SENSITIVITY ANALYSIS OF HURRICANE EVACUATION CASUALTIES AND COSTS IN FLORIDA

A Thesis in

Meteorology

by

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Submitted in Partial Fulfillment of the Requirements for the Degree of

Master of Science

August 2012
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ABSTRACT

Evacuations associated with hurricane events are an expensive endeavor, compounded by the potential for casualties and other significant costs owing to forecast error at the time that evacuation orders are announced. A synthetic climatology of over eighty-two thousand hurricanes is created based on the historical climatology of hurricanes that struck Florida between 1900 and 2010. Five evacuation events, which include issuance of evacuation orders and a logistic model of cumulative population evacuation, are simulated for each synthetic hurricane. At the end of each model run, associated costs are calculated for the total number of households that evacuated, as well as casualty costs for the individuals who stayed in areas that were ultimately struck. A sensitivity analysis is performed for three major variables: the accuracy of program generated hurricane forecasts, evacuation order lead time, and length of coastline evacuated beyond the cone of uncertainty based on past hurricane forecast skill. A reduction in forecast track error reduces the total overall cost of evacuation, but may result in higher casualties if too short a distance of coastline is evacuated. Evacuating approximately 250 km on each side of the cone of uncertainty is optimal because casualties are not appreciably decreased with a larger evacuation area. Longer evacuation order lead time results in a decrease in casualty costs, while the combined costs of evacuation and casualties increase only slightly. Implications for both the forecasting enterprise and for policy-makers are discussed.
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LIST OF ACRONYMS

AOV: Add-On Value
COU: Cone of Uncertainty
ECU: Expanded Cone of Uncertainty
MWS: Maximum Wind Speed
MWST: Maximum Wind Speed Tendency
NHC: National Hurricane Center
NOAA: National Oceanic and Atmospheric Administration
RMW: Radius of Maximum Winds
SC: Synthetic Climatology
SSHS: Saffir-Simpson Hurricane Scale
TC: Tropical Cyclone
TCG: Tropical Cyclone Game
LIST OF EQUATIONS

(1) \( f(\varepsilon) = \frac{1}{1+e^{-\varepsilon}} \) §2.2.2

(2) \( \bar{x}_0 = \bar{x}_{0,HD} + \bar{d} \) §3.2.1

(3) \( \bar{x}_l = \bar{x}_{l,HD} + \bar{d} \) §3.2.1

(4) \( \tan^{-1}\left(\frac{3.46}{23.81}\right) \approx 8.27^\circ \) §3.2.2

(5) \( \alpha = \tan^{-1}\left(\frac{3.46\eta}{23.81}\right) \) §3.2.2

(6) \( \beta_i = \beta_{i,HD} + \delta \) §3.2.2

(7a) \( \theta_i = \theta_{i-1} + T_{l-1,HD} \cdot \sin \beta_{i-1} \) §3.2.2

(7b) \( \varphi_i = \varphi_{i-1} + T_{l-1,HD} \cdot \cos \beta_{i-1} \) §3.2.2

(8) \( v'_{\text{max},i,HD} = \frac{(v'_{\text{max},i+1,HD} - v'_{\text{max},i,HD})}{\Delta t} \) §3.2.4

(9) \( v'_{\text{max},i} = v'_{\text{max},i,HD} + \delta_{i,\text{random}} \) §3.2.4

(10) \( v_{\text{max},i+1} = v_{\text{max},i} + \Delta t \cdot v'_{\text{max},i} \) §3.2.4

(11) \( v'_{\text{max},i} = \max(v'_{\text{max},i,HD}, -3) + \delta_{i,\text{random}} \) (Case 1) §3.2.4

(12) \( v'_{\text{max},i} = -0.095(v_{\text{max},i-1} - 49.4484) + \delta_{i,\text{random}} \) [adapted from Kaplan and DeMaria (1995); Case 2] §3.2.4

(13*) \( R_{\text{max},i} = \exp(-0.3480 - 0.0063 \cdot v_{\text{max},i} + 0.0109 \cdot \varphi_i) \cdot \varepsilon_R \) [adapted from Willoughby and Rahn (2004), *with best-fit coefficients from the present study substituted for their variable coefficients] §3.2.5

(14) \( v_i(r) = v_{\text{max},i} \exp\left(\frac{-(r-R_{\text{max},i})}{x_{i,l}}\right) \) [from Willoughby et al. (2006)] §3.2.6

(15) \( r = R_{\text{max},i} + X_{1,i} \ln\left(\frac{v_{\text{max},i}}{v_i}\right) \) (rearrangement of Equation 14) §3.2.6
(16) \( X_{1,i} = 270.5 - 4.78v_{\text{max},i} + 6.176\varphi_i \) [adapted from Willoughby et al. (2006)]

\( \text{§3.2.6} \)

(17) \( v_{i,\text{total}} = v_i(r) + T_i^{0.63} \cdot \cos \omega \) [from NWS-23 (1979)] \( \text{§3.2.6} \)

(18) \( \beta_{i,j} = \beta_{i,HD} + \delta + \delta_{\alpha} \) \( \text{§3.3.1} \)

(19a) \( \theta_{i,j+1} = \theta_{i,j} + T_{j,HD} \cdot \sin \beta_{i,j} \) \( \text{§3.3.1} \)

(19b) \( \varphi_{i,j+1} = \varphi_{i,j} + T_{j,HD} \cdot \cos \beta_{i,j} \) \( \text{§3.3.1} \)

(20) \( r_{\text{ECU},j} = 1.5 \cdot \eta \cdot r_{\text{COU},j} + \text{AOV} \) \( \text{§3.3.2} \)

(21) \( P_i^* = \frac{1}{1+e^{-z}} \) [from Fu and Wilmot (2004)] \( \text{§3.3.4} \)

(22) \( P_i = P_i^* \prod_{n=1}^{i-1} [1 - P_n^*] \) [from Fu and Wilmot (2004)] \( \text{§3.3.4} \)

(23) \( z = \gamma_1 - 2.8238 - 0.7995 \text{dist} + 1.4512TD_1 + 2.0244TD_2 + 0.1463 \text{speed} + 0.5401 \text{evac} + 0.7809 \text{flood} + 1.6496 \text{mobile} \) [adapted from Fu and Wilmot (2004)] \( \text{§3.3.4} \)

(24) \( \text{dist} = \begin{cases} 0, & d(t) \leq 94 \text{ mi} \\ \ln[d(t) - 94], & d(t) > 94 \text{ mi} \end{cases} \) [from Fu and Wilmot (2004)] \( \text{§3.3.4} \)

(25) \( z = \gamma_2 - 2.292 + 1.018TD_1^* + 2.123TD_2^* + 1.949TD_3^* + 2.111 \text{notice}_1 + 2.356 \text{notice}_2 + 0.019 \text{windspeed} - 1.748 \ln(\text{onset}) \) [adapted from Fu et al. (2007)] \( \text{§3.3.4} \)
LIST OF VARIABLES AND PARAMETERS

General indexes

\( i \) – index representing the current time step. When paired with \( j \), this index represents the time step at which the forecast was issued.

\( j \) – index representing the valid time of a forecast.

\( HD \) – index denoting that the variable represents data from a historical TC (from HURDAT). Variables without the \( HD \) designation apply to the synthetic vortex.

Variables used in creation of a synthetic TC (see Figure 10); equations 2-17

\( \vec{x}_i \) – the position vector of the synthetic TC at time \( i \).

\( \vec{x}_{i,HD} \) – the position vector of the historical TC at time \( i \).

\( \vec{d} \) – the initial position perturbation vector. \( \vec{d} = (|\vec{d}|, \lambda_d) \), where \(|\vec{d}| \leq 100 \text{ km and} 0 \leq \lambda_d < 2\pi \).

\( \alpha \) – one half of the angle at which the COU opens up for a given fraction \( \eta \).

\( \eta \) – the fractional increase in the width of the COU from current skill.

\( \beta_i \) – the direction of forward motion of the synthetic TC at time \( i \).

\( \beta_{i,HD} \) – the direction of forward motion of the historical TC at time \( i \).

\( \delta \) – random angle perturbation from the direction of forward motion of the historical TC to that of the synthetic TC, sampled from a normal distribution with \( \mu = 0 \) and \( \sigma = 12.30^\circ \), truncated at \( 2\sigma \).

\( \theta_i \) – the latitude of the synthetic TC at time \( i \).

\( \varphi_i \) – the longitude of the synthetic TC at time \( i \).

\( T_i \) – the forward translational speed of the synthetic TC.

\( T_{i,HD} \) – the forward translational speed of the historical TC at time \( i \).

\( v_{max,i} \) – the maximum wind speed for the synthetic TC at time \( i \).
\(v_{\text{max},i,\text{HD}}\) – the maximum wind speed for the historical TC at time \(i\).

\(v'_{\text{max},i}\) – the maximum wind speed tendency for the synthetic TC at time \(i\).

\(v'_{\text{max},i,\text{HD}}\) – the maximum wind speed tendency for the historical TC at time \(i\).

\(\Delta t\) – the change in time. For purposes in the TCG, \(\Delta t = 1\ h\).

\(\delta_{i,\text{random}}\) – random maximum wind speed tendency perturbation from the maximum wind speed tendency of the historical TC to that of the synthetic TC, sampled from a normal distribution with \(\mu = 0\) and \(\sigma = 2\ \text{km h}^{-2}\).

\(R_{\text{max},i}\) – the radius of maximum winds of the synthetic TC at time \(i\).

\(\varepsilon_R\) – random multiplier to perturb the value of the radius of maximum winds, sampled from a continuous distribution between 0.8 and 2.0.

\(v_i(r)\) – the tangential wind speed at a radius \(r\) from the center of the synthetic TC.

\(r\) – the radius from the center of the synthetic TC.

\(X_{1,i}\) – an \(e\)-folding length parameter from Willoughby et al. (2006).

\(v_{i,\text{total}}\) – the total tangential + translational wind speed of the synthetic TC at a coastal point at time \(i\).

\(\omega\) – the difference between the TC angle of forward motion and the direction of the tangential wind at the coastal point.

**Variables used to create a forecast TC path (see Figure 13); equations 18-19b**

\(\vec{d}_{\text{f,cst}}\) – the initial forecast position perturbation vector. (\(|\vec{d}_{\text{f,cst}}|\) sampled from a normal distribution with \(\mu = 0\) and \(\sigma = 22.06\ \text{km}\), truncated at \(2\sigma\); \(0 \leq \text{the angle of } \vec{d}_{\text{f,cst}} < 2\pi\).)

\(\beta_{i,j}\) – the direction of forward motion of the forecast TC, valid at time \(j\), for the forecast issued at time \(i\).

\(\beta_{i,\text{HD}}\) – the direction of forward motion of the historical TC at time \(i\).

\(\delta\) – random angle perturbation from the direction of forward motion of the historical TC to that of the synthetic TC, sampled from a normal distribution with \(\mu = 0\) and \(\sigma = 12.30^\circ\), truncated at \(2\sigma\).
\( \delta_\alpha \) – random angle perturbation from the direction of forward motion of the synthetic TC to that of the forecast TC, sampled from a normal distribution with \( \mu = 0 \) and \( \sigma = \alpha \), truncated at \( 2\sigma \).

\( \theta_{i,j} \) – the latitude of the forecast TC, valid at time \( j \), for the forecast issued at time \( i \).

\( \varphi_{i,j} \) – the longitude of the forecast TC, valid at time \( j \), for the forecast issued at time \( i \).

\( T_{i,HD} \) – the forward translational speed of the historical TC at time \( i \).

\( R_{\text{avg}} \) – the average radius of hurricane-force winds in the right front quadrant of a major hurricane; \( R_{\text{avg}} = 80 \) km.

Variables and parameters used for evacuation modeling (see Figure 16 and Figure 17): equations 20–25

\( r_{\text{ECU},j} \) – the radius of the expanded cone of uncertainty around the forecast location at forecast time \( j \).

\( r_{\text{COU},j} \) – the radius of the 2011 cone of uncertainty at forecast time \( j \).

AOV – the add-on value to the radius of the cone of uncertainty, used to test sensitivity to length of coastline ordered to evacuate.

\( P_{i}^* \) – the fraction of the population who has not yet evacuated that chooses to evacuate at time \( i \).

\( z \) – a linear combination of parameters used to determine the number of people who will evacuate at time \( i \).

\( P_{i} \) – the fraction of the total population that chooses to evacuate at time \( i \).

\( \gamma_{1} \) – a random perturbation used to prevent the evacuation fraction component of the TCG from perfectly following the Fu and Wilmot (2004) profile, sampled from a normal distribution with \( \mu = 0 \) and \( \sigma = 0.1 \).

\( \text{dist} \) – a parameter based on the distance from the synthetic TC to the county in question by the relationship in Equation 24.

\( TD_1 \) – a Boolean parameter that represents morning: set to 1 if between 6am and 11am, inclusive, and 0 otherwise.

\( TD_2 \) – a Boolean parameter that represents afternoon: set to 1 if between 12pm and 5pm, inclusive, and 0 otherwise.
speed – a parameter representing the current forward speed in mph of the synthetic TC.

evac – a Boolean parameter that represents evacuation order: set to 1 if an evacuation order has been issued for the county in question, and 0 otherwise.

flood – a Boolean parameter that represents flood danger: set to 1 if the zone in question is at risk of flooding, and 0 otherwise.

mobile – a Boolean parameter that represents living in substandard housing: set to 1 for mobile home residents, or residents who have been warned to evacuate, and 0 otherwise.

d(t) – the distance in miles from the TC to the county in question.

γ₂ – a random perturbation used to prevent the hourly evacuation component of the TCG from perfectly following the Fu et al. (2007) profile, sampled from a normal distribution with μ = 0 and σ = 0.1.

TD₁* – a Boolean parameter that represents morning: set to 1 if between 6am and 9am, inclusive, and 0 otherwise.

TD₂* – a Boolean parameter that represents midday: set to 1 if between 10am and 3pm, inclusive, and 0 otherwise.

TD₃* – a Boolean parameter that represents late afternoon: set to 1 if between 4pm and 7pm, inclusive, and 0 otherwise.

notice₁ – a Boolean parameter that represents a voluntary evacuation order: set to 1 if the zone in question is under a voluntary evacuation order, and 0 otherwise.

notice₂ – a Boolean parameter that represents a mandatory evacuation order: set to 1 if the zone in question is under a mandatory evacuation order, and 0 otherwise.

windspeed – a parameter representing the current maximum wind speed in mph of the synthetic TC.

onset – time in hours until expected onset of tropical storm force winds in the county in question.
AKNOWLEDGMENTS

The author would like to thank Dr. Jenni Evans, Dr. George Young, Dr. Chris Forest, Thomas Sabbatelli, Jeff Waters, Holly Hamilton, Casey Webster, Michael Hernandez, Ben Green, Erin Munsell, Robbie Manion, Dan Sarmiento, and Alex Kowaleski for their contributions, insights, and support. He would also like to thank his family, William, JoAnn, Meghan, Andy, Melissa, Jeff, Chloe, Natalie, and Preston, as well as Tim Morrell, Wesley Vosper, and Dominic Ramunni for all of their support throughout this project.
Chapter 1. INTRODUCTION

1.1 Background

Landfalling tropical cyclones (TCs) are among the most expensive natural disasters to routinely occur in the United States. Over the past decade, most hurricanes (tropical cyclones with maximum winds exceeding 117 km h\(^{-1}\)) that have struck the mainland United States have resulted in economic costs of a billion dollars or greater per storm. In some instances, such as Hurricanes Katrina (2005), Wilma (2005), Rita (2005) and Andrew (1992), those costs have been well over $10 billion per storm, and in some cases far higher (Blake et al. 2006).

Storm damage imposes heavy costs on the economy, but evacuations carry high expenses as well. Businesses must close; local governments must pay overtime for emergency personnel and open storm shelters. The cost to individuals and families for lodging, food, gas, and lost wages can be prohibitive, especially for lower-income households. Using the oft-cited value of $1 million per mile of coastline evacuated, it has been estimated that incorrectly evacuating locations that do not ultimately get struck by a hurricane carries a cost of nearly $1 billion annually in the United States (Regnier 2008).

In a perfect evacuation, everybody would leave from areas affected by the hurricane, and no one would leave in areas not affected. Real evacuations are not perfect; some people evacuate from regions that ultimately do not get struck by the storm, and some people do not evacuate from areas that do eventually get struck. There are two worst-case scenarios that result in much higher costs than necessary. In the first case, the false-negative scenario, no evacuations or incomplete evacuations occur in places that bear the full brunt of the storm, resulting in high casualties. In the second case, the false-positive scenario, attempts to avoid the false-negative scenario as much as possible result in the population evacuating from places that do not get hit, incurring unnecessary evacuation costs on the community.

Although a perfect evacuation would eliminate these issues, forecasting errors and sociological issues make perfect evacuations virtually impossible. Forecasts of TCs have improved over the past few decades, especially regarding storm track, but much work remains to be done in reducing errors in forecasts of storm track, size, intensity, and speed (Willoughby et al. 2007). This study focuses on quantifying how the amount of error in storm track forecasting, the amount of error in storm arrival time forecasting, and the lead-time for evacuations affect
evacuation costs. To accomplish this goal, a computer simulation is created, taking its inspiration from the 1980s software program: the *Hurricane Game* (George Young personal communication 2009).

### 1.2 History of the Tropical Cyclone Game (TCG)

The *Hurricane Game* was developed by two graduate students at Colorado State University (CSU), Greg Holland and Robert Merrill, during the early 1980s. George Young, a fellow CSU graduate student, coded the original *Hurricane Game* in BASIC. The three young scientists were avid war-gamers, and they decided to create what was essentially a hurricane war game. Playing as a forecaster for the National Hurricane Center (NHC), user-input decisions were made given updated TC position, intensity, and steering-level wind forecasts. These “end use” decisions involved calling for watches and warnings along stretches of the coasts, ordering evacuations, sending out hurricane hunter aircraft, where to deploy dropsondes, and so on. At the end of the simulation, the number of fatalities predicted by the game served as the scoring metric. A later version of the *Hurricane Game* developed for the Tropical Cyclone Warning Centre in Perth, Australia (Holland et al. 1985) used economic costs as its scoring metric.

Over the subsequent quarter-century the original program faded into obscurity, but in the late 2000s, Young, now a faculty member at Pennsylvania State University, and Jenni Evans brought the *Hurricane Game* back for an honors project with undergraduate Allyson Clark. Portions of the *Hurricane Game* were updated into the MATLAB programming language, with the focus of the program restored to the State of Florida from Western Australia, and a sensitivity study was performed for Clark’s honors thesis.

This study represents a continuation in the evolution of this program, now known as the *Tropical Cyclone Game* (TCG). For the purposes of this study, the evacuation components of the Hurricane Game have been augmented using modern techniques and research, and the hurricane forecasting components have been updated for present forecasting skill and methods. Additionally, all decision-making has been fully parameterized to support sensitivity analyses of various forecast skill and evacuation policy parameters that affect hurricane evacuation costs.
1.3 Project Motivation and Key Questions

The State of Florida is selected as the focus of this study for a variety of reasons. First, over the past 110 years Florida has experienced more hurricane strikes and major hurricane strikes [Categories 3-5 on the Saffir-Simpson Hurricane Scale (SSHS)] than any other American state (Gibney 2000), allowing for use of a broader climatology than for any other state. Second, Florida has experienced rapid population growth, with a nearly six-fold increase over the past 60 years (U.S. Census Bureau 2011), resulting in millions of residents vulnerable to hurricanes. Third, a ranking of greatest relative hurricane risk for all United States Atlantic and Gulf coastal counties, combining both frequency of hurricanes and coastal county wealth, found that seven of the top 10 counties most at-risk for economic losses from TCs in the U.S. are in Florida (Gibney 2000). Finally, a wealth of data is available for the State of Florida, including historical hurricane strikes, county evacuation zone populations, and so on.

Between the rapidly escalating costs of hurricane strikes and the continued slow economy, pressure is building to reduce evacuation costs. Evacuations are a ripe area for cost reductions: while buildings and businesses cannot be moved out of the way of an oncoming hurricane, people can. By reducing the number of false-positive and false-negative evacuations, costs are decreased and lives are saved. The overall amount that TC forecast errors and evacuation lead-times contribute to higher evacuation costs, however, is an open question that this study will attempt to answer.

Four key questions motivate this study:

- What is the sensitivity of casualties and evacuation costs to improved track forecasts?
- Is there an optimal length of warned coastline relative to casualties and evacuation costs? What is that length?
- Is there an optimal evacuation order lead time relative to casualties and evacuation costs? What is that lead time?
- Which Florida counties tend to incur greater costs of evacuations and casualties for evacuation events?
Chapter 2. LITERATURE REVIEW

2.1 Tropical Cyclone Characteristics

An informative hurricane evacuation simulation requires modeling physically realistic TCs. A synthetic climatology of Florida hurricanes should reasonably fit historical distributions of TC tracks, intensities, and sizes. Additionally, to maintain track and timing uncertainty in simulated evacuations, the synthetic TCs should also fit a realistic hurricane forecast error profile. This information may be based on theoretical models, empirical data, or some combination of the two.

2.1.1 Florida Tropical Cyclone Climatology

The North Atlantic Hurricane Season extends from June 1 through November 31 (NHC 2011a). TCs have formed during all months of the year, but the vast majority form during that six-month time frame. Every hurricane strike\(^1\) in Florida since 1900 has occurred during the “official” hurricane season. Florida hurricanes may develop in any of the main development regions of the North Atlantic basin: the Gulf of Mexico, the Caribbean Sea, the North Atlantic off the Florida coast and the Bahamas, and the low-latitude North Atlantic stretching across the ocean to West Africa (Kossin et al. 2010).

Florida has the longest coastline of all Atlantic and Gulf states and extends the furthest into the tropics, rendering it especially susceptible to hurricane strikes. Part of the reason for the state’s susceptibility is its shape: it literally sticks out like a sore thumb off the southeastern United States into the Atlantic Ocean and Gulf of Mexico. This shape allows for TCs to strike the peninsula from both the east and west, and TCs may also strike the Florida Panhandle, Gulf coast, and the southern peninsula from the south. Given its geography, it is no surprise that Florida has experienced more hurricane strikes over the past century than any other U.S. state (Gibney 2000).

---

\(^1\) A hurricane strike is defined to have occurred in a county or state if sustained hurricane-force winds were experienced at any point in that county or state over the duration of the TC event (NHC, 2011a); thus, a single hurricane can result in strikes in multiple counties or states, even inland. Importantly, no landfall is necessary for a strike to have occurred.
Although Florida is climatologically the state that is most often struck by hurricanes, not all regions in Florida are struck at the same rate. The southern portion of the state, from approximately Naples around to Cape Canaveral, tends to be struck most often (Figure 1 and Figure 2). A secondary maximum occurs in the western Panhandle, from Pensacola to Panama City. The Big Bend area between the Panhandle and Gulf peninsular coast, and the northeastern Florida coast, are both less susceptible to hurricane strikes than the rest of the state (NHC 2011a).

Figure 1. Total number of hurricane strikes by county for coastal Florida and surrounding states from 1900-2009. Red and orange colors represent a greater number of strikes; greens and blues represent fewer strikes. Figure from http://www.nhc.noaa.gov/climo/images/strikes_egulf.jpg.
2.1.2 Tropical Cyclone Path

Tropical cyclones are typically steered by the prevailing synoptic deep-layer environmental flow in the region. Easterly trade winds steer TCs westward in low latitudes until interactions with adjacent weather systems (e.g. mid-latitude troughs, other TCs) modify this steering so that the TC recurves poleward into the mid-latitude westerlies where it ultimately decays. An “environmental β–effect” (due to variation in the Coriolis parameter; see e.g. Evans et al. 1991) modifies the TC motion away from pure steering (Elsberry et al. 1987). Approximately 30-80% of the variability of TC motion in the Atlantic Basin in the 24-72 hour period can be attributed to environmental steering of the TC (Neumann 1979), with the
environmental β–effect and other factors (e.g. landfall, dry air, internal processes etc.) complicating the TC motion and thus making track forecasting more challenging.

A recent cluster analysis by Kossin et al. (2010) separated TCs in the Atlantic Basin into four clusters (Figure 3). In general, Cluster 1 TCs tend to form in the Atlantic above 15°N and recurve fairly quickly; Cluster 2 TCs tend to form in the Gulf of Mexico and move towards the north or northeast; Cluster 3 TCs tend to form in the central to eastern Atlantic between 10°N and 15°N and track westward for long distances before recurving; and Cluster 4 TCs tend to form nearer to or in the Caribbean Sea, tracking westward before recurving or landfalling in
Mexico or Central America. TCs from all four clusters have made landfall in Florida, for example: Earl (1998, Cluster 1), Katrina (2005, Cluster 2), Andrew (1992, Cluster 3), and Wilma (2005, Cluster 4). Kozar et al. (2011) have related the relative frequency of membership in these clusters to factors such as the El Niño Southern Oscillation (ENSO), North Atlantic Oscillation (NAO) and sea surface temperature (SST) variability in the Atlantic Main Development Region (a center of action for tropical cyclone formation).

2.1.3 Tropical Cyclone Wind Field and Maximum Winds

A realistic distribution of synthetic hurricane strikes in Florida requires models of TC size\(^2\) and the extent of hurricane and tropical-storm force winds that reasonably replicate the historical climatology. The Extended Best Track Dataset (Demuth et al. 2006) provides a first step at compiling these data for the recent historical period (slightly over 20 years to date). Because the size of the TC and outer core wind strength are poorly correlated with the intensity of the TC, the size and outer core wind strength cannot be confidently determined from intensity alone (Elsberry et al. 1987). Various attempts have been made to model the TC radial wind strength profile using a variety of characteristics, including maximum radial wind velocity, the radius of maximum winds (RMW), central pressure, environmental pressure, and latitude.

Early work on the simulation of the spatial distribution of tropical cyclone surface winds focused on modeling the radial distribution of the rotational winds using a Rankine vortex (Depperman 1947), a modified Rankine vortex (Hughes 1952), and negative exponential relations (Schloemer 1954 and others). Holland (1980) developed a negative exponential equation for wind velocity at any radius by assuming a negative exponential for radial variation of pressure and requiring gradient wind balance.

Willoughby and Rahn (2004) analyzed 493 hurricane profile observations and found that the Holland model overestimates the annulus of the strongest winds in the vicinity of the eyewall and the width of the nearly calm wind at the center of the TC, and that the wind decreases too rapidly beyond 2-3 times the eye radius. In a follow-up study, they proposed both a single-exponential and a double-exponential wind profile model (Willoughby et al. 2006). The double-exponential model was a better representation in approximately 1/3 of the cases; in the remaining cases the model single-exponential form was an acceptable fit to the data. The single-exponential

\(^2\) TC size is defined as the radius from the center of the low pressure system to the outermost closed isobar.
model, owing to its relative simplicity, is deemed acceptable for the purposes of hurricane wind field modeling in this study (see §3.2.6).

2.1.4 Generating Synthetic Hurricane Tracks and Intensities

Previous studies on hurricane risk have used a variety of methods to generate synthetic hurricane tracks. Casson and Coles (2000) produced synthetic tracks by perturbing all points along a historical track by the same displacement. Vickery et al. (2000) created synthetic tracks by beginning with a historical initial position and using a Markov chain Monte Carlo process to advance the TC in 6-hour increments. The coefficients that described the TC’s forward direction and speed were constrained by Vickery et al. using historical data which depended on the TC’s current position in a 5° × 5° grid of the Atlantic basin. Emanuel et al. (2006) use two methods for

Figure 4. NHC forecast cone product for Tropical Storm Dean, valid 5pm EDT on August 14, 2007. Figure from http://www.nhc.noaa.gov/aboutcone.shtml.
producing synthetic tracks. In their first method, a Markov chain process similar to Vickery et al. (2000) is used, but here Emanuel et al. use both the properties of the previous 6-hour step, as well as climatological distributions of changes in displacement at the TC’s current location. In their second method, Emanuel et al. moves the TCs using a weighted average of the steering flow at 850 and 250 hPa, along with a constant beta-drift correction.

The intensity of a synthetic hurricane, measured by either maximum wind speed or minimum central pressure, can also be generated in a variety of ways. Casson and Coles (2000) simply sample historical intensity time profiles from TCs that did not make landfall for their synthetic hurricanes, updating them with formulas for decay over land for landfalling TCs. Vickery et al. (2000) measure central pressure uses a Markov chain process similar to the one they use to model track, but with parameters and coefficients based on sea surface temperatures, latitude, intensity, and heading. Emanuel et al. (2006) use a coupled deterministic axisymmetric balance and one-dimensional ocean model to calculate maximum wind speed.

### 2.1.5 Forecast Cone of Uncertainty

NHC releases a forecast advisory of the position and intensity of a TC in the Atlantic basin at six-hour intervals for the duration of the life of the TC. The NHC forecast cone product is a graphical representation of the forecast positions and intensities, valid at 12, 24, 36, 48, 72, 96, and 120 hours from the forecast time (Figure 4) plotted to indicate a representative level of forecast uncertainty based on past forecast skill. The forecast positions are connected by a piecewise linear curve on the forecast cone product map.

<table>
<thead>
<tr>
<th>Forecast Period (hours)</th>
<th>Radius of 2/3 Probability Circle Applied for 2011 Hurricane Season Forecasts in nautical miles (km)</th>
<th>Radius of 2/3 Probability Circle Applied for 2010 Hurricane Season Forecasts in nautical miles (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>12</td>
<td>36 (67)</td>
<td>36 (67)</td>
</tr>
<tr>
<td>24</td>
<td>59 (109)</td>
<td>62 (115)</td>
</tr>
<tr>
<td>36</td>
<td>79 (146)</td>
<td>85 (157)</td>
</tr>
<tr>
<td>48</td>
<td>98 (182)</td>
<td>108 (200)</td>
</tr>
<tr>
<td>72</td>
<td>144 (267)</td>
<td>161 (298)</td>
</tr>
<tr>
<td>96</td>
<td>190 (352)</td>
<td>220 (407)</td>
</tr>
<tr>
<td>120</td>
<td>239 (443)</td>
<td>285 (528)</td>
</tr>
</tbody>
</table>

Table 1. Radii of the 2/3 probability circle in the Atlantic basin for the 2011 NHC forecast cone product. Corresponding values of radii valid during the 2010 hurricane season are given for comparison.
One circle is drawn for each of forecast times with the corresponding forecast point as its center. The radius of each circle is set to enclose 2/3 of the previous five years’ official forecast errors at the corresponding forecast time (NHC 2011b). These circles connected by tangents form a cone. The circle radii change from year to year as forecast errors from the previous season are included and forecast errors older than five years are removed, so the cone may get wider or thinner each year. Radii of the 2/3 probability circles for 2011 are given in Table 1, with the 2010 radii for comparison. Each radius in 2011 is smaller than, or the same size as, its 2010 counterpart, but this is not always the case (NHC 2011c).

A linear fit of the 2011 cone of uncertainty radii demonstrates a very high linear correlation with lead time (Figure 5). The 2010 cone of uncertainty also demonstrated a high degree of linearity, and so it appears that linearity is designed into the cone of uncertainty product. This linearity is crucial to the method used in this study for the creation of a climatology of synthetic TCs (see §3.2.2).

![Radii of 2/3 Probability Circles](image)

**Figure 5.** Radii of 2/3 probability circles at 12-, 24-, 36-, 48-, 72-, 96-, and 120-hour lead times for the 2011 NHC forecast cone product, Atlantic Ocean basin, with best fit line and equation. The 2010 figures are provided for comparison.
2.2 Hurricane Evacuations

Realistic simulations of hurricane evacuations rely on reasonable representations of individual and/or collective evacuation behavior, location-specific evacuation constraints (such as county evacuation zones), and costs to each individual for evacuating. This information may be based on theoretical models, empirical data, or some combination of the two.

2.2.1 Evacuations Zones in Florida

Evacuations in the State of Florida are ordered on a county-by-county basis. Evacuation orders may be issued by either the governor or by the county executive (Urbina and Wolshon 2003). Each coastal county has designated anywhere from two to six different evacuation zones based on anticipated storm surge depths. In some counties the forecast SSHS category that may strike the county is used as a proxy for storm surge when determining which zones to evacuate.

Miami-Dade and Hillsborough Counties in Florida demonstrate different zone design philosophies. In Miami-Dade County (Figure 6) there are three evacuation zones, divided by waterways or major highways (Miami-Dade County 2011). On the other hand, Hillsborough County (Figure 7) has far more intricately-drawn evacuation zones, down to a block-by-block scale for zone design in Tampa. Each of the five zones in Hillsborough County evacuate for a certain SSHS hurricane category threshold value (Hillsborough County 2011).

2.2.2 Modeling Evacuations

A realistic model of the aggregate population that evacuates ahead of a hurricane is crucial for this sensitivity study. Logistic regression modeling is best-suited for the task of modeling the hurricane evacuation response curve [e.g., Dixit et al. (2008); Pel et al. (2010)], because a logistic equation asymptotes to zero as one goes into the past (so no one has evacuated long before the TC) and also asymptotes to one (1) as one travels forward in time (so given enough lead-time, 100% of the population will evacuate). A logistic equation is of the form

\[
f(z) = \frac{1}{1+e^{-z}}
\]  

(1)

where the exponent \( z \) is a linear combination of parameters that affect the value of \( f \).
Figure 6. Evacuation zone map for Miami-Dade County, Florida. Zone A (red) includes all coastal islands, Zone B (yellow) includes mainland coastal regions, and Zone C (green) includes areas further inland. Figure from http://www.miamidade.gov/oem/library/hurricane_evacuation_zones.pdf.
Figure 7. Evacuation zones for portions of Tampa in Hillsborough County, Florida. Zone A (red) evacuates for Cat-1 or higher; Zone B (orange) for Cat-2 or higher; Zone C (yellow) for Cat-3 or higher; Zone D (green) for Cat-4 or higher; and Zone E (blue) for Cat-5. Figure from http://www.hillsboroughcounty.org/realestate/geomatics/resources/publications/sheltersMap.pdf.
A large number of parameters may be considered for a logistic evacuation equation: demographic variables, TC characteristics, hurricane watch/warning status, evacuation order status, and so on. Determining which variables should or should not be included in a logistic model can be a difficult task. Fu and Wilmot (2004) used a regression analysis to determine which parameters combine to most closely predict 6-hour evacuation figures from a survey of Louisiana residents affected by Hurricane Andrew (1992). These figures were then used to predict the total fraction of individuals who evacuate from a hurricane. In a following study, Fu et al. (2007) used a regression analysis to determine which parameters combine to most closely predict hour-by-hour evacuation figures from a survey of South Carolina residents affected by Hurricane Floyd (1999), and then tested the resulting model against the Hurricane Andrew data. These figures were then used to predict the timing of evacuations for the fraction of individuals who ultimately choose to evacuate. Both the Fu and Wilmot (2004) and Fu et al. (2007) logistic models are crucial for the evacuation modeling in this study (see §3.3.4).

2.2.3 Hurricane Evacuation Costs

The most frequently cited cost of a hurricane evacuation is the “one-million dollar per mile of coastline” estimate (Whitehead 2003). This high cost value was one of the impetuses behind a drive to reduce hurricane track error, and therefore unnecessary evacuations. More recent studies have called this value into question. In particular, Whitehead (2003) used evacuation data for Hurricane Bonnie (1998) to calculate that evacuations in North Carolina cost between $1 million and $50 million per county per event, well less than the $1 million per mile estimate.

While evacuations are costly for governments, businesses, and individuals alike, this study focuses on evacuation costs to Florida residents exclusively. A comprehensive breakdown of individual evacuation costs is found in Czajkowski (2007). Combining data such as direct costs (food, lodging, and entertainment), travel costs (the cost of gasoline for the evacuation), travel time (opportunity cost of time spent in transit), and lost wages, Czajkowski developed a cost profile for an evacuee leaving at one of the forecast periods before the TC strike. The lowest cost per person to evacuate in his model occurs when the evacuee leaves between 48-24 hours before the TC arrives. The cost of evacuating quickly increases on the day leading up to the strike as food, lodging, and gasoline become scarce, and as traffic becomes heavier. After
compiling the costs for a Cat-3 hurricane, he uses multipliers to decrease the costs for Cat-1 and -2 hurricanes and to increase the costs for Cat-4 and -5 hurricanes.

Czajkowski (2011) also breaks down costs to the individuals who choose not to evacuate and instead experience the hurricane strike. Using estimates of the percentage of non-evacuees who receive hurricane-related injuries, as well as average costs of injuries ranging from minor to critical, he calculates the expected casualty costs per person that does not evacuate given the SSHS category experienced by those individuals. The present study uses Czajkowski’s figures, adapted to remove a mathematical error in their calculations which resulted in their figures being too high by a factor of 5 (Table 2).

<table>
<thead>
<tr>
<th>SSHS Category</th>
<th>Probability of Injury</th>
<th>Expected Casualty Cost per Person</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.050%</td>
<td>$338.80</td>
</tr>
<tr>
<td>2</td>
<td>0.200%</td>
<td>$1,355.00</td>
</tr>
<tr>
<td>3</td>
<td>0.450%</td>
<td>$3,048.80</td>
</tr>
<tr>
<td>4</td>
<td>0.850%</td>
<td>$5,759.00</td>
</tr>
<tr>
<td>5</td>
<td>0.950%</td>
<td>$6,436.40</td>
</tr>
</tbody>
</table>

Table 2. Average casualty costs per person for each SSHS category. Adapted from Czajkowski (2011), their Table 5.
Chapter 3. METHODS

3.1 Motivation

A realistic hurricane evacuation simulation (Figure 8) requires modeling physically realistic TCs. The simplest way to do this is by sampling historical hurricane paths and running simulated evacuations for those TCs; however, a more rigorous sensitivity analysis requires a far greater number of TCs than exist in the historical record. Creating a realistic synthetic climatology of Florida hurricanes based on historical storm tracks, intensity, and size distributions addresses the concern with the sparse historical landfall database. Additionally, to maintain track and timing uncertainty in evacuations, the synthetic TCs should also fit a realistic hurricane forecast error profile.

Eighty-two historical TCs that struck Florida with hurricane force winds between 1900 and 2010 are selected for this study (Figure 9; see Table 3 for a detailed list of hurricanes). This is a small sample for statistical significance, so to model hurricane evacuations a larger “synthetic climatology” (SC) of Florida hurricanes is created based upon the existing historical climatology.

The SC contains over 82,000 synthetic TCs based upon the 82 historical TCs. To begin the process of creating a synthetic TC, data for the historical TCs are taken from the NOAA/NHC HURDAT database. The six-hour HURDAT position and maximum wind speed data are interpolated in time using a cubic spline interpolation to create hourly data for each historical storm. The hourly-interpolated dataset includes time of day, latitude and longitude, zonal and meridional forward velocity, maximum wind speed, and radius of maximum winds. These data are computed for the lifetime (total number of hours) of the historical TC in the HURDAT database.

---

3 The position of a TC is measured in degrees latitude and longitude. The TCG uses a rectangular map grid in which one degree latitude equals one degree longitude, at approximately 110 km per degree unit.
BEGIN

Create 1,010 synthetic TCs for each historical TC, yielding a total of 82,820 synthetic TCs.

See Figure 10.

Create 120 h forecast for each time step for each synthetic TC.

Forecast skill can be tuned relative to NHC.

Develop database of counties impacted within a 72 h forecast period.

Calculate percent likelihood by county of an individual evacuating.

See Figure 12.

Calculate time series by county of population evacuation.

Develop database of counties impacted within a 72 h forecast period.

Calculate total evacuation costs upon end of synthetic TC lifetime.

Calculate casualty costs.

See Figure 17.

EXIT

Figure 8. Flow chart of the overall schematic of the TCG.
<table>
<thead>
<tr>
<th>Historical TC</th>
<th>HURDAT Genesis</th>
<th>Initial Point in TCG</th>
<th>Historical TC</th>
<th>HURDAT Genesis</th>
<th>Initial Point in TCG</th>
</tr>
</thead>
<tbody>
<tr>
<td>NN (1901)</td>
<td>8/2  0 UTC</td>
<td>8/6  12 UTC</td>
<td>NN (1947b)</td>
<td>10/9  6 UTC</td>
<td>10/9  6 UTC</td>
</tr>
<tr>
<td>NN (1903)</td>
<td>9/9  6 UTC</td>
<td>9/9  6 UTC</td>
<td>NN (1948a)</td>
<td>9/18  6 UTC</td>
<td>9/18  6 UTC</td>
</tr>
<tr>
<td>NN (1904)</td>
<td>10/12 6 UTC</td>
<td>10/12 6 UTC</td>
<td>NN (1948b)</td>
<td>10/3 18 UTC</td>
<td>10/3 18 UTC</td>
</tr>
<tr>
<td>NN (1906a)</td>
<td>6/14 6 UTC</td>
<td>6/14 6 UTC</td>
<td>NN (1949)</td>
<td>8/23 6 UTC</td>
<td>8/23 12 UTC</td>
</tr>
<tr>
<td>NN (1906b)</td>
<td>9/19 12 UTC</td>
<td>9/21 18 UTC</td>
<td>Baker (1950)</td>
<td>8/20 6 UTC</td>
<td>8/25 0 UTC</td>
</tr>
<tr>
<td>NN (1906c)</td>
<td>10/8 6 UTC</td>
<td>10/13 0 UTC</td>
<td>Easy (1950)</td>
<td>9/1 6 UTC</td>
<td>9/1 6 UTC</td>
</tr>
<tr>
<td>NN (1909)</td>
<td>10/6 12 UTC</td>
<td>10/8 0 UTC</td>
<td>King (1950)</td>
<td>10/13 6 UTC</td>
<td>10/13 6 UTC</td>
</tr>
<tr>
<td>NN (1910)</td>
<td>10/9 6 UTC</td>
<td>10/12 6 UTC</td>
<td>Florence (1953)</td>
<td>9/23 12 UTC</td>
<td>9/23 12 UTC</td>
</tr>
<tr>
<td>NN (1911)</td>
<td>8/8 12 UTC</td>
<td>8/8 12 UTC</td>
<td>Flossy (1956)</td>
<td>9/21 6 UTC</td>
<td>9/21 6 UTC</td>
</tr>
<tr>
<td>NN (1915a)</td>
<td>7/31 6 UTC</td>
<td>7/31 6 UTC</td>
<td>Donna (1960)</td>
<td>8/29 18 UTC</td>
<td>9/5 0 UTC</td>
</tr>
<tr>
<td>NN (1915b)</td>
<td>8/31 12 UTC</td>
<td>8/31 12 UTC</td>
<td>Ethel (1960)</td>
<td>9/14 12 UTC</td>
<td>9/14 12 UTC</td>
</tr>
<tr>
<td>NN (1916a)</td>
<td>6/28 12 UTC</td>
<td>7/1 0 UTC</td>
<td>Cleo (1964)</td>
<td>8/20 18 UTC</td>
<td>8/23 0 UTC</td>
</tr>
<tr>
<td>NN (1916b)</td>
<td>10/9 6 UTC</td>
<td>10/14 0 UTC</td>
<td>Dora (1964)</td>
<td>8/28 12 UTC</td>
<td>9/5 12 UTC</td>
</tr>
<tr>
<td>NN (1917)</td>
<td>9/20 0 UTC</td>
<td>9/21 18 UTC</td>
<td>Isbell (1964)</td>
<td>10/8 12 UTC</td>
<td>10/10 0 UTC</td>
</tr>
<tr>
<td>NN (1919)</td>
<td>9/12 0 UTC</td>
<td>9/5 0 UTC</td>
<td>Betsy (1965)</td>
<td>8/27 0 UTC</td>
<td>9/1 0 UTC</td>
</tr>
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<td>NN (1921)</td>
<td>10/20 0 UTC</td>
<td>10/21 0 UTC</td>
<td>Alma (1966)</td>
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<td>6/5 0 UTC</td>
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<td>NN (1924a)</td>
<td>9/13 0 UTC</td>
<td>9/13 0 UTC</td>
<td>Inez (1966)</td>
<td>9/21 12 UTC</td>
<td>9/28 0 UTC</td>
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<td>10/14 0 UTC</td>
<td>Gladys (1968)</td>
<td>10/13 12 UTC</td>
<td>10/13 12 UTC</td>
</tr>
<tr>
<td>NN (1925)</td>
<td>11/27 0 UTC</td>
<td>11/27 0 UTC</td>
<td>Camille (1969)</td>
<td>8/14 18 UTC</td>
<td>8/14 18 UTC</td>
</tr>
<tr>
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<td>7/23 12 UTC</td>
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<td>6/14 12 UTC</td>
<td>6/16 0 UTC</td>
</tr>
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<td>9/11 12 UTC</td>
<td>9/14 12 UTC</td>
<td>Eloise (1975)</td>
<td>9/13 6 UTC</td>
<td>9/16 0 UTC</td>
</tr>
<tr>
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<td>10/17 0 UTC</td>
<td>David (1979)</td>
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<td>8/30 0 UTC</td>
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<td>8/3 12 UTC</td>
<td>Frederick (1979)</td>
<td>8/29 6 UTC</td>
<td>9/4 0 UTC</td>
</tr>
<tr>
<td>NN (1928b)</td>
<td>9/6 12 UTC</td>
<td>9/13 0 UTC</td>
<td>Elena (1985)</td>
<td>8/28 0 UTC</td>
<td>8/28 0 UTC</td>
</tr>
<tr>
<td>NN (1929)</td>
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<td>Kate (1985)</td>
<td>11/15 18 UTC</td>
<td>11/15 18 UTC</td>
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<td>NN (1932)</td>
<td>8/26 18 UTC</td>
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<td>Floyd (1987)</td>
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<td>10/10 0 UTC</td>
</tr>
<tr>
<td>NN (1933a)</td>
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<td>Andrew (1992)</td>
<td>8/16 18 UTC</td>
<td>8/21 0 UTC</td>
</tr>
<tr>
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<td>8/28 6 UTC</td>
<td>8/29 6 UTC</td>
<td>Erin (1995)</td>
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<td>7/31 0 UTC</td>
</tr>
<tr>
<td>NN (1933c)</td>
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<td>9/1 0 UTC</td>
<td>Opal (1995)</td>
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<td>10/1 0 UTC</td>
</tr>
<tr>
<td>NN (1933d)</td>
<td>10/1 18 UTC</td>
<td>10/1 18 UTC</td>
<td>Danny (1997)</td>
<td>7/16 12 UTC</td>
<td>7/16 12 UTC</td>
</tr>
<tr>
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<td>Earl (1998)</td>
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<td>11/1 6 UTC</td>
<td>Irene (1999)</td>
<td>10/12 12 UTC</td>
<td>10/12 12 UTC</td>
</tr>
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<td>7/27 6 UTC</td>
<td>Charley (2004)</td>
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<td>8/10 12 UTC</td>
</tr>
<tr>
<td>NN (1939)</td>
<td>8/7 18 UTC</td>
<td>8/7 18 UTC</td>
<td>Frances (2004)</td>
<td>8/25 0 UTC</td>
<td>8/31 12 UTC</td>
</tr>
<tr>
<td>NN (1941)</td>
<td>10/3 18 UTC</td>
<td>10/3 18 UTC</td>
<td>Ivan (2004)</td>
<td>9/2 18 UTC</td>
<td>9/10 0 UTC</td>
</tr>
<tr>
<td>NN (1944)</td>
<td>10/12 18 UTC</td>
<td>10/12 18 UTC</td>
<td>Jeanne (2004)</td>
<td>9/13 18 UTC</td>
<td>9/16 0 UTC</td>
</tr>
<tr>
<td>NN (1945a)</td>
<td>6/20 12 UTC</td>
<td>6/20 12 UTC</td>
<td>Dennis (2005)</td>
<td>7/4 18 UTC</td>
<td>7/5 12 UTC</td>
</tr>
<tr>
<td>NN (1945b)</td>
<td>9/12 0 UTC</td>
<td>9/12 18 UTC</td>
<td>Katrina (2005)</td>
<td>8/23 18 UTC</td>
<td>8/23 18 UTC</td>
</tr>
<tr>
<td>NN (1946)</td>
<td>10/8 6 UTC</td>
<td>10/5 6 UTC</td>
<td>Rita (2005)</td>
<td>9/18 0 UTC</td>
<td>9/18 0 UTC</td>
</tr>
<tr>
<td>NN (1947a)</td>
<td>9/4 6 UTC</td>
<td>9/13 12 UTC</td>
<td>Wilma (2005)</td>
<td>10/15 18 UTC</td>
<td>10/18 12 UTC</td>
</tr>
</tbody>
</table>

Table 3. The 82 historical hurricanes used in this study. NN represents TCs with “No Name” prior to 1950. Years before 1950 with multiple unnamed cyclones in this study are denoted with letters a-d. The initial genesis date and hour in HURDAT is included for each storm, as is the initial date and hour used for each TC in the TCG.
3.2 Creating a Synthetic TC

To create a synthetic TC based on a historical hurricane, the initial point of the historical TC is perturbed and then the rest of the historical path is translated by the initial perturbation and rotated by a randomly proscribed angle. The forward motion is also sped up or retarded by a random multiplier. A flow chart schematic of the process for creating a synthetic TC is found in Figure 10. Details follow in the paragraphs below.

In the TCG, all cyclones are tracked on the domain from 12-35°N by 95-60°W. For the 82 TCs in this study, if the initial HURDAT position is outside those bounds, the first HURDAT position at least one degree inside this domain is used as the initial position to increase the
likelihood of a Florida strike for TCs derived from that historical TC. (See Table 3 for the initial HURDAT time used for all 82 historical TCs).

3.2.1 Initial TC Position

The initial position of the synthetic TC is perturbed from the initial HURDAT TC position using the equation

\[ \tilde{x}_0 = x_{0,HD} + \tilde{d} \]  

(2)

where \( \tilde{d} \) is the position perturbation vector. This perturbation guarantees that the initial position of the synthetic TC is not the same as that for the historical TC. To allow the genesis point of the synthetic TC to occur up to 100 km from the genesis of the historical TC\(^5\), the magnitude of \( \tilde{d} \) is calculated by sampling a random number from a uniform distribution between 0 and 1 and then multiplying by 100 km. The direction \( \lambda_d \) of the perturbation is calculated by again sampling from the uniform distribution between 0 and 1 and then multiplying by \( 2\pi \).

As no historical TC has formed less than 50 km from the coast and struck Florida as a hurricane, in the event that the initial position \( \tilde{x}_0 \) of the synthetic TC occurs less than 50 km from the coast, a new \( \tilde{d} \) is sampled. Once an appropriate \( \tilde{d} \) is found, the historical storm track is translated at all times \( t_i \) by the position perturbation vector:

\[ \tilde{x}_i = \tilde{x}_{i,HD} + \tilde{d} \]  

(3)

3.2.2 Synthetic TC Track

Once the historical TC track is translated by the initial location perturbation vector, the synthetic TC track is created by rotating the track by an angle \( \alpha \) around the initial synthetic TC location. This rotational method is preferable in this study to using a Markov chain Monte Carlo method (e.g. Emanuel et al. 2006) to create synthetic TC tracks because of the forecasting component: the rotational method allows the resultant SC to accurately recreate the 2/3

\(^4\) In all equations in this thesis, a subscript HD represents a historical position or velocity from HURDAT, and all other vectors are for the synthetic TC.

\(^5\) The value of 100 km is chosen arbitrarily small enough to ensure that the majority of the synthetic TCs will strike Florida.
Figure 10. A basic flow chart schematic for the creation of a single synthetic TC in the TCG. Equation numbers that correspond to each step appear in parentheses.
probability circles in the NHC’s COU. See §3.2.7 for a discussion of the verification of the climatology created using this rotational method.

As described in §2.1.5, a linear fit of the 2011 COU radii demonstrates a very high linear correlation with lead time (see Figure 5). The 2010 COU also demonstrated a high degree of linearity, and so it appears that linearity is designed into the COU product. Therefore, for a TC moving forward at a constant speed, the COU opens at a constant angle. While it is generally unrealistic for a TC to maintain a constant forward speed for 120 hours, calculating the angle at which the COU opens for the average forward speed of a TC allows an accurate reproduction of the 2/3 probability circle radii when averaged over the entire synthetic climatology. For the 82 TCs in the historical climatology, the average forward velocity is 23.81 km h\(^{-1}\), and from the best-fit slope of 3.46 km h\(^{-1}\) in Figure 5 the average angle at which the COU opens is

\[
\tan^{-1}\left(\frac{3.46}{23.81}\right) \approx 8.27^\circ
\]  

(4)

Equation 5 can be generalized to find the angle \(\alpha\) at which the COU opens for a given fraction \(\eta\) of the size of the 2/3 radii:

\[
\alpha = \tan^{-1}\left(\frac{3.46\eta}{23.81}\right)
\]  

(5)

For example, for a 50% reduction in track forecasting skill over present, the 2/3 radii would be 150% of current. This yields a value of \(\eta = 1.50\), which results in \(\alpha = 12.30^\circ\).

It may seem logical to calculate the value of \(\alpha\) for a given improvement (or reduction) in track forecasting skill using the above method, and then to use that angle as a baseline to rotate the historical TC path to create a synthetic TC. However, including forecasting skill when creating the SC actually creates an unrealistic climatology, one where the spread of synthetic TC tracks around the historical TC track becomes narrower for improved forecasting skill. Forecasting ability should have no bearing on the actual path traveled by the TC.

To avoid this issue, the largest value of \(\eta\) that will be tested in the evacuation component of the TCG, \(\eta = 1.50\), is used as the baseline for creation of all synthetic TC paths. To create those paths, a random angle perturbation \(\delta\) is sampled from a normal distribution with \(\mu = 0\) and \(\sigma = \alpha = 12.30^\circ\), truncated at \(2\alpha\). The new direction of forward motion \(\beta\) of the synthetic TC at \(t_i\) is
\[ \beta_i = \beta_{i,HD} + \delta \] (6)

The position of the synthetic TC at \( t_i \) in degrees latitude \( \theta \) and degrees longitude \( \phi \) is then

\[ \theta_i = \theta_{i-1} + v_{HD,i-1} \cdot \sin \beta_{i-1} \] (7a)

\[ \phi_i = \phi_{i-1} + v_{HD,i-1} \cdot \cos \beta_{i-1} \] (7b)

where \( v_{HD} \) is the forward speed of the TC from HURDAT. Iterating this method out for the lifetime of the historical TC results in a synthetic TC whose path has been rotated by angle \( \delta \) around its initial position.

### 3.2.3 Forward Speed of Synthetic TC

To create a realistic synthetic climatology, it is not sufficient to merely vary the storm tracks; the forward speed of the synthetic TCs must be varied as well. Once a synthetic TC path has been created, a random number \( s \) from a uniform distribution between 0.8 and 1.2 is sampled. This random number is a multiplier for the forward speed: a value of \( s = 0.8 \) will result in a TC moving 80% as fast as the corresponding historical TC, a value of \( s = 1.2 \) will result in a TC moving 120% as fast as the corresponding historical TC, and so on.

The cubic-spline interpolated path of the synthetic TC is retained. To create new hourly positions for the synthetic TC along that path, the TC location at \( t_{old} = s \cdot n \) hours is mapped to become the position at \( t_{new} = n \) hours, where \( n \) is a positive integer. For example, for \( s = 0.8 \), the location of the synthetic TC at time 0.8 hours becomes the location of the new synthetic TC at time 1 hour, the location at 1.6 hours becomes the 2-hour location for the new synthetic TC, and so on.

Although this method produces TCs with a variety of forward speeds and tracks, it is necessary to verify that synthetic TCs which travel faster than their corresponding historical TC do not behave unrealistically. In particular, increased forward speeds should not allow for sharp changes in the direction of forward motion. A test is run on each synthetic TC to ensure that it does not violate the speed/direction change constraints as found in Hart (2003) (see Table 4). If a synthetic TC violates those constraints, it is thrown out and a new one is created in its place.
3.2.4 Maximum Wind Speed

For each synthetic TC, the maximum wind speed (MWS) in km h\(^{-1}\) is calculated at each time \(t_i\). To allow variation in the initial MWS of the synthetic TCs, the initial HURDAT MWS is perturbed by a value drawn from a random distribution with \(\mu = 0\) and \(\sigma = 5\) km h\(^{-1}\).

The MWS at all subsequent \(t_i\) is found by perturbing the maximum wind speed tendency (MWST), which is defined by the equation

\[
v'_{max,i,HD} = \frac{(v_{max,i+1,HD} - v_{max,i,HD})}{\Delta t}
\]

(8)

where \(v'_{max,i}\) is the MWST in km h\(^{-2}\), \(v_{max,i}\) is the MWS in km h\(^{-1}\) at \(t_i\) and \(\Delta t\) is 1 hour. The MWST in the synthetic TC is varied by a perturbation term:

\[
v'_{max,i} = v'_{max,i,HD} + \delta_{i,random}
\]

(9)

The value of \(\delta_{i,random}\) is sampled from a normal distribution with \(\mu = 0\) and \(\sigma = 2\) km h\(^{-2}\). Because this standard deviation is about two orders of magnitude smaller than the MWS, the basic intensification/weakening time series of the corresponding HURDAT TC is generally preserved in the synthetic TC; however, the use of a normal distribution without truncation allows the potential for a rapid intensification or decay of the maximum winds beyond those of the historical TC. The MWS \(v'_{max,i}\) in the synthetic TC at \(t_i\) is then

\[
v_{max,i+1} = v_{max,i} + \Delta t \cdot v'_{max,i}
\]

(10)

where \(\Delta t = 1\) hour.

<table>
<thead>
<tr>
<th>TC Forward Speed Between Two Consecutive Analysis or Forecast Times (m/s)</th>
<th>Maximum Allowed Change in TC Direction of Motion (°)</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 10</td>
<td>No restriction</td>
</tr>
<tr>
<td>10</td>
<td>135</td>
</tr>
<tr>
<td>15</td>
<td>90</td>
</tr>
<tr>
<td>20</td>
<td>75</td>
</tr>
<tr>
<td>25</td>
<td>60</td>
</tr>
<tr>
<td>≥ 30</td>
<td>45</td>
</tr>
</tbody>
</table>

Table 4. Maximum allowed change in TC direction of motion given TC forward speed between two analysis or forecast times. Adapted from Hart (2003, his Table 1).
There are two cases where this formula is not followed. In Case 1, if at \( t_i \) the synthetic TC is over water but the corresponding historical TC is over land, the MWS of the synthetic TC are allowed to decay by the formula
\[
\nu'_{\text{max},i} = \max(\nu'_{\text{max},i,\text{HD}}, -3) + \delta_{i,\text{random}}
\] (11)
to prevent an unrealistically steep decay over the ocean. In Case 2, whenever the synthetic TC is over land, the MWS decays following an exponential formula derived by Kaplan and DeMaria (1995), plus a random perturbation term as described above:
\[
\nu'_{\text{max},i} = -0.095(\nu_{\text{max},i-1} - 49.4484) + \delta_{i,\text{random}}
\] (12)
Although a follow-up study by DeMaria et al. (2006) augmented their overland decay model for TCs making landfall on narrow landmasses like islands or peninsulas, Eq. 12 is considerably less computationally intensive, and therefore it is deemed a better selection for use in the TCG.

### 3.2.5 Radius of Maximum Winds

A realistic synthetic wind profile is necessary for determining the extent of counties that are struck by a synthetic TC. The radius of maximum winds (RMW) at \( t_i \) is simulated based on the formula derived by Willoughby and Rahn (2004):
\[
R_{\text{max},i} = \exp(a + b \cdot v_{\text{max},i} + c \cdot \varphi_i) \cdot \varepsilon_R
\] (13)
where \( R_{\text{max},i} \) is the RMW in km, \( v_{\text{max},i} \) is measured in km h\(^{-1}\), and \( \varphi_i \) is the latitude of the center of the synthetic TC in degrees. The \( \varepsilon_R \) factor is added to Willoughby and Rahn’s formula in the TCG to ensure that each synthetic TC does not perfectly follow their RMW profile. This \( \varepsilon_R \) factor is a random number sampled from a continuous distribution between 0.8 and 2.0, and is only sampled once per synthetic TC.\(^6\)

The values of \( a, b, \) and \( c \) are calculated by fitting data from Mark DeMaria’s Extended Best Track File (see Demuth et al. 2006). The Extended Best Track contains over 8,000 data sets for all North Atlantic TCs from 1988 to 2009. Of those sets, 6,297 contain data for all three

\(^6\) The bounds of 0.8 and 2.0 were determined by fitting the distribution of RMW from the Willoughby and Rahn equation to the historical RMW data from the Extended Best Track Dataset.
variables $R_{\text{max},i}$, $v_{\text{max},i}$, and $\varphi_i$. Using a linear fit of those complete sets for $\ln(R_{\text{max},i})$, $v_{\text{max},i}$, and $\varphi_i$ results in best-fit values of $a = -0.3480$, $b = -0.0063$ h km$^{-1}$, and $c = 0.0109$ deg$^{-1}$. This fit accurately captures that the RMW tends to vary inversely with MWS and vary directly with latitude.

**3.2.6 Outer Winds**

The radial profile of tangential wind speed for a synthetic TC outside the RMW is modeled using a single-exponential formula as developed by Willoughby et al. (2006):

$$v_i(r) = v_{\text{max},i} \exp\left(\frac{-(r-R_{\text{max},i})}{X_{1,i}}\right)$$  \hspace{1cm} (14)

where $v_i(r)$ and $v_{\text{max},i}$ are measured in m s$^{-1}$ and $r$, $R_{\text{max},i}$, and $X_{1,i}$ are measured in km. Although Willoughby et al. found that a dual exponential profile was a better fit in about 1/3 of their tested storms, because the dual profile cannot be algebraically solved for $r$ and is therefore computationally intensive, the single exponential profile is deemed preferable for use in the TCG. Solving Equation 14 for $r$ yields

$$r = R_{\text{max},i} + X_{1,i} \ln\left(\frac{v_{\text{max},i}}{v_i}\right)$$  \hspace{1cm} (15)

Willoughby used a linear regression to find the parameter $X_{1,i}$ in terms of the maximum wind velocity and TC latitude:

$$X_{1,i} = 270.5 - 4.78v_{\text{max},i} + 6.176\varphi_i$$  \hspace{1cm} (16)

Using Eqs. 13 and 16, the radius of winds of velocity $v_i$ in Eq. 15 is now fully decomposed into a function of the MWS, the latitude, and the wind velocity in question.

The wind radii are used to determine the maximum wind speed that affects each county in Florida. The radius of 50 km h$^{-1}$ winds is calculated by solving Eq. 15 for $v_i(r) = 13.89$ m s$^{-1}$. If at some time $t_i$ the distance from the storm to any Florida coastal county is less than the radius of 50 km h$^{-1}$ winds, the maximum wind speed experienced by such a county is calculated.

The maximum wind speed that a county experiences incorporates both the tangential wind speed component, as found in Eq. 14, and a component for the forward translational speed.
of the TC. The line segment representing the coastline of an affected county is divided into ten segments of equal length using eleven equidistant points, one at each endpoint and nine others evenly spaced along the segment. At each of those points, the wind speed is calculated using an equation derived from NWS-23 (1979):

\[ v_{i,\text{total}} = v_i(r) + T_i^{0.63} \cdot \cos \beta \]  

(17)

where \( v_i(r) \) is the tangential wind speed at the coastal point a distance \( r \) away from the center of the TC, and \( T_i^{0.63} \cdot \cos \beta \) is the forward translational speed component: \( T \) is the TC forward translational speed, and \( \beta \) is the difference between the TC angle of forward motion and the direction of the tangential wind at the coastal point. For each of the ten segments, the SSHS category of the greater of the two endpoint wind speeds is recorded as the category strike for that segment at hour \( t_i \). The greatest category strike for each segment in each county over the duration of the TC is recorded, as is the time of onset of tropical-storm force winds in each county, as this information will be crucial in the evacuation component of the TCG.

### 3.2.7 Creation and Verification of the Synthetic Climatology

The above process to create one synthetic TC path is repeated thousands of times to create the entire SC. For each of the 82 historical TCs in this study, 10 synthetic TCs are created for each integer percent improvement/reduction in forecast skill, from a 50% improvement to a 50% reduction. Ten synthetic TCs for each of 101 possible skills yield 1,010 synthetic TCs per historical TC, and so the SC has a total of 82,820 synthetic TCs.

A variety of tests are run on the SC to verify that it comprises an accurate representation of the historical climatology of Florida hurricanes. These tests verify that the hurricanes in the SC maintain the general Florida strike profile as the historical climatology (Figure 11), although the Big Bend and southwest Gulf coast regions are struck at a slightly higher rate in the SC than historically. This is due to the fact that “fanning” the synthetic tracks around their historical counterpart tends to smear out some of the variability between the maximums and minimums in number of strikes per county. Despite this smoothing tendency, the SC maintains a historically accurate ratio of major hurricane strikes to minor hurricane strikes for each Florida county. Additional tests are performed which verify that the hurricanes in the SC maintain a realistic maximum wind speed distribution, RMW size distribution, and radius of hurricane-force winds.
distribution. Given the results of these verification tests, we are comfortable that the SC can be used as a reasonable augmentation of the historical climatology.

3.3 Evacuation Modeling

Once the synthetic climatology is created, evacuations are then modeled for each synthetic TC, one TC at a time (see Figure 12 for creation of background information to be used in the evacuation, and Figure 17 for the evacuation itself). Although all 82,820 synthetic TCs are modeled, not all cyclones in the SC result in an evacuation: some of the synthetic TCs stay well out to sea, and others exit the model domain without a close approach to Florida. Additionally, some TCs with multiple strikes in different portions of Florida (a hurricane that strikes the Atlantic coast and then the Panhandle, for example) require separate evacuations for each strike.
3.3.1 Forecast TC Locations and Cone of Uncertainty

In order to model hurricane evacuations, it is necessary to have a reasonable representation of the information consumed by the public when making the decision to evacuate or wait (see Figure 13 for a flow chart schematic of the creation of a forecast TC). One of the primary forms of information is the forecast storm track and COU. Throughout the life of the synthetic TC, a new forecast path for the storm is simulated every six hours, starting from the present location of the TC, following the NHC’s method for releasing the COU product.

The new forecast track begins at the synthetic TC location at $t_i$. If the linear fit for the NHC forecast cone radii in Figure 5 included an intercept of 0, it would be sufficient to use an initial forecast position $\hat{x}_{i,j=0} = \hat{x}_i$. However, the linear fit intercept varies from year to year, with an implied $-\frac{2}{3}$ probability circle at forecast time 0 hours with radius 22.06 km. Therefore, the initial forecast location is perturbed from the initial TC location using the same method as described by Eqs. 2-3 in §3.2.1, except that the distance perturbation is sampled from a normal distribution with $\mu = 0$ and $\sigma = 22.06$ km, truncated at $2\sigma$.

It is now appropriate to include the forecast skill calculations. Eq. 5 is used to find the value of $\alpha$ for the desired forecast skill. A random angle perturbation $\delta_\alpha$ is sampled from a normal distribution with $\mu = 0$ and $\sigma = \alpha$, truncated at $2\alpha$. The direction of forward motion of the forecast TC at $t_{i,j}$ is

$$\beta_{i,j} = \beta_{j,HD} + \delta + \delta_\alpha$$

where $\delta$ is the random angle perturbation used to create the synthetic TC path (see §3.2.2). The forecast position of the synthetic TC at $t_{i,j}$ in degrees latitude $\theta$ and degrees longitude $\phi$ is then

$$\theta_{i,j+1} = \theta_{i,j} + v_{j,HD} \cdot \sin \beta_{i,j}$$

$$\phi_{i,j+1} = \phi_{i,j} + v_{j,HD} \cdot \cos \beta_{i,j}$$

\[\text{In the equations in this section, } t_i \text{ is the time at which the forecast was issued, and } t_j \text{ is the valid time of the forecast. Unless otherwise noted, } t_j \geq t_i.\]
Input HURDAT TC and synthetic TC. Initialize at \( t_i = 0 \) and at first county.

Is \( t_i \) evenly divisible by 6?

Update forecast hurricane path, COU, & expected time until tropical storm force winds strike each county. (2, 5, 18, 19a-b) 

See Figure 13.

Is expected lead time to county within 96 hours?

Deactivate the county if it satisfies any of the deactivation rules. 

See Figure 15.

Is this the last time step for this synthetic TC?

Advance to next \( t_i \).

Is this the last county?

Is this county within the expanded COU?

no

yes

Advance to next \( t_i \).

no

yes

no

yes

no

yes

no

yes
Activate the county if it is not already activated.

Is this county active?

Is expected lead time ≤ evacuation order lead time?

Issue the appropriate voluntary or mandatory evacuation order based on lead time and forecast landfall intensity.

Is $t$, evenly divisible by 6?

Calculate fraction of county that evacuates in this 6-hour time period. (20, 21, 22, 23) (Fu and Wilmot 2004)  
See Figure 16.

Is this the last county evaluated for this time?

On the completion of the last time step, the total fraction of people who evacuate each county is calculated by summing all the 6-hour evacuation fractions for that county. Output and archive activation history, evacuation order history, evacuation compliance fractions for each county.

Advance to next county.

Figure 12. Flow chart schematic for portion of the TCG that produces background information to be used for the hurricane evacuation steps. Equation numbers that correspond to some steps appear in parentheses.
Input HURDAT TC, synthetic TC, current time step, and strike history. Perturb the initial forecast location, where $j = i$, to a new point, with displacement $\vec{d}_{f_{\text{cst}}}$ sampled from a normal distribution with $\mu = 0$ and $\sigma = 22.06$ km, truncated at $2\sigma$. (2)

Calculate $\alpha$ from the fractional increase $\eta$ in the width of the COU from current skill. (5)

Select a random $\delta_{\alpha}$ from a normal distribution with $\mu = 0$ and $\sigma = \alpha$, truncated at $2\sigma$.

Calculate the forward direction $\beta_{i,j}$ of the forecast TC from valid time $j$ to $j + 1$. (18)

Find the forecast TC position at valid time $j + 1$. (19a-b)

Is $j + 1 = 120$ h?  

no  

Advance one valid time step.

yes  

Find forecast strike time for each county (see §3.3.2). Output forecast strike times.

Figure 13. Flow chart describing the creation of a forecast TC. Equation numbers that correspond to some steps appear in parentheses.
This process is used to create a five-day (up to \( j = 120 \)) forecast track. Note that the forecast track maintains the same shape as both the historical and synthetic TCs, but it is rotated around a different angle. Additionally, the forecast speed equals the speed for the historical TC to preserve timing error for hurricane strikes. Between the path rotation and timing error, this method preserves the forecast COU profile in the TCG.

To accurately model the NHC forecast COU product, only the forecast points at \( j = i + \{0, 12, 24, 36, 48, 72, 96, \text{and} 120\} \) are retained. Each of those points are then assigned the corresponding radius of the 2/3 probability circle values for 2011 (see §2.1.5), multiplied by the fractional improvement in COU width. All forecast points between those values of \( j \) are interpolated using a linear interpolation, as are the values of the 2/3 probability circle at each of those forecast points.

### 3.3.2 Activation of County Evacuations

For the purposes of this model, all counties in Florida are assumed to have three evacuation zones (see Figure 14). Zone A evacuates for Cat 1 hurricanes or above, Zone B evacuates for Cat 2 hurricanes or above, and Zone C evacuates for Cat 4 or 5 hurricanes. While this is not the current evacuation zone configuration used by many Florida counties, there are two reasons this configuration is used. First, a standard zone configuration allows for apples-to-apples comparisons of evacuations between all Florida counties. Second, the county population data set used in this study was broken down in this fashion. It is assumed for purposes of this study that these evacuation zones are correctly drawn: a Category 3 hurricane should produce casualties in only Zones A and B, and so on.

An expanded COU (ECU) based upon the simulated COU is used as the basis for activating evacuations in Florida coastal counties. At all forecast times \( t_j \), where \( 0 \leq j \leq 96 \text{ h} \), the radius of the ECU around the forecast location at \( t_j \) is

\[
r_{\text{ECU},j} = 1.5 \cdot \eta \cdot r_{\text{COU},j} + \text{AOV}
\]

where \( \eta \) is the fraction of the size of the 2/3 radii as described in §3.2.2, \( r_{\text{COU},j} \) is the radius of the 2011 cone of uncertainty at \( t_j \), and AOV is an add-on value. The radius of the cone of uncertainty is multiplied by 1.5 so that approximately 90% of the synthetic TC tracks stay within an ECU with AOV = 0, as opposed to only 60-70% without the multiple of 1.5 included. The AOV term is used to further increase the percent of synthetic TC tracks that stay within the ECU. This term
Figure 14. Evacuation zones in the TCG for a portion of Tampa in Hillsborough County (see Figure 7 in Lit Review for comparison). Zone A has large polka-dots (red), Zone B has medium polka-dots (orange and yellow), and Zone C has small polka-dots (green and blue).
is an integer multiple of \( R_{avg} = 80 \text{ km} \), the average radius of hurricane-force winds in the right front quadrant of a major hurricane (Bell and Ray 2004). Five separate evacuation runs are performed on the SC using AOV ranging from 0 km to 4\( R_{avg} = 320 \text{ km} \).

All 35 Florida coastal counties are tested for activation. If at any forecast time from 0 to 96 h, the distance from a particular county to the forecast location of the TC is less than \( r_{ECU,j} \), that county is activated – evacuations will occur in this county. Four days are used instead of the full five-day cone because evacuation numbers at lead times longer than four days are negligible. Note that the two terms defining \( r_{ECU,j} \) in Eq. 20 represent two components in the ECU: the first term represents forecast accuracy as defined by the width of the COU, while the AOV term represents the political decision of how large a stretch of coastline beyond the COU to evacuate.

To limit the sensitivity analysis in this study to only the size of the ECU and evacuation order lead-time, a “perfect” intensity\(^8\) forecast is used. If a synthetic TC strikes with a strongest intensity as Cat-2, this information is used to call for evacuations of only Zones A and B in the activated counties, as well as any individuals living in substandard housing throughout the county – individuals not living in substandard housing in Zone C is not evacuated. All activated counties then evacuate expecting a Cat-2 strike, although due to forecast track errors, not all of those counties will actually be struck by Cat-2 winds.

For synthetic TCs that make multiple landfalls in Florida, the intensity of the next upcoming landfall is used to activate evacuation zones. For example, if a synthetic TC strikes southeast Florida at Cat-1 and then strikes the Panhandle as a Cat-4, a Cat-1 evacuation (Zone A and substandard housing only) will be activated until the Cat-1 strike occurs, at which point Cat-4 evacuations (all Zones A-C, plus substandard housing in the remainder of the county) will be activated.

Some coastal Florida counties may lie within the activation area for a synthetic TC forecast, but lie on the coast opposite to landfall, where storm surge effects are considerably lower. In those cases, the affected counties are not activated except in the case of a category 4 or 5 hurricane.

Once a county is activated, evacuations in that county will remain activated until one of three possible deactivations (Figure 15):

---

\( ^8 \) Here, “intensity” refers to the SSHS category of the maximum wind speed experienced by any county segment, with the combined tangential and translational wind speed.
1. A county is deactivated upon onset of tropical-storm force winds (greater than 63 km h\(^{-1}\)). This is generally considered the time when it becomes impossible to safely evacuate, as evidenced by the NHC using lead time before onset of tropical-storm force winds as criteria for issuing hurricane watches or warnings.

2. A county is deactivated upon being outside the forecast cone of uncertainty for 24 hours (four straight forecast periods). This county may be reactivated if it is later back within the forecast cone.

3. A county that does not experience tropical-storm force winds is deactivated if it is forecast to move further away from the county over the 6-, 12-, 24-, and 48-hour forecast periods.

Note that deactivation does not mean that individuals return to the evacuated areas. Deactivation simply stops further evacuation, barring another future activation.

### 3.3.3 Voluntary and Mandatory Evacuation Orders

Not only does this study perform a sensitivity analysis on improvements in hurricane forecast error, but it also aims to quantify how varying lead times for issuance of evacuation orders affects personal evacuation costs. Therefore, a simultaneous sensitivity analysis is performed for voluntary evacuation lead time.

Once a county is activated, evacuation orders are issued for that county if the forecast time until onset of tropical-storm force winds is less than the randomly selected lead-time for a voluntary or mandatory evacuation. To determine the lead-time for a voluntary evacuation order, a random integer is sampled from a uniform distribution between 16 and 72. This number is used as the lead time, in hours, that a voluntary evacuation order will be issued before the expected onset of tropical-storm force winds in a county. Once the voluntary evacuation lead time is determined, the lead time for a mandatory evacuation is \(\frac{3}{4}\) the lead time of the voluntary evacuation order, rounded to the nearest hour.

The forecast onset of tropical-storm force winds is calculated for all counties during the creation of the forecast cone. Because the forward speed of the forecast TC is equal to that of the historical TC, the evacuation lead times for each forecast will not be perfect; they may be too long or too short for a synthetic TC whose forward velocity was increased or decreased, respectively. For counties have been activated but are outside the forecast cone, the distance from the center of the TC to the county is divided by the TC’s forward velocity to generate an appropriate lead time.
Input evacuation decision data: time until onset of tropical storm winds, status inside or outside of COU, county activation status.

- Has the county already been struck by tropical storm force winds?
  - yes
  - no
    - Is the county outside the COU?
    - yes
      - Has the county been outside the COU for 4 consecutive forecasts (24 h)?
        - yes
          - County is deactivated (activation status set to 0). Output activation status.
        - no
          - County remains active (activation status set to 1). Output activation status.
    - no
      - Has the TC forecast to move away from the county over the 6-, 12-, 24-, 48-hour forecast periods?
        - yes
          - County is deactivated (activation status set to 0). Output activation status.
        - no
          - County remains active (activation status set to 1). Output activation status.

(Remaining citizens must ride out storm at home.)
3.3.4 Modeling Population Evacuations

Any county which is activated will undergo an evacuation, whether an official order is given or residents simply evacuate of their own accord. A logistic model (see Eq. 1 for the basic form) is used to model the number of people who have evacuated at a given time. A variant of the logistic model from Fu and Wilmot (2004) is used in the TCG. The fraction \( p_i^* \) of the population who has not yet evacuated that evacuates at \( t_i \) is

\[
p_i^* = \frac{1}{1 + e^{-z}}
\]

where \( z \) is a linear combination of parameters that affect the evacuation. The actual fraction \( p_i \) of the total population who evacuate at time \( t_i \) is then

\[
p_i = p_i^* \prod_{n=1}^{i-1} [1 - p_n^*]
\]

Two separate logistic models are run to model the evacuation: the first model determines the total fraction of the population that will choose to evacuate (see Figure 16), and the second model determines the hour-by-hour evacuation numbers. The parameters for the first model are selected from Fu and Wilmot (2004) because their model has been fit to actual evacuation data, capturing the diurnal cycle, propensity to leave nearer to landfall, and effects of evacuation orders. The linear combination of parameters used in the TCG is

\[
z = \gamma_1 - 2.8238 - 0.7995 \text{dist} + 1.4512TD_1 + 2.0244TD_2 + 0.1463 \text{speed} + 0.5401 \text{evac} + 0.7809 \text{flood} + 1.6496 \text{mobile}
\]

where

\[
dist = \begin{cases} 
0, & d(t) \leq 94 \text{ mi} \\
\ln[d(t) - 94], & d(t) > 94 \text{ mi}
\end{cases}
\]

Definitions of the parameters in Eqs. 23 and 24 are found in Table 5.

Equation 23 is used starting at 72 hours before forecast onset of tropical storm force winds in a county. At 6-hour increments, the percent of individuals who evacuate are tallied for three constituencies: individuals who live in zones which are ordered to evacuate (whether in substandard housing or not), individuals who live outside of the active evacuation zones but live in substandard housing, and individuals who live outside of the active evacuation zones and do not live in substandard housing (the shadow evacuation). The population in active evacuation zones has both \text{flood} and \text{mobile} parameters set equal to 1. Although not all of these residents live in substandard housing, setting only \text{flood} = 1 results in a final evacuation percentage of at
To model the shadow evacuation, set mobile = 0 and flood = 0 to calculate the number of people who evacuate in this 6-hour period who are not in zones at risk for flooding and who do not live in mobile homes. (21, 22, 23, 24)

Input forecast TC path, synthetic TC, activation history, evacuation order history. Initialize at first county.

Is this county active?

yes

Calculate number of people who evacuate in flood zones over this 6-hour period. Set mobile and flood both = 1 for all zones that may be flooded. (21, 22, 23, 24)

Is this the last county?

yes

Output percentages who evacuate areas at risk of flooding and not at risk of flooding (shadow evacuation) for all counties in this 6-hour period.

no

Set mobile = 1 and flood = 0 to calculate the number of people who evacuate in this 6-hour period who are not in zones at risk for flooding but who are ordered to evacuated because they live in substandard housing. (21, 22, 23, 24)

no

Advance to next county.

Figure 16. Flow chart of the portion of the TCG that calculates the fraction of each county that evacuates in each 6-hour period. Equation numbers that correspond to some steps appear in parentheses.
most approximately 70%, which is considerably lower than found by previous studies (Baker 1991). The population outside of the evacuation zones but living in substandard housing have $flood = 0$ and $mobile = 1$. The population outside of the evacuation zones who do not live in substandard housing has both $flood$ and $mobile$ set equal to 0. At the end of the hurricane event, the 6-hour evacuation percentages are summed for each of the three population subsets in each county to determine the fraction of each subset that evacuates through the event.

Once the fraction of the population in each population subset in each county is calculated, a second evacuation simulation is run to determine the actual number of individuals who evacuate at each hour for the duration of the TC (Figure 17). Another logistic model is used, this time using the linear combination of parameters from Fu et al. (2007):

$$z = \gamma_2 - 2.292 + 1.018TD_1^* + 2.123TD_2^* + 1.949TD_3^* + 2.111notice_1 + 2.356notice_2 + 0.019\text{windspeed} - 1.748\ln(\text{onset})$$

(25)

Definitions of the parameters in Eq. 25 are found in Table 6.

The coefficients of all terms in the exponent remain the same as in Fu, but Fu’s measure of time until landfall is replaced in the TCG with the time until expected onset of tropical-storm force winds for each county. Additionally, at each hour a random number sampled from a
normal distribution with mean 0 and standard deviation 0.1 is added to the intercept value of −2.292 so that the resulting evacuation does not exactly match the Fu profile. Fu et al. note that while their model was developed by modeling individual evacuation decisions, none of the statistically-significant variables contain individual household attributes. Therefore, their model may appropriately be used as an aggregate evacuation model.

The evacuated population is updated every hour for all activated counties. Once a county is deactivated, the evacuation numbers are held constant until either the county is reactivated or the synthetic TC run comes to an end. Since the logistic evacuation model in Fu et al. (2007) was produced for a continuous evacuation, it does not accurately account for reactivation of deactivated counties, or late activation of counties that had not previously activated. For example, if a county had deactivated with 10% of the population evacuated, and then is reactivated with a mandatory evacuation 12 hours before landfall, the logistic model may immediately say that 70% of the county has evacuated in that hour. To prevent such an unrealistic evacuation, the rate at which a county zone may evacuate is capped at 7% of the county zone population per hour, or 5% of the county zone population per hour in the Keys. This represents a full evacuation in about 15 hours in most Florida counties, or 20 hours for a full

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_2$</td>
<td>a random perturbation used to prevent the hourly evacuation component of the TCG from perfectly following the Fu et al. (2007) profile, sampled from a normal distribution with $\mu = 0$ and $\sigma = 0.1$.</td>
</tr>
<tr>
<td>$TD_1^*$</td>
<td>a Boolean parameter that represents morning: set to 1 if between 6am and 9am, inclusive, and 0 otherwise.</td>
</tr>
<tr>
<td>$TD_2^*$</td>
<td>a Boolean parameter that represents midday: set to 1 if between 10am and 3pm, inclusive, and 0 otherwise.</td>
</tr>
<tr>
<td>$TD_3^*$</td>
<td>a Boolean parameter that represents late afternoon: set to 1 if between 4pm and 7pm, inclusive, and 0 otherwise.</td>
</tr>
<tr>
<td>$notice_1$</td>
<td>a Boolean parameter that represents a voluntary evacuation order: set to 1 if the zone in question is under a voluntary evacuation order, and 0 otherwise.</td>
</tr>
<tr>
<td>$notice_2$</td>
<td>a Boolean parameter that represents a mandatory evacuation order: set to 1 if the zone in question is under a mandatory evacuation order, and 0 otherwise.</td>
</tr>
<tr>
<td>$windspeed$</td>
<td>a parameter representing the current maximum wind speed in mph of the synthetic TC.</td>
</tr>
<tr>
<td>$onset$</td>
<td>time in hours until expected onset of tropical storm force winds in the county in question.</td>
</tr>
</tbody>
</table>

Table 6. Definitions of the parameters in Equation 25.
Input synthetic TC, activation history, evacuation order history, hourly costs of evacuation per person for each county, evacuation compliance fractions for each county. Initialize at \( i = 1 \) and at first county.

Is the county currently active?

Calculate the number of people who evacuate the county in this time step. (21, 22, 25) (Fu et al. 2007)

Multiply by the cost of evacuation per person to calculate the total cost of evacuation in this time step for this county. (Czajkowski 2011)

Is this the last county?

Is this the last time step?

Sum to find the total number of people who evacuated each county, and the total cost of evacuation in each county. Output county evacuation profile and county evacuation and casualty costs profile.

Advance to next county.

Advance to next time step. Initialize at first county.

Figure 17. Flow chart of the process for calculating the population evacuation figures and associated evacuation and casualty costs. Equation numbers that correspond to some steps appear in parentheses.
evacuation of Monroe County, where there is only one highway out of the Keys. These numbers are chosen to represent an optimistic case in which evacuations proceed with high efficiency, and to allow for any counties to be entirely evacuated in less than the 24 hours mandated by the State of Florida (Chen et al. 2006).

3.3.5 Modeling Evacuation Costs

At each hour, the number of households\(^9\) that evacuate each county is multiplied by an average evacuation cost per household, and a running tally is kept for total cost of evacuation per county. Three separate cost profiles are considered: the cost profile from Czajkowski (2007), a modified Czajkowski profile, and a flat daily costs profile.

The first cost profile is taken from Czajkowski (2007). Non-wage evacuation costs comprise direct costs (such as food and housing), travel costs (such as gasoline), and travel time (an opportunity cost); those cost values for a Cat-3 hurricane at varying forecast times before landfall are found in Table 7. The total non-wage costs for SSHS intensities other than Cat 3 are calculated by multiplying the total non-wage costs for Cat 3 by a constant: 0.6318 for Cat 1; 0.78 for Cat 2; 1.11 for Cat 4; and 1.1433 for Cat 5. Once the non-wage costs are determined, lost wages are added on at a rate $79 per day before onset of tropical-storm force winds.

The modified Czajkowski profile does not assume that the four forecast periods before onset of tropical-storm force winds all constitute only one day of lost wages. For a hurricane where the onset of tropical-storm force winds is before 6pm, that day is not included in lost wages. It is assumed that work day would be lost anyway due to the hurricane whether an individual evacuated or not. Therefore, lost wages are calculated by the number of days prior to onset of tropical-storm force winds that an individual chooses to evacuate. This number of days is multiplied by the average daily wage value of $79, in 2004 dollars, as found in Czajkowski (2007). The total cost of evacuation per person is then the sum of the total non-wage costs and the lost wages at the hour that household evacuates. Additionally, in the modified Czajkowski profile households who evacuate are penalized 1.5 times the daily wage for the time it requires to return from evacuation after the hurricane has passed.

\(^9\) Calculated by taking the number of evacuees in a given county and dividing by the number of individuals per household in that county, as reported in the 2010 US Census.
Finally, for the flat daily costs profile, an average daily non-wage evacuation cost of $83.20 is calculated from the data in Table 7. The average daily wage of $79 is added to achieve a daily cost of $162.20 per household. This value is used as a flat daily cost, so it is multiplied by the number of days before onset of tropical-storm force winds at which each household evacuates. The same 1.5 day wage penalty is applied as in the modified Czajkowski profile.

### 3.3.6 Modeling Casualty Losses and Total Storm Costs

After the synthetic TC has run its course, the casualty losses are calculated. Using the SSHS intensity with which the synthetic TC struck each county, the number of people who should have evacuated but did not is calculated for each affected county. These individuals who incorrectly remained behind are potential casualties. The losses from casualties are calculated using the average casualty cost figures adapted from Czajkowski (2011, see Table 2 in §2.2.3), weighted by the fraction of the ten county segments that are struck by each SSHS category. This weighted average is multiplied by the number of individuals who did not evacuate from zones that were struck, or live in substandard housing in other zones, in that county. These total casualty costs are added to the total evacuation costs for each county to get a per-county total storm cost.

It should be reinforced that a casualty is not necessarily a fatality; fatalities are a subset of casualties. Following Czajkowski (2007, 2011), a casualty is defined in this study as any individual that experiences a hurricane-related injury, even if minor. As described in §2.2.3, the casualty cost figures in this study are adapted directly from Czajkowski, who calculated expected

<table>
<thead>
<tr>
<th>Cat 3 (T*-11)</th>
<th>(T*-10)</th>
<th>(T*-9)</th>
<th>(T*-8)</th>
<th>(T*-7)</th>
<th>(T*-6)</th>
<th>(T*-5)</th>
<th>(T*-4)</th>
<th>(T*-3)</th>
<th>(T*-2)</th>
<th>(T*-1)</th>
<th>T*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Direct</td>
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<td>$193</td>
<td>$193</td>
<td>$193</td>
<td>$128</td>
<td>$128</td>
<td>$128</td>
<td>$153</td>
<td>$184</td>
<td>$215</td>
<td>$256</td>
</tr>
<tr>
<td>Travel Costs</td>
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<td>$16</td>
<td>$21</td>
<td>$25</td>
<td>$28</td>
<td>$33</td>
<td>$40</td>
<td>$59</td>
<td>$71</td>
<td>$83</td>
<td>$99</td>
</tr>
<tr>
<td>Travel Time</td>
<td>$11</td>
<td>$15</td>
<td>$20</td>
<td>$23</td>
<td>$26</td>
<td>$31</td>
<td>$37</td>
<td>$46</td>
<td>$55</td>
<td>$67</td>
<td>$78</td>
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<td>$159</td>
<td>$159</td>
<td>$79</td>
<td>$79</td>
<td>$79</td>
</tr>
<tr>
<td>Total</td>
<td>$454</td>
<td>$461</td>
<td>$472</td>
<td>$479</td>
<td>$341</td>
<td>$351</td>
<td>$364</td>
<td>$383</td>
<td>$401</td>
<td>$456</td>
<td>$526</td>
</tr>
</tbody>
</table>

Table 7. Total costs at all forecast periods in the TCG for a Cat-3 hurricane using the Czajkowski (2007) profile. T* represents the last forecast period before onset of tropical-storm force winds, and T* – n represents n forecast periods before T*. Total physical costs in the TCG at time periods before T* – 11 are equal to those at T* – 11. All dollar values are in 2004 dollars. From Czajkowski (2007).
casualty costs by finding average casualty costs for injuries ranging from minor to critical and weighting them by the fraction of individuals expected to receive each severity of injury. Because fatalities are considered a subset of the critically injured, explicitly calculating the number of fatalities or associated costs of fatalities is unnecessary for purposes of this study.

### 3.3.7 Selection of Cost Curve for Use in Results Chapter

In order to cleanly describe the results, it is important to specify the hourly evacuation cost profile used to create the figures. As described in §3.3.5, three cost profiles are used for collection of the evacuation costs data: a profile from Czajkowski (2011), a modified Czajkowski profile, and a flat daily costs profile. The modified Czajkowski profile produces results curves that are nearly identical to the results from the Czajkowski (2011) profile with a vertical shift upwards. This is as expected because the major modification is the addition of a 1.5-day wage penalty per household, which will affect the ordinates of the curve, but not its slope or curvature.

The flat daily costs profile also produces result curves with nearly identical slope and curvature to those of the Czajkowski profiles for sensitivity of costs to forecast accuracy, albeit with higher ordinates than the two Czajkowski curves. The inclusion of the 1.5 day wage penalty raises it to the level of the modified Czajkowski curve, while the remainder of the additional cost is due to the shift in the minimum household evacuation cost from 5-8 forecast periods before storm onset in the Czajkowski profiles to the last few periods before onset in the flat daily costs profile. This shift in the timing of the minimum household evacuation cost does cause the evacuation costs curve for flat daily costs to be steeper than the two Czajkowski curves for sensitivity of costs to evacuation order lead time, however.

The modified Czajkowski profile is selected for the purposes of the following results chapter because it produces values that are approximately the average of the three cost profile curves. Additionally, the average evacuation cost per household in the modified Czajkowski profile is about $515, which is comparable to the evacuation cost values in Whitehead (2003), updated for inflation and adding lost wages, which are not included in Whitehead’s figures. In all figures that follow, the modified Czajkowski cost profile is plotted for any evacuation cost curves.
Chapter 4. ANALYSIS AND RESULTS

4.1 Review of Key Questions

As stated in §1.3, this study is motivated by four key questions:

- What is the sensitivity of casualties and evacuation costs to improved track forecasts?
- Is there an optimal length of warned coastline relative to casualties and evacuation costs? What is that length?
- Is there an optimal evacuation order lead time relative to casualties and evacuation costs? What is that lead time?
- Which Florida counties tend to incur greater costs of evacuations and casualties for evacuation events?

To answer these questions, data is collected from the five simulated evacuations for each of the 82,820 TCs in the synthetic climatology (SC). These data include total number of evacuees per county, total cost of evacuation per county, total number of individuals who should have evacuated but did not per county and zone, and total casualty cost per county. The total overall costs per county are then calculated by summing the evacuation cost and the casualty cost for each county. These results are subjected to series of sensitivity tests to (i) the percent decrease/increase in the forecast COU radii, (ii) the voluntary evacuation lead-time, and (iii) the add-on value (AOV) for length of coastline evacuated.

Recall from §3.3.7 that the modified Czajkowski evacuation costs profile is used because it produces values that most closely represents average evacuation costs from the literature (Whitehead 2003), but updated for inflation and lost wages.
4.2 Improvement in Forecast Accuracy

In Figure 18, the average cost of evacuation per event\(^{10}\) is plotted as a function of the percent improvement in forecast accuracy beyond current skill. A decrease in accuracy beyond current skill is to the left of zero, and improvement is to the right of zero. The five curves

![Figure 18](image)

Figure 18. Average cost of evacuation per event (in 10^8 USD) as a function of the percent improvement in forecast accuracy over current skill. Recall that multiples of $R_{avg} = 80$ km are used to determine the size of the add-on value to the cone of uncertainty used to find sensitivity to the length of coastline ordered to evacuate.

\(^{10}\) An event is defined as any county or series of consecutive counties evacuating from a hurricane or, in absence of an evacuation, accruing casualties. An event does not necessarily mean a strike, as an evacuation may be called for a hurricane which ultimately does not strike. Some hurricanes in the SC result in more than one event, for example a hurricane which causes separate evacuations in southeastern Florida and in the Panhandle.
represent AOV which are integer multiples of $R_{\text{avg}}$ from zero to four inclusive\textsuperscript{11}. The smaller zigzags within each curve are due to each point representing 820 hurricanes; had a larger synthetic climatology been used, those zigzags would become smaller. For a constant AOV, the average total cost of evacuation tends to decrease as the forecast accuracy improves; more accurate hurricane track forecasting reduces the width of the COU, thereby decreasing the cost of evacuation because a shorter stretch of coastline evacuates.

The percent reduction in evacuation cost increases as AOV decreases – that is, as the length of warned coastline decreases for a given forecast accuracy (COU). A 50% reduction in COU width beyond the current COU leads to up to a 50% reduction in the length of coastline

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure19.png}
\caption{Average distance of coastline evacuated (in km, given by color) by percent improvement in forecast accuracy beyond current skill and the average casualty costs per event (in $10^9$ USD). The top row is the average of all casualty events for the given improvement in forecast accuracy with costs greater than $3.5 \times 10^9$ USD.}
\end{figure}

\textsuperscript{11} Recall that $R_{\text{avg}} = 80$ km. This value is an estimate of the climatological mean radius of hurricane-force winds and is used to determine the AOV.
evacuated with an AOV of zero, whereas for \( \text{AOV} = 4R_{\text{avg}} \) the same percent reduction in COU width yields at most about a 23\% reduction in the length of coastline evacuated. In Figure 18, however, the cost reductions are only about 33\% for \( \text{AOV} = 0 \) and 6\% for \( \text{AOV} = 4R_{\text{avg}} \). This difference is owing to two factors. First, only the state of Florida is considered, so for an evacuation that would cross state boundaries if the entire coastline were considered, any cost reductions in evacuated areas in surrounding states are not included. Second, the southern end of the Florida peninsula behaves similarly to the state boundaries because evacuations do not usually “wrap around” the southern tip of the peninsula; any reduction in COU width to the south of the peninsula has no benefit to reducing evacuation costs because the reduction occurs over open waters. These differences increase as AOV increases: the total length of coastline evacuated for \( \text{AOV} = 4R_{\text{avg}} \) is longer than the entire Atlantic coastline of Florida from the Keys to the Georgia border, further limiting the average cost improvement.

The average length of coastline evacuated for a given total casualty cost and percent improvement in forecast accuracy is plotted in Figure 19. The plot becomes less smooth as casualty costs increase because the number of data points becomes sparse: the vast majority of evacuations in the TCG result in total costs less than $1 billion. The average length of evacuated coastline tends to decrease as forecast accuracy increases, and it decreases for increasing casualty costs, if forecast accuracy is held constant. This makes sense: reducing the length of evacuated coastline while keeping forecast accuracy constant will increase the probability of a hurricane striking outside the evacuated area, thereby increasing casualty costs. More accurate forecasting reduces the casualty costs for evacuating a specific distance of coastline. For example, evacuating approximately 350 km of coastline yields casualty costs of around $3 billion at a 10\% improvement in forecast accuracy, but evacuating the same distance of coastline at a 20\% improvement in forecast accuracy yields casualty costs under $1 billion. Additionally, for a given tolerance to casualty cost, improved forecast accuracy allows for a large reduction in the length of evacuated coastline.

If AOV is held constant, the casualty costs per evacuation tend to increase for improved forecast accuracy (Figure 20), especially for the \( \text{AOV} = 0 \) and \( \text{AOV} = 1R_{\text{avg}} \) cases. While this may initially appear counter-intuitive, improved forecast accuracy translates to a narrower cone of uncertainty in our model. This means that a shorter length of the coastline will be warned,
increasing the likelihood that households in a stretch of coastline will not evacuate, but ultimately be struck.

Consider the case with perfect forecast accuracy. The COU would be a straight line along the track of the hurricane. For AOV = 0, only individuals directly in the path of the center of the hurricane would be ordered to evacuate, and so casualties would be high on each side of the track where the hurricane strikes (recall that a strike is the entire region affected by hurricane-force winds, not simply the landfall point) outside of the COU but no evacuation is called. This issue is mitigated for AOV = 1R_{avg}, but if the radius of hurricane-force winds is larger than R_{avg}, there will still be a length of coastline on each side of the evacuated area which should have been

![Figure 20. Average casualty cost per event (in 10^8 USD) as a function of the percent improvement in forecast accuracy over current skill.](image-url)
evacuated but was not. For AOV of $2R_{\text{avg}}$ or greater on each side of the COU, the entire area which is struck will have been evacuated, and so the only casualties come from people who failed to follow evacuation orders.

Recall that the COU represents a $1\sigma$ track forecast error. For AOV = 0, coastline is evacuated out to $1.5\sigma$, but the actual track is allowed to be up to $2\sigma = 2\alpha$ away from forecast in the truncated distribution (see §3.3.1). Therefore, approximately 9% of hurricanes at AOV = 0 will track outside the warned area, causing large casualty costs upon strike. An AOV of $1R_{\text{avg}}$ eliminates this issue for most of the hurricanes that track between $1.5\sigma$ and $2\sigma$ away from the forecast track, but although the landfall location is now usually evacuated, there may still be higher casualties where hurricane-force winds extend beyond the evacuated area. At AOV = $2R_{\text{avg}}$, this issue is eliminated for all cases except where the hurricane tracks $2\sigma$ away from the forecast track and has a radius of hurricane-force winds larger than $R_{\text{avg}}$. For AOV of three or four, this issue is eliminated entirely.

Recall that as forecast accuracy improves, the size of the COU (and therefore the $1.5\sigma$ and $2\sigma$ regions as well) is reduced. Consider for the AOV = 0 case, a hurricane with a 100-km radius of hurricane-force winds which is tracking $1.4\sigma$ away from its forecast track. Because the distance from $1.4\sigma$ to $1.5\sigma$ is smaller for increasing forecast accuracy, the hurricane has a larger portion of its hurricane-force wind field outside of the $1.5\sigma$ warned zone. Therefore, a larger stretch of coastline is not ordered to evacuate but is ultimately struck than for lower forecast accuracy. Similar arguments can be made for the AOV = $1R_{\text{avg}}$ and AOV = $2R_{\text{avg}}$ cases.

Note that the decrease in casualty costs as AOV increases from two to four is quite small; at this point, the vast majority of the casualty costs incurred for those AOV are from individuals who are ordered to evacuate but fail to heed evacuation orders, rather than from areas that are not warned to evacuate in the first place. Paired t-tests to check if the AOV = $2R_{\text{avg}}$, AOV = $3R_{\text{avg}}$, and AOV = $4R_{\text{avg}}$ casualty cost curves are the same result in extremely low p-values, and so the null hypothesis that they are the same curve is rejected. However, the very small decrease in casualty costs from AOV of 2 to 4 shows that the marginal benefit to casualty costs of evacuating beyond AOV = $2R_{\text{avg}}$ is minimal.
When the combined total of evacuation and casualty costs are considered, more accurate forecasting generally reduces the average cost per event (Figure 21). Given approximately the same casualty costs for AOV of two through four, all of which are lower than for AOV of zero or one, any of those three AOV would be preferable to zero or one. Of those three, the lowest evacuation and total costs occur for AOV = 2R_{avg}. In addition, an AOV of 2 has a greater percent cost reduction with better forecast accuracy than AOV of 3 or 4. Therefore, using an AOV of two appears to be the optimum AOV for evacuations, with more “bang for the buck” for improvements to forecast skill.

Breaking down the total costs of evacuations and casualties by hurricane category reveals important differences between evacuations for minor and major hurricanes (Figure 22). For Cat 1
hurricanes (Figure 22a), the total costs are greater than the cost of casualties in the absence of any evacuation. For Cat 2 hurricanes (Figure 22b), total costs are roughly equal to casualty costs in absence of an evacuation for current practice and skill (zero percent improvement, AOV of zero to one). Improving forecast accuracy and maintaining the same AOV as at present drops the total cost below the cost of casualties for in the absence of an evacuation. For major hurricanes (Cat 3, 4, and 5; Figure 22c, Figure 22d, and Figure 22e, respectively), in all cases the total cost of evacuating is lower than the casualty costs in the absence of an evacuation. It should be recalled, however, that hurricane evacuations in the TCG use a “perfect” forecast of maximum
strike intensity – the maximum strike category is known ahead of time, but the location and timing of that maximum strike is not. In reality, techniques for forecasting hurricane intensity remain nearly a generation behind current best techniques for forecasting track (Willoughby et al. 2007). Rapid intensification events are especially challenging to forecast. One cannot safely assume that a particular storm will indeed make landfall as a category one. Thus, evacuation is always called for, as is current policy. Looking at the average costs for all categories of hurricanes combined (Figure 22f), the overall total cost is always lower than casualty costs of failing to evacuate; the cost savings of evacuating for major category hurricanes outweigh the additional costs of evacuating for minor hurricanes.

Figure 23. Average cost of evacuation per event (in $10^8$ USD) as a function of the voluntary evacuation lead time in hours.
4.3 Voluntary Evacuation Lead Time

As with improved forecast accuracy, a sensitivity analysis is also conducted for voluntary evacuation lead time. The average cost of evacuation decreases with shorter lead time for all AOV (Figure 23). Multiple factors contribute to this decrease.

The analyses depicted in Figure 24 allow us to deconstruct the evacuation cost trends depicted in Figure 23. Actual evacuation lead time (abscissa) is plotted against percent evacuating at that lead time (ordinate) for a range of official evacuation lead times (colored bars in Figure 24). The actual evacuation lead time along the abscissa is measured relative to the actual time of observed landfall, whereas the official evacuation lead times are measured from

![Figure 24](image-url)

Figure 24. The percent of households that evacuate in each 12-hour period before onset of tropical storm force winds, broken down by voluntary evacuation lead time. The cluster of bars farthest to the left is the percent of households that do not evacuate. Only evacuations from substandard housing and the affected evacuation zones in counties that are ultimately struck by hurricane force winds are included.
the expected time of landfall based on the forecast. First, as voluntary evacuation order lead time decreases from 65-72 hours before onset to 16-24 hours before onset (maroon through to dark blue bars), the number of households that fail to evacuate increases by about 4 percentage points. Second, a larger cohort of households waits to evacuate until closer to onset, when per-household evacuation costs are slightly lower on average. Third, the expanded cone of uncertainty (ECU) intersects a shorter distance of coastline at shorter lead times, and so people are ordered to evacuate from fewer counties. All of these factors contribute to the decrease in average total evacuation costs for shorter voluntary evacuation lead times. On the other hand, casualty costs increase for shorter lead times because the number of people remaining in harm’s way increases (“STAY” on Figure 24).

Figure 25. Average casualty cost per event (in $10^8$ USD) as a function of the voluntary evacuation lead time in hours.
As with improvement in forecast accuracy, increasing AOV values beyond $2R_{\text{avg}}$ has little effect on decreasing casualty costs (Figure 25). The decrease in casualty costs from AOV of two to three and four is statistically significant, albeit quite small, whereas there is little statistical difference between the AOV three and four curves\ref{footnote:12}.

When evacuation and casualty costs are considered simultaneously, an increase in voluntary evacuation lead time tends to result in a slightly larger total expense for each

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure26}
\caption{Average combined evacuation and casualty cost per event (in $10^8$ USD) as a function of the voluntary evacuation lead time in hours. The thinner curves are the evacuation costs only.}
\end{figure}

\footnote{\ref{footnote:12} These results are based on paired t-tests in which the null hypothesis that the two, three, and four AOV curves are the same is rejected at the 0.05 significance level, although the null hypothesis cannot be rejected for the AOV $= 3R_{\text{avg}}$ and AOV $= 4R_{\text{avg}}$ curves at the 0.01 significance level.}
evacuation event (Figure 26). The small magnitude of this increase occurs because the decrease in evacuation costs for shorter lead times is barely larger than the increase in casualty costs for shorter lead times. The practical implications of this result will be discussed in Chapter 5.

4.4 Effects of Along-Track and Across-Track Forecast Errors

Up to this point in the analysis, forecasting accuracy has been considered in the aggregate, with no discrimination between the different types and magnitudes of forecasting errors that can occur. The effects of along-track and across-track forecast errors on the timing of household evacuations are now considered.

The population evacuation behavior for hurricanes with an accurate (less than 1% error) forward speed forecast (Figure 27a) is similar to that for all hurricanes (Figure 24) because the effects of hurricanes that are faster than expected and those that are slower than expected tend to cancel out. For hurricanes that travel faster than forecast (Figure 27b), fewer households evacuate more than 2 days before the hurricane strikes because they expect the storm to arrive later than it actually does. Therefore, more households evacuate with a shorter time before strike, as it becomes apparent they do not have as much time to leave as expected. The resulting evacuation itself is less expensive because fewer households leave at later times, but a higher number of casualties result. The pattern is reversed for hurricanes that travel slower than forecast (Figure 27c). A greater percent of households leave early, thinking they have less time to evacuate than they actually do, leaving fewer households to evacuate at later times. The result is a more expensive evacuation, but with fewer casualties.

Hurricanes with an accurate (less than 1° error) across-track forecast (Figure 28a) have a similar population evacuation to both Figure 24 and Figure 27a because the effects of hurricanes going to the left of forecast and going to the right of forecast tend to cancel each other out. If the forecast is to the left of the actual track (Figure 28b), the profile is similar to that of a hurricane that travels faster than forecast in Figure 27b. Owing to the average recurvature, a hurricane that is forecast to the left of the actual track will activate evacuations along the actual track with longer lead times than actually required, causing households to think they have more time than
they actually do. On the other hand, when the forecast is to the right of the actual track (Figure 28c), the profile is similar to that of a hurricane traveling slower than forecast in Figure 27c, albeit with a less pronounced effect. In this case, the recurvature of a forecast to the right will activate evacuations along the actual track with shorter lead times than actual, thereby causing households to evacuate earlier because they expect to have less lead time than they actually do.
4.5 County Cost Factor

Although the previous results have focused on the state of Florida as a whole, a county-by-county breakdown of the data from the TCG allows for the development of a county cost factor. This cost factor is calculated by taking the average per-event total cost of evacuation and casualties for each county and dividing by the total population of the county. This cost factor, then, is a per-person cost of an evacuation event in their county: the economic impact by county based on local hurricane climatology (frequency and category distribution) and population.
exposure (percentage near the coast and percentage in substandard housing), moderated by forecast skill in the region.

The resulting cost factor shows that the counties with the highest per-person cost of an evacuation event are in the eastern Panhandle / Big Bend region, on the Gulf coast south of Tampa Bay, and the Florida Keys (Figure 29). Interestingly, the correlation between the cost factor and the average category of hurricane to strike the county is quite weak: counties in the western Panhandle and southeast Florida tend to have stronger hurricanes than in the Big Bend or southwest peninsula, but they have a lower county cost factor. Counties with a high cost factor instead tend to have a large share of their population in low-lying areas or in substandard

Figure 29. The average per-person cost of evacuation and casualties per event for all 35 Florida coastal counties: blue bars for events with no strike in the county; red bars for events with a strike in the county, and green bars for all events in the county. The bars are not cumulative; blue is to the front, red is to the back, green is in the middle. The black line is the percent of each county’s population that should evacuate for Cat 2-3 hurricanes, plotted for comparison.
housing. Indeed, the cost factor curve most closely resembles the fraction of each county’s residents who are ordered to evacuate for a Cat 2-3 hurricane (Figure 29, black line). This result is logical because a higher proportion of the residents of those counties will either incur evacuation costs or potentially incur casualty costs if they fail to evacuate and a strike occurs.

Note that the height of the green bars (all evacuation events, strike or no strike) is the average of the heights of the red (strikes only) and blue (no strikes) bars, weighted for the percentage of evacuation events that produce strikes versus no strikes. In the Keys (tallest bar), nearly 50% of the time when an evacuation occurs, a strike will also occur. On the other hand, in the counties farthest to the northeast, a strike will occur only approximately 10% of the time when an evacuation takes place.
Chapter 5. DISCUSSION

5.1 Answers to Key Questions

This study has been undertaken seeking the answer to four key questions, which may now be succinctly answered:

1. **What is the sensitivity of casualties and evacuation costs to improved track forecasts?**

   A reduction in track forecast error reduces hurricane evacuation costs simply because a smaller length of coastline (COU) is ordered to evacuate, requiring fewer households to evacuate on average (Figure 18). The percent reduction in evacuation cost is greater for smaller AOV. Note that an approximately 35% improvement in forecast accuracy beyond current skill allows for the additional evacuation of one AOV on each side of the COU beyond current practice (AOV = 1R_{avg}) while maintaining the same cost of evacuation.

   Casualty costs remain roughly flat with improved forecast accuracy for larger AOV, while they tend to increase with improved forecast accuracy for smaller AOV (Figure 20). It is clear that for AOV of zero and one, too small a length of coastline is called to evacuate upon the first issuance of evacuation orders. New stretches of coastline may be ordered to evacuate at subsequent times. This will lead to shorter evacuation lead times as new forecasts shift the COU into coastal areas that had not previously been under orders, resulting in a larger percentage of individuals remaining in harm’s way when the hurricane strikes (Figure 24, “STAY”). Evacuating with an AOV of zero or one is not sufficient to ensure that the entire stretch of coastline that will be struck by the hurricane is ordered to evacuate, resulting in high casualties. For AOV of two or larger, the length of coastline ordered to evacuate covers all areas that are ultimately struck, which leads directly into the second key question.
2. **Is there an optimal length of warned coastline relative to casualties and evacuation costs? What is that length?**

For constant forecast accuracy, the decrease in casualty costs as AOV increases from two to four is generally around $10,000,000 (Figure 20). At AOV = 2R_{avg} the additional coastline evacuated beyond the COU is large enough that any further decrease in casualties must come from increasing compliance with evacuation orders, not from evacuating an even larger length of coast. Assuming initial evacuation orders are issued with a 48-hour lead time, when the NHC currently issues hurricane watches, evacuating with an AOV of two corresponds to a stretch of coastline enclosed by a circle of diameter 864 km.

From a purely cost-oriented standpoint, evacuating the coastline with AOV = 0 results in both the lowest cost of evacuation and combined cost of evacuation and casualties (Figure 22). However, considering the moral imperative of saving as many lives as possible, the optimal solution is AOV = 2R_{avg}, as evacuating with a larger AOV than two adds to the total evacuation cost with a minimal reduction in casualty costs.

3. **Is there an optimal evacuation order lead time relative to casualties and evacuation costs? What is that lead time?**

In general, longer evacuation order lead times have higher costs of evacuation (Figure 23) but lower casualty costs (Figure 25). When summed together, the increase in evacuation costs for longer lead times is nearly offset by the decrease in casualty costs, resulting in only a slight increase in total costs for longer lead times (Figure 26). In 2010 the NHC increased the lead time for issuing hurricane watches and warnings by 12 hours (from 36 to 48 hours and 24 to 36 hours, respectively) to provide emergency managers a longer lead time for issuing evacuation orders. In doing so, casualty costs are expected to decrease by approximately $20 million on average, while the total costs of evacuation and casualties would only be expected to increase by approximately $10 million on average.

4. **Which Florida counties tend to incur greater costs of evacuations and casualties for evacuation events?**

Counties with larger populations will clearly have larger costs in the aggregate simply because more people need to move out of harm’s way, or are left in danger of injury or death.
When those costs are normalized by county population, however, the higher per-person costs tend to occur in counties with a larger percentage of their residents in evacuation zones or substandard housing because if a greater percentage of the population is effected, the costs are incurred by a larger share of the residents.

5.2 Additional Implications of Results

Willoughby et al. (2007) speculate that the best-case scenario for decreasing the warned area of coastline for improvements in forecast track accuracy would only be “a few tens of miles,” and that a greater decrease than that would result in a more marginal gain or a net loss due to increased casualty costs. Our study confirms these assertions. In fact, if reducing casualties is the primary concern of emergency managers and policy makers, an even longer stretch of coastline may need to be evacuated than at present [approximately 480-640 km (Willoughby et al. 2007)] to reach the optimal value of \( AOV = 2R_{avg} \), which is approximately 865 km for a 48-hour lead time. Given that the cost reduction of decreasing warned area comes at the price of increased casualties, the two primary means remaining of decreasing evacuation costs are increasing the compliance with evacuation orders and minimizing the shadow evacuation.

As the average cost per individual of evacuating is lower than the average casualty cost per individual for hurricanes of all categories (Figure 22), as the share of households that obey evacuation orders increases, the overall costs decrease. Perhaps the simplest way to increase compliance with evacuation orders is to reduce the costs of evacuations. Opening neighborhood shelters within the evacuation zones themselves would eliminate the lodging costs of local residents and reduce the time needed for them to evacuate, potentially allowing the working members of the neighborhood to miss less time at work. New schools and other public buildings to be used as shelters may be elevated on an artificial hill to keep them above the surge zone, although a cost-benefit analysis of any mitigation measures is the prerogative of the policy-makers.
Decreasing the shadow evacuation of individuals who are not at risk from flooding or in substandard housing would also lower evacuation costs. Better education and outreach with members of the public who are do not live in an evacuation zone or substandard housing may help to reduce their concerns about hunkering down for a hurricane.

It is important to note that all of the hurricanes in the TCG are designed to be reasonably “well-behaved” in that the forecast tracks can vary from the actual track by at most $2\sigma$. Additionally, the TCG assumes that improvements in forecast track accuracy are equal across-the-board, rather than increasing the overall accuracy by being very accurate a majority of the time but still having large errors the rest of the time. Such outcomes could be potentially catastrophic if a hurricane made a “surprise” strike on a major metropolitan area. Due to the impracticality of evacuating much beyond an AOV of two (it should be noted, an AOV of two represents approximately 865 km with 48 hours of lead time, which is nearly the 1000-km length of Florida’s Atlantic coast), resources should be devoted to better forecasting hurricanes in more difficult environments, not simply improving forecast accuracy of hurricanes in more easily predictable synoptic environments.

Although the hurricanes in the TCG are well-behaved, there is still the potential for high casualties. Twenty-nine events carry casualty costs of greater than $10 billion. These events have three major things in common: small AOV, category of 4 or 5, and tracks that take the brunt of the hurricane through multiple high-population areas (Figure 30). All make landfall near Miami, and most have an inland track paralleling the Atlantic coast (thereby keeping the strongest winds right along the shore) before exiting in the vicinity of Jacksonville. Hurricanes that ride along the Atlantic coast of Florida may be perilous for forecasters as well: a shift in the track of only 100-200 km east to west can make the difference between a hurricane that passes safely out to sea and one that causes a great loss of life.
5.3 Future Work

In order to perform this sensitivity analysis on track forecast accuracy and evacuation lead time, some other variables need to be standardized or simplified. One major simplification is that all evacuations use a “perfect” forecast of landfall intensity: evacuations are ordered knowing that a certain category of strike will occur, but not the specific location or time of the strike. Given the difficulties in skillfully forecasting hurricane intensity, a follow-on sensitivity analysis to intensity forecasting is recommended.
Although this study focuses on hurricane strikes in Florida, the state is not an island. The inclusion of neighboring states in a future study could help gain a better handle on costs of hurricanes that strike the Alabama and Georgia borders, causing evacuations and casualties across multiple states, as well as various island nations in the Caribbean. As each state and nation has its own rules regarding issuance of evacuation orders, such a study could also test which state’s policies lead to the lowest evacuation and casualty costs. Along the same vein, the three-zone system used for Florida counties in this study is not universal across the state; it is only used in this study to standardize across all counties. A future analysis could test whether a particular county evacuation zone configuration is optimal for reducing casualties and evacuation costs or if the evacuation zone structure should be guided by bathymetry/coastal topography, infrastructure available for evacuation, or other factors contributing to local societal vulnerability.

It should be reinforced that the TCG only models evacuation costs to residents; hurricane evacuation costs incurred by the various levels of government, local and regional businesses, vacationers, etc., are not included. An evacuation of a popular tourist spot on Labor Day weekend may require an earlier evacuation order than modeled in this study, for example. It may be more advantageous for businesses in evacuation zones to remain open as long as possible before the onset of the hurricane to minimize losses, while some businesses further inland, such as food preparation or lodging, may make additional money selling their goods and services to evacuees. Therefore, this study should only represent a portion of what policy makers and emergency managers take into account when determining when, where, and how to order an evacuation. Further studies are necessary to quantify additional evacuation costs borne by governments, businesses, schools, and other institutions.


National Hurricane Center (NHC), cited 2011a: Tropical Cyclone Climatology. [Available online at http://www.nhc.noaa.gov/climo/.]


