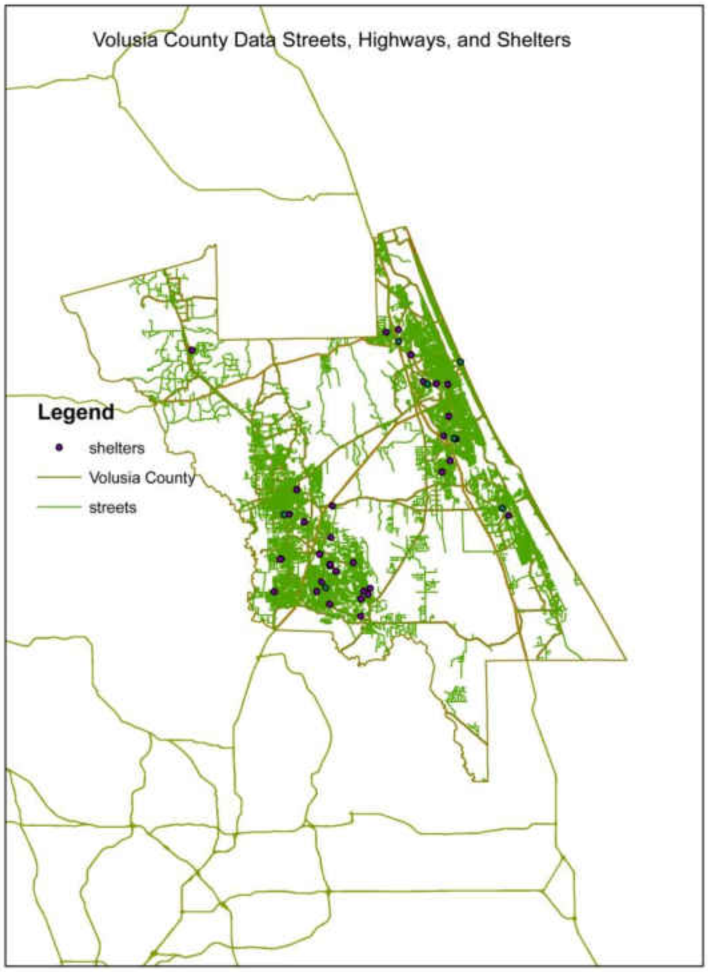


Figure 10: Overlay of Volusia county streets, highways, and emergency shelters

In the next map, the highway and street network was used to find all distances within ten miles of one of the designated shelters. The distances which are less than or equal to ten miles are shown in an aqua color. Using the road network provides a distance from the shelter along the network as opposed to creating a straight-line distance (radius) around the shelter. This method of calculating distance provides a more realistic representation of the data as it mitigates anomalies with the data including physical barriers such as structures and topography.

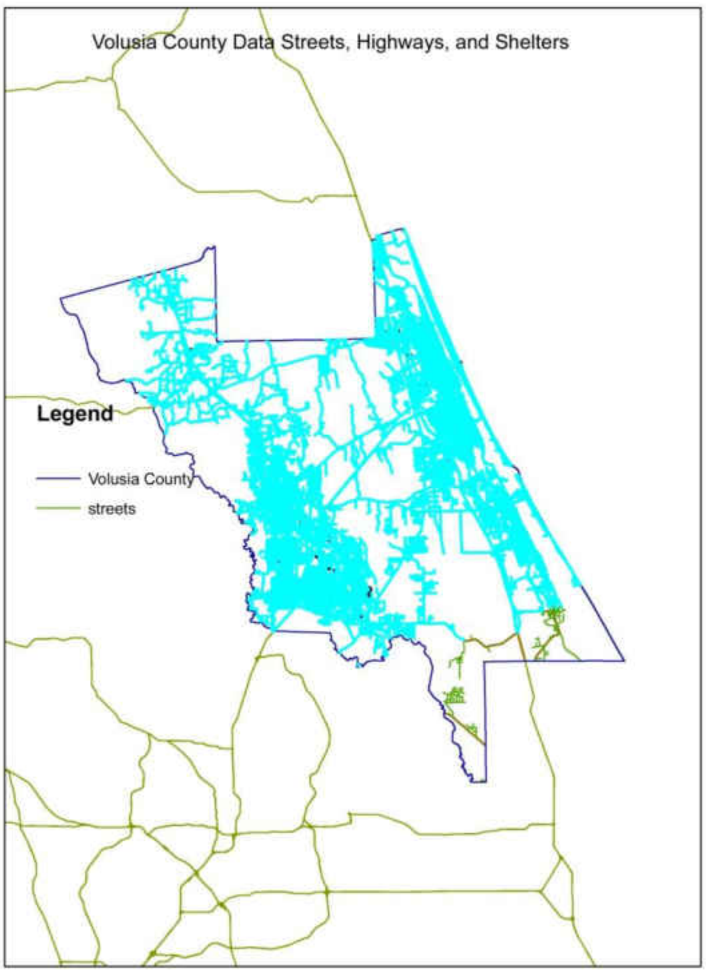


Figure 11: Volusia county streets and highways within 10 miles of a designated shelter

The highway and street network shown in green are greater than ten miles from the closest shelter whereas those streets shown in aqua are within ten miles of the closest shelter. This information can be used to identify areas that could be considered a remote location requiring special consideration in mass care provision.

3.3.4 Spatial Statistics

Spatial statistics involves the mathematical analysis of existing data to make predictions. Spatial statistics tools available in ArcGIS 9.3 include the average nearest neighbor (clustering by location), Getis-Ord General G (clustering by value), multidistance clustering, or Ripley's K function (clustering by location using multiple features and distances), spatial autocorrelation, or global Moran's I (clustering by both location and value), cluster/outlier analysis, or Anselin local Moran's I (clustering by location and similarities in magnitude), and Getis-Ord hot-spot analysis, of Gi* (clustering of high and low values).

According to Blendon et al. (2006), another key demographic attribute associated with mandatory evacuation compliance was low income households who often cited lack of resources and transportation as a reason for not evacuating. As such, spatial analysis was completed at the state level to determine the clusters of low and high rent areas in the major cities within the state. The following map shows the rental costs associated with the corresponding city compared to median rent for the state. It was created using the Gi* function of ArcGis 9.3. The Gi statistic uses both the local and the value, in our map the city is the local and the median rent is the value, in the pattern calculations. It is important to note that the rental prices of rural areas are not displayed on the map as city data was used in the analysis. Our area of interest, Volusia County is highlighted for identification purposes.

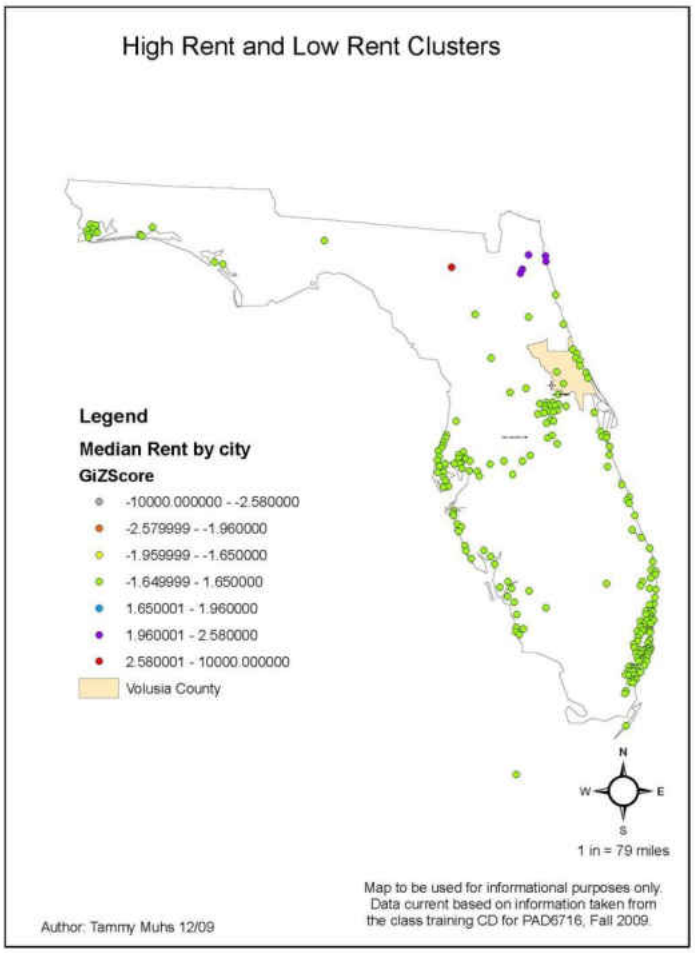


Figure 12: High rent and low rent clusters

3.4 Meal Preparation and Delivery

When a disaster occurs, Community Services workers must get meals and snacks quickly and efficiently to the people affected (American Red Cross of Central Florida, 2005). In a large scale disaster, where meals will be needed for a large number of people for more than three days, a kitchen is typically opened or the Red Cross works in partnership with other organizations who are equipped to prepare meals. Meals are provided until the majority of those affected can prepare meals for themselves.

Key tasks involved in the provision of meals by the Red Cross and other key service agencies include food preparation and cooking, preparing to serve or deliver the meals, and sanitation. In the preparation and cooking stage, supplies are delivered to the kitchen; ingredients are washed, chopped, and mixed for cooking. The main dishes and side items are cooked using industrial kitchen equipment. As one meal is completed, preparation for the next meal begins. In most cases, these tasks will be completed in a kitchen in a separate geographical location from the distribution site. For the delivering and/or serving stage, food is packed into insulated containers called Cambros and loaded into the emergency response vehicle (ERV). The ERV travels to the distribution site where the beverages, food, plates, utensils, and any other necessary supplies are laid out and then the food is served to the victims and emergency responders. The Cambros and other supplies are stowed in the ERV prior to leaving the distribution site in route to the sanitation site. At the sanitation site, the Cambros and other equipment are sanitized and restocked to prepare for the next replication.

The supplies and resources necessary for the meal preparation and delivery are determined by a resource spreadsheet that was previously developed by the State. The number of meals estimated by the tool resulting from this research can be used by the State in the same resource spreadsheet to produce the supplies and resources necessary to produce the needed number of meals.

3.5 Initial Model Assumptions

In the Xu and Brown (2008) article on hurricane simulation including frequency, intensity, and duration, for a typical year in the state of Florida, the intent was to determine the average effect of a large group of simulations instead of reproducing a particular hurricane. We take a similar approach in that we are not attempting to model a specific hurricane, instead the modeling tool is used to determine the average number of meals, and the amount of resources required for the provision of said meals, needed during the first fourteen days following a storm for a hurricane that falls into a group of storms based on storm specifics and a geographic area based on demographic specifics.

There are certain assumptions that need to be made when creating a modeling tool used for mass care resource provision post hurricane. As debris removal must take place prior to vehicular traffic entering the impacted area, it is assumed that mass care resources outside of the disaster area will be unable to enter the impacted area until day four. Debris removal will be a priority for routes to shelters and hospitals. Once mass care resource delivery vehicles are able to enter, they will receive priority of entry in an effort to begin the distribution of resources. Community shelter populations will be limited to no more than 5,000 persons per site. The model will estimate the resource needs for the first fourteen days following the storm making landfall.

CHAPTER 4: RESULTS

The selection of model type as well as the modeling process used to create the estimating tool is described in detail. The resulting tool is used to provide the estimated number of meals required for the first fourteen days following a hurricane, which is then used as input into the existing State tool for projecting the resources necessary to supply the required meals.

4.1 Selection of Model Type

In selecting the model type, strong consideration was given to the end users technical background. As a strong technical background for the end user could not be guaranteed, it was important that the model was able to be interpreted by a non-technical user. A decision tree model was selected as this type of model enables the user, either technical or non-technical, to see the "big picture" of what is happening with the data.

In modeling, supervised learning takes place when there are both a predictor variable(s) and a target variable to be used as inputs, and the process learns how to model or predict the target variable value based on the predictor variable(s). While "learning", the model uses the predictor (independent) variable(s) in different combinations to best predict the values of the target (dependent) variable. A decision tree is an example of supervised learning.

A decision tree is a prediction model that is structured as a tree where each internal node denotes a test on an attribute. Both of the outgoing branches provide an outcome of the test and each terminal leaf node gives the final outcome. A regression tree is a specific type of decision tree that uses a target variable that is continuous, as opposed to categorical, which gives a numeric value for the final outcomes as opposed to a classification.

The models produced by regression trees are represented by a tree-like structure. Depending on the number of predictor variables, there can be many rows in the tree. In each row, the node is either a terminal node or it will have two branches that create the next row. The mean value of the target variable is used as the predicted value of the target variable.

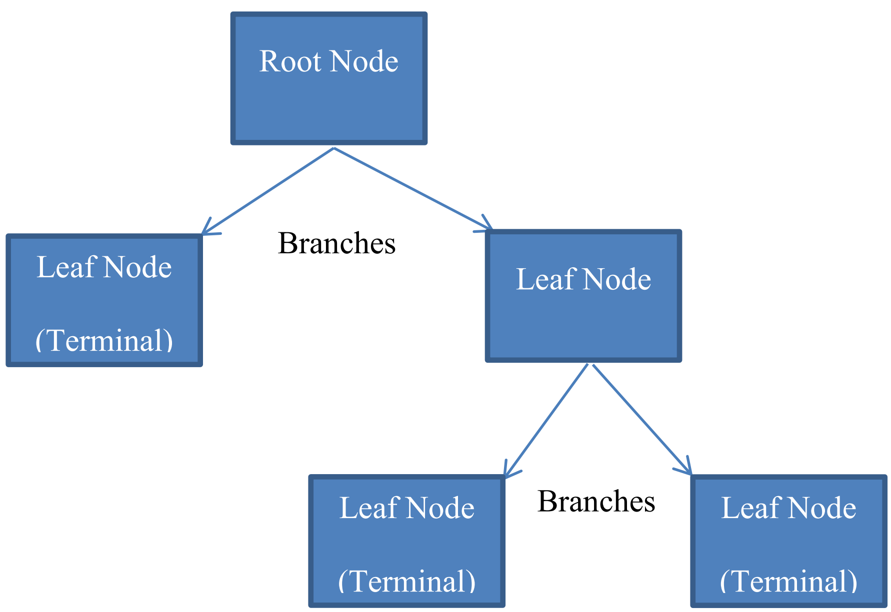


Figure 13: Decision Tree Structure

In a regression tree, the node typically contains the node number which allows you to map the node to the written report for analysis, the name of the predictor variable that was used to generate the split from the parent node as well as an inequality or equal sign that is used to determine the values that go into the node. The number of rows (N) that were placed in the node and the sum of the row weights (W) if different weights are used for respective rows are included in the node. If no weight variable was specified, the row number and weight will be the same often resulting in the weight being omitted from the node. The name and mean value of the target variable and the standard deviation for the mean target value are also shown in the node.

The general idea behind a decision tree is that the dataset is split based on homogeneity of data. The split can either be forced or it can be determined by the following method. First, a regression model is fit to the target variable using each of the predictor variable(s). The data are then split at several points for each predictor variable. The error between the predicted and actual value is calculated and squared at each split and the sum of these is called the Sum of Squared Errors (SSE). The lowest SSE from among all the splits is chosen as the split point. The process is a recursive one that ends when the split will no longer produce a valuable reduction in error.

The size of the tree is very important with a smaller or simpler tree typically being the preferred given that the two trees provide equivalent predictive accuracy. Additionally, for unseen data, smaller trees may provide greater predictive accuracy (Sherrod, 2011). The later reason is due to the process of selecting the optimal splits to fit the tree to the learning dataset. Generalization occurs when the tree fits not only the learning dataset, but also is able to predict the values of any future cases after the tree construction is complete. Generalization accuracy can be reduced if the tree is so large that it fits the learning dataset with extreme accuracy hence modeling noise in the data as opposed to only the significant data factors (Sherrod, 2011). A pruning process is used to generate the optimal sized tree that can be generalized.

One drawback of a decision tree model is that the model can be over-fit. When this happens, the training data error is considerably less than the validation error. Using v-fold cross validation helps eliminate over-fitting as the data are used as both training and validation data hence making v-fold cross validation the most reliable validation for this type of decision tree (Sherrod, 2011). In v-fold cross validation, the total number of cases are divided into v subsamples Z_1, Z_2, Z_3,…, Z_v of almost equal size. Of the v subsamples, one is retained as validation data and the $(v-1)$ subsamples are used for training data. This process is completed v times which results in each case being used as validation data one time and as training data $(v-1)$ times. The v results from this process can then be averaged to produce a single estimation.

4.2 Meal Count Data

State of Florida Mass Care Coordinator, Michael Whitehead, provided the meal count data from six hurricanes, Charley, Frances, Ivan, Jeanne, Dennis, and Wilma that were considered in the analysis. (See Appendices F through I) Hurricanes Charley, Frances, Ivan, and Wilma were selected for inclusion in the final model to be consistent with the previous State decision to exclude data from hurricanes Jeanne and Dennis in all estimations.

Although the meal counts provided are considered the official counts, the method by which the data were collected and reported by a variety of volunteers varied from storm to storm, county to county, facility to facility, and day to day. Therefore, variability between the true and reported number of meals served is to be expected. In future storms, it would be beneficial for a methodical approach to data collection to be in place before the emergency response.

When reviewing the data, it was noticed that some of the meals served were combined into a single number as opposed to the number being broken down to the county level. The idea of proportionally distributing the combined meal counts across the directly impacted counties based on their respective populations was investigated, but this was found to increase the variability in the data as these combined counts were not consistent in either origin or calculation. With the exception of the combined counts, all other data provided for the four storms were used, which resulted in 135 observations being included in the modeling process.

The recorded number of meals served in the county during the first fourteen days of the storm was divided by the population of the county to get a “meals per population” value to be used as the target variable value for each county during each storm.

4.3 Demographic Information

Demographic information was obtained from Census reports for each of the sixty-seven counties in Florida. Characteristics investigated were not limited to those identified as significant in previous evacuation studies. The following county characteristics were investigated. (See Appendices J through O)

- Population
- Housing units
- Age
- Gender
- Race
- Education
- Disability
- Mean travel time to work
- Homeownership
- Housing units in multi-unit structures
- Median value of owner-occupied housing units
- Households
- Persons per household
- Median household income
- Per capita money income
- Persons below poverty level

- Land area
- Persons per square mile
- Dense Urban Land Area designation

According to the evacuation and State studies, residents below the poverty level are more likely to utilize the mass care resources provided when compared to residents of a higher income level. As such, the poverty level of the county is a demographic used in the model. If a county has a proportion of residents below the poverty level that is higher than the state average, this is considered when estimating the number of meals needed. The proportion of residents over the age of 65 years was also investigated as a predictor variable but was eliminated as it increased the variance in the model.

4.4 Hurricane Path

Hurricane decision support software, Hurrevac 2010 version 1.0.492, is readily available to the State for use in emergency management. When using the meal estimating tool, the State will need to use Hurrevac when considering the hurricane path and entering wind field size information.

Hurrevac was used to create a map containing the date, time, maximum wind speed, Saffir-Simpson hurricane category, forward speed, and path for each of the four hurricanes used in the model. In the following maps, which were created using Hurrevac 2010 software, the counties that were included in the actual hurricane paths are easily identified. .

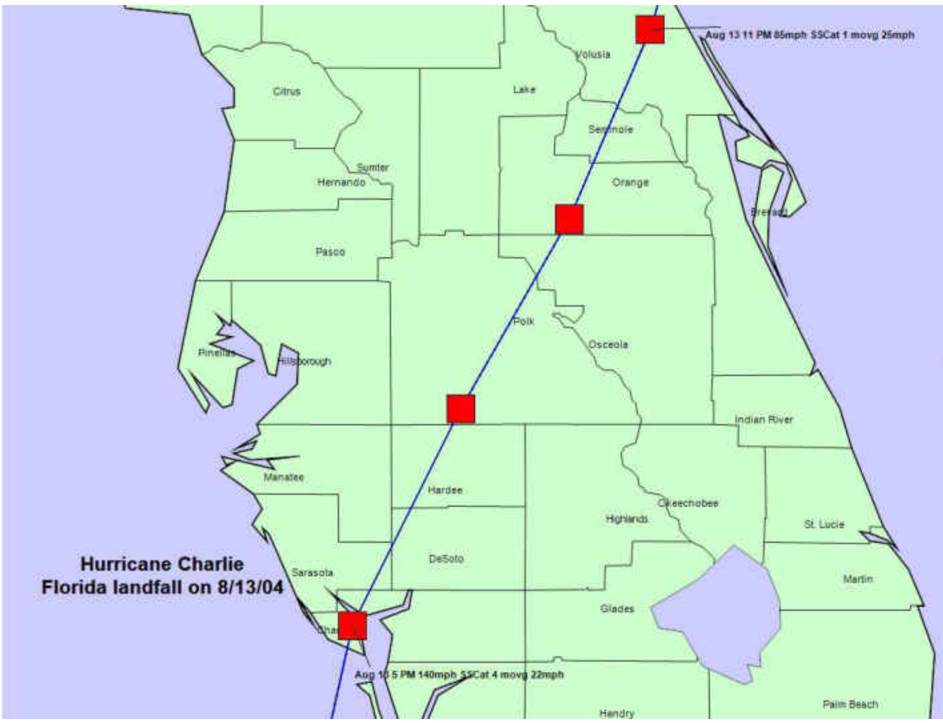


Figure 14: Path of Hurricane Charlie

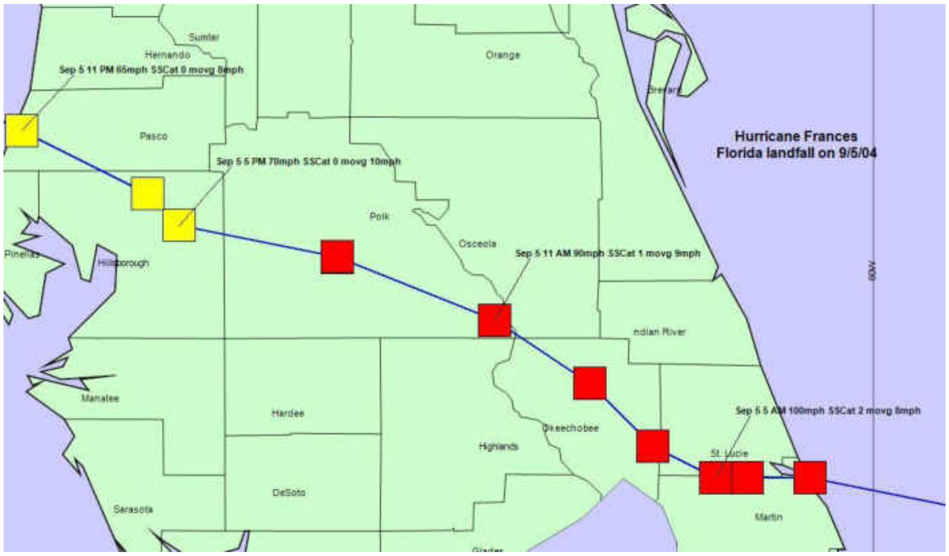


Figure 15: Path of Hurricane Frances

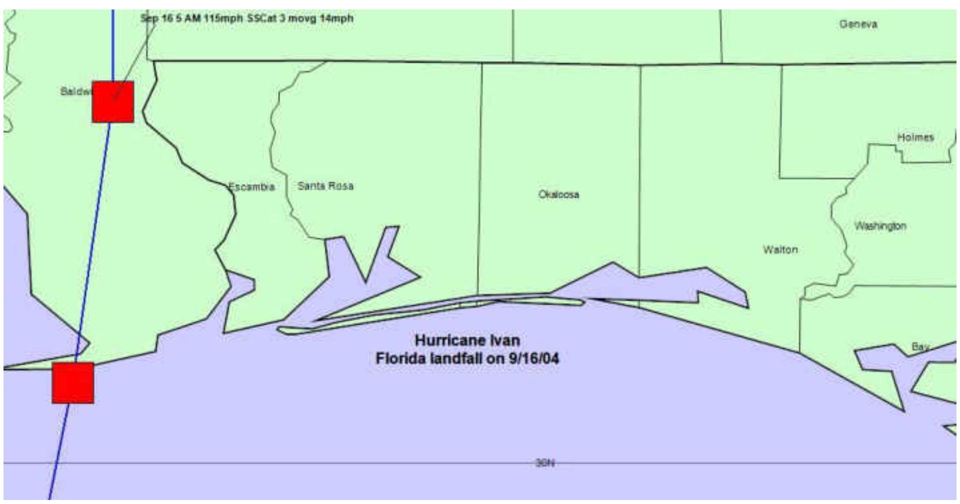


Figure 16: Path of Hurricane Ivan

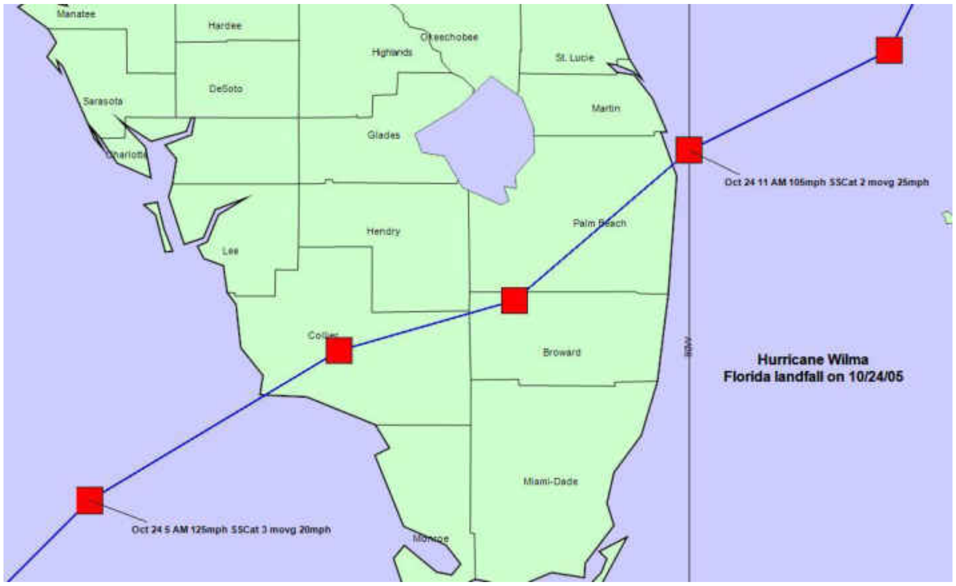


Figure 17: Path of Hurricane Wilma

Identifying the counties in the path of the hurricane is a key component of the model. Although hurricanes typically follow a curvature trajectory from origin to finish, it is reasonable to assume that the storm will travel along a straight path when making landfall in Florida due to the narrow shape (Xu & Brown, 2008). As such, the approach angle of the storm could be used to provide a straight path if the forecast models have paths involving different counties. Of course, this would not be the preferred method due to the curvature trajectory that is typically seen in a hurricane path and should be used as a last resort.

For the purposes of the model, regardless of path method, a county is considered directly impacted if the county is in the actual path or is adjacent to a county that is in the actual path of the hurricane. The path effect of the model is coded as a yes if the county is in the direct path or is in an adjacent county to the direct path, or a no if the county is not in the direct path or is not adjacent to a county that is in the direct path.

4.5 Hurricane Specifics

Hurricane specific information was collected for each of the four storms including the date of the storm, the Saffir-Simpson category of storm, maximum wind speed, hurricane intensity as defined by the HSI, hurricane size as defined by HSI, and the total hurricane severity index. These specific values are used in the model indirectly to calculate an overall score representing the expected impact of the hurricane.

Table 7: Hurricane Specific Characteristics

Name	Date of Storm	Saffir-Simpson Category	Maximum Wind Speed	Intensity (Based on HSI)	Size (Based on HSI)	Hurricane Severity Index
Charley	2004 Aug 9-14	4	130	19	4	23
Frances	2004 Aug 25-Sept 8	2	90	9	17	26
Ivan	2004 Sept 2-24	3	105	12	20	32
Wilma	2005 Oct 15-25	3	105	12	21	33

4.6 Hurricane Impact Score

For the model, a hurricane impact score was created for each storm in every county to quantify the expected impact the storm would have on the respective county. The hurricane impact score considers the category of the storm, the size and intensity of the storm based on the HSI, and where the storm makes landfall.

The hurricane impact score begins with the Saffir-Simpson hurricane scale category which is an integer between one and five. Added to the category number is the HSI effect, which is a value of one if the hurricane severity index for the storm is greater than the midpoint of the HSI range for that category of storm or a zero if it not greater than the midpoint. The following table gives the HSI range for each category of storm.

Table 8: Hurricane Severity Index Range

Saffir-Simpson Hurricane Scale	HSI Size		HSI Intensity		HSI Total		HSI Total
	Low	High	Low	High	Low	High	Midpoint
Category 1	3	15	5	7	8	22	15
Category 2	3	25	8	10	11	35	23
Category 3	4	25	11	13	15	38	26.5
Category 4	4	25	15	20	19	45	32
Category 5	4	25	22	25	26	50	38

(Hebert et al., 2010)

Finally, a value of one is added for the landfall effect if the storm makes landfall in the county or is adjacent to the landfall county, or a zero if it is not a landfall or adjacent to landfall county.

$$\text{Hurricane Impact Score} = \text{Category} + \text{HSI effect} + \text{Landfall effect} \qquad (3)$$

The hurricane impact score is used in the model to identify like counties in terms of the impact of the hurricane characteristics including category, intensity, size, and landfall, as opposed to considering the hurricane by category only which is the State's current method.

4.7 Decision Tree Model

The analysis for the model was completed using DTREG predictive modeling software, which is commercially available and capable of building regression decision trees. A dataset containing a row for each county reporting meals during each storm was created using Excel. There was a column for each of the predictive variables, direct impact, poverty level, and hurricane impact score as well as a column for the target variable, meals per population. The variables direct impact and poverty level were entered as yes or no, the hurricane impact score was the number of points such as "four points", and "meals per population" was entered as a number accurate to six decimal places.

DTREG gives the user several options when creating a model, however it requires certain inputs. Required inputs include the type of model to build which was selected to be a single decision tree and whether the model is a time series forecasting model or a predictive model. As the dataset is not a time series, the latter was selected. Next, the user is required to specify whether the variable is a target or predictor variable, a variable weight if desired, and whether the variable is categorical or not. The variable "meals per population" was selected as the continuous target variable. Direct impact and poverty level were selected as categorical predictor variables with both having the classification of yes or no. Although the impact score could be considered a variable with magnitude, in this model, it is used as a classification variable so it was also set as a categorical predictor variable.

After the variable information is entered, the validation method is selected. For this model, the validation type selected was v-fold cross validation with $v = 10$, where v represents the number of folds. For tree size controls, the minimum number of rows (cases) in a node was set to one, the minimum size of node to split was set to five, and the maximum tree level was set to ten. Pruning was allowed to the minimum cross-validated error.

After executing the program, a regression decision tree was formed. The results of the regression decision tree model are shown in the following figure.

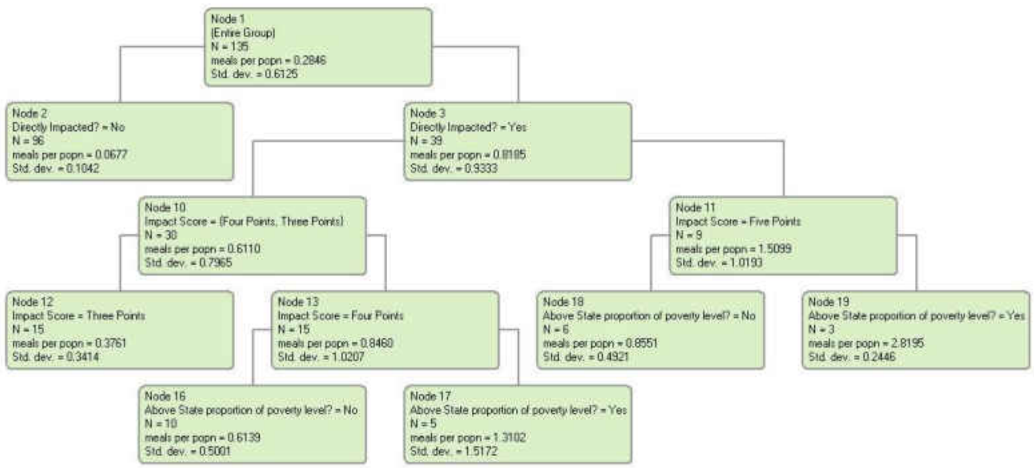


Figure 18: Regression Decision Tree

At the top of the tree is Node 1 that includes all 135 observations in the initial dataset with a mean number of meals per population stated as 0.2846 and a standard deviation of 0.6125. This means that 0.2846 times the number of residents in the counties under consideration will be the estimated number of meals that are needed on average for the first fourteen days following the storm.

After completing the process to determine the next split, the observations are split into two new nodes, not directly impacted and directly impacted where the mean number of meals per population is 0.0677 for those counties serving meals that are not in the direct path or adjacent to a direct path county (not directly impacted) and 0.8185 for those counties serving meals that are in the direct path or adjacent to a direct path county (directly impacted). Node 2, those counties that are not directly impacted, did not substantially benefit from a further division so this is considered a terminal node. This means that 0.0677 times the number of residents in a county that will be serving meals, but not directly impacted, can be used as an estimate of the number of meals needed for the first fourteen days of the storm for that particular county.

Node 3 benefits from an additional division and the split is made by grouping the counties that are in the direct path or adjacent to a direct path county into a node containing counties with a hurricane impact score of three points or four points having a mean meals per population value of 0.6110 being grouped into Node 10 and a separate node, Node 11, is used for counties with a hurricane impact score of five points which has a mean of 1.5099. Even though neither of these nodes are considered terminal nodes, the information contained is consistent with what we would expect as there appears to be a positive correlation between an increase in hurricane impact score and an increase in meals per population.

Node 10 is split further into Nodes 12 and 13 with Node 12 containing all counties directly impacted by a hurricane where the hurricane impact score is three points and Node 13 containing all counties directly impacted by a hurricane where the hurricane impact score is four points. Node 12 is a terminal node which will not be split further. If a county is directly impacted, and has a hurricane impact score of three points, an estimate of 0.3761 times the number of residents in the affected county can be used as an estimate of the number of meals needed during the first fourteen days following the storm.

Nodes 13 and 11 are split a final time into Nodes 16 and 17 for Node 13 and Nodes 18 and 19 for Node 11. Both of these splits are based on a higher or lower than average proportion of residents below the poverty level residing in the county when compared to the state average proportion of residents below the poverty level.

In the following table, the information contained in the regression decision tree model is summarized in tabular format.

Table 9: Regression Decision Tree Model Summary

Is the county considered a direct impact county?	Hurricane Impact Score of the storm	Is the county proportion of residents below the poverty level above the state proportion of residents below the poverty level?	Mean value of Meals per Population estimated by the model
No	Three Points, Four Points, or Five Points	No or Yes	0.0677
Yes	Three Points	No or Yes	0.3761
Yes	Four Points	No	0.5001
Yes	Four Points	Yes	1.3102
Yes	Five Points	No	0.8551
Yes	Five Points	Yes	2.8155

Importance scores are computed by using information about how variables were used as splitters. The importance score for the most important predictor is scaled to a value of 100.00 with all other predictors having some lower score. It is intuitive that a predictor used as a splitter either first or very early in the tree would have a higher importance score than one used later in the process. The following chart depicts the importance scores for the predictor variables direct impact, poverty, and hurricane impact score.

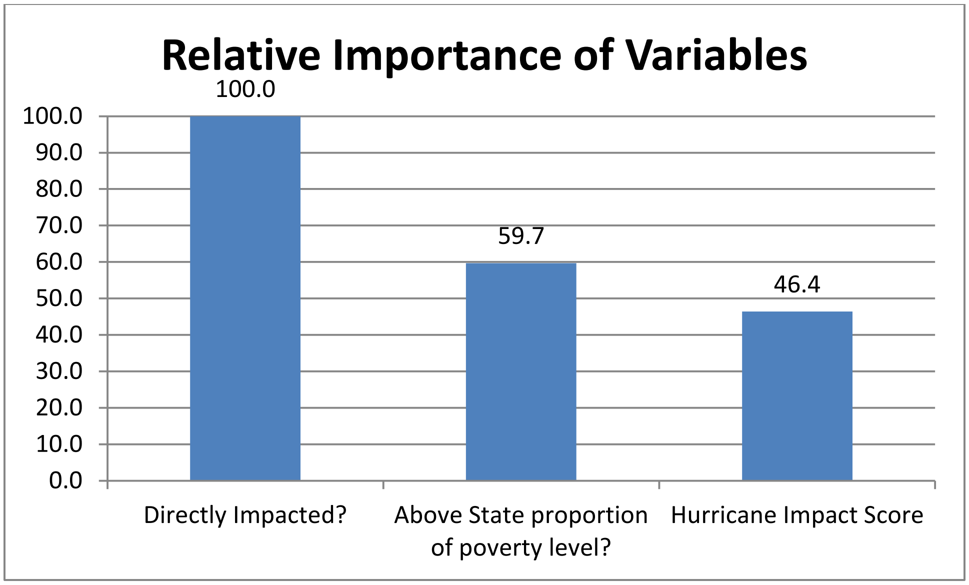


Figure 19: Relative Importance of Variables

4.8 Decision Tree Model Validation

Validation is an important component of any modeling process. The validation process for the model was completed by the software. “The variance explained by the generated tree is the best measure of how well the tree fits the data” (Sherrod, 2011). The following table provides a description of the information used or produced during the model validation.

Table 10: Validation Terms and Descriptions

Term	Description
Variance in initial data sample	This is the variance in the entire learning dataset before any splits have been made. The following algorithm is used to compute variance: (1) Compute the mean value of the target variable for all rows. (2) For each row, subtract the row's target value from the mean target value, square the difference and sum the squared differences. The difference between the target value of a row and the mean value of the target value is called the *residual* value for the row. The sum of the squared residuals is the *variance*.
Residual (unexplained) variance after tree fitting	This is the remaining variance after the tree is applied to the data to predict the target values. This is computed by (1) computing the mean value of the target variable for all rows in a terminal node; (2) use this mean to compute the residual for each row in the node; (3) add the residuals to compute the variance within the node; (4) add the variance for all nodes. If the tree perfectly predicted the dataset, the residual variance would be 0.0.
Proportion of variance explained (R^2)	This is the proportion of the initial, total variance explained by the fitted tree. The larger the value, the better the tree fits and explains the data. If the tree perfectly fitted the data and exactly predicted the target value for every row, the explained variance proportion would be 1.0 (100%).

(Sherrod, 2011)

The analysis of variance is calculated for both the training dataset and the validation dataset. The variance in the initial data sample was 0.3751821 with a residual variance of 0.1365356 after tree fitting in the training dataset and 0.15507 after tree fitting in the validation dataset. Typically, a proportion of explained variance (R^2) value of 0.50 or higher is acceptable for a single regression decision tree. Using the R^2 value as an indicator of fit, the training dataset has a value of 0.63608 (63.608%) and the validation dataset has a value of 0.58668 (58.668%), which provides support that the model is a good fit as they are both over 0.50 (50%).

4.9 Estimating Tool User Interface

The tool has an intuitive interface and is based on Excel software which is readily available to emergency response planners. There are several integrated parts for the tool. The first part is where storm data including the maximum wind speed and wind field information are entered into a worksheet that auto-calculates the HSI score for the storm. The HSI score is used in conjunction with the category of storm and the first impact information to calculate the hurricane impact score. In an effort to improve user interface, instead of entering information for all 67 counties, the user enters information only into cells that meet the specified criteria. For example, the user would enter a 1 for each of the counties that are in the direct path or are adjacent to a county in the direct path and leave the cells of the remaining counties blank. The counties adjacent to the direct path are easily identified by the county map pictures embedded in the tool. The user is also required to enter a 1 in the county cell if the county is considered the first impact (landfall) county or adjacent to the first impact county. Similar to the direct impact classification, the counties adjacent to the first impact county are also easily identified by viewing the county map pictures embedded in the tool. The poverty column is auto-populated by formulas embedded in the tool. The hurricane impact score is auto-populated by the integrated HSI calculation worksheet.

The final output is the total estimated meals required which is then input into the State resource tool to determine the resources necessary to have available to provide the estimated number of meals. Although the final output is a total at the state level, there is a column indicating an estimate for each county which can be used in emergency response planning and efforts.

CHAPTER 5: CONCLUSIONS

5.1 Summary

Just as no two geographical areas are identical, no two storms are identical either in structure or in after-storm response needs. If the estimated number of meals is higher than what is actually required, it is not fiscally efficient, however if the estimate is too low the end consequence could be that hurricane survivors would not have access to much needed mass care resources. Using an accurate tool when estimating meal needs can reduce waste while ensuring that the State is adequately prepared.

The State data were used to produce a regression decision tree model that can be used to estimate the average number of meals required during the first fourteen days following storm landfall. Storm specifics including the Saffir-Simpson Hurricane Scale storm category at landfall, the county of landfall, the hurricane path, maximum winds, and wind field radii were included when creating the model. These specifics, with the exception of the hurricane path, were combined into a single value referred to as the hurricane impact score.

The use of first impact counties in the calculation of the hurricane impact score with a first impact county having one additional point added to the hurricane impact score, results in the inclusion of consideration of the storm degradation which typically occurs while the storm is crossing over land into the model. The maximum sustained wind speed and the wind field size are included in the hurricane impact score as these are both used in the calculation of the HSI. Additionally, the Saffir-Simpson Hurricane Scale storm category is included in the hurricane impact score calculation. The use of a hurricane impact score to categorize a storm is a more inclusive description when compared to using the Saffir-Simpson Hurricane Scale storm category exclusively.

Although similarities in the different behavioral studies completed were noted, the actions of residents who are faced with the decision to evacuate involve past experiences as well as current conditions so the decision to evacuate cannot be predicted. The combination of past experiences and current conditions make the prediction of behavior extremely difficult. Poverty was consistently found to impact evacuation response, hence also impacting the mass care response efforts required. Using State data, it was shown that a higher proportion of residents below the poverty level increased the meals per population estimates for storms of greater impact.

Estimating the number of meals following a low impact hurricane is a limitation of the model. For example, a category one storm would not reach a hurricane impact score of three points, the lowest score in the model, unless its HSI was greater than the midpoint of the HSI scale for a category one storm and the county was a first impact county. Although the State data did not include any category one storms, nor did it include any category two storms which were below the midpoint of the HSI scale, these storms do exist. If a future storm has a hurricane impact score less than three points, 0.25 meals per population is a starting estimate that could be used as this estimate is often used by emergency planners and service organizations.

5.2 Future Research

According to Han, Guan, and Shi (2007), delivery of emergent material is an important problem that varies from a typical material supply problem due to:

1. The supply system which is established for a temporary situation in a rushed manner
2. Amount of materials to be delivered and the time critical needs of the recipients
3. Demand deadlines are critical

The routing used in the delivery of the resources (emergent material) is considered an NP Hard problem. A prototype simulation tool that can be used to simulate the delivery of meals to disaster survivors could be created. The results of the simulation could then be used to determine the feasibility of predetermined meal delivery routes in an effort to increase efficacy in the delivery process.

In addition to investigating possible effects from other demographics, other storm factors could be considered including tornadoes, storm surge, storm tide, rainfall and associated flooding. For example, there were 101 tornadoes associated with Frances of which twenty-three were in the state of Florida compared to sixteen tornadoes associated with Charley nine of which occurred in Florida. Also, the potential of a diminishing return of evacuation due to the effects of "crying wolf" is an area that could be investigated in future research.

Finally, in the model type selected, supervised learning takes place. Future work should include the addition of new data as it is collected so that the model can be refined. It is possible, that future storms will provide data involving hurricane impact scores less than three points and/or greater than five points. Including the data from these storms in the learning dataset would provide information to better estimate the needs following a low impact or catastrophic storm. If the future storm data involves hurricane impact scores between three points and five points inclusive, the new data will refine the model.

APPENDIX A: SAFFIR-SIMPSON HURRICANE SCALE

The Saffir-Simpson Hurricane Scale is a 1-5 rating based on the hurricane's present intensity. This is used to give an estimate of the potential property damage and flooding expected along the coast from a hurricane landfall. Wind speed is the determining factor in the scale, as storm surge values are highly dependent on the slope of the continental shelf and the shape of the coastline, in the landfall region. Note that all winds are using the U.S. 1-minute average.	
Category One Hurricane:	Winds 74-95 mph (64-82 ktor 119-153 km/hr). Storm surge generally 4-5 ft above normal. No real damage to building structures. Damage primarily to unanchored mobile homes, shrubbery, and trees. Some damage to poorly constructed signs. Also, some coastal road flooding and minor pier damage.
Category Two Hurricane:	Winds 96-110 mph (83-95 ktor 154-177 km/hr). Storm surge generally 6-8 feet above normal. Some roofing material, door, and window damage of buildings. Considerable damage to shrubbery and trees with some trees blown down. Considerable damage to mobile homes, poorly constructed signs, and piers. Coastal and low-lying escape routes flood 2-4 hours before arrival of the hurricane center. Small craft in unprotected anchorages break moorings.
Category Three Hurricane:	Winds 111-130 mph (96-113 kt or 178-209 km/hr). Storm surge generally 9-12 feet above normal. Some structural damage to small residences and utility buildings with a minor amount of curtain wall failures. Damage to shrubbery and trees with foliage blown off trees and large trees blown down. Mobile homes and poorly constructed signs are destroyed. Low-lying escape routes are cut by rising water 3-5 hours before arrival of the center of the hurricane. Flooding near the coast destroys smaller structures with larger structures damaged by battering from floating debris. Terrain continuously lower than 5 feet above mean sea level may be flooded inland 8 miles (13 km) or more. Evacuation of low-lying residences with several blocks of the shoreline may be required.
Category Four Hurricane:	Winds 131-155 mph (114-135 kt or 210-249 km/hr). Storm surge generally 13-18 feet above normal. More extensive curtain wall failures with some complete roof structure failures on small residences. Shrubs, trees, and all signs are blown down. Complete destruction of mobile homes. Extensive damage to doors and windows. Low-lying escape routes may be cut by rising water 3-5 hours before

	arrival of the center of the hurricane. Major damage to lower floors of structures near the shore. Terrain lower than 10 ft above sea level may be flooded requiring massive evacuation of residential areas as far inland as 6 miles (10 km).
Category Five Hurricane:	Winds greater than 155 mph (135 kt or 249 km/hr). Storm surge generally greater than 18 feet above normal. Complete roof failure on many residences and industrial buildings. Some complete building failures with small utility buildings blown over or away. All shrubs, trees, and signs blown down. Complete destruction of mobile homes. Severe and extensive window and door damage. Low-lying escape routes are cut by rising water 3-5 hours before arrival of the center of the hurricane. Major damage to lower floors of all structures located less than 15 feet above sea level and within 500 yards of the shoreline. Massive evacuation of residential areas on low ground within 5-10 miles (8-16 km) of the shoreline may be required.

(National Hurricane Center, n.d.)

APPENDIX B: SAFFIR-SIMPSON HURRICANE WIND SCALE

Category	The impact statements below were derived from recommendations provided by experts [Bruce Harper, Forrest Masters, Mark Powell, Tim Marshall, Tim Reinhold, and Peter Vickery]
Category One Hurricane (Sustained winds 74-95 mph, 64-82 kt, or 119-153 km/hr). *Very dangerous winds will produce some damage*	People, livestock, and pets struck by flying or falling debris could be injured or killed. Older (mainly pre-1994 construction) mobile homes could be destroyed, especially if they are not anchored properly as they tend to shift or roll off their foundations. Newer mobile homes that are anchored properly can sustain damage involving the removal of shingle or metal roof coverings, and loss of vinyl siding, as well as damage to carports, sunrooms, or lanais. Some poorly constructed frame homes can experience major damage, involving loss of the roof covering and damage to gable ends as well as the removal of porch coverings and awnings. Unprotected windows may break if struck by flying debris. Masonry chimneys can be toppled. Well-constructed frame homes could have damage to roof shingles, vinyl siding, soffit panels, and gutters. Failure of aluminum, screened-in, swimming pool enclosures can occur. Some apartment building and shopping center roof coverings could be partially removed. Industrial buildings can lose roofing and siding especially from windward corners, rakes, and eaves. Failures to overhead doors and unprotected windows will be common. Windows in high-rise buildings can be broken by flying debris. Falling and broken glass will pose a significant danger even after the storm. There will be occasional damage to commercial signage, fences, and canopies. Large branches of trees will snap and shallow rooted trees can be toppled. Extensive damage to power lines and poles will likely result in power outages that could last a few to several days. Hurricane Dolly (2008) is an example of a hurricane that brought Category 1 winds and impacts to South Padre Island, Texas.
Category Two Hurricane (Sustained winds 96-110 mph, 83-95 kt, or 154-177 km/hr). *Extremely dangerous winds will cause extensive damage*	There is a substantial risk of injury or death to people, livestock, and pets due to flying and falling debris. Older (mainly pre-1994 construction) mobile homes have a very high chance of being destroyed and the flying debris generated can shred nearby mobile homes. Newer mobile homes can also be destroyed. Poorly constructed frame homes have a high chance of having their roof structures removed especially if they are not anchored properly. Unprotected windows will have a high probability of being broken by flying debris. Well-constructed frame homes could sustain major roof and siding damage. Failure of aluminum, screened-in, swimming pool enclosures will be common. There will be a substantial percentage of roof and siding damage to apartment buildings and industrial buildings. Unreinforced masonry walls can collapse. Windows in high-rise buildings can be broken by

	flying debris. Falling and broken glass will pose a significant danger even after the storm. Commercial signage, fences, and canopies will be damaged and often destroyed. Many shallowly rooted trees will be snapped or uprooted and block numerous roads. Near-total power loss is expected with outages that could last from several days to weeks. Potable water could become scarce as filtration systems begin to fail. Hurricane Frances (2004) is an example of a hurricane that brought Category 2 winds and impacts to coastal portions of Port St. Lucie, Florida with Category 1 conditions experienced elsewhere in the city.
Category Three Hurricane (Sustained winds 111-130 mph, 96-113 kt, or 178-209 km/hr). *Devastating damage will occur*	There is a high risk of injury or death to people, livestock, and pets due to flying and falling debris. Nearly all older (pre-1994) mobile homes will be destroyed. Most newer mobile homes will sustain severe damage with potential for complete roof failure and wall collapse. Poorly constructed frame homes can be destroyed by the removal of the roof and exterior walls. Unprotected windows will be broken by flying debris. Well-built frame homes can experience major damage involving the removal of roof decking and gable ends. There will be a high percentage of roof covering and siding damage to apartment buildings and industrial buildings. Isolated structural damage to wood or steel framing can occur. Complete failure of older metal buildings is possible, and older unreinforced masonry buildings can collapse. Numerous windows will be blown out of high-rise buildings resulting in falling glass, which will pose a threat for days to weeks after the storm. Most commercial signage, fences, and canopies will be destroyed. Many trees will be snapped or uprooted, blocking numerous roads. Electricity and water will be unavailable for several days to a few weeks after the storm passes. Hurricane Ivan (2004) is an example of a hurricane that brought Category 3 winds and impacts to coastal portions of Gulf Shores, Alabama with Category 2 conditions experienced elsewhere in this city.
Category Four Hurricane (Sustained winds 131-155 mph, 114-135 kt, or 210-249 km/hr). *Catastrophic damage will occur*	There is a very high risk of injury or death to people, livestock, and pets due to flying and falling debris. Nearly all older (pre-1994) mobile homes will be destroyed. A high percentage of newer mobile homes also will be destroyed. Poorly constructed homes can sustain complete collapse of all walls as well as the loss of the roof structure. Well-built homes also can sustain severe damage with loss of most of the roof structure and/or some exterior walls. Extensive damage to roof coverings, windows, and doors will occur. Large amounts of windborne debris will be lofted into the air. Windborne debris damage will break most unprotected windows and penetrate some protected windows. There will be a high percentage of structural damage to the top

	floors of apartment buildings. Steel frames in older industrial buildings can collapse. There will be a high percentage of collapse to older unreinforced masonry buildings. Most windows will be blown out of high-rise buildings resulting in falling glass, which will pose a threat for days to weeks after the storm. Nearly all commercial signage, fences, and canopies will be destroyed. Most trees will be snapped or uprooted and power poles downed. Fallen trees and power poles will isolate residential areas. Power outages will last for weeks to possibly months. Long-term water shortages will increase human suffering. Most of the area will be uninhabitable for weeks or months. Hurricane Charley (2004) is an example of a hurricane that brought Category 4 winds and impacts to coastal portions of Punta Gorda, Florida with Category 3 conditions experienced elsewhere in the city.
Category Five Hurricane (Sustained winds greater than 155 mph, greater than 135 kt, or greater than 249 km/hr). *Catastrophic damage will occur*	People, livestock, and pets are at very high risk of injury or death from flying or falling debris, even if indoors in mobile homes or framed homes. Almost complete destruction of all mobile homes will occur, regardless of age or construction. A high percentage of frame homes will be destroyed, with total roof failure and wall collapse. Extensive damage to roof covers, windows, and doors will occur. Large amounts of windborne debris will be lofted into the air. Windborne debris damage will occur to nearly all unprotected windows and many protected windows. Significant damage to wood roof commercial buildings will occur due to loss of roof sheathing. Complete collapse of many older metal buildings can occur. Most unreinforced masonry walls will fail, which can lead to the collapse of the buildings. A high percentage of industrial buildings and low-rise apartment buildings will be destroyed. Nearly all windows will be blown out of high-rise buildings resulting in falling glass, which will pose a threat for days to weeks after the storm. Nearly all commercial signage, fences, and canopies will be destroyed. Nearly all trees will be snapped or uprooted and power poles downed. Fallen trees and power poles will isolate residential areas. Power outages will last for weeks to possibly months. Long-term water shortages will increase human suffering. Most of the area will be uninhabitable for weeks or months. Hurricane Andrew (1992) is an example of a hurricane that brought Category 5 winds and impacts to coastal portions of Cutler Ridge, Florida with Category 4 conditions experienced elsewhere in south Miami-Dade County.

(National Hurricane Center, n.d.)

APPENDIX C: COMMONLY USED NHC HURRICANE MODELS

The following table was taken from National Hurricane Center (2009).

"E" refers to early and "L" refers to late in the timeliness column. "Trk" refers to track and "Int" refers to intensity the parameters forecast column.

Name/Description	ATCF ID	Type	Timeliness (E/L)	Parameters
Official NHC forecast	OFCL			Trk, Int
NWS/Geophysical Fluid Dynamics Laboratory (GFDL) model	GFDL	Multi-layer regional dynamical	L	Trk, Int
NWS/Hurricane Weather Research and Forecasting Model (HWRF)	HWRF	Mutlti-layer regional dynamical	L	Trk, Int
NWS/Global Forecast System (GFS)	GFSO	Multi-layer global dynamical	L	Trk, Int
National Weather Service Global Ensemble Forecast System (GEFS)	AEMN	Consensus	L	Trk, Int
United Kingdom Met Office model, automated tracker (UKMET)	UKM	Multi-layer global dynamical	L	Trk, Int
UKMET with subjective quality control applied to the tracker	EGRR	Multi-layered global dynamical	L	Trk, Int

Navy Operational Global Prediction System (NOGAPS)	NGPS	Multi-layer global dynamical	L	Trk, Int
Navy version of GFDL	GFDN	Multi-layer regional dynamical	L	Trk, Int
Environment Canada Global Environmental Multiscale Model	CMC	Multi-level global dynamical	L	Trk, Int
European Center for Medium-range Weather Forecasting (ECMWF) Model	EMX	Multi-layer global dynamical	L	Trk, Int
Beta and advection model (shallow layer)	BAMS	Single-layer trajectory	E	Trk
Beta and advection model (medium layer)	BAMM	Single-layer trajectory	E	Trk
Beta and advection model (deep layer)	BAMD	Single-layer trajectory	E	Trk
Limited area barotropic model	LBAR	Single-layer regional dynamical	E	Trk
NHC98 (Atlantic)	A98E	Statistical-dynamical	E	Trk
NHC91 (Pacific)	P91E	Statistical-dynamical	E	Trk
CLIPER5 (Climatology and Persistence model)	CLP5	Statistical (baseline)	E	Trk
SHIFOR5 (Climatology and Persistence model)	SHF5	Statistical (baseline)	E	Int
Decay-SHIFOR5 (Climatology and Persistence model)	DSF5	Statistical (baseline)	E	Int

Statistical Hurricane Intensity Prediction Scheme (SHIPS)	SHIP	Statistical-dynamical	E	Int
SHIPS with inland decay	DSHP	Statistical-dynamical	E	Int
Logistic Growth Equation Model	LGEM	Statistical-dynamical	E	Int
Previous cycle OFCL, adjusted	OFCI	Interpolated	E	Trk, Int
Previous cycle GFDL, adjusted	GFDI	Interpolated-dynamical	E	Trk, Int
Previous cycle GFDL, adjusted using a variable intensity offset correction that is a function of forecast time. Note that for track, GHMI and GFDI are identical	GHMI	Interpolated-dynamical	E	Trk, Int
Previous cycle HWRF, adjusted	HWFI	Interpolated-dynamical	E	Trk, Int
Previous cycle GFS, adjusted	GFSI	Interpolated-dynamical	E	Trk, Int
Previous cycle UKM, adjusted	UKMI	Interpolated-dynamical	E	Trk, Int
Previous cycle EGRR, adjusted	EGRI	Interpolated-dynamical	E	Trk, Int
Previous cycle NGPS, adjusted	NGPI	Interpolated-dynamical	E	Trk, Int
Previous cycle GFDN, adjusted	GFNI	Interpolated-dynamical	E	Trk, Int
Previous cycle EMX, adjusted	EMXI	Interpolated-dynamical	E	Trk, Int
Average of GHMI, EGRI, NGPI, and GFSI	GUNA	Consensus	E	Trk

Version of GUNA corrected for model biases	CGUN	Corrected consensus	E	Trk
Previous cycle AEMN, adjusted	AEMI	Consensus	E	Trk, Int
Average of GHMI, EGRI, NGPI, HWFI, and GFSI	TCON	Consensus	E	Trk
Version of TCON corrected for model biases	TCCN	Corrected consensus	E	Trk
Average of at least 2 of GHMI, EGRI, NGPI, HWFI, GFSI, GFNI, EMXI	TVCN	Consensus	E	Trk
Version of TVCN corrected for model biases	TVCC	Corrected consensus	E	Trk
Average of LGEM, HWFI, GHMI, and DSHP	ICON	Consensus	E	Int
Average of at least 2 of DSHP, LGEM, GHMI, HWFI, and GFNI	IVCN	Consensus	E	Int
FSU Super-ensemble	FSSE	Corrected consensus	E	Trk, Int

APPENDIX D: HIGH-RISK AREA HURRICANE SURVEY

The following survey is taken from the study completed by Blendon et al., (2006).

The study was conducted for Harvard School of Public Health via telephone by **ICR**, an independent research company. Interviews were conducted from July 5 – July 11, 2006, among a representative sample of 2,029 respondents age 18 and older in the states of Texas, Louisiana, Mississippi, Alabama, Florida, Georgia, South Carolina, and North Carolina. Interviewing was conducted in all counties within fifty miles of the coastline for each of these states. The margin of error for total respondents is +/-4.4 percentage points at the 95% confidence level.

1. How worried are you that a major hurricane will hit your community during the next 6 months?

	Very	Somewhat	Not too	Not at all	Don't know	Refused
7/11/06 Total	22	32	27	18	1	*

2. Overall, how prepared are you if a major hurricane were to strike your community during the next 6 months?

	Very	Somewhat	Not too	Not at all	Don't know	Refused

7/11/06 Total	35	42	9	12	1	1

3. Compared to last year, are you more prepared for a major hurricane this year, less prepared, or is your preparation about the same?

	More prepared	Less prepared	Preparation about the same	Don't know	Refused
7/11/06 Total	38	2	59	1	*

4. I'm going to read you a list of things some people have in their homes that could be used in case of a hurricane emergency. For each one, please tell me if that is something you currently have or do not have.

7/11/06 TOTAL	Yes	No	Don't know	Refused
a. Enough food for three days for each member of your family	86	13	*	*
b. Enough water for three days for each member of your family	70	29	1	--
c. A battery operated radio that you know works	80	19	1	--
d. A flashlight that you know works	95	4	*	--

e. A first aid kit	77	23	*	--
f. Extra batteries	81	19	*	--
g. A cell phone	83	17	--	--
h. At least $300 in cash to take with you if you had to leave your home	58	40	1	*
i. Sterno for heating food	43	56	1	--

5. Do you or does anyone else in your household take prescription drugs on a regular or ongoing basis, or not?

	Yes, on a regular or ongoing basis	No, not on a regular or ongoing basis	Don't know	Refused
7/11/06 Total	59	41	*	*

(Asked of total who take Rx drugs regularly; n = 1429)

6. In the event of a major hurricane, do you and other household members have at least an extra three week supply of the prescription drugs you take regularly, or not?

	Yes	No	Don't know	Refused
7/11/06 Total	60	37	3	--

7. Are you, yourself now covered by any form of health insurance or health plan, or do you not have health insurance at this time?

	Yes, covered	No, not covered	Don't know	Refused
7/11/06 Total	77	23	*	*

8. Do you have homeowner's or renter's insurance or don't you have this insurance at this time?

	Yes, have homeowner's or renter's insurance	No, don't have at this time	Don't know	Refused
7/11/06 Total	74	24	2	*

9. Do you have or don't you have a social security number?

	Yes, have a SS #	No, don't have a SS#	Don't know	Refused
7/11/06 Total	95	5	*	*

10. If government officials said that you had to evacuate the area because there was going to be a major hurricane in the next few days, would you leave the area or would you stay?

	I would leave the area	I would stay	Depends	Don't know	Refused
7/11/06 Total	67	24	7	2	*

(Asked of total who would/might leave if there were an evacuation; n = 1502)

11. If you had to evacuate the area where you live because of a major hurricane, where would you go? Would you…?

	Stay with friends/family members in another area	Go to a hotel/ motel	Go to an evacuation center run by the Red Cross/ government	Sleep in a car or outdoors	Don't know where you would go	Refused
7/11/06 Total	56	18	12	1	11	1

(Asked of total who would/might leave if there were an evacuation and who would stay at an evacuation center; n = 110)

12. Do you know the location of the evacuation center where you would go?

	Yes	No	Don't know	Refused
7/11/06 Total	45	54	2	--

(Asked of total who would/might leave if there were an evacuation; n = 1502)

13. If you had to evacuate because of a major hurricane, how far away would you go?

	Less than 10 miles	10 to 50 miles	50 to 100 miles	100 to 200 miles	More than 200 miles	Don't know	Refused
7/11/06 Total	6	11	15	21	36	11	*

(Asked of total who would/might leave if there were an evacuation; n = 1502)

14. If you had to evacuate, how would you get to where you are going? Would you…?

	Go in your car	In a friend's car	Use public transportation	Walk or ride a bike	Don't know how you would evacuate	Refused
7/11/06	91	3	4	1	2	*

Total						

15. I'm going to read a list of documents that people sometimes take with them when they evacuate. For each one, please tell me if you would be able to take this document with you if you only had 6 hours until you had to leave. How about (INSERT)?

(Asked of total who would/might leave if there were an evacuation and they are covered by health insurance; n = 1296)

a. Proof of health insurance

	Yes, would be able to take with me	No, would not be able to take with me	Don't know	Refused
7/11/06 Total	98	1	1	--

(Asked of total who would/might leave if there were an evacuation and they or someone in their household take Rx drugs on a regular basis; n = 1055)

b. Proof of prescriptions for the drugs you and your family are taking

	Yes, would be able to take with me	No, would not be able to take with me	Don't know	Refused
7/11/06 Total	91	8	1	--

(Asked of total who would/might leave if there were an evacuation and they have homeowner's or renter's insurance; n = 1222)

c. Proof of homeowner's or renter's insurance

	Yes, would be able to take with me	No, would not be able to take with me	Don't know	Refused
7/11/06 Total	91	7	2	*

(Asked of total who would/might leave if there were an evacuation and they have a SS#; n = 1472)

d. Your social security card

	Yes, would be able to take with me	No, would not be able to take with me	Don't know	Refused
7/11/06 Total	96	4	*	--

(Asked of total who would/might leave if there were an evacuation; n = 1502)

16. If you had to evacuate because of a major hurricane, when would you return home? Would you…?

	Return to your home as soon as the hurricane is over	Wait until officials say it is safe to go back	Don't know	Refused
7/11/06 Total	20	79	2	*

(Asked of total who would/might stay in area if there were an evacuation; n = 669)

17. I'm going to read a list of reasons some people might have for not evacuating the area where they live if there were a major hurricane. For each one, please tell me if it is a reason why you (would not /might not) evacuate.

7/11/06 Total	Yes	No	Don't know	Refused
a. You don't know where to go	18	82	1	*
b. You don't have a car or know anyone who could give you a ride	12	88	*	*
c. You have medical or physical problems that would make it difficult to leave	12	87	1	--
d. You have to take care of someone who would be physically unable to leave	16	83	*	*

e. You would be worried your possessions would be stolen or damaged if you left	31	69	*	*
f. You would not want to leave your pet	18	79	3	*
g. You would not be able to afford to leave	17	82	1	--
h. You would not be able to leave your job	15	82	3	*
i. You think your home is well-built and you will be safe at home.	68	28	4	*
j. You think evacuating would be dangerous	36	61	3	*
k. You think the roads would be too crowded to leave	54	42	4	--

18. If a major hurricane were to hit your community and for whatever reason you did not leave your home, how confident are you that you would be rescued if you needed to be?

	Very	Somewhat	Not too	Not at all	Don't know	Refused
7/11/06 Total	31	35	16	14	4	*

19. Do you or any other household members have any pets in your home, such as dogs, cats, birds and the like?

	Yes, have pets	No, do not have pets	Don't know	Refused
7/11/06 Total	49	51	*	*

(Asked of total who have pets; n = 1100)

20. If you had to evacuate because of a hurricane, do you have a place you can go where you can take your pet, or not?

	Yes, have place to go and take pet	No, do not have a place to go and take pets	Don't know	Refused
7/11/06 Total	77	19	4	*

21. Has your family agreed on a phone number outside the region that all members of your immediate family could call in the event of a hurricane if you are unable to communicate, or haven't you done that?

	Yes, family has agreed on a phone number outside the region	No, haven't done that	Don't know	Refused
7/11/06 Total	50	49	1	*

22. Has your family agreed on a place you could meet after a hurricane is over if you got separated and could not go back home, or haven't you done that?

	Yes, family has agreed on a place to meet	No, haven't done that	Don't know	Refused
7/11/06 Total	35	63	2	*

23. During the past year, have you attended any meetings, classes, or workshops that taught you how to be better prepared in case of a hurricane, or not?

	Yes, have attended	No, have not attended any	Don't know	Refused
7/11/06 Total	13	87	*	--

24. If you had to go to an evacuation shelter because of a hurricane, how worried would you be about the conditions and your safety?

	Very	Somewhat	Not too	Not at all	Don't know	Refused
7/11/06 Total	35	32	16	14	2	1

25. I’m going to read a list of concerns people sometimes have about going to a hurricane evacuation center or shelter. If you had to go to a shelter because of a hurricane, please tell me how worried you would be about each one.

a. You wouldn’t have enough clean water to drink

	Very	Somewhat	Not too	Not at all	Don’t know	Refused
7/11/06 Total	46	24	15	14	1	1

b. You wouldn’t have enough food to eat

	Very	Somewhat	Not too	Not at all	Don’t know	Refused
7/11/06 Total	34	29	18	18	1	*

c. You wouldn’t have the prescription drugs or medicines that you need

	Very	Somewhat	Not too	Not at all	Don’t know	Refused
7/11/06 Total	30	17	16	37	1	*

d. You would be threatened by violence

	Very	Somewhat	Not too	Not at all	Don't know	Refused
7/11/06 Total	37	24	18	20	1	*

e. You would need medical care and wouldn't be able to get it

	Very	Somewhat	Not too	Not at all	Don't know	Refused
7/11/06 Total	43	23	16	17	1	1

f. The conditions of the shelter would be unsanitary

	Very	Somewhat	Not too	Not at all	Don't know	Refused
7/11/06 Total	53	26	10	10	1	*

g. You would be exposed to sick people and could catch their illness

	Very	Somewhat	Not too	Not at all	Don't know	Refused
7/11/06 Total	42	29	14	14	1	*

h. The shelter would be too crowded and you would not have any privacy

	Very	Somewhat	Not too	Not at all	Don't know	Refused
7/11/06 Total	43	24	17	15	*	*

i. You would have a hard time communicating with family outside of the shelter

	Very	Somewhat	Not too	Not at all	Don't know	Refused
7/11/06 Total	39	26	18	16	1	*

26. At any time in your life, did you leave your home because of a hurricane, or haven't you done this?

	Yes, did leave home	No, haven't done this	Don't know	Refused
7/11/06 Total	48	52	*	*

27. Thinking back over the past year was your community threatened or hit by a major hurricane, or not?

	Yes, community was threatened or hit by major hurricane	No, community was not threatened	Don't know	Refused
7/11/06 Total	62	37	1	--

(Asked of those whose community was threatened/hit by a major hurricane; n = 1208)

28. Was your community damaged by this hurricane, or not?

27/28. Combo Table

	Community threatened/hit by a major hurricane			Community has not been threatened/ hit by a major hurricane	Don't know	Refused
	NET	Yes, my community was damaged	No, my community was not damaged			
7/11/06 Total	62	45	17	37	1	--

(Asked of those whose community was threatened/hit by a major hurricane; n = 1208)

29. Because of this hurricane, did you leave your home where you lived, or did you stay in your home?

27/29. Combo Table

	Community threatened/hit by a major hurricane			Community has not been threatened/ hit by a major hurricane	Don't know	Refused
	NET	Left home	Stayed in home			
7/11/06 Total	62	27	34	37	1	--

(Asked of those whose community was threatened/hit by a major hurricane; n = 1208)

30. Most people say they get their information about various health issues and problems from TV, radio, or newspapers. Still thinking back to this hurricane that impacted your community last year, I am going to read you a list of OTHER places where you might have looked for information about the health problems that people may have had because of the hurricane. For each source, please tell me whether or not you contacted or looked at their website to try to get health information.

a. The CDC, or Centers for Disease Control and Prevention

	Contacted/looked at their website to try to get health information	Did not contact/look at website	Don't know	Refused

7/11/06 Total	6	94	*	*

b. The Red Cross

	Contacted/looked at their website to try to get health information	Did not contact/look at website	Don't know	Refused
7/11/06 Total	19	81	*	--

c. Other non-profit groups including church groups

	Contacted/looked at their website to try to get health information	Did not contact/look at website	Don't know	Refused
7/11/06 Total	18	82	*	*

d. Your state or local health department

	Contacted/looked at their website to try to get health information	Did not contact/look at website	Don't know	Refused

7/11/06 Total	10	89	*	*

e. Your doctor

	Contacted/looked at their website to try to get health information	Did not contact/look at website	Don't know	Refused
7/11/06 Total	10	89	1	*

f. Your local emergency services, like the fire department or police

	Contacted/looked at their website to try to get health information	Did not contact/look at website	Don't know	Refused
7/11/06 Total	15	85	*	*

31. Thinking about where your home is located, how likely is your home to be flooded or damaged due to wind in a major hurricane?

	Very	Somewhat	Not very	Not at all	Don't	Refused

	likely	likely	likely	likely	know	
7/11/06 Total	23	37	25	14	2	*

32. Is your home located in an evacuation zone or not, or don't you know if it is in an evacuation zone?

	Yes, located in an evacuation zone	No, not located in an evacuation zone	Don't know	Refused
7/11/06 Total	37	37	26	*

33. Next I have a question about your IMMEDIATE NEIGHBORS. These are the 10 or 20 households that live closest to you. If a major hurricane were to strike your neighborhood and you needed help, how much would you be able to rely on your immediate neighbors?

	A lot	Some	Not much	Not at all	Don't know	Refused
7/11/06 Total	44	29	12	12	2	*

34. Now thinking about your own health status… In general, would you say your health is…?

	Excellent	Very good	Good	Fair	Poor	Don’t know	Refused
7/11/06 Total	26	33	23	12	5	*	*

35. Do you or does anyone in your household have a chronic illness or disability that would require you to get help if you had to evacuate because of a major hurricane, or not?

	Yes, someone in household has a chronic illness or disability	No, no one in household	Don’t know	Refused
7/11/06 Total	14	85	1	*

(Asked of total who have or someone in HH has a chronic illness or disability; n = 349)

36. Do you have help lined up for this person with the chronic illness or disability if you need to evacuate because of a major hurricane or not?

	Yes, have help lined up	No, do not have help lined up	Don’t know	Refused
7/11/06 Total	57	40	3	--

37. Do you live in a home you or your family own, are you renting a house or apartment, or do you live somewhere else?

	Live in family owned home	Renting a house or apartment	Live somewhere else	Don't know	Refused
7/11/06 Total	73	24	2	*	*

38. Do you live in a single family home, a duplex or multi-family home, an apartment building or condominium, or a mobile home?

	Live in a single family home	A duplex or multi-family home	An apartment building or condominium	A mobile home	Don't know	Refused
7/11/06 Total	73	6	13	8	*	*

39. How long have you lived in your community?

	Less than 1	1-5	6-10	11-20	More than 20	Your whole	Don't	

	year	years	years	years	years	life	know	Refused
7/11/06 Total	9	32	16	15	18	10	--	*

Harvard School of Public Health Project on the Public and Biological Security

HIGH-RISK AREA HURRICANE SURVEY: July 5-11, 2006

N=2,029 adults in high hurricane risk counties of

Alabama, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, and Texas

Research Team:

Robert J. Blendon, Harvard School of Public Health, Project Director
John M. Benson, Harvard School of Public Health
Tami Buhr, Harvard School of Public Health
Kathleen J. Weldon, Harvard School of Public Health
Melissa J. Herrmann, ICR/International Communications Research

APPENDIX E: SURVEY STATED PREFERENCE QUESTIONS

The following instructions and questions were used in the Whitehead et al. (2000) survey.

Please consider the following information:

Hurricanes are rated on a scale of 1 to 5. Category 1 is a minimal hurricane, 2 is moderate, 3 is extensive, 4 is extreme, and 5 is a catastrophic hurricane. Bonnie was a category 3 (if asked: Fran was a 3, Bertha was a 2, and Hugo was a 4).

Suppose a category 1 hurricane is approaching North Carolina. The hurricane has winds between 74 and 95 miles per hour and a storm surge about 4 to 5 feet above normal (If asked: Storm surge is the rise in sea level during a hurricane).

1. If a Hurricane Watch is announced, would you evacuate your home to go someplace safer?

2. If you were given a voluntary evacuation order, would you evacuate your home to go someplace safer?

3. If you were given a mandatory evacuation order, would you evacuate your home to go someplace safer?

4. If a Hurricane Warning is announced would you evacuate your home to go someplace safer?

APPENDIX F: STATE DATA– MEAL COUNTS FOR HURRICANE CHARLEY

COUNTY	Directly Impacted?	Above State Proportion of Poverty Level?	Hurricane Impact Score	Meals Served	Population	Meals per Population
Charlotte	Yes	No	Five Points	277130	156281	1.7732802
Collier	No	No	Four Points	5000	295453	0.0169232
DeSoto	Yes	Yes	Five Points	103916	34240	3.0349299
Hardee	Yes	Yes	Four Points	106734	27657	3.8592038
Lafayette	No	Yes	Four Points	600	7438	0.0806668
Lee	Yes	No	Five Points	206990	512180	0.4041353
Manatee	Yes	No	Four Points	30217	294894	0.1024673
Orange	Yes	Yes	Four Points	78170	993478	0.0786832
Osceola	Yes	No	Four Points	98785	220191	0.4486332
Polk	Yes	Yes	Four Points	75078	521029	0.1440956
Sarasota	Yes	No	Five Points	139274	354095	0.3933238
Sumter	No	No	Four Points	1290	60069	0.0214753
Taylor	No	Yes	Four Points	3	19573	0.0001533
Volusia	Yes	No	Four Points	60782	476695	0.1275071

APPENDIX G: STATE DATA– MEAL COUNTS FOR HURRICANE FRANCES

COUNTY	Directly Impacted?	Above State Proportion of Poverty Level?	Hurricane Impact Score	Meals Served	Population	Meals per Population
Alachua	No	Yes	Three Points	6476	228346	0.0283605
Baker	No	Yes	Three Points	136	23789	0.0057169
Bay	No	No	Three Points	4592	157841	0.0290926
Bradford	No	Yes	Three Points	2412	27791	0.0867907
Brevard	Yes	No	Three Points	462989	515890	0.8974568
Broward	No	No	Three Points	42027	1741272	0.0241358
Calhoun	No	Yes	Three Points	621	13058	0.0475571
Charlotte	No	No	Three Points	62266	156281	0.3984234
Citrus	No	Yes	Three Points	11074	129208	0.0857068
Clay	No	No	Three Points	9474	162473	0.0583112
Collier	No	No	Three Points	13746	295453	0.0465252
Columbia	No	Yes	Three Points	6150	61457	0.10007
Dade	No	Yes	Three Points	69256	2381215	0.0290843
DeSoto	Yes	Yes	Three Points	39475	34240	1.1528914
Dixie	No	Yes	Three Points	6759	14199	0.4760194
Duval	No	No	Three Points	3741	821644	0.0045531
Escambia	No	Yes	Three Points	25921	301768	0.0858971
Flagler	No	No	Three Points	11484	68241	0.1682859
Gadsden	No	Yes	Three Points	355	45506	0.0078012
Gilchrist	No	Yes	Three Points	2560	15714	0.1629121
Glades	Yes	Yes	Three Points	2629	11123	0.2363571
Hamilton	No	Yes	Three Points	216	13894	0.0155463
Hardee	Yes	Yes	Three Points	19736	27657	0.7135987
Hendry	Yes	Yes	Three Points	11311	37221	0.3038876
Hernando	Yes	No	Three Points	111141	149114	0.7453425
Highlands	Yes	Yes	Three Points	20768	92752	0.2239089
Hillsborough	Yes	Yes	Three Points	51934	1099688	0.0472261
Holmes	No	Yes	Three Points	463	18819	0.0246028
Indian River	Yes	No	Four Points	146045	124105	1.1767858
Jackson	No	Yes	Three Points	70	47424	0.001476
Jefferson	No	Yes	Three Points	712	13723	0.0518837
Lafayette	No	Yes	Three Points	1478	7438	0.1987093
Lake	Yes	No	Three Points	41527	260829	0.1592116

Lee	No	No	Three Points	36087	512180	0.0704577
Leon	No	Yes	Three Points	10380	250863	0.0413772
Levy	No	Yes	Three Points	22471	36729	0.6118054
Liberty	No	Yes	Three Points	1076	7292	0.147559
Madison	No	Yes	Three Points	1316	18859	0.069781
Manatee	No	No	Three Points	13644	294894	0.0462675
Marion	No	Yes	Three Points	61843	289817	0.2133864
Martin	Yes	No	Four Points	235271	137009	1.7171938
Nassau	No	No	Three Points	767	62909	0.0121922
Okaloosa	No	No	Three Points	4840	182220	0.0265613
Okeechobee	Yes	Yes	Four Points	87597	38672	2.2651272
Orange	Yes	Yes	Three Points	81587	993478	0.0821226
Osceola	Yes	No	Three Points	30475	220191	0.1384026
Palm Beach	Yes	No	Three Points	144711	1240191	0.1166844
Pasco	Yes	No	Three Points	39628	404697	0.0979202
Pinellas	No	No	Three Points	23997	924605	0.0259538
Polk	Yes	Yes	Three Points	55247	521029	0.1060344
Putnam	No	Yes	Three Points	18662	72019	0.2591261
Santa Rosa	No	No	Three Points	2439	138284	0.0176376
Sarasota	No	No	Three Points	36109	354095	0.1019755
Seminole	No	No	Three Points	16579	392099	0.0422827
St. Johns	No	No	Three Points	6160	151916	0.0405487
St. Lucie	Yes	No	Four Points	176775	225240	0.7848295
Sumter	Yes	No	Three Points	37249	60069	0.6201035
Suwannee	No	Yes	Three Points	3508	37103	0.0945476
Taylor	No	Yes	Three Points	977	19573	0.0499157
Union	No	Yes	Three Points	1038	14086	0.0736902
Volusia	No	No	Three Points	187902	476695	0.3941766
Wakulla	No	No	Three Points	785	26691	0.0294107
Walton	No	Yes	Three Points	2254	47684	0.0472695
Washington	No	Yes	Three Points	1876	21651	0.0866473

APPENDIX H: STATE DATA– MEAL COUNTS FOR HURRICANE IVAN

COUNTY	Directly Impacted?	Above State Proportion of Poverty Level?	Hurricane Impact Score	Meals Served	Population	Meals per Population
Alachua	No	Yes	Four Points	900	228346	0.003941
Bay	No	No	Four Points	1278	157841	0.008097
Brevard	No	No	Four Points	1031	515890	0.001998
Charlotte	No	No	Four Points	2989	156281	0.019126
Clay	No	No	Four Points	924	162473	0.005687
DeSoto	No	Yes	Four Points	400	34240	0.011682
Dixie	No	Yes	Four Points	800	14199	0.056342
Duval	No	No	Four Points	135	821644	0.000164
Escambia	Yes	Yes	Five Points	889071	301768	2.946207
Flagler	No	No	Four Points	2380	68241	0.034876
Gilchrist	No	Yes	Four Points	425	15714	0.027046
Hardee	No	Yes	Four Points	500	27657	0.018079
Hernando	No	No	Four Points	368	149114	0.002468
Hillsborough	No	Yes	Four Points	2706	1099688	0.002461
Indian River	No	No	Four Points	2600	124105	0.020950
Lake	No	No	Four Points	1000	260829	0.003834
Lee	No	No	Four Points	1592	512180	0.003108
Levy	No	Yes	Four Points	494	36729	0.013450
Marion	No	Yes	Four Points	18	289817	0.000062
Martin	No	No	Four Points	15064	137009	0.109949
Nassau	No	No	Four Points	50	62909	0.000795
Okaloosa	No	No	Four Points	32089	182220	0.176100
Okeechobee	No	Yes	Four Points	7389	38672	0.191068
Orange	No	Yes	Four Points	435	993478	0.000438
Osceola	No	No	Four Points	693	220191	0.003147
Palm Beach	No	No	Four Points	9838	1240191	0.007933
Pasco	No	No	Four Points	236	404697	0.000583
Polk	No	Yes	Four Points	1350	521029	0.002591
Putnam	No	Yes	Four Points	805	72019	0.011178
Santa Rosa	Yes	No	Five Points	126799	138284	0.916946
Sarasota	No	No	Four Points	900	354095	0.002542
Seminole	No	No	Four Points	120	392099	0.000306
St. Johns	No	No	Four Points	5610	151916	0.036928

St. Lucie	No	No	Four Points	6903	225240	0.030647
Walton	No	Yes	Four Points	9482	47684	0.198851

APPENDIX I: STATE DATA– MEAL COUNTS FOR HURRICANE WILMA

COUNTY	County Code	Directly Impacted?	Above State Proportion of Poverty Level?	Hurricane Impact Score	Meals Served	Population
Bradford	27	No	Yes	Four Points	1313	28191
Brevard	44	No	No	Four Points	31535	526088
Broward	64	Yes	No	Four Points	536170	1766620
Collier	65	Yes	No	Five Points	158088	306640
Dade	67	Yes	Yes	Four Points	492412	2413583
DeSoto	53	No	Yes	Four Points	7879	34258
Glades	59	No	Yes	Four Points	1505	11270
Hendry	62	Yes	Yes	Five Points	95429	38521
Hernando	39	No	No	Four Points	308	156478
Highlands	54	No	Yes	Four Points	1890	95174
Indian River	56	No	No	Four Points	16958	126778
Lee	61	Yes	No	Four Points	58831	541542
Manatee	50	No	No	Four Points	5300	305054
Martin	58	Yes	No	Four Points	72916	138474
Monroe	66	Yes	No	Five Points	85823	76135
Okeechobee	55	No	Yes	Four Points	1507	39380
Palm Beach	63	Yes	No	Four Points	1064739	1262956
Pinellas	48	No	No	Four Points	94	924628
Sarasota	51	No	No	Four Points	7207	363146
Seminole	42	No	No	Four Points	364	402834
St. Lucie	57	No	No	Four Points	6477	237569
Volusia	37	No	No	Four Points	98	485940

APPENDIX J: CENSUS DATA– POPULATION AND HOUSING UNITS

COUNTY	Population July 1,2005 based on 2009 estimates	Population July 1,2004 based on 2009 estimates	Housing Units July 1,2005	Housing Units July 1,2004
Alachua County	231849	228346	104801	102847
Baker County	24382	23789	8364	8135
Bay County	161586	157841	89846	86100
Bradford County	28191	27791	10012	9907
Brevard County	526088	515890	252647	243959
Broward County	1766620	1741272	791742	783519
Calhoun County	13352	13058	5421	5373
Charlotte County	153407	156281	91698	88099
Citrus County	132947	129208	70493	67908
Clay County	168280	162473	65705	62608
Collier County	306640	295453	181226	174518
Columbia County	63916	61457	25180	24739
Miami-Dade County	2413583	2381215	929736	908201
DeSoto County	34258	34240	14306	14123
Dixie County	14600	14199	7723	7625
Duval County	830828	821644	367068	357921
Escambia County	302476	301768	134679	132182
Flagler County	75420	68241	42830	37766
Franklin County	10055	9981	8077	7831
Gadsden County	45863	45506	18383	18143
Gilchrist County	16217	15714	6385	6251
Glades County	11270	11123	6011	5936
Gulf County	15658	15364	8543	8356
Hamilton County	13762	13894	5183	5133
Hardee County	27846	27657	10263	10166
Hendry County	38521	37221	12797	12622
Hernando County	156478	149114	73188	70174
Highlands County	95174	92752	52179	51152
Hillsborough County	1132025	1099688	491228	478016
Holmes County	18882	18819	8280	8214
Indian River County	126778	124105	70531	66328
Jackson County	48460	47424	20441	20248
Jefferson County	13831	13723	5632	5535
Lafayette County	7868	7438	2800	2765

Lake County	275559	260829	128209	121996
Lee County	541542	512180	314359	294393
Leon County	253978	250863	116519	113682
Levy County	37357	36729	17576	17281
Liberty County	7577	7292	3259	3229
Madison County	18801	18859	8165	8080
Manatee County	305054	294894	161375	154831
Marion County	301714	289817	146351	140863
Martin County	138474	137009	73096	71660
Monroe County	76135	77901	53127	52711
Nassau County	64526	62909	30425	29134
Okaloosa County	183398	182220	87745	85124
Okeechobee County	39380	38672	16380	16133
Orange County	1029447	993478	423684	409671
Osceola County	231926	220191	102319	93474
Palm Beach County	1262956	1240191	619565	605748
Pasco County	425683	404697	204265	194993
Pinellas County	924628	924605	496232	492880
Polk County	538638	521029	258088	247736
Putnam County	72750	72019	35324	34975
Santa Rosa County	142364	138284	74920	70022
Sarasota County	363146	354095	117099	108210
Seminole County	402834	392099	56909	54904
St. Johns County	160508	151916	209283	201604
St. Lucie County	237569	225240	166016	162140
Sumter County	63405	60069	35962	31863
Suwannee County	38055	37103	16525	16269
Taylor County	19861	19573	9996	9887
Union County	14350	14086	3922	3876
Volusia County	485940	476695	237276	231018
Wakulla County	27799	26691	12093	11554
Walton County	49581	47684	37523	34971
Washington County	21822	21651	10024	9876
TOTALS (FL)	17783868	17375259	8277009	8027188

APPENDIX K: CENSUS DATA – AGE AND GENDER

COUNTY	Proportion of persons under 18 years old, 4/1/2000	Proportion of persons 65 years old and over, 4/1/2000	Proportion of female persons, 4/1/2000	Proportion of male persons, 4/1/2000
Alachua County	0.3041545273	0.0959739396	0.5118	0.4881971049
Baker County	0.3567994968	0.0920975785	0.47491	0.5250909744
Bay County	0.3087297678	0.1337026117	0.50474	0.4952603278
Bradford County	0.2871818461	0.1294081570	0.44051	0.5594909537
Brevard County	0.2811057682	0.1988135985	0.51035	0.4896499591
Broward County	0.2945685137	0.1608786840	0.51742	0.4825775192
Calhoun County	0.2996082047	0.1395098717	0.4604	0.5396020588
Charlotte County	0.2003149117	0.3471583808	0.52235	0.4776490358
Citrus County	0.2203497481	0.3218867765	0.51991	0.4800863785
Clay County	0.3569389407	0.0978027753	0.50761	0.4923871206
Collier County	0.2519045100	0.2447041694	0.49933	0.5006663299
Columbia County	0.3285261798	0.1399501000	0.49293	0.5070691699
Miami-Dade County	0.3169525495	0.1333715506	0.51677	0.4832323844
DeSoto County	0.3024309975	0.1897916731	0.43795	0.5620478748
Dixie County	0.2871917263	0.1713314530	0.46742	0.5325811817
Duval County	0.3330067957	0.1049623883	0.51497	0.4850316930
Escambia County	0.3174756292	0.1330423559	0.50347	0.4965286505
Flagler County	0.2293706855	0.2863421095	0.52065	0.4793506181
Franklin County	0.2602502798	0.1758062875	0.48988	0.5101231051
Gadsden County	0.3432474993	0.1216980504	0.5243	0.4757025307
Gilchrist County	0.3243748701	0.1363164092	0.4706	0.5294036157
Glades County	0.2815809380	0.1881618759	0.45149	0.5485060514
Gulf County	0.2553571429	0.1491071429	0.42672	0.5732829670
Hamilton County	0.3044195993	0.1118031065	0.42545	0.5745479103
Hardee County	0.3576360532	0.1392085530	0.45634	0.5436558022
Hendry County	0.3930405965	0.1005523336	0.44435	0.5556476112
Hernando County	0.2410360698	0.3085044571	0.52501	0.4749927371
Highlands County	0.2478653023	0.3300254103	0.5124	0.4876038734
Hillsborough County	0.3209976896	0.1197990286	0.51071	0.4892867296
Holmes County	0.2999353588	0.1480823098	0.46962	0.5303813833
Indian River County	0.2483288622	0.2919245310	0.5163	0.4837047465
Jackson County	0.2990482301	0.1455245428	0.47529	0.5247139343

Jefferson County	0.2962331421	0.1445512324	0.48992	0.5100759572
Lafayette County	0.2861008260	0.1237539163	0.40188	0.5981201937
Lake County	0.2544471730	0.2641086416	0.51614	0.4838619274
Lee County	0.2469765564	0.2542845348	0.5112	0.4887953403
Leon County	0.3155037335	0.0830688405	0.52335	0.4766466766
Levy County	0.3041219158	0.1791582003	0.51553	0.4844702467
Liberty County	0.2837202678	0.1019797750	0.40835	0.5916536106
Madison County	0.3327283404	0.1455186035	0.48166	0.5183366252
Manatee County	0.2600851509	0.2486609950	0.51686	0.4831364914
Marion County	0.2736176984	0.2452069397	0.51743	0.4825696365
Martin County	0.2347728654	0.2823776345	0.50926	0.4907402293
Monroe County	0.2174044152	0.1463518828	0.46753	0.5324730805
Nassau County	0.3165981652	0.1260253542	0.50674	0.4932625774
Okaloosa County	0.3178864268	0.1211509812	0.49466	0.5053431712
Okeechobee County	0.3306321359	0.1632971317	0.46408	0.5359231412
Orange County	0.3231817249	0.1003621378	0.50497	0.4950286943
Osceola County	0.3403384485	0.1142597091	0.5071	0.4929011612
Palm Beach County	0.2671485187	0.2316876637	0.51667	0.4833312853
Pasco County	0.2536604325	0.2680237145	0.5202	0.4797951086
Pinellas County	0.2440783726	0.2252481023	0.52364	0.4763596113
Polk County	0.3116377778	0.1833717691	0.5095	0.4905026409
Putnam County	0.3139457280	0.1847265808	0.50597	0.4940289394
Santa Rosa County	0.3371665407	0.1101721546	0.49841	0.5015924514
Sarasota County	0.2060675970	0.3147216998	0.52627	0.4737345879
Seminole County	0.3214904751	0.1063885717	0.51046	0.4895358421
St. Johns County	0.2949770577	0.1590043448	0.51424	0.4857595322
St. Lucie County	0.2857884221	0.2270583046	0.51156	0.4884350917
Sumter County	0.2068984910	0.2740275565	0.46927	0.5307339020
Suwannee County	0.3154345081	0.1694696361	0.51177	0.4882332683
Taylor County	0.3172517657	0.1406314915	0.48935	0.5106460324
Union County	0.2864901056	0.0746168725	0.3533	0.6467043595
Volusia County	0.2649506139	0.2206215052	0.51423	0.4857660998
Wakulla County	0.3311901325	0.1027861610	0.48231	0.5176923413
Walton County	0.2773084407	0.1583951134	0.4874	0.5125982119
Washington County	0.3006246126	0.1570113956	0.48586	0.5141372240
TOTALS (FL)	0.2915971545	0.1756667032	0.51211	0.4878942545

APPENDIX L: CENSUS DATA – RACE

COUNTY	Proportion of white persons, 4/1/2000	Proportion of black persons, 4/1/200	Proportion of other persons, 4/1/2000	Proportion of persons of Hispanic or Latino origin, 4/1/2000
Alachua County	0.7598999794	0.1988483861	0.0412516345	0.0573191714
Baker County	0.8494990790	0.1414708657	0.0090300553	0.0188238465
Bay County	0.8603061727	0.1101695487	0.0295242786	0.0242279900
Bradford County	0.7763722784	0.2114382091	0.0121895124	0.0238423796
Brevard County	0.8891040044	0.0885307519	0.0223652437	0.0461331709
Broward County	0.7483213372	0.2217369123	0.0299417505	0.1673746071
Calhoun County	0.8193132058	0.1605592686	0.0201275255	0.0377967274
Charlotte County	0.9401173505	0.0472861813	0.0125964682	0.0329527562
Citrus County	0.9621459118	0.0250074099	0.0128466782	0.0265994834
Clay County	0.8989731135	0.0718607525	0.0291661340	0.0430283921
Collier County	0.9332039128	0.0548896677	0.0119064194	0.1961038599
Columbia County	0.8121317219	0.1736414630	0.0142268151	0.0273565374
Miami-Dade County	0.7633938376	0.2164129668	0.0201931955	0.5732394347
DeSoto County	0.8459126331	0.1312676581	0.0228197088	0.2489676798
Dixie County	0.9000506256	0.0919216027	0.0080277718	0.0180082447
Duval County	0.6802943718	0.2851033344	0.0346022938	0.0410153567
Escambia County	0.7439387249	0.2194015149	0.0366597602	0.0269522095
Flagler County	0.8911542784	0.0926513084	0.0161944132	0.0509110612
Franklin County	0.8719096551	0.1196459457	0.0084443992	0.0244175399
Gadsden County	0.4182136758	0.5758200812	0.0059662430	0.0617029299
Gilchrist County	0.9214518252	0.0719678604	0.0065803145	0.0279836531
Glades County	0.8347201210	0.1078857791	0.0573940998	0.1507186082
Gulf County	0.7842719780	0.2048076923	0.0109203297	0.0204670330
Hamilton County	0.6088391986	0.3828318451	0.0083289563	0.0635551887
Hardee County	0.8960947361	0.0897616750	0.0141435890	0.3567822407
Hendry County	0.8320905827	0.1518641259	0.0160452914	0.3959127313
Hernando County	0.9454519044	0.0430803810	0.0114677146	0.0503585572
Highlands County	0.8848178925	0.0979671726	0.0172149349	0.1206647895
Hillsborough County	0.8117089178	0.1573054854	0.0309855968	0.1798812351
Holmes County	0.9173130791	0.0668498168	0.0158371041	0.0192846369
Indian River County	0.9033263389	0.0850930082	0.0115806529	0.0653492346
Jackson County	0.7170142231	0.2705165223	0.0124692546	0.0291091862
Jefferson County	0.6057975508	0.3859091614	0.0082932879	0.0224771353

Lafayette County	0.8417829678	0.1471090857	0.0111079465	0.0914269439
Lake County	0.9008155723	0.0854522223	0.0137322054	0.0560878177
Lee County	0.9159605160	0.0707163724	0.0133231115	0.0953575511
Leon County	0.6786036450	0.2968361091	0.0245602459	0.0351093330
Levy County	0.8783744557	0.1117561684	0.0098693759	0.0388679245
Liberty County	0.7900583962	0.1884346959	0.0215069078	0.0450078336
Madison County	0.5850637912	0.4079432018	0.0069930070	0.0320290397
Manatee County	0.9002053015	0.0857304111	0.0140642874	0.0929538413
Marion County	0.8669027793	0.1195484250	0.0135487957	0.0603129973
Martin County	0.9319976959	0.0558426904	0.0121596137	0.0750092716
Monroe County	0.9343879179	0.0512633655	0.0143487165	0.1577228009
Nassau County	0.9111388585	0.0784731977	0.0103879437	0.0151396910
Okaloosa County	0.8637227416	0.0976023179	0.0386749405	0.0428274818
Okeechobee County	0.9028125870	0.0819548872	0.0152325258	0.1861319967
Orange County	0.7599136046	0.1963877708	0.0436986246	0.1878307882
Osceola County	0.8797922235	0.0868614958	0.0333462807	0.2940814990
Palm Beach County	0.8297131077	0.1492771778	0.0210097145	0.1243600771
Pasco County	0.9617278866	0.0225397949	0.0157323185	0.0568585252
Pinellas County	0.8798712961	0.0931801041	0.0269485998	0.0464028562
Polk County	0.8429567453	0.1412577182	0.0157855366	0.0949177970
Putnam County	0.8157704159	0.1734518552	0.0107777289	0.0591852094
Santa Rosa County	0.9268151822	0.0450132917	0.0281715261	0.0252074433
Sarasota County	0.9442816779	0.0440911643	0.0116271579	0.0433855584
Seminole County	0.8658731267	0.1016596431	0.0324672302	0.1115309735
St. Johns County	0.9208592196	0.0647663134	0.0143744670	0.0263450684
St. Lucie County	0.8233373985	0.1622979320	0.0143646696	0.0816471626
Sumter County	0.8473333958	0.1406879745	0.0119786297	0.0629112382
Suwannee County	0.8659453564	0.1234358857	0.0106187579	0.0488749857
Taylor County	0.7914935604	0.1928230162	0.0156834233	0.0153199003
Union County	0.7552447552	0.2330010415	0.0117542032	0.0354857908
Volusia County	0.8879806380	0.0965189481	0.0155004139	0.0656624780
Wakulla County	0.8722389888	0.1181384770	0.0096225342	0.0193762848
Walton County	0.9063569863	0.0717470013	0.0218960124	0.0216743430
Washington County	0.8365517570	0.1404186335	0.0230296095	0.0230296095
TOTALS (FL)	0.8216594264	0.1544518040	0.0238887696	0.1678635140

APPENDIX M: CENSUS DATA – EDUCATION AND DISABILITY

COUNTY	Proportion of persons age 25 years or older who are high school graduates, 2000	Proportion of persons age 25 years or older who have earned a Bachelor's degree or higher, 2000	Number of persons age 5 years or older with a disability, 2000
Alachua County	0.881	0.387	32822
Baker County	0.719	0.082	4015
Bay County	0.81	0.177	29261
Bradford County	0.742	0.084	5260
Brevard County	0.863	0.236	97120
Broward County	0.82	0.245	310454
Calhoun County	0.691	0.077	2749
Charlotte County	0.821	0.176	33423
Citrus County	0.783	0.132	31729
Clay County	0.864	0.201	24107
Collier County	0.818	0.279	49125
Columbia County	0.747	0.109	13424
Miami-Dade County	0.679	0.217	473992
DeSoto County	0.635	0.084	6634
Dixie County	0.659	0.068	4016
Duval County	0.827	0.219	149290
Escambia County	0.821	0.21	57340
Flagler County	0.859	0.212	10410
Franklin County	0.683	0.124	2278
Gadsden County	0.707	0.129	10181
Gilchrist County	0.724	0.094	3072
Glades County	0.698	0.098	2547
Gulf County	0.726	0.101	3012
Hamilton County	0.629	0.073	2761
Hardee County	0.58	0.084	5655
Hendry County	0.542	0.082	7251
Hernando County	0.785	0.127	33524
Highlands County	0.745	0.136	22763
Hillsborough County	0.808	0.251	197799
Holmes County	0.652	0.088	4402
Indian River County	0.816	0.231	24462
Jackson County	0.691	0.128	10915
Jefferson County	0.732	0.169	2756

Lafayette County	0.682	0.072	1153
Lake County	0.798	0.166	49474
Lee County	0.823	0.211	90925
Leon County	0.891	0.417	31077
Levy County	0.739	0.106	8927
Liberty County	0.656	0.074	1494
Madison County	0.675	0.102	4620
Manatee County	0.814	0.208	56897
Marion County	0.782	0.137	62180
Martin County	0.853	0.263	25082
Monroe County	0.849	0.255	17536
Nassau County	0.81	0.189	10462
Okaloosa County	0.88	0.242	29071
Okeechobee County	0.651	0.089	8639
Orange County	0.818	0.261	165831
Osceola County	0.791	0.157	35044
Palm Beach County	0.836	0.277	224178
Pasco County	0.776	0.131	87787
Pinellas County	0.84	0.229	205955
Polk County	0.748	0.149	109479
Putnam County	0.704	0.094	19711
Santa Rosa County	0.854	0.229	22201
Sarasota County	0.871	0.274	68356
Seminole County	0.887	0.31	58390
St. Johns County	0.872	0.331	21474
St. Lucie County	0.777	0.151	45066
Sumter County	0.773	0.122	12552
Suwannee County	0.732	0.105	9095
Taylor County	0.7	0.089	4561
Union County	0.725	0.075	1934
Volusia County	0.82	0.176	97779
Wakulla County	0.784	0.157	4047
Walton County	0.76	0.162	10123
Washington County	0.712	0.092	4917
TOTALS (FL)	0.799	0.223	3274566

APPENDIX N: CENSUS DATA – HOUSEHOLDS AND INCOME

COUNTY	Number of households, 2000	Number of persons per household, 2000	Median household income, 2008
Alachua County	87509	2.34	42980
Baker County	7043	2.86	48443
Bay County	59597	2.43	45655
Bradford County	8497	2.58	41154
Brevard County	198195	2.35	49473
Broward County	654445	2.45	51594
Calhoun County	4468	2.53	33613
Charlotte County	63864	2.18	46378
Citrus County	52634	2.2	38476
Clay County	50243	2.77	61057
Collier County	102973	2.39	61379
Columbia County	20925	2.56	38816
Miami-Dade County	776774	2.84	43921
DeSoto County	10746	2.7	37478
Dixie County	5205	2.44	31443
Duval County	303747	2.51	50660
Escambia County	111049	2.45	41690
Flagler County	21294	2.32	49014
Franklin County	4096	2.28	34787
Gadsden County	15867	2.69	34316
Gilchrist County	5021	2.61	37120
Glades County	3852	2.51	39251
Gulf County	4931	2.42	38632
Hamilton County	4161	2.6	32444
Hardee County	8166	3.06	34385
Hendry County	10850	3.09	38771
Hernando County	55425	2.32	39552
Highlands County	37471	2.3	33703
Hillsborough County	391357	2.51	49762
Holmes County	6921	2.43	33251
Indian River County	49137	2.25	48267
Jackson County	16620	2.44	37707
Jefferson County	4695	2.53	36482
Lafayette County	2142	2.66	39293

Lake County	88413	2.34	45517
Lee County	188599	2.31	50863
Leon County	96521	2.34	47318
Levy County	13867	2.44	35267
Liberty County	2222	2.51	38608
Madison County	6629	2.57	32502
Manatee County	112460	2.29	46573
Marion County	106755	2.36	40266
Martin County	55288	2.23	52743
Monroe County	35086	2.23	52908
Nassau County	21980	2.59	59514
Okaloosa County	66269	2.49	54420
Okeechobee County	12593	2.69	35724
Orange County	336286	2.61	50674
Osceola County	60977	2.79	45766
Palm Beach County	474175	2.34	52807
Pasco County	147566	2.3	42407
Pinellas County	414968	2.17	45899
Polk County	187233	2.52	44350
Putnam County	27839	2.48	35168
Santa Rosa County	43793	2.63	54174
Sarasota County	149937	2.13	49001
Seminole County	139572	2.59	58175
St. Johns County	49614	2.44	67238
St. Lucie County	76933	2.47	44788
Sumter County	20779	2.27	48106
Suwannee County	13460	2.54	34427
Taylor County	7176	2.51	36349
Union County	3367	2.76	42734
Volusia County	184723	2.32	45831
Wakulla County	8450	2.57	48012
Walton County	16548	2.35	43779
Washington County	7931	2.46	34632
TOTALS (FL)	6337929	2.46	47802

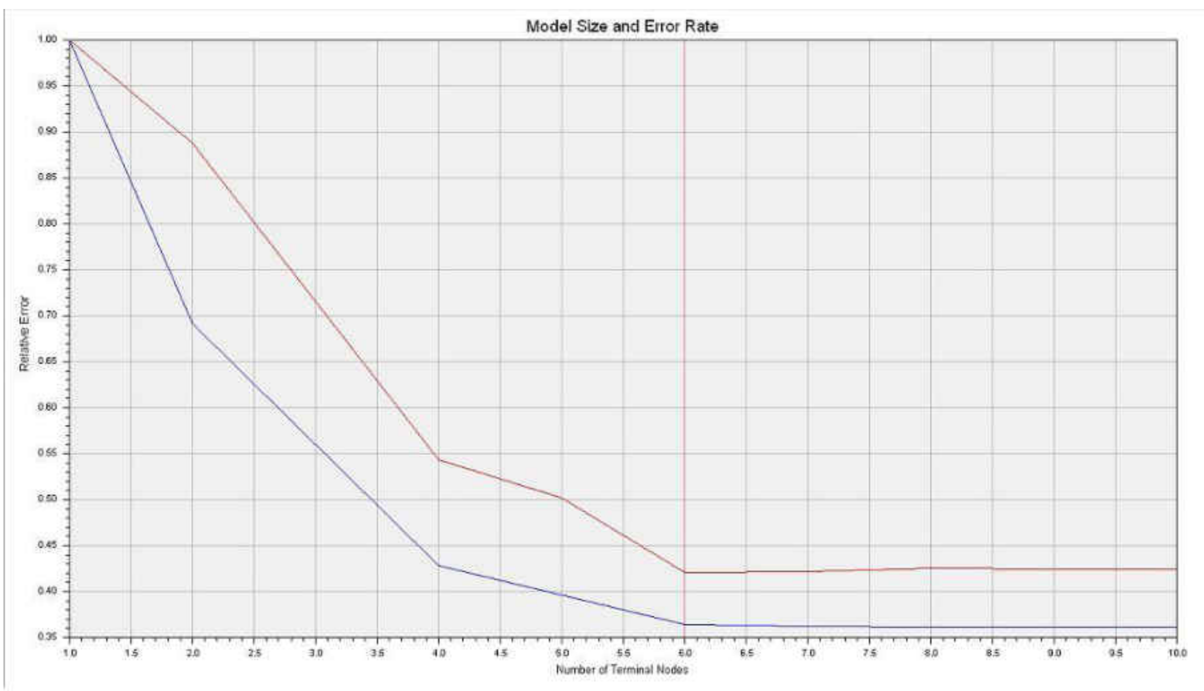
APPENDIX O: CENSUS DATA – HOME OWNERSHIP

COUNTY	Proportion of homeowner rate, 2000	Proportion of housing units in multi-unit structures, 2000	Median value of owner-occupied housing units, 2000
Alachua County	0.549	0.363	97300
Baker County	0.812	0.031	80900
Bay County	0.686	0.249	93500
Bradford County	0.79	0.051	71700
Brevard County	0.746	0.225	94400
Broward County	0.695	0.475	128600
Calhoun County	0.802	0.034	58500
Charlotte County	0.837	0.157	97000
Citrus County	0.856	0.057	84400
Clay County	0.779	0.119	108400
Collier County	0.756	0.466	168000
Columbia County	0.772	0.079	73600
Miami-Dade County	0.578	0.455	124000
DeSoto County	0.747	0.096	69900
Dixie County	0.864	0.015	61700
Duval County	0.631	0.277	89600
Escambia County	0.673	0.204	85700
Flagler County	0.84	0.097	116200
Franklin County	0.792	0.085	105300
Gadsden County	0.78	0.059	70100
Gilchrist County	0.863	0.018	78000
Glades County	0.817	0.043	72400
Gulf County	0.81	0.085	77200
Hamilton County	0.774	0.054	54600
Hardee County	0.734	0.058	59600
Hendry County	0.724	0.082	71500
Hernando County	0.865	0.043	87300
Highlands County	0.797	0.112	72800
Hillsborough County	0.641	0.288	97700
Holmes County	0.815	0.034	56200
Indian River County	0.776	0.255	104000
Jackson County	0.779	0.065	66700
Jefferson County	0.809	0.031	77000
Lafayette County	0.806	0.028	67100

Lake County	0.815	0.098	100600
Lee County	0.765	0.289	112900
Leon County	0.57	0.309	110900
Levy County	0.836	0.038	75800
Liberty County	0.818	0.009	66300
Madison County	0.784	0.061	54800
Manatee County	0.738	0.269	119400
Marion County	0.798	0.094	81300
Martin County	0.798	0.291	152400
Monroe County	0.624	0.244	241200
Nassau County	0.806	0.164	126700
Okaloosa County	0.664	0.246	101200
Okeechobee County	0.748	0.054	77600
Orange County	0.607	0.315	107500
Osceola County	0.677	0.2	99300
Palm Beach County	0.747	0.411	135200
Pasco County	0.824	0.107	79600
Pinellas County	0.708	0.351	96500
Polk County	0.734	0.139	83300
Putnam County	0.8	0.06	68500
Santa Rosa County	0.804	0.092	106000
Sarasota County	0.791	0.252	122000
Seminole County	0.695	0.255	119900
St. Johns County	0.764	0.208	158400
St. Lucie County	0.78	0.203	86100
Sumter County	0.865	0.025	100400
Suwannee County	0.809	0.044	68500
Taylor County	0.798	0.045	66000
Union County	0.746	0.055	71700
Volusia County	0.753	0.217	87300
Wakulla County	0.842	0.019	96200
Walton County	0.79	0.239	96400
Washington County	0.819	0.031	70000
TOTALS (FL)	0.701	0.299	105500

APPENDIX P: MODEL SIZE AND ERROR RATE

The following chart created by DTREG software depicts the Model Size and Error Rate of the model. The Model Size chart shows how the error rate changes with the size of the model where the number of terminal nodes in the tree is considered the model size. The blue line on the chart represents the error rate for the training data whereas the red line shows the error rate for the validation data. The red vertical line shows the tree size with the minimum error for the validation data.



APPENDIX Q: OUTPUT FROM DTREG

============ Project Parameters ============

Number of predictor variables: 3
Type of model: Single tree
Maximum splitting levels: 10
Type of analysis: Regression
Splitting algorithm: Least squares
Variable weights: Equal
Minimum size node to split: 5
Minimum rows allowed in a node: 1
Tree pruning and validation method: Cross validation
Number of cross-validation folds: 10

============ Input Data ============

--- Statistics for target variable: meals per population ---
Mean value = 0.2845605
Standard deviation = 0.6125211
Minimum value = 0.0000621
Maximum value = 3.8592038

============ Summary of Categories ============

(Predictor Variable, Classification, number of observations, percentage of observations)
Directly Impacted?
No: 96 71.11%;
Yes: 39 28.89%
Above State proportion of poverty level?
No: 72 53.33%;
Yes: 63 46.67%
Hurricane Impact Score
Five Points: 9 6.67%
Four Points: 66 48.89%
Three Points: 60 44.44%

============ Model Size Summary Report ============

Maximum depth of the tree = 5
Total number of group splits = 9
The full tree has 10 terminal (leaf) nodes.
The minimum validation relative error occurs with 6 nodes.
The relative error value is 0.4209 with a standard error of 0.1101
The tree will be pruned from 10 to 6 nodes.

------ Validation Statistics ------

Nodes	Val cost	Val std. err.	RS cost	Complexity
-----	--------	-------------	-------	--------------
10	0.4244	0.1103	0.3613	0.000000
9	0.4248	0.1104	0.3614	0.000040
8	0.4250	0.1104	0.3616	0.000070
7	0.4219	0.1101	0.3618	0.000078
6	0.4209	0.1101	0.3639	0.000789 <-- Min. validation error
5	0.5021	0.1524	0.3958	0.011971
4	0.5434	0.1527	0.4285	0.012269
2	0.8879	0.0962	0.6913	0.049300
1	1.0000	0.0000	1.0000	0.115806

============ Analysis of Variance ============

--- Training Data ---

Number of data rows = 135
Variance in initial data sample = 0.3751821
Residual (unexplained) variance after tree fitting = 0.1365356
Proportion of variance explained (R^2) = 0.63608 (63.608%)
Correlation between actual and predicted = 0.797547

--- Validation Data ---

Number of data rows = 135
Variance in initial data sample = 0.3751821
Residual (unexplained) variance after tree fitting = 0.15507
Proportion of variance explained (R^2) = 0.58668 (58.668%)
Correlation between actual and predicted = 0.766515

============ Overall Importance of Variables ============

Variable	Importance
---------------------------------------	----------
Directly Impacted?	100.000
Above State proportion of poverty level?	59.703
Impact Score	46.371

APPENDIX R: ASSUMPTIONS FOR RESOURSE PROJECTION TOOL

The following assumptions are required for projecting the resources necessary to provide meals for the non-evacuees.

- Mobile ERV's can feed 600 meals per day (300 meals per trip x two trips).
- Fixed site ERV's can feed 1,200 meals per day (600 meals per trip x two trips).
- Mobile food distribution vehicles are employed at the rate of 60% for fixed sites and 40% for mobile routes, resulting in an average of 960 meals per day.
- Mobile kitchens (canteens) are used as follows: 70% for preparation of meals at fixed sites and 30% for mobile feeding.
- Approximately 30% of urban and 10% of rural field kitchen meals are distributed to walk in traffic.
- The majority of the shelf stable meals, 85%, will be distributed through Points of Distribution (PODs) and 15% will be delivered by mass care vehicles.
- Field kitchens are placed at the rate of 65% in urban areas and 35% in rural areas.
- Cambros are needed at the rate of three Cambros per 100 meals requiring distribution.
- Cambros are available in two sizes. A standard ARC MPCHL 100 Cambro holds 100 servings of eight ounce per serving entrées. The smaller style Cambros hold 100 servings of six ounce per serving sides. These capacities assume that plastic bag liners are used instead of the hard plastic or stainless steel inserts.
- Each ERV normally carries six large Cambros, but they can carry up to twelve large Cambros. Approximately 20% of Canteens carry six Cambros each.

- An ARC/TSA standard meal consists of three items, an eight ounce entrée, six ounces of vegetable, and six ounces of fruit. For each 100 standard meals, three Cambros, one for the entrées, one for the vegetables, and one for the fruit, are required.
- Overall, a minimum of two times as many Cambros used per meal is needed.
- An alternative to Cambros are twenty quart or larger coolers with aluminum liners or inserts. Coolers can only be used for hot food products if they are able to withstand temperatures of 200 -250 degrees Fahrenheit. Some aluminum lined coolers still melt when hot food is placed in them. A solution is to put cold or room temperature food (fruit, pudding, etc.) in the coolers and use Cambros for hot food.
- Each field kitchen is provided at least one kitchen support trailer. Each support trailer has 100 additional Cambros. Some ARC Chapters have smaller feeding trailers that carry forty Cambros.
- To sustain mobile food distribution vehicles, at the rate of 960 meals per day, 28.8 Cambros (9.6 x three) per feeding vehicle are required.
- Field kitchens require at least one refrigerated trailer and one dry trailer for food storage per 10,000 meals production capacity. The size of each trailer should be 53' x 102' or equivalent square footage. It is preferred to have both units be refrigerated to provide secondary cooling capabilities in the event of mechanical failure. Due to the limited space for trailers at kitchen sites, one 53' trailer is preferred as opposed to two 30' cargo containers.
- Trailers of raw food for the resupply of field kitchens carry approximately 20,000 meals per trailer.

- Tarps or tents, available in 20'x20' or 20'X40', can be used in lieu trailers at the rate of one 20'X40' or two 20'X20' tents per trailer.
- A kitchen will require a 40 yard roll-off dumpster or equivalent. During maximum capacity operations, the dumpster needs to be emptied every three to four days. In the event the large capacity dumpsters are not available, two smaller dumpsters can be used provided they are emptied daily.
- Forklift fuel consumption is either 22 gallons per day or 30 pounds of propane.
- 75% of forklifts consume gas and 25% consume propane.
- ARC ERV's and TSA Canteen's average eight miles per gallon of fuel. Mobile route ERV's travel 200 miles per day and fixed site ERV's travel 100 miles per day.
- 95% of ERV's use diesel and 85% of TSA Canteens use gasoline. The remaining ERVs and TSA Canteens use diesel.
- Kitchen generators are 75% diesel, 15% propane, and 10% gas.
- The diesel generators used in a large field kitchen will consume about fifty gallons of diesel per day.
- The propane generators used in a large field kitchen will consume about 150 lbs. of propane a day.
- The gasoline generators used in a large field kitchen will consume about fifty gallons of gasoline per day.
- A large kitchen consumes about ten gallons of gasoline per day for pressure washers used to wash Cambros.
- Refrigerated trailers require fifty gallons of diesel a day.

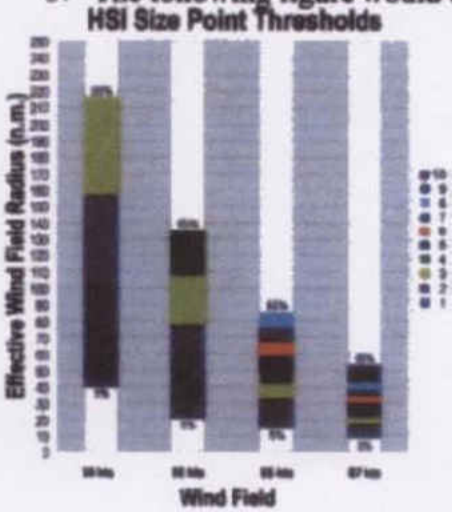
APPENDIX S: COPYRIGHT PERMISSIONS

October 1, 2011

Dear Fred Rogers:

I am completing a doctoral dissertation at the University of Central Florida entitled "Modeling Mass Care Resource Provision Post Hurricane." I would like your permission to reprint in my dissertation the following from the article titled "Hurricane Severity Index: A New Way of Estimating a Tropical Cyclone's Destructive Potential" by Christopher Hebert, Robert Weinzapfel, and Mark Chambers:

1. The method used to calculate the HSI would be explained in my Literature Review section with the equations also being included as formulas in my integrated Excel modeling tool.
2. Table 2 from your article would be reproduced and included in the section describing how to calculate the HSI and referenced in the methodology chapter.
3. The following figure would be used to show the HSI Size Point Thresholds



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Sincerely,

Tammy Muhs

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Signature	Fred Rogers Printed Name	10 OCT 2011 Date

October 1, 2011

Dear Dr. Blendon:

I am completing a doctoral dissertation at the University of Central Florida entitled "Modeling Mass Care Resource Provision Post Hurricane." I would like your permission to reprint in my dissertation the following from Blendon, R., Benson, J., Buhr, T. Weldon, K. & Herrmann, M. (2006, July) *Project on the Public and Biological Security, High-Risk Area Hurricane Survey*. Harvard School of Public Health. Topline results retrieved from http://www.hsph.harvard.edu/hurricane/topline.doc

1. The following figure would be used to show the geographic area included in your study which is a major resource in my research.

2. The high risk area hurricane survey questions and results that were previously sent to me via email would be an appendix to support references to the results. There are 39 questions and results in the requested survey with the first question and results listed below.

How worried are you that a major hurricane will hit your community during the next 6 months?

	Very	Somewhat	Not too	Not at all	Don't know	Refused
7/11/06 Total	22	32	27	18	1	*

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Sincerely,
Tammy Muhs

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[signature] Robert Blendon 10-17-11

Signature Printed Name Date

LIST OF REFERENCES

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