The Use of Physically Based Models and Ensemble Forecasting for Storm Surge Risk Assessment in a Changing Climate

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THE USE OF PHYSICALLY BASED MODELS AND ENSEMBLE FORECASTING FOR STORM SURGE RISK ASSESSMENT IN A CHANGING CLIMATE

by

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ABSTRACT

Storm surge has been the deadliest and costliest hurricane induced hazard in the coastal United States. In order to save property and lives, emergency managers must issue advisories guided by numerical models in a timely manner. However, these surge models are highly dependent on weather forecasts which contain uncertainties themselves as hurricanes traverse through the waters before making landfall. This dissertation aims to understand the contribution of uncertainties in hurricane properties, particularly the wind intensity which can contribute to uncertainties in storm surge models. Investigating these properties through numerical modeling is both computationally and time intensive. However by developing a methodology that takes into account the natural variability of wind intensities in the recent decade, it is only necessary to conduct a small number of simulations which reflect 90% of the variation of what has been observed. Using this method results in a more robust surge prediction in coastal locations by producing statistics of the expected range of storm surges, including minimum and maximum inundation volumes. Additionally, although the use of machine learning and statistical models have proven to be fast and computationally efficient, it is demonstrated that there is still a great need for deterministic modeling, especially in the changing climate. Deterministic modeling is used to show that we can expect increases in both inundation volume and area under future climate conditions. This study also showed that at the end of the century, hurricanes may produce larger surge magnitudes in concentrated areas as opposed to surges that are lower in magnitude and widespread. One notable finding of this study is that there is no single storm property that dictates the magnitude of surge inundation. Even when these properties
are considered together, the results are still difficult to anticipate without explicit numerical simulation. Due to dynamic hurricane properties, storm surge risk communication has been challenging. Despite communication changes from the National Hurricane Center, we have found that there is a lingering association between the Saffir-Simpson Hurricane Wind Scale (SSHWS) and storm surge risk by the general public. However, findings suggest that although improving communication can indeed improve risk perception, it only addresses one component of a multidisciplinary system that defines storm surge risk. To be truly effective, resilience efforts will require multidisciplinary approaches.
Para sa bayan kong ginigiliw.
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CHAPTER 1: INTRODUCTION

1.1 Background and Motivation

Hurricane driven storm surge has been reported as the leading cause of hurricane related death in the years 1963-2012 (Rappaport, 2014), although many of the fatalities are due to Hurricane Katrina in 2005 (Chapter 2). To save property and lives, emergency managers issue evacuation orders based on guidance from the National Hurricane Center, which uses storm surge models for information. Results from these models need to be accurate, but they also need to be issued in a timely manner. Due to this, some researchers have focused on machine learning or surrogate modeling to produce faster and more computationally inexpensive results. However, a lot of these surrogate models depend on data from the past that may be sparse or just do not exist. On the other hand, these gaps can also be filled by numerical modeling, but these models are often time consuming and computationally intensive. This dissertation presents evidence that there is still a need for deterministic or physically based modeling of storm surge and the need is becoming even greater as we seek to understand storm surge under future climate conditions where climate change can cause more uncertainties due to unknown hurricane impacts. Storm surge risks are highly dependent on hurricane properties, and physics based modeling can give a clearer picture of how surge risk may change in the future.

Storm surge is one of the primary drivers of coastal flooding, and concerns about it has been increasing in the past few years and rightfully so. The population in coastal counties
increased from 47.4 million in 1960 to 127 million in 2014 (US Department of Commerce). Coastal counties, according to the US Census bureau is land that is adjacent to territorial coastal waters or sea. These communities are directly exposed to hurricanes, which bring related hazards along its path.

The rise in hurricane activity especially in the last few years has been concerning and may potentially increase due to expected increases in sea surface temperatures (Knutson et al., 2008; Saunders & Lea, 2008). In 2020 alone, there were over 30 named meteorological disturbances in the Atlantic basin which was consequently the most active hurricane season on record. Thirteen were hurricane strenghnt and 12 of them made landfall in the coastal United States (Blackwell, 2020).

Increases in hurricane activity also mean that the risk of storm surge in coastal regions will increase. Although long term hazard mitigation against coastal flooding include relocation and building protective barriers is important, immediate life-saving actions through evacuation is something individuals can do to protect themselves during high water events.

In order to prompt evacuation response from the public during storm surge events, the messaging or warnings need to elicit emotion from the public. In Chapter 2 we look at how storm surge is communicated by the National Hurricane Center to the public. Earlier versions of the Saffir-Simpson Scale (Saffir-Simpson Hurricane Wind Scale or SSHWS thereafter) included estimates of storm surge heights with the intensity of hurricanes. However, due to a number of hurricanes that caused surges that exceeded the values listed on the scale, storm surge risk was eventually removed. We surveyed literature and discovered that despite changes in the way surge risk is communicated by officials, there is still a
lingering dependency on the SSHWS. Most importantly, the study also demonstrates how other factors play into both short term and long term decision making of individuals for the personal protection against storm surge, allowing us to explore how we might improve it.

Different counties have pre-planned maps that designate levels of evacuation during storm surge events, depending on the anticipated severity of coastal flooding. In some instances, not all areas are flooded and do not need to be issued evacuation orders. If evacuation plans are solely dependent of these maps, and are not updated with timely forecasts, they will result in “false positives,” i.e. closure of areas that are not affected by surge. Numerical models can aide in communicating surge through mapping and indicating areas that will be impacted. Since hurricanes are very dynamic and there are an infinite number of possible combinations of their properties, there are also a myriad of possibilities of surge impacts that can result from a given storm. To explore these possibilities, we can run all possible scenarios using Monte Carlo type methods. However this is not only time consuming but computationally expensive.

The results of these surge models are also highly dependent on how accurate the wind models are. There is limited access to wind models that are verified or assimilated for most researchers. However, the Best Track Data from the National Hurricane Center is freely available. The best-track is “subjectively-smoothed” and even for post storm analyses it will not reconstruct the exact identical hurricane event (Landsea & Franklin, 2013). It contains inherent uncertainties such as the natural variability of the hurricane itself, measurement errors, and subjectivity from the forecasters themselves.
Given that Best Track Data is often the main source of wind information for numerical models, how does the uncertainty from it propagate through the storm surge model? In Chapter 3, we propose a methodology that creates an ensemble of wind information that is representative of the uncertainties in the wind data. Unlike traditional Monte Carlo methods, we are able to use a small sample based on historical data to generate ensembles used to assess the uncertainty propagation. We use our method to explore the impacts of uncertainties in the intensities of six different hurricanes and propagate it through the ADCIRC (ADvanced CIRCulation) model.

After looking at how uncertainties in wind intensity affect storm surge, we broaden our scope in Chapter 4 by using results from the WRF (Weather Research Forecasting) Model which unlike parametric models, which only contain information in a limited area of the hurricane, it describes a fully gridded wind and pressure field as input to the ADCIRC model. Using historical hurricanes that were produced from WRF, we investigated how combinations of hurricane properties (wind intensity, pressure, translation speed, and size) when taken as a whole affect storm surge volumes. It is widely accepted that storms with high intensities, large sizes, slow translation speeds, and low central pressures produce large surges, however, we find that this is not entirely true. Using the same storms that resulted in introducing the RCP 8.5 (high emission) scenario (Gutmann et al., 2018), and we show how projected changes in hurricanes affect storm surges and what we might expect in the next 100 years. Learning about how surges behave in the future can aide in future urban and resiliency planning.

This dissertation shows that even though numerical methods are relatively costly and time
intensive, it is still central to and necessary for emergency planning and response in coastal regions. This is even more important in future scenarios where the uncertainty in hurricane behavior is quite high. We also demonstrate that although widely accepted, we cannot really assume the behavior of surge based on the given meteorology, and it is much more nuanced than believed.

1.2 Objectives

This dissertation aims to answer the following objectives:

- How does the historical association of hurricane wind intensity and storm surge influence risk communication?
- How do uncertainties in wind intensities affect storm surge risk / inundation?
- How does wind intensity and other hurricane characteristics affect storm surge, and how might projected changes to the climate influence storm surges over the next 100 years?
2.1 Introduction

It is widely recognized that nearly half of the 2325+ deaths directly caused by U.S. land-falling hurricanes since the mid 20th century have resulted from storm surges (Rappaport, 2014); however, this statistic is significantly influenced by Hurricane Katrina, whose storm surges caused an estimated 1500 fatalities in August 2005 (Knabb et al., 2005). Storm surge fatalities, like extreme surges themselves, are low probability events, i.e. most hurricanes do not generate deadly storm surges (Figure 2.1). However, when extreme surges do occur, they can cause large scale devastation. Hurricane Sandy, which occurred in October 2012, caused 72 deaths in the U.S. from hurricane related hazards and drowning was identified as the major cause. Forty-one of these deaths have been directly attributed to storm surge (Blake et al., 2013; Casey-Lockyer et al., 2013), and it had the second highest death toll from 1990-2019. At the time of this manuscript submission, the most recent hurricane that caused fatalities directly attributed to storm surges was Hurricane Michael, which occurred in October 2018 and resulted in 5 deaths from storm surges as high as 14
feet above ground level (Beven II et al., 2019).

Storm Surge Fatalities (1990 - 2019)

Figure 2.1: Fatalities directly attributed or assumed related to storm surge in the years 1990-2018 as reported in NHC Tropical Cyclone Reports (National Hurricane Center, ndd). Listed in the corresponding table are the storm category at landfall, storm name, year of occurrence, and number of fatalities.

Storm surge risk is the product of hazard, exposure, and vulnerability, and thus greatly increases with any of these factors (Kron, 2005). Hurricane Katrina was especially devastating because of the combined intensities of each. Specifically, exposure in New Orleans was and remains high, as it lies below sea level and is densely populated. Its residents were also some of the most socially vulnerable, i.e. susceptible to harm from social factors and forces, including restricted access to “health care, [livable] places, . . . , goods, services, emergency response personnel, capital, and political representation” (Cutter et al., 2006). Finally, the surge hazard was high, as Hurricane Katrina was a large, intense storm that
traversed the shallow continental shelf of the Gulf of Mexico and made landfall nearly per-
pendicularly to the Gulf Coast. In general, these storm characteristics, along with a slow 
translational speed, are expected to produce large storm surges, although the relationships 
are not always direct (Camelo et al., 2020; Senkbeil et al., 2011). The storm surge risk dur-
ing Hurricane Katrina was notably exacerbated by levee failures, which caused widespread 
inundation of New Orleans (United States Congress House Select Bipartisan Committee 
to Investigate the Preparation for & Response to Hurricane Katrina, 2006).

Over the next century, it is expected that changes to the climate will significantly increase 
the storm surge hazard in coastal regions. It is expected that the local mean sea level will 
increase in many places (Kopp et al., 2014). The wind speeds and frequencies of the most 
intense hurricanes are also expected to increase (Emanuel, 2020; Gutmann et al., 2018; 
Knutson et al., 2010; Walsh et al., 2016). Additionally, the coastal population in the U.S. 
is expected to increase by more than 50 percent by 2060 (Neumann et al., 2015). Together, 
these elements put an increasing number of people at risk of storm surge, however it is 
difficult to precisely understand and quantify the magnitude of this risk. As coastal com-
munities and individuals work to improve their resilience, effective, comprehensive com-
munication of storm surge risk will become increasingly important. Historically, storm 
surge risk has been explicitly and implicitly associated with the Saffir-Simpson Hurricane 
Wind Scale (SSHWS), however both storm surge development and impact are a complex 
interplay of a number of characteristics and can be difficult to predict with storm intensity 
alone. Much of the work to be done in effective risk communication includes eliminating 
this association.
In this work, we examine the lingering role of the SSHWS and other influences on hurricane storm surge risk communication. We discuss recent advances in official storm surge guidance and the residual effects of the historical association of storm intensity and surge. In Section 2.2, we discuss how hurricane properties beyond wind intensity and SSHWS Categories affect the generation of storm surge. In Section 2.3, we discuss two official storm surge products that have been developed by the NHC to improve risk communication with the general public. We discuss factors that influence public response in addition to and in spite of changes in messaging in Section 2.4. Finally, we conclude in Section 2.5 by discussing the broader challenges to effective mitigation and resilience efforts and illustrate the need for comprehensive, multidisciplinary approaches.

2.2 The Influence of Hurricane Properties on Storm Surge Generation

The strength of an impending hurricane is largely communicated through the Saffir-Simpson Hurricane Wind Scale (SSHWS). The SSHWS was originally developed to estimate the potential of a hurricane to cause property damage due to its high windspeeds. Early versions also included ranges of expected storm surge heights and expected damages (Figure 2.2; adapted from (Blake et al., 2011)). A number of scholars have criticized use of the scale, arguing that it is insufficient in warning the public of hurricane hazards other than wind, particularly coastal flooding (Bloemendaal et al., 2020; Bryant et al., 2019; Durbin, 2017; Kantha, 2006; Song et al., 2020). Others have suggested implementing a storm surge hazard scale entirely separate from the existing SSHWS (Irish & Resio, 2010; Kantha, 2013; Walker et al., 2018).
Over time, studies have demonstrated that the relationship between wind intensity or the SSHWS is not always linear (Bloemendaal et al., 2020; Irish & Resio, 2010; Kantha, 2006; Powell & Reinhold, 2007). For example, Hurricane Katrina, which intensified to a Category 5 storm while traversing the Gulf of Mexico but made landfall in southeast Louisiana as a Category 3 storm, produced higher surge heights at Pass Christian Station in Mississippi than Hurricane Camille, which made landfall nearby in Mississippi as a Category 5 storm in 1969. The latter produced surges of 24.6 ft, while the former, lower category storm produced storm surges of 27.8 ft at the same station (Barry et al., 2019; Knabb et al., 2005). Hurricane Sandy was a Category 1 storm when it made landfall along the Atlantic Coast, but produced large storm surges of 12.65 ft at Kings Point, NY and 8.57 ft at Sandy Hook, NJ (Blake et al., 2013). These examples highlight that the magnitude of peak surge is not always directly proportional to the hurricane intensity at landfall, and higher intensities alone do not always equate to higher peak surges. Solely relying on this one hurricane property as a predictor of surge magnitude can leave coastal residents
unprepared. In fact, among the hurricanes whose storm surges have caused fatalities, only Hurricane Michael and Hurricane Irma were categorized as greater than Category 3 (Figure 2.1).

Hurricane Camille and Hurricane Katrina highlighted another hurricane property that is often not considered when using the SSHWS to estimate storm surge impact: size, e.g., radius of maximum winds. Irish et al. (2008) showed that for shallow basins, like the Gulf of Mexico, given a specific intensity, the generation of storm surge can greatly vary with storm size. Hurricane Katrina had a large radius of maximum winds of 27.2 mi (47 km), double that of Hurricane Camille’s of 13.7 mi (22 km) (Irish et al., 2008). Hurricane Ike, which made landfall in 2008 as a Category 2 storm, had a large radius of maximum winds of 46 mi (74 km) (Sebastian et al., 2014). It generated storm surge heights of 10-15 ft in Galveston Bay, claiming the lives of 14 people and causing $2.26 Billion in damages due to coastal and inland flooding across Texas, Louisiana, and Arkansas (Berg, 2009). Hurricane Rita, a smaller storm with a radius of maximum winds of 24.9 mi (40 km), was a comparable storm that affected the same area (Irish et al., 2008); it made landfall as a Category 3 storm at the Texas/Louisiana border. Although it was a higher intensity storm, it produced much smaller storm surges (Knabb et al., 2006).

The effect of a hurricane’s forward speed to an inundated area’s flood volume can be comparable to the effect of a one category shift on the SSHWS. Slower moving storms tend to generate surges further inland with lower peak surges, while faster moving storms tend to flood smaller areas closer to the coastlines but with higher peak surges (Rego & Li, 2009). This implies that slower moving storms can be far more damaging because
their storm surges can reach areas far from the coastline causing widespread area flooding. This phenomenon was observed during Hurricane Ike, where surge travelled as far as Interstate 10 in Jefferson and Orange County in Texas Ike (Berg, 2009) near Lake Charles in Louisiana, nearly 32 mi (51 km) from the coastline (National Weather Service, nd).

From the examples above, we expect that a large, slow moving, and intense storm generates the highest peak storm surges; however, the storms discussed traversed and made landfall in the Gulf of Mexico where the waters are relatively shallow. Storm systems that traverse the Atlantic Ocean may behave differently than those in the Gulf (Nielsen, 2009; Peng et al., 2004). Thus, while it is tempting to assume that a combination of these storm properties will unquestionably produce large storm surges, the topography of the impacted coastline must also be considered. The relationship between hurricane characteristics and coastal geomorphology is complex and this can make predicting the magnitude of storm surge beforehand very challenging without numerical modeling of individual storms (Camelo et al., 2020). Storm surge should ideally be explicitly modeled for every hurricane event, although doing so with the lead times necessary for effective evacuation guidance and aide allocation by emergency managers and public officials presents an additional challenge (Cyriac et al., 2018; Fossell et al., 2017). It is important that coastal residents fully understand these challenges.
2.3 Storm Surge Risk Communication by the National Hurricane Center

The National Hurricane Center (NHC) is well aware of the limitations of the SSHWS in comprehensively communicating hurricane related hazards. In 2012, storm surge was removed from the wind scale to avoid misrepresenting risk to the public (The Saffir-Simpson Team, 2019). Storm surge risk is now communicated separately and the NHC has developed storm surge products for general public audiences, which can be categorized into two distinct groups: real time/storm specific products and general risk hazard maps that are available all year round. Here, we will limit our discussion to storm surge advisories and storm surge hazard maps. Over time, the NHC together with other agencies such as FEMA and the U.S. Army Corps of Engineers has developed a number of other storm surge decision support products, including Probabilistic Hurricane Storm Surge Forecasts (P-Surge), ET-Surge (for extra-tropical storms), and HURREVAC, and while these are available for public access, the primary target audience are emergency managers.

2.3.1 Storm Surge Advisories

During a hurricane, the NHC continuously issues storm surge advisories, which include storm surge watches and warnings. Storm surge watches are issued when there is a possibility of life-threatening inundation as a result of the hurricane over the subsequent 48 hours. Storm surge warnings are issued when there is a danger of life-threatening inundation as a result of the hurricane over the subsequent 36 hours. These watches and warnings are issued under public advisories in text form (Figure 2.3 a) and are accompanied by
graphics (Figure 2.3 b). The stretch of coastline with the potential of being impacted by the hurricane is highlighted with two distinct colors used to indicate respective regions of the watch (light purple) and warning (pink).

During the 2020 hurricane season an experimental graphic, the “Peak Storm Surge Forecast Graphic” was implemented (Figure 2.4). The new graphic does not include the watch and warnings but instead highlights stretches of the coastline with the potential of being impacted in red, with various ranges of expected storm surge heights delineated in space by points. The estimated surge heights denoted in this graphical advisory correspond to the storm surge heights issued in the text form of the NHC public advisories.

These products intentionally emphasize the threat of one particular hazard only, i.e. storm surge. No other hurricane related threats are mentioned and the SSHWS is purposely excluded, clear advancements to storm surge risk communication.

2.3.2 National Storm Surge Hazard Map

The National Storm Surge Hazard Map is available all year round and is intended to more generally describe regional storm surge risk, including prior to the issuance of storm surge watches and warnings during a storm (Figure 2.5). It is accessible through the NHC website and shows probable storm surge heights along the continental US, Hawaii, Puerto Rico and the U.S. Virgin Islands, and Hispaniola coastlines. These maps are created from a combination of results of numerically modeling storm surges from synthetic storm scenarios using the SLOSH model. In this case, these storms are not based on any approach-
Figure 2.3: Hurricane Dorian Public advisory containing storm surge watch and warning in (a) text form, along with other hazards and hurricane descriptions, and (b) graphic form with two colors to differentiate locations under storm surge watch and warning.

Instead, they simulate a large number of storms of the same SSHWS Category by varying a combination of hurricane properties. The maximum surges produced from these model simulations are extracted resulting in a composite product, i.e. there is no individual storm will exactly produce the flooding shown in these maps. For example, Figure 2.5 shows a composite of the maximum storm surges produced by the
hypothetical Category 2 storms. While the storm surge threat is the only hazard depicted in this product, the explicit demarcation of risk by the SSHWS Category reinforces the historical association of storm surge risk and intensity.

2.4 Other Influences on Storm Surge Risk Communication and Response

Issuing guidance about hurricane hazards such as storm surge is one of the ways the NHC fulfills its mission to “save lives, mitigate property loss, and improve economic efficiency” (National Hurricane Center, nda), as the primary method of preventing personal harm from storm surge is by evacuating away from the hazard (Morrow et al., 2015). To encourage evacuation, the use of strong language has been included in their advisories. The use of strong language in advisories is not new; “certain death” was used to urge evacuation during Hurricane Ike in 2008 (Morss & Hayden, 2010; Wei et al., 2014). Storm surge has
been described as “life threatening,” “catastrophic,” and most recently, “unsurvivable” during Hurricane Laura in 2020 in public advisories and other mediums used to communicate official messages (Figure 2.6).

In spite of these efforts in changing storm surge messaging, it is clear that there are still coastal residents who do not evacuate when they should. As the climate changes and storm surge risk increases, it is increasingly important that we understand the reasons why. Evidence from past storms may shed light onto the limitations of messaging and storm surge risk communication to personal decision making.

Geographical location plays a major role in residents’ hurricane hazard concerns. Those who live near trees or are further inland are primarily threatened by wind related haz-
Unsurvivable storm surge with large, destructive waves will cause catastrophic damage from Sea Rim State Park, TX, to Intracoastal City, LA. Surge could penetrate up to 30 miles inland.

If you need to evacuate, do so NOW. Surge will begin today, well ahead of the strongest winds.

Figure 2.6: A tweet from the NHC during Hurricane Laura containing the words "unsurvivable" along with the experimental peak storm surge graphic (National Weather Services, 2020)

ards and inland flooding due to precipitation, however those who live closer to the coast whose are primarily threatened by storm surges (Baker et al., 2012; Marlon et al., 2015; Meyer et al., 2014,1; Saunders & Senkbeil, 2017; Senkbeil et al., 2020). When coastal residents consider storm surges, the perceived magnitude of risk is often directly related to
the intensity of the SSHWS Category, despite the best efforts of scholars and emergency managers. For example, it is well documented that residents who experienced both Hurricane Rita, a Category 3 storm at landfall that occurred near the Texas /Louisiana border in 2005, and Hurricane Ike, a Category 2 storm that made landfall in the same area three years later, expected a lower storm surge threat due to the comparatively lower SSHWS Category. Despite public warnings, the large storm surges from Hurricane Ike came as a surprise to many (Morss & Hayden, 2010; Wei et al., 2014). Additionally, the public often concentrates on hurricane intensity at landfall; however, several studies have shown that hurricane intensity in the hours prior to landfall is a better measure of the magnitude of storm surge, and thus more attention should be given to hurricane development along its track (Drake, 2012; Jordan & Clayson, 2008; Needham & Keim, 2014a). Solely using the hurricane’s Category at landfall as an indicator of surge risk can be misleading, at best.

This continual association of storm surge risk and the SSHWS can partly be explained by the findings of a 2011 study which discusses two important contributors to the reliance of coastal residents on the SSHWS as a catch-all for hazards: an anchoring effect and difficulty in understanding hurricane damage nonlinearity (Stewart, 2011). Since the inception of the SSHWS, the public has used it as a basis for understanding hurricane damage. This has caused what is known as the “anchoring effect,” i.e. people use SSHWS Categories as an informative guide for hurricane destructiveness, but have difficulty appropriately adjusting their expectations from the anchor when necessary. Consequentially, coastal residents often do not pay as much attention to lower Category storms as they do Category 4 or 5 storms, and the intent to evacuate increases as the SSHWS of a hurricane increases (Lazo et al., 2010). Additionally, coastal residents generally have difficulty understanding
the nonlinearity in hurricane damage. People often “are prone to perceive covariation in linear rather than exponential or other nonlinear terms … [which may] contribute to an underestimation of hurricane destructiveness” (Stewart, 2011).

In some cases, the lack of adequate response of coastal residents to an impending hurricane hazard is not due to misunderstanding storm surge information or inadequate risk communication, and is instead largely influenced by their own personal experiences (Arlikatti et al., 2006; Wei et al., 2014). Coastal residents in Mexico Beach, Florida who did not evacuate during Hurricane Michael explained that when they had evacuated during prior storms, the storms typically weakened before making landfall near their communities (Senkbeil et al., 2020). This expectation of stationary risk, along with the rapid intensification of Hurricane Michael, was one of the reasons residents found themselves without sufficient time to evacuate despite strong, early warnings from emergency managers and broadcast meteorologists. The same coastal residents also directly indicated that that they did not fully understand that each storm carries with it different hazards. Although similar literature has not yet been developed for Hurricane Sally, which made landfall in the same area of the Florida-Alabama coastline in 2020, early interviews and anecdotal evidence suggest similar findings (Accuweather, 2020). In general, the actions of individuals with prior hurricane experience are situationally dependent, but there is often a reluctance to evacuate (Dow & Cutter, 2012; Sherman-Morris, 2013).

A number of other factors also influence the risk perception and consequential behavior of coastal residents, including race, income, age, gender, disability status, and educational attainment (Dash & Gladwin, 2007). However, the intersection of these factors can
have complex and unpredictable implications. Several studies have shown that the first ones to evacuate during a hurricane are African-Americans, individuals with disabilities, and women (Bateman & Edwards, 2002; Marlon et al., 2015; Petrolia & Bhattacharjee, 2010). In contrast, Bowser & Cutter (2015) discussed how “the non-evacuation of many of poor, female, African-Americans in New Orleans during Hurricane Katrina [attest] to the importance of [demographic characteristics] in behavioral decision making, if not in personal risk perception itself.” Black coastal residents cited financial constraints as one of the barriers to evacuation, particularly because Hurricane Katrina made landfall towards the end of the month, immediately prior to the distribution of funds from employers and social welfare programs for many people. A lack of security and fear of theft of their valuables also slowed evacuation efforts (Eisenman et al., 2007; Elder et al., 2007). Though complex, demographics play a significant role in risk perception and response of individuals.

Confidence in authorities can also play a substantial role (Kim & Oh, 2015; Wachinger et al., 2013). People with little prior hazard experience heavily rely on information from the government and emergency managers (Siegrist & Cvetkovich, 2000); however, this reliance is dependent on ongoing relationships between residents and officials. For example, the repeated failure of government officials to develop promised infrastructure caused distrust by New Orleans residents, causing them to heavily rely on their local church groups for information and guidance rather than the scientific experts and emergency managers who may have been more knowledgeable of the impending storm surge risk during Hurricane Katrina (Cole & Fellows, 2008). Additionally, individuals who were confident that they would be rescued by government officials if necessary indicated that they would gen-
erally be less likely to evacuate regardless of their perceived risk (Petrolia & Bhattacharjee, 2010).

2.5 Going Forward

Effective risk communication is critical to encouraging evacuation and minimizing the exposure of individuals to the storm surge hazard (Cuite et al., 2017; Morrow et al., 2015; Morss et al., 2018). Particularly since the early 2000s, the NHC has continuously improved products and messaging describing storm surge risk, and has made great strides toward helping the public to disassociate it from the SSHWS. It is likely that these improvements are at least partly responsible for the decreased storm surge fatalities seen in recent years, however the impacts of these improvements should be more thoroughly examined. In particular, to date much of the strong language used in official communication has been accompanied by “near misses,” and expected surge has not been as severe as expected. Although previous studies (i.e., those conducted prior to the adoption of such language by the NHC) have not indicated a negative impact of false alarms or “crying wolf” (Dow & Cutter, 2012), it is important to routinely assess the psychological implications of messaging as storm surge risk and society evolves. Additionally, further multidisciplinary research exploring the influence of experience with hurricanes, confidence in authorities, and demographics on risk perception is needed to understand how these factors impede effective storm surge risk communication as a first step in understanding how such barriers might be overcome.
While effective storm surge risk communication can improve risk perception, this alone is not always sufficient for impacting behavior. As made clear by Hurricane Katrina, socioeconomic factors also play a major role on an individual’s ability to respond to risk, and this can have critical impacts on risk mitigation. Effective mitigation strategies must account for this. At minimum, resources to evacuate must be widely available to coastal residents in harm’s way, regardless of their socioeconomic conditions (Bukvic & Owen, 2017). Thus, more multidisciplinary research that examines risk communication between coastal scientists and policymakers is necessary for effective mitigation efforts.

Improvements to risk communication and many broader risk mitigation strategies have the potential to prevent imminent storm surge deaths caused by landfalling hurricanes, however the potential to minimize longer-term consequences are limited. Specifically, little can be done to protect the homes and property of the millions of people who live along the 95,000 miles of United States coastline as a hurricane makes landfall (National Ocean Service, nd). Historically, property damage due storm surge has been staggering. Estimates of damage and losses from surge and flooding during Hurricane Katrina were estimated at $108 Billion (Knabb et al., 2005), and flood losses incurred during Hurricane Ike were estimated at $29.52 Billion (National Weather Service, nd). During Hurricane Sandy, an estimated 346,000 houses were damaged in New Jersey while 305,000 homes were damaged in New York, largely due to storm surge (Blake et al., 2013). Recovery has been disproportionately more feasible for those who are able to afford flood insurance and are thus able to rebuild quicker (Colten et al., 2008; Cutter et al., 2006; Fussell, 2015). These numbers clearly illustrate that beyond loss of life, property damage and the potential loss of livelihood that can result is another substantial problem coastal residents face in the
aftermath of a storm. Continued multidisciplinary research exploring risk communication between coastal scientists and urban planners and developers will be essential to comprehensive resilience efforts.

Finally, long-term risk assessment is also critical to risk mitigation and coastal resilience. Sea levels and storm properties are changing with the changing climate, and storm surge risk is increasing as a result (Camelo et al., 2020; Lin & Emanuel, 2016). The infrastructure developed today will be subject to this increased risk, and should be designed to promote long-term coastal resilience so that coastal communities can move away from reactive emergency response tactics (Aerts et al., 2014; Cutter & Zoback, 2013). A recent study quantified this idea and found that proactive disaster mitigation costs federal agencies 1/6th of the cost society pays for reactive disaster response (National Institute of Building Sciences, 2018). More multidisciplinary research connecting climate change research and impacts on risk to civil engineering and design will be critical to coastal resilience in the coming decades.

In summary, here we have examined the role of the SSHWS on storm surge risk communication, and we have found that while official communication has gradually moved away from linking the two hazards, residual effects of the historical association remain. Perhaps more importantly, however, we have concluded that truly mitigating storm surge risk is far more nuanced than effectively communicating the storm surge hazard alone. In addition to understanding how to best communicate the storm surge hazard to coastal residents, there is also a pressing need to more comprehensively understand storm surge exposure and vulnerability, including the factors that influence risk perception, response,
and the implications of both. Unfortunately, these factors do not fit squarely into one disciplinary box, nor should solutions that seek to address them. Ultimately, storm surge risk has deep, far-reaching consequences beyond immediate loss of human life, which include aspects of psychology, sociology, economics, public policy, urban planning, and the geosciences, to name just a few. Thus, true efforts toward storm surge resilience must take a comprehensive, multidisciplinary approach to their development.
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CHAPTER 3: QUANTIFYING THE EFFECT OF UNCERTAINTY IN WIND INTENSITY ON STORM SURGE

3.1 Introduction

Hurricane storm surge modeling is incredibly important for a vast array of practical applications. It is often used operationally during a tropical storm event when there is an impending threat of flooding in coastal areas (CERA, nd; Glahn et al., 2009). It has also been used to recreate surge events in the past to understand impacts of hurricanes when records are not available (Siverd et al., 2019; Soria et al., 2016), as well as to simulate surge events that may happen in the future due to changes in climate (Bilskie et al., 2016; Camelo et al., 2020; Lin et al., 2012; Liu et al., 2019; Shepard et al., 2012). Surge hindcasts and sensitivity studies are also useful in understanding the physics of the interactions between hurricanes and the magnitude of water levels they produce (Fossell et al., 2017; Irish et al., 2008; Rego & Li, 2009; Sebastian et al., 2014; Thomas et al., 2019).

Other applications of surge models that go beyond hurricane-surge interactions are particle movement monitoring and public health. For example, storm surge models have been used to predict fate and transport in oil spills amid growing concerns about movement of oil, e.g. in the Gulf of Mexico, during hurricane season (Dietrich et al., 2012a). In the past few years we also have seen increasing impacts of storm surge flooding on public health. Storm surge models have been used to show that highly urban areas may be increasingly affected by coastal flooding in a warming climate and damage to infrastructure due to storm surge
and rain can have long term mental and physical health outcomes to vulnerable populations (Lane et al., 2013).

Given these important applications, accurate storm surge simulation is critical. This is particularly true for real time prediction where accuracy is needed quickly, making more probabilistic modeling approaches that might be used to assess uncertainties impractical.

The state and accuracy of numerical storm surge modeling has advanced significantly since the first models were developed in the 1960s. For example, the SLOSH model can predict the high watermarks of surges within 20% (Jelesnianski, 1992; Mayo & Lin, 2019), however uncertainties from hurricane parameters as the storm is developing can significantly minimize its accuracy (Taylor & Glahn, 2008). Currently accurate storm surge predictions are largely dependent on the accurate prediction of the meteorological wind field. While meteorological advances have been made toward track prediction, prediction of intensity remains difficult. Additionally, in real time, data is limited and it is difficult to accurately represent the full wind field. There are a number of parametric wind models that can be used to model the wind field with limited data, but each of these have their own strengths and weaknesses and their skill depends on the structure of hurricane, which is also an active research area (Chavas et al., 2017).

Errors in wind models can contribute substantial errors to storm surge models by up to 50% (Torres et al., 2019). Aside from errors, representation of the winds in the surge model are important and can significantly affect the results (Dietrich et al., 2018; Gao et al., 2013; Mayo & Lin, 2019; Ramos Valle et al., 2018). Better wind data can be obtained following the storm for hindcasting, but best track data and data assimilated winds are also subject
Given the dependence of storm surge modeling on wind, understanding how the uncertainties in wind data affect estimates of storm surges is important to the modeling applications described above. There are a number of techniques that can be used to evaluate model response to uncertain model parameters, which are collectively known as uncertainty propagation techniques. Sampling methods, which include popular Monte Carlo techniques, randomly sample from probability distributions describing the uncertain input parameters and then use this ensemble of samples and the model of interest to produce an ensemble of model outputs. This ensemble of output can then be used to calculate response statistics and quantify the uncertainty propagation (Smith, 2013). Sampling methods are intuitive and advantageous over other uncertainty propagation methods as they do not assume linearity of the model. However, they are often prohibitively computationally expensive, as a large number of simulations is required to accurately estimate the probability distribution of the model response. This is especially true for high fidelity storm surge models such as those we seek to explore in this study.

In this work, we use a computationally efficient sampling method to explore the propagation of uncertainties in wind intensity to storm surge inundation. We implement methods from statistical data assimilation to utilize information regarding the covariance structure of wind data in a way that minimizes the computational cost of our assessment. In Section 2, we discuss the methodology we will be using for this work, and in Section 3 we present the results and discussion. We conclude our study in Section 4.
3.2 Methodology

3.2.1 ADvanced Circulation Model

The ADvanced CIRCulation (ADCIRC) model simulates coastal hydrodynamics and storm surge inundation (Luettich et al., 1992). Water levels are estimated by solving a modified version of the shallow water equations using a finite element method for the spatial derivatives. The use of a finite element method allows the spatial domain to be discretized using an unstructured mesh, which allows the model to have finer resolution in regions closer to shore where flooding is of concern, and coarser resolutions farther in the open ocean. The model can be tightly coupled to the SWAN model to predict wave contributions to water levels (Dietrich et al., 2012b).

ADCIRC is also able to utilize different meteorological models to process wind and pressure data into its computation. Two different kinds of wind information that ADCIRC is able to process are: grid based data and parametric models. Grid based wind data such as those developed by WRF, HRD and OWI, specify wind intensities and pressures for every point of the meteorological grid. Parametric models use a small number of meteorological parameters such as those described by “best track data” to model the hurricane structure. The ADCIRC model has been extensively verified in a number of studies using different types of meteorological models (Cyriac et al., 2018; Dietrich et al., 2004,1; Sebastian et al., 2014).

For this study, we will be using the ADCIRC model along with the high fidelity computa-
tional grid HSOFS or Hurricane Surge On-Demand Forecast System (Riverside Technology & AECOM, 2015). The mesh spans the Gulf of Mexico and the Atlantic Ocean, and extends up to land up to 10m in topographic heights. The nearshore coastal regions have finer resolution. This mesh has been used in several inundation studies (Asher et al., 2019; Camelo et al., 2020; Fossell et al., 2017; Moghimi et al., 2020; Thomas et al., 2019) and will be suitable for our purposes.

### 3.2.2 Wind Field Modeling

During a monitored disturbance, the National Hurricane Center keeps a record of forecasts and guidance called the ATCF or automated tropical cyclone format. This includes a B-deck or operational best track data that contains the type of disturbance, its name, wind intensity, location, central pressure, and radius. This dataset gets updated post hurricane season and is known as "Best Track" (BT) (Vigh, nd). The best track contains a 1-minute averaged wind intensity, position, central pressure and radius of 34, 50, and 64kt wind speeds; specified in 6 hour increments (Landsea & Franklin, 2013). The BT data is still subject to errors in measurements and subjective bias of forecasters who analyze it. Landsea & Franklin (2013) has estimated absolute uncertainty based on satellite observations of NHC best track data as: 15% for tropical storms, 10% for category 1 and 2 storms, and 8% for categories 3, 4, and 5 storms, i.e. major storms.

For our study, we analyze storms that have occurred in the Atlantic Basin over the last 20 years, 2000-2019. As of this writing, the best track data for the year 2020 is not yet complete. The storms are grouped according to their highest recorded SSHWS category
over its lifespan based on the Tropical Cyclone Reports (TCR). We only include storms that have recorded storm surge readings from NOS tidal gauges according to the TCR and impacted landfall in the continental United States. The number of hurricanes sampled and their categorizations are shown in Table 3.1. A complete list of the storms that are included in the study and their corresponding landfall locations, intensities, and pressures are listed in Table A.1 in Appendix A.

Table 3.1: Hurricane Samples

<table>
<thead>
<tr>
<th>Grouping</th>
<th>SSHWS Categories</th>
<th>Storms</th>
</tr>
</thead>
<tbody>
<tr>
<td>all</td>
<td>1,2,3,4,5</td>
<td>35</td>
</tr>
<tr>
<td>minor</td>
<td>1,2</td>
<td>14</td>
</tr>
<tr>
<td>major</td>
<td>3,4,5</td>
<td>21</td>
</tr>
</tbody>
</table>

The duration of each tropical cyclone greatly varies so for uniformity, we extract hurricane wind speeds beginning 72 hours before landfall in the continental United States, and ending 24 hours after landfall for a total of 96 hours. We use the synoptic time-steps (every 6 hours), thus each storm has 17 corresponding wind intensities in total. For storms that made several landfalls in the US coastline, the highest landfall intensity was recorded.

We model the hurricanes using the Holland parametric wind model, which uses a parametric relationship between the wind intensity and the central pressure while keeping the radius of maximum winds constant (Holland, 1980). It uses a scaling parameter, called the Holland B, which holds the shape of the wind profile and the radius of maximum winds.
constant. The value of the Holland B parameter is limited to 1-2.5. For this study, we let

\[ B = \frac{V_{\text{max}}^2 \rho_e}{P_n - P_c}. \]  

\[ (3.1) \]

\( B \), is the Holland Parameter, \( V_{\text{max}} \) is the wind intensity in m/s, \( \rho \) is the density of wind at 1.15 kg/m\(^3\), \( P_n \) is the far field pressure at 1013mb, and \( P_c \) is the central pressure of the hurricane.

This parametric model assumes an ideal symmetric wind field for hurricanes, i.e. all of the radius of maximum winds are assumed constant in space. However, this is not always the case because most hurricanes have stronger winds in its right quadrant due to circulation.

The "Generalized Asymmetric Holland Model" (GAHM), another parametric wind model, was introduced for the ADCIRC model. It still uses the best track data format to take in meteorological forcing, but represents a better range of hurricane structures (Gao et al., 2013). In order to use the GAHM wind model in ADCIRC, the best track data is input to an ADCIRC auxiliary program called \( \text{aswip} \), which generates a GAHM formatted file that uses all available isotachs (34, 50 and 64 kts winds) to compute spatially variable radii of maximum winds.

\[ 3.2.3 \text{ Ensemble Member Generation} \]

We use a sampling method to explore the impact of uncertainties in wind intensity on storm surge inundation. We generate the ensemble using a computationally efficient sampling method that has been used in statistical data assimilation applications (Butler et al., 2012;
Mayo et al., 2014). Specifically, we use best track data and a low rank approximation of a covariance matrix describing the variability in maximum wind speeds observed in historical storms to optimally generate a small ensemble of wind speeds that are then used along with ADCIRC to investigate the model response.

Given an \( n \)-dimensional “state vector,” \( \mathbf{x} \), whose variability is characterized by the \( n \times n \) covariance matrix, \( \mathbf{P} \), a representative sample of states \( \mathbf{x}_i \) can be generated using matrix decompositions. A low rank approximation of \( \mathbf{P} \) can be generated through an eigenvalue decomposition. The covariance matrix is first factored as \( \mathbf{P} = \mathbf{LUL}^T \), where the columns of \( \mathbf{L} \) are the eigenvectors, \( v_1, v_2, \ldots, v_n \), of \( \mathbf{P} \), and \( \mathbf{U} \) is a diagonal matrix whose elements are the associated eigenvalues, \( \lambda_1, \lambda_2, \ldots, \lambda_n \). A low rank approximation of \( \mathbf{P} \) can be obtained by truncating \( \mathbf{L} \) and \( \mathbf{U} \) to the \( n \times r \) and \( r \times r \) matrices \( \tilde{\mathbf{L}} = [v_1, v_2, \ldots, v_r] \) and \( \tilde{\mathbf{U}} = \text{diag}(\lambda_1, \lambda_2, \ldots, \lambda_r) \), i.e. by only retaining the first \( r \) eigenpairs of \( \mathbf{P} \). Assuming \( \lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n \), the relative error in the approximation can be computed as \( \sum_{j=r+1}^n \lambda_j / \text{Tr}(\mathbf{P}) \), where \( \text{Tr}(\mathbf{P}) \) is the trace of \( \mathbf{P} \). We then have \( \tilde{\mathbf{P}} = \tilde{\mathbf{L}} (\tilde{\mathbf{C}}^{-1})^T \Omega^T \Omega \tilde{\mathbf{C}}^{-1} \tilde{\mathbf{L}}^T \), where \( \tilde{\mathbf{C}} \) is produced from the Cholesky decomposition of \( \tilde{\mathbf{U}} \), i.e. \( \tilde{\mathbf{U}}^{-1} = \tilde{\mathbf{C}} \tilde{\mathbf{C}}^T \), and \( \Omega \) is a random orthonormal matrix with zero column sums. A sample of states \( \mathbf{x}_i \) with mean \( \mathbf{x} \) and covariance \( \tilde{\mathbf{P}} \) can then be generated as \( \mathbf{x}_i = \mathbf{x} + \sqrt{r+1} \tilde{\mathbf{L}} \left( \Omega \tilde{\mathbf{C}}^{-1} \right)^T, i = 1, \ldots, r+1 \). Additional details can be found in Tuan Pham et al. (1998).

For a given hurricane, we let \( \mathbf{x} \) be the maximum wind speeds recorded every six hours 72 hours prior to through 24 hours after landfall as described in Section 3.2.2. We use the NHC Best Track Database for these data (National Hurricane Center, ndb). We estimate \( \mathbf{P} \) by computing the sample covariance of maximum wind speeds of major (Category 3,
4, and 5) historical hurricanes (Table 3.1). An ensemble of maximum wind speeds is then generated using the low rank approximation described above. We use an ensemble size of 8, which retains at least 95% of the variation described by $P$. Corresponding minimum central pressures are determined from these wind ensembles by assuming a constant Holland B parameter at each synoptic time step, which maintains the shape of the original best track data. The remaining hurricane data is kept constant, i.e. the location of the center of the storm, radius of maximum winds, and translation speed remains the same.

Research has shown that most people fixate on a hurricane’s category at landfall instead of its development (Drake, 2012), and this has been problematic since hurricane properties can change over time along with its hazards. Using this method of sampling, we are able to propagate the uncertainty in wind forecasts that may come from error in estimation, representation of data, or simply its natural variability with a few ensemble members. Using these ensembles, we are able to see how such uncertainties might impact storm surge inundation.

3.3 Results and Discussion

3.3.1 Wind Intensity Ensembles

We have taken the best track data of 6 storms: Isabel 2003, Katrina 2005, Rita 2005, Ike 2008, Sandy 2012, and Matthew 2016, and produced ensembles for each of them as described in the previous section. All ensemble members share the same hurricane
properties from the beginning of the best track data up to 72 hours before landfall. Only the wind intensity and pressure is changed for each of the members for the length of the 96 hour time period until 24 hours after landfall, at which point the wind and pressure data is again specified as the best track data.

Figure 3.1 shows an example of the wind intensity ensembles created for Hurricane Isabel and Ike in the 96 hour augmented period. Wind intensity from the best track data for Hurricane Isabel 72 hours prior to landfall is 115 kts, 85 kts at synoptic time landfall, and 30 kts 24 hours after landfall. The ensemble winds created had a range of 66 to 175 kts 72 hrs prior to landfall, 60 to 109 kts at landfall, and 5 to 59 kts 24 hours after landfall. The standard deviation for these time steps are 36.74 kts, 20.83 kts, and 22.15 kts, respectively. Notably, the ensemble winds developed for this storm all fall within 2 standard deviations of the mean of the best track data (plotted in dark red). The average wind intensity at each time step remains equal to that of the best track data but the range for each is substantially varied based on the hurricane data set. Our ensembles are developed so that we sample at least 95% of the distribution of historical storms with 8 ensemble members.

For Hurricane Ike (Figure 3.1), we again see that the wind ensemble created does not necessarily follow the trend of the Best Track data (also plotted in dark red) but instead, it represents the natural variability of the particular time step from the sampled (historical) data set. The ranges of wind intensity for 72 hours before landfall, at landfall, and 24 hours after landfall were 18 to 133 kts, 66 to 131 kts, and 6 to 65 kts, respectively. All of the resulting intensities also fall within 2 standard deviations from the mean.

Figure 3.2 illustrates the distribution of the ensemble members created for each hurricane
Figure 3.1: Ensemble members of Hurricane Isabel and Ike Wind Perturbations
analyzed here. The average range wind intensity for all hurricanes is about 47.58 kts, which means that the lowest and highest wind intensity for each ensemble member spans up to two categories of the SSHWS. The shaded areas represent how many members are above or below the average wind intensity of each hurricane. The Gulf of Mexico storms, i.e. Katrina, Rita and Ike, generally had more ensemble members with wind intensities below the average, while the Atlantic storms, i.e. Isabel, Sandy and Matthew had more members above the average, though not by much.

The SSHWS, which categorizes hurricanes based on their wind intensities, is summarized in Table 3.2 (The Saffir-Simpson Team, 2019). Table 3.3 summarizes the statistics of the hurricane wind intensities of all of the generated ensemble members. Hurricane Rita had the highest maximum winds as well as the highest winds across the entire duration of the storm, while Hurricane Katrina had the highest landfall winds and winds over the 18 hour period leading up to landfall. Standard deviations are the same for all hurricanes in the different categories except the maximum overall winds. One standard deviation above or below the average of the storm can mean a difference of one category increase or decrease in the SSHWS. For example, Hurricane Katrina is categorized as SSHWS Category 3 at landfall, and the spread of the ensemble members allows us to examine the impacts of landfall as a Category 2 or Category 4 storm. This allows us to see how uncertainties in the category at landfall can affect storm surge inundation.
Table 3.2: Saffir-Simpson Hurricane Wind Scale

<table>
<thead>
<tr>
<th>Category</th>
<th>Wind Speed (knots)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>64-82</td>
</tr>
<tr>
<td>2</td>
<td>83-95</td>
</tr>
<tr>
<td>3</td>
<td>96-112</td>
</tr>
<tr>
<td>4</td>
<td>113-136</td>
</tr>
<tr>
<td>5</td>
<td>137 or higher</td>
</tr>
</tbody>
</table>

Table 3.3: Wind Intensities

<table>
<thead>
<tr>
<th>Hurricane</th>
<th>Over Duration</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean (knots)</td>
<td>std (knots)</td>
</tr>
<tr>
<td>Katrina</td>
<td>96.47</td>
<td>16.81</td>
</tr>
<tr>
<td>Rita</td>
<td>105.00</td>
<td>16.81</td>
</tr>
<tr>
<td>Ike</td>
<td>78.53</td>
<td>16.81</td>
</tr>
<tr>
<td>Isabel</td>
<td>83.24</td>
<td>16.81</td>
</tr>
<tr>
<td>Sandy</td>
<td>63.82</td>
<td>16.81</td>
</tr>
<tr>
<td>Matthew</td>
<td>95.88</td>
<td>16.81</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Hurricane</th>
<th>Landfall -18hr to LF</th>
<th>-18hr to LF</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean (knots)</td>
<td>std (knots)</td>
</tr>
<tr>
<td>Katrina</td>
<td>110.00</td>
<td>20.83</td>
</tr>
<tr>
<td>Rita</td>
<td>100.00</td>
<td>20.83</td>
</tr>
<tr>
<td>Ike</td>
<td>95.00</td>
<td>20.83</td>
</tr>
<tr>
<td>Isabel</td>
<td>85.00</td>
<td>20.83</td>
</tr>
<tr>
<td>Sandy</td>
<td>70.00</td>
<td>20.83</td>
</tr>
<tr>
<td>Matthew</td>
<td>80.00</td>
<td>20.83</td>
</tr>
</tbody>
</table>

3.3.2 Effect on Inundation Volume and Area

A summary of results for storm surge inundation volume and area per storm is presented in Table 3.4. The inundated volume and areas recorded were those that were initially
Figure 3.2: Distribution of the ensemble member wind intensity. This modified violin plot shows how the ensemble members were distributed against the average (middle bar) wind intensity for 96 hours. The bottom bar and top bar represents the lowest and highest range of the distribution.

dry land before simulation, but became inundated by coastal waters at any point in the simulation. The largest inundation volumes and areas for the 6 storms that were simulated were produced by Hurricane Ike. Hurricane Isabel was second, followed by Hurricane Katrina, Sandy, Rita, and lastly Hurricane Matthew. It is worth noting that all storms, except for Hurricane Matthew made landfall almost perpendicular to the main coastline, which may explain the low inundation volume and areas observed in the corresponding simulations. A complete figure list of maximum surge heights created for all ensemble members of each storm can be found in Appendix B (Figures C.1 to C.12).
Table 3.4: Inundation Volume and Area

| Hurricane | Volume (km$^3$) | | | | Area ($10^3$km$^2$) | | | |
|-----------|----------------|---|---|---|-----------------|---|---|
|           | min  | max  | mean | sd  | min  | max  | Mean  | sd  |
| Katrina   | 4.55 | 7.62 | 6.39 | 1.19 | 5.94 | 7.50 | 6.89  | 0.63 |
| Rita      | 3.92 | 6.12 | 4.71 | 0.79 | 5.83 | 7.23 | 6.42  | 0.50 |
| Ike       | 17.65| 34.83| 27.48| 5.52 | 12.64| 14.51| 13.83 | 0.61 |
| Isabel    | 5.01 | 26.44| 15.59| 7.66 | 5.69 | 12.79| 9.54  | 2.59 |
| Sandy     | 3.82 | 9.16 | 5.28 | 1.99 | 5.70 | 8.23 | 6.64  | 1.07 |
| Matthew   | 1.51 | 3.22 | 2.03 | 0.55 | 2.84 | 3.92 | 3.25  | 0.32 |

Hurricane Matthew had the smallest average inundation volume, area, and standard deviation. There variability between each ensemble members for this case is very small and there is not any significant difference between the areas that were affected by surge, and the surge heights. Figure 3.3 shows side by side the least and most producing inundation volume and area simulation. The major difference between the two, is that portions of the Neuse River, NC are now inundated by water.

The largest producing storms in terms of volume and area is Hurricane Ike. It had a very significant standard deviation with its inundation volume, however when compared to its inundated area, the deviation from the mean is significantly small. Ike large standard deviation across all simulations signifies that the results among 8 ensemble members are very varied. When compared side by side to the smallest and largest inundated volume producing ensemble as seen on Figure 3.4, the contrast can be easier seen. The smallest inundation volume for Ike is 17.65 km$^3$ while the largest volume is doubled that at 34.83 km$^3$, with a percentage difference in inundation volume between these two simulations is 33%. Despite the huge difference in volume, the inundated area affected by Hurricane
Figure 3.3: Ensemble member#3 produced the least amount of inundated volume and area; while ensemble member#7 produced the highest inundated volume and area for Hurricane Matthew. Encircled in red is the the added only difference in inundated area between the two.

Ike for these two simulations $12.64 \times 10^3 \text{ km}^2$ and $14.51 \times 10^3 \text{ km}^2$, for the smallest and largest respectively. Compared to the difference in volume, the inundated areas had only 7% difference between them. The big difference between changes in areas and volume show that while changes in wind intensity for Hurricane Ike are substantial, it affects the surge heights mostly and does not significantly add more inundated areas.

In terms of average inundation volume and area, Hurricane Isabel ranked second; however, it had the largest standard deviation of all, with Hurricane Sandy placing second. Across eight simulations, Hurricane Isabel had more variability which can be see on Figure 3.5 comparing the least and the most inundated volume. This large standard deviation in volume and area meant that there is a large spread for both volume (as illustrated by surge
Figure 3.4: Ensemble member#3 produced the least amount of inundated volume and area; while ensemble member#5 produced the highest inundated volume and area for Hurricane Ike.

Figure 3.5: Ensemble member#8 produced the least amount of inundated volume and area; while ensemble member#2 produced the highest inundated volume and area for Hurricane Isabel.
heights) and inundated area. The smallest volume produced is 5.01 km$^3$, while the largest is 26.44 km$^3$; and in terms of percentage difference, it is about 68%. The smallest and the largest inundated areas were 5.69x10$^3$ km$^2$ and 12.79x10$^3$ km$^2$, or about an increase of 38%. These values are at most that double that of the difference between the two members produced in Hurricane Ike. This indicates that uncertainties in wind intensities, have a different effect for this region as compared to the Gulf of Mexico as well. Changes in wind not only affect the height of storm surge but changes the span of area that is affected.

3.3.3 Storm Surge Heights at Stations

Listed in Table 3.5 are maximum surge heights in selected recording stations. In terms of recorded heights, Hurricane Ike had the heights maximum surges and a substantial standard deviation as well at up to 1.0m. It did not however have the overall average highest wind intensity of the 6 storms. Hurricane Rita had the highest overall intensity average, and affected the same region as Ike but the maximum heights are still lower. Its possible range of heights is also substantially lower than that of Ike.

For storms that have affected the Atlantic side, Hurricane Matthew had the highest over all average wind intensity but had the lowest surge readings. Both Hurricane Sandy and Isabel had surges that are over 1m, and a standard deviation of over 1m as well. Stations that are further inland especially close to estuaries and rivers have also seen high storm surge values as well.

The effect of uncertainties in wind intensity does not only affect the range of surge heights,
<table>
<thead>
<tr>
<th>Hurricane</th>
<th>Location</th>
<th>mean</th>
<th>stdev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Katrina</td>
<td>Lake Pontchartrain, LA</td>
<td>1.19</td>
<td>0.44</td>
</tr>
<tr>
<td></td>
<td>Grand Pass, LA</td>
<td>0.58</td>
<td>0.33</td>
</tr>
<tr>
<td></td>
<td>Southeast Pass, LA</td>
<td>1.18</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>Intracoastal City, LA</td>
<td>1.12</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>Calcasieu Pass, LA</td>
<td>0.38</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>Sabine Pass, TX</td>
<td>0.98</td>
<td>0.62</td>
</tr>
<tr>
<td></td>
<td>Galveston Bay (South Jetty), TX</td>
<td>1.15</td>
<td>0.24</td>
</tr>
<tr>
<td>Rita</td>
<td>San Jacinto River, TX</td>
<td>1.70</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td>Shell Island, LA</td>
<td>0.95</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>East Calcasieu Lake, LA</td>
<td>1.24</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>Sabine Pass, TX</td>
<td>5.00</td>
<td>1.01</td>
</tr>
<tr>
<td></td>
<td>Port Arthur, TX</td>
<td>2.19</td>
<td>1.00</td>
</tr>
<tr>
<td>Ike</td>
<td>Galveston Channel, TX</td>
<td>2.19</td>
<td>0.86</td>
</tr>
<tr>
<td></td>
<td>Intracoastal City, LA</td>
<td>2.19</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>Calcasieu Pass, LA</td>
<td>4.22</td>
<td>0.41</td>
</tr>
<tr>
<td></td>
<td>Atlantic City, NJ</td>
<td>0.77</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td>Delaware City, DE</td>
<td>2.65</td>
<td>0.53</td>
</tr>
<tr>
<td>Isabel</td>
<td>Washington Naval Yard, DC</td>
<td>3.58</td>
<td>1.41</td>
</tr>
<tr>
<td></td>
<td>Duck, NC</td>
<td>2.34</td>
<td>1.02</td>
</tr>
<tr>
<td></td>
<td>Oregon Inlet, NC</td>
<td>1.84</td>
<td>0.71</td>
</tr>
<tr>
<td>Sandy</td>
<td>Beaverdam Creek Entrance, NJ</td>
<td>1.81</td>
<td>0.60</td>
</tr>
<tr>
<td></td>
<td>Delaware City, DE</td>
<td>1.56</td>
<td>1.30</td>
</tr>
<tr>
<td></td>
<td>Washington Naval Yard, DC</td>
<td>2.29</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>Baltimore, MD</td>
<td>2.29</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>Oregon Inlet, NC</td>
<td>0.59</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>Norfolk, VA</td>
<td>0.93</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>Duck, NC</td>
<td>0.75</td>
<td>0.17</td>
</tr>
<tr>
<td>Matthew</td>
<td>Wrightsville Beach, NC</td>
<td>0.88</td>
<td>0.32</td>
</tr>
<tr>
<td></td>
<td>Garden City Pier, SC</td>
<td>0.79</td>
<td>0.26</td>
</tr>
<tr>
<td></td>
<td>Mayport, FL</td>
<td>0.23</td>
<td>0.06</td>
</tr>
</tbody>
</table>
but in some places, we have seen differences in arrival times of peak surges as well. This is especially true in areas that have more complex estuaries. Figure 3.6 shows some of the selected stations that were affected by storm surge from Hurricane Isabel. Station A is located in the upper reach of Delaware Bay shows that although the general trend of the surge is the same for all simulations, the smaller peaks arrive first and the larger peaks arrive last. The difference between them are about 7 hours. This is less pronounced at Station B, closer to the mouth of Delaware Bay. Station C on Chesapeake Bay also has this similar lag in peak arrivals as well. But Station D in Duck, NC that is fronting the Atlantic does not have this 7 hour lag in arrival. Although there is a difference, it is less than 3 hours.

Figure 3.6: Hurricane Isabel time series for selected stations A, B, C, D, and E. Each of the ensemble runs (different colors) are plotted against the time series results from the HURDAT Best Track (*)
In the gulf side, the behavior of surge for simulations for Hurricane Katrina is different. There were a total of 3 landfalls in this time frame, the first one in Florida, and two landfalls in Louisiana (Knabb et al., 2005). The ensemble winds were created from the time span of 72 hours prior to the second landfall at Louisiana (2005-08-29 1110 UTC) up to 24 hours after it. Figure 3.7 shows the time series for all 5 recording stations, the result of the best track simulation is also shown as * in the plots. All ensembles have phase as the best track data results. The highest storm surges were observed on station B, south of New Orleans in the Mississippi River with a maximum surge over 4m. The peak surge for this location happened a few hours before landfall. For all stations, the rising limb of the surges start at the same time, however, surge peaks at least an hour earlier for the smaller ensemble compared to the largest producing ensemble. Stations A, C, D and E all have returned returned to sea level (surge = 0m) right after the the lower limb of the surge, however, station B’s water levels have remained elevated after a day of landfall. This is most likely due to the station being located near a river and restricts the water from draining back to the gulf. In terms of spread, Station B also had the most significant standard deviation of up to 0.80m across 8 ensembles, while the rest deviate 0.10-0.20m from the mean.
Figure 3.7: Hurricane Katrina time series for selected stations A, B, C, D, and E. Each of the ensemble runs (different colors) are plotted against the time series results from the HURDAT Best Track (*)

3.3.4 Distribution of Ensemble Member Area and Volume

Each of the ensemble storms were created through a covariance method which reflects the natural variability of the wind intensities from 72 hour prior to landfall up to 24 hours after landfall, through a dataset of storms that made landfall and have a recorded storm surge signal in the NOAA tidal gauge. We are assuming that these ensemble of storms follow the natural behavior of the past hurricanes in the last two decades. The distribution of the
inundation volume of storm surges created from the hurricane decadal dataset is shown in Figure 3.8. These plots are modified violin plots where the shaded areas indicate the distribution of the inundation volume with respect to the average (middle bar. The top and the bottom bars represent the highest inundation volume and the lowest inundation volume respectively, recorded from all of the ensemble member simulation per storm. Hurricane Isabel had the largest range, followed by hurricane Ike; and these large range in volumes are clearly seen in Figure 3.5 and Figure 3.4 where the surge heights have increased by more than 2m in the same areas. Three storms (Katrina, Ike and Isabel) had its distribution of members producing inundation volume larger than the mean; while for the other three (Rita, Sandy and Matthew) the mean is lower and most of the members produced are lower than the average. The smallest range of inundation volume produced was coming from Hurricane Matthew; and Figure 3.3 shows that there is very little change between the smallest and largest producing member in surge both spatially and in magnitude.

The distribution of inundated area from simulating all members per storm are shown in Figure 3.9. Again, Hurricane Isabel had the largest range in inundated area, while Hurricane Ike had a smaller range this time. This difference between the distribution in Ike between the areas and the volume was clearly illustrated when Ike had more change in magnitude than in space for the surges produced by its smallest and largest member. Hurricane Isabel on the other hand has shown both increase in magnitude of surge and affected area.

The range of the distribution in Figure 3.2 are more uniform across all storms compared to the ranges shown in Figure 3.8 and Figure 3.9. This shows that there are storms that are
Figure 3.8: Volume Distribution of the ensemble winds. This modified violin plot shows where the volumes are distributed against the average (middle bar). The bottom bar and top bar represents the lowest and highest range of the distribution.

very sensitive to uncertainties in wind like Isabel for example, and storms like Matthew, Katrina and Rita which did not show much difference despite of the changes in wind intensities. Hurricane Ike on the other hand showed more sensitivity to magnitude than in inundated area to uncertainties in wind.

These differences clearly show that uncertainties in wind intensities can affect surge in both ways, changes in surge magnitude and inundated area. However the range of change expected is different for each individual storms. The differences can be attributed to other storm properties that can have more influence on the surge more than its wind intensity.
Figure 3.9: Area Distribution of the ensemble winds. This modified violin plot shows where the inundated area are distributed against the average (middle bar). The bottom bar and top bar represents the lowest and highest range of the distribution.

In order to fully analyze this contribution, there is a need to do sensitivity studies for each individual hurricane parameter using numerical models. And what we’ve shown in this study is that wind intensity does not only have an effect on the magnitude of surge but also on the range of inundated areas as well, however this can vary in each individual storms.
3.4 Conclusions

We have shown that by using a few number of ensembles, wind uncertainties can be represented for storm surge simulations, without having to do thousands of samples to represent every possible combinations. The range of these resulting wind ensembles were within 2 standard deviations of the ensemble mean, and represents at least 95% of the variability observed in historical storms. Using this methodology allows us to represent the natural variability of hurricane wind intensity as it makes landfall, instead of increasing and decreasing by a single constant throughout the simulation.

These uncertainties in wind intensities can substantially affect storm surges as well. The effects are varied for all 6 storms because each of them had unique hurricane parameters and made landfall in different areas that also contribute to the complexity of wind-surge interaction. The range of inundation volumes across all storms on average were 2.03km$^3$ to 27.48 km$^3$; with a spread that ranges from 0.55km$^3$ to 7.66km$^3$. Although it is generally believed that increase wind speed will increase storm surge heights, we have shown that this increase is seldom linear or easy to predict. Inundated areas on the other hand have a smaller range in average from 3.25km$^3$ to 13.83km$^3$, and a spread of 0.32x10$^3$km$^2$ to 2.59x10$^3$km$^2$. However this would mean that the affected area of surge can range from a small coastline to whole city or county. These differences in range of inundation volume and area can affect coastal planners as well in zoning areas that will be inundated by coastal flooding due to surge often.

We have also seen that not only the surge heights and extent of inundation area vary, the
arrival of peak surges also were affected by uncertainties in the wind intensity. Arrival
times vary differently across different topographies as well, with more complex estuaries
have seen lag times that can reach up to 7 hours, while a more simple coastline can expect
peak arrivals of an hour difference. These arrivals times of peak surge is very important
especially for emergency managers who need to decided when to issue evacuate orders to
avoid shadow evacuations and traffic jams.

Given that the formation of storm surge is highly dependent on the characteristics of hur-
ricanes, a future direction of this work is to use the same method with other hurricane
parameters such as radius of maximum winds, translation speed, minimum sea level pres-
sure, and track.
4.1 Introduction

Climate change will have significant implications for built environments, particularly those that lie within coastal regions. Coastal regions are routinely threatened by hazards including beach erosion and flooding from tropical cyclones. Climate change is intensifying these hazards due to several factors, e.g. increases in local sea levels, wave energy, and hurricane intensity (Hemer et al., 2013; Kopp et al., 2014; Walsh et al., 2016). As the number of coastal residents continues to increase (Neumann et al., 2015), it is increasingly important that the impacts of climate change on tropical cyclones and their ensuing hazards are explored.

Storm surges are of particular concern, as they pose a great threat to life and property. Storm surges occur when the high wind speeds and low pressure areas of tropical cyclones force ocean water toward and into coastal regions. Historically, it has been assumed that storm surge is directly and solely related to hurricane intensity, i.e. maximum sustained wind speed and minimum central pressure. However, over time, historical evidence and
research have shown that other meteorological properties of hurricanes including size, translation speed, and angle of approach, as well as geophysical characteristics of impacted areas (e.g. coastal geography, topography, and bottom friction) have significant impacts on the generation and propagation of storm surges (Akbar et al., 2017; Fossell et al., 2017; Irish & Resio, 2010; Irish et al., 2008; Mayo et al., 2014; Needham & Keim, 2014b; Ramos-Valle et al., 2020; Rego & Li, 2009,1; Resio et al., 2009; Thomas et al., 2019; Weaver & Slinn, 2010). A rich body of work investigating the impacts of climate change on the meteorological properties of tropical cyclones has been developed in recent decades. Among studies that have explored impacts on hurricane intensity, most agree maximum wind speeds and minimum pressures are likely to intensify by the end of the 21st century. Both theoretical and numerical models have consistently shown that the globally averaged intensity (i.e. maximum wind speeds) of tropical cyclones will shift towards stronger storms, with intensity increases of 2–11% by 2100 (Knutson et al., 2010; Walsh et al., 2016). Emanuel (2005) developed a destruction index and used it to demonstrate that climate change may increase the intensity-based destruction of tropical cyclones in the future. This is supported by their earlier finding that peak wind speeds of tropical cyclones should increase by 5% for every 1 °C increase in tropical ocean temperature (Emanuel, 1987). Holland & Bruyère (2014) developed a climate change index and showed that, globally, the number of intense hurricanes (Category 4 and Category 5) was increasing, although they also proposed the existence of a saturation level that prevented unbounded increases in the future.

Lynn et al. (2009) were among the first to project increases in hurricane intensity using numerical global climate modeling, and used simulations of Hurricane Katrina under cli-
climate change scenarios to show that wind speeds greater than 60 m/s at landfall could be sustained for increasing duration at the end of the 21st century. Hill & Lackmann (2011) found an average increase in intensity of 14% for 75 of 78 high resolution simulations of hurricanes, and Patricola & Wehner (2018) also found significant increases in intensity for 11 of 15 storms simulated. Knutson et al. (2013) compared multimodel ensemble projections of downscaled climate models using data from the Intergovernmental Panel on Climate Change (IPCC) Third and Fifth Coupled Model Intercomparison Projects (i.e. CMIP3 and CMIP5) under the Representative Concentration Pathway (RCP) 4.5 (moderate) emissions scenario and found that the maximum hurricane intensity increased by 4–6%. Knutson et al. (2015) used a similar methodology using only CMIP5 data, and found a significant increase in average tropical cyclone intensity by the late 21st century (+4.1% globally and +4.5% in the North Atlantic basin). Kim et al. (2014) used numerical climate simulations to show that the intensity of tropical cyclones will increase by 2.7% in a climate with double the atmospheric concentration of CO₂. Mudd et al. (2014) simulated 10K years of synthetic hurricane events for the Atlantic basin and found a significant increase in hurricane intensity when considering the effects of changes to SST (Sea Surface Temperature) only, hurricane genesis frequency only, and both climate change impacts simultaneously. Yates et al. (2014) simulated Hurricane Sandy under climate scenarios representative of 2020, 2050, and 2090, and found that intensity was generally within 5% of the control simulation, however in Lackmann (2015)’s exploration of Hurricane Sandy, they found that numerical models depicted a “significantly more intense system” in future climate scenarios.

Fewer studies have explored climate change impacts on hurricane size, another meteoro-
logical property that greatly influences storm surge inundation (Irish et al., 2008). There is not a strong consensus on the expected direction of the impact. Knutson et al. (2015) used numerical simulation to show changes to storm size at the end of the 21st century under the IPCC CMIP5 RCP 4.5 emissions scenario. They found a substantial increase (+11%) in the median size of storms in the North Atlantic basin, although, globally, the median storm size stayed nearly constant. Mudd et al. (2014) focused on the Northeast coastline of the U.S., and also found that for the year 2100, hurricane size would increase under current projections of changes to hurricane genesis. Kim et al. (2014) showed that tropical cyclone size would moderately increase, by about 3%, both globally and in the North Atlantic in response to doubling of the atmospheric concentration of CO$_2$. Lin et al. (2015) used observational data to examine rainfall area, which directly reflects storm size. While they found storm size was related to relative sea surface temperature (i.e. spatially), they did not find it was related to absolute SST, and thus concluded changes in storm size were not expected in a warmer climate, provided changes to SST are relatively uniform in space. Lynn et al. (2009) used numerical simulations to demonstrate that the radius of strong winds in a storm like Hurricane Katrina would decrease in the latter part of the 21st century.

Even fewer studies have explored climate change impacts to the translation speed of tropical cyclones, which also plays an important role in storm surge inundation (Rego & Li, 2009; Thomas et al., 2019). Both the global and regional climate models of Knutson et al. (2013) demonstrated slight decreases (-3% and -1.9%, respectively) in the translation speed of hurricanes by the late 21st century, however neither result was statistically significant. Kim et al. (2014) found small increases (+0.6% globally and +2.7% in the
North Atlantic basin), however their results also lacked statistical significance and they concluded that the translation speed of tropical cyclones would not significantly change over the 21st century with projected increases in atmospheric CO₂ levels. More recently, Kossin (2018) discussed that anthropogenic warming is expected to decrease translation speeds of tropical cyclones in the future. They examined observational data and found that over the 68-year period 1949-2016, translation speeds of tropical cyclones had decreased by 10% and 16% globally and within the North Atlantic, respectively. However, Lanzante (2019) argued that although subtle effects due to anthropogenic climate change cannot be ruled out entirely, Kossin’s findings were most likely not indicative of changes in the climate system, and were instead strongly influenced by natural climate variability and changes in measurement practices. Based on these findings, the impacts of climate change on the translation speed of tropical cyclones remain uncertain.

Although these storm characteristics are known to individually influence the extent and severity of storm surge flooding, questions surrounding their collective impact on storm surge remain. In general, coastal storm surges must be explicitly modeled using numerical simulation (Jelesnianski, 1992; Luettich et al., 1992; Mandli & Dawson, 2014). While an increasing number of studies have taken various approaches to exploring how climate change will impact coastal flood risk in the future (Chen et al., 2020; Garner et al., 2017; Lin & Emanuel, 2016; Lin et al., 2012; Marsooli et al., 2019; Murdughayeva et al., 2013; Needham et al., 2012; Rahmstorf, 2017; Takayabu et al., 2015; Yates et al., 2014; Yin et al., 2020), it is unclear how these impacts specifically relate to individual tropical cyclone characteristics. Few studies have considered climate change impacts to tropical cyclone characteristics at all, and fewer studies have focused exclusively on the effects on storm
surges, i.e. without introducing uncertainties related to sea level rise.

In Gutmann et al. (2018), projected climate change data were used with a convection-permitting regional climate model to reproduce U.S. landfalling hurricanes that occurred from 2000-2013 under an end of century climate scenario. The same hurricanes were hindcasted using present day atmospheric conditions, and changes to hurricane intensity, size, and translation speed were investigated. (Precipitation was also investigated; however, this meteorological property generally has implications for inland and compound flood risk, hazards which are beyond the scope of this paper.) In an effort to understand the influence of climate change on storm surge risk, we use the projected and hindcasted hurricanes as the atmospheric forcing inputs to a high fidelity storm surge model, and investigate the changes to simulated inundation.

The paper is organized as follows. In Section 4.2, we discuss the atmospheric and hydrodynamics models used for this work. We also describe the metrics used to quantify storm characteristics and storm surges. In Section 4.3, we discuss the results of our storm surge simulations, and in Section 4.4, we discuss the implications of our findings. We conclude by summarizing our results and identifying illustrated research needs in Section 4.5.
4.2 Materials and Methods

4.2.1 Overview

Storm surge is modeled using the Advanced Circulation (ADCIRC) Model, which numerically simulates coastal hydrodynamics (Luettich et al., 1992). ADCIRC can be forced with meteorological input, and here we force it with data produced by the Weather Research and Forecasting (WRF) Model (Skamarock et al., 2005). The WRF simulations are produced using initial and boundary conditions representative of present day and end of century climate scenarios to depict hurricanes characteristic of both time periods. We use the existing WRF simulations of Liu et al. (2017), and specifically the hurricanes presented in Gutmann et al. (2018).

4.2.2 Atmospheric modeling

4.2.2.1 WRF Model

The WRF Model is a three-dimensional, convection-permitting, regional climate model. It is a system that numerically solves the compressible, non-hydrostatic Euler equations, and can be used for a range of applications through a number of physics packages and data assimilation methods (e.g. weather forecasting and research (Schwartz et al., 2015), climate simulations (Rasmussen et al., 2011) and atmosphere-ocean coupling (Nicholls & Decker, 2015)). It can simulate both observed and hypothetical atmospheric conditions, and has
been used for atmospheric research and operational forecasting since it was developed. Here, we use the output from simulations of the atmosphere created using WRF version 3.4.1 with a 5440 km (east–west) by 4064 km (north–south) domain spanning the contiguous U.S. and portions of Canada and Mexico (Figure 4.1). In the horizontal direction, a 4 km grid spacing is used on a lambert conformal-conic grid. In the vertical direction, 51 layers are used with the top level set to 50 hPa. Seven observational datasets were used to demonstrate that this model “faithfully captures the spatial and temporal pattern of sub-seasonal/seasonal/annual precipitation and temperature in most of” the Continental U.S (Liu et al., 2017). Additional details on the WRF configuration, physics parameterization, and uncertainty of the data used in this study can be found in Liu et al. (2017) and Gutmann et al. (2018).

The WRF Model is implemented to produce high resolution simulations of hurricanes that impacted the U.S. between October 2000 and September 2013. The domain is not large enough to study changes in hurricane genesis, however removing this chaotic process facilitates comparison of otherwise identical storms from different climates. To simulate hurricanes under present day climate conditions (CTRL), WRF is forced with initial and boundary conditions derived from the ERA-Interim dataset (Dee et al., 2011). This data set specifies atmospheric characteristics, e.g., wind, temperature, humidity, and pressure, with temporal and spatial resolution of 6 h and 0.7°, respectively. Sea surface temperatures (SST) are also used to define the lower boundary condition throughout the simulation.

To simulate hurricanes under an end of century climate scenario, the pseudo-global warming (PGW) method is used (Rasmussen et al., 2011; Schär et al., 1996). A climate change
signal is calculated using the RCP 8.5 (high) scenario as simulated by 19 different models in the IPCC CMIP5. The perturbation is calculated by averaging across the two periods 2071–2100 and 1976–2005, and then computing the difference. Thus, even though we only use 13 years of simulated weather for our study, the climate change signal itself is based on traditional 30 years averages imposed on the same weather. This approach avoids problems caused by internal variability (Deser et al., 2012), and is comparable to approaches used to study hurricanes in similar studies (Carroll-Smith, 2018; Chen et al., 2020; Jung & Lackmann, 2019; Lackmann, 2015). Inputs to the radiative transfer scheme are also modified to account for projected changes in greenhouse gases. The climate change signal is then applied to the WRF boundary conditions describing the zonal and
meridional wind speeds, sea level pressure, geopotential height, air temperature, relative humidity, sea surface temperature, and initial soil temperature. The PGW changes in 700 hPa air temperature and relative humidity range by +3 to +4K and +2 to -2% over the Gulf of Mexico and North Atlantic during hurricane season. SSTs over the region increase by 3.2K. Changes to the other boundary conditions are modest.

4.2.2.2 Hurricane Simulations

Over the time period of interest (2000–2013), 32 named storms in the National Hurricane Center (NHC) best track hurricane (HURDAT) database (Landsea & Franklin, 2013) have track centers that come within 400 km of the WRF model domain. Of these, the WRF model is able to reasonably simulate the tracks, intensities, sizes, and translation speeds of 26 of them, although the more extreme intensities are slightly underestimated (i.e., the tails of the maximum wind speed and minimum central pressure distributions are under- and overestimated, respectively; see Figure 4 in Gutmann et al. (2018)). When the PGW method is implemented, WRF is able to successfully simulate all but one of these 26 storms, however three have relatively large changes between the simulated tracks of the present day and end of century climate scenarios. This makes it difficult to attribute changes in storm surge inundation to changing meteorological characteristics rather than changing storm tracks (i.e., landfall location). The latter is not examined in this study, thus we exclude these three storms from our analysis. More detail can be found in Gutmann et al. (2018). Finally, of the 22 remaining storms, one (Hurricane Gustav, 2002) causes numerical instabilities within the ADCIRC model, likely due to the position of this storm
at the edge of the ADCIRC domain. The 21 storms that remain for analysis are listed chronologically in Table B.1 in Appendix A.

Of note, Hurricane Katrina is not included in this study. It is one of the six storms that was not well-simulated by the WRF model, and specifically its track did not accurately reflect HURDAT data. This is likely due to the placement of the southern boundary of the WRF domain, which is too close to the storm center for much of the track. Climate change impacts to the meteorological properties of Hurricane Katrina were investigated in Lynn et al. (2009) using a coarser 9 km WRF model with boundary conditions derived from the comparable A2 emissions scenario of the IPCC Fourth Assessment Report, and it was suggested that the storm would likely intensify in a warmer climate. We expect that storm surge would intensify as well, though as discussed in section 4.2, this is difficult to predict without explicit modeling.

4.2.2.3 Hurricane Intensity Metrics

Gutmann et al. (2018) computed the average maximum windspeed, minimum central pressure, radius of hurricane force winds, and translation speed of each simulated hurricane, taken across the duration of each storm. For each point along the simulated track, these statistics were computed using data from a 400 × 400 km region centered at a point of minimum pressure. Thus, the point of minimum pressure is computed as the point at the center of this region by definition. The maximum wind speed is simply the maximum (instantaneous) value in the region. The radius of the 33 ms-1 winds is computed as the average distance from the track center to the easternmost and westernmost points that
The translation or forward speed is computed by dividing the distance between the track center and the track center calculated 3,600 s prior by 3,600 s. Further details can be found in Gutmann et al. (2018). These values were used to determine statistically significant increases to the maximum wind speed, damage potential, and maximum rainfall rate, and statistically significant decreases to the translation speed and minimum central pressure of hurricanes over the 21st century. In this work, we use these metrics to assess how climate change impacts to tropical cyclone characteristics can be expected to influence storm surge inundation in the future.

4.2.3 Storm Surge Modeling

4.2.3.1 ADCIRC Model

The Advanced Circulation (ADCIRC) model is a numerical hydrodynamics model (Luetich et al., 1992). It solves a modified form of the shallow water equations through the discretization of spatial derivatives using a finite element method. The use of a finite element method allows the equations to be modeled using unstructured meshes, which offers the advantage of discretization with high resolution in regions of interest without the computational expense of increasing resolution uniformly throughout the entire spatial domain. This is especially advantageous for coastal hydrodynamics applications, where more spatial resolution is often desired near the coastline than in the deep ocean. Time derivatives are discretized using centered and forward finite differencing.

The ADCIRC model has been continually developed since its inception in the early 1990s,
becoming increasingly robust for a number of applications. Notably, wetting and drying algorithms have been implemented to allow modeling of overland flooding (Dietrich et al., 2004; Luettich & Westerink, 1995). Especially important to modeling overland surge and flooding in regions of shallow water, bottom friction can be specified through spatially variable parameters (Mayo et al., 2014; Passeri et al., 2013). The ADCIRC model can also utilize various forms of meteorological input, including parametric wind profiles and gridded wind field data (Cyriac et al., 2018; Houston et al., 1999; Mayo & Lin, 2019). It has been extensively validated and verified for tropical cyclones around the world, and has been used for a range of modeling, planning, and emergency operations applications (Butler et al., 2012; Dietrich et al., 2010; Fleming et al., 2008; Lin et al., 2012). In this work we use the parallel implementation of version 53.04.

We convert WRF data to an ADCIRC readable format through several preprocessing steps. First, we project the simulated wind and pressure fields onto the Cartesian coordinates of the ADCIRC mesh. Then, pressure and directional wind data are used to create the meteorological forcing input files used in ADCIRC. Both of these steps are accomplished using Matlab and Python scripting. The data are also manually trimmed to exclusively span the spatial extent and duration of simulated hurricanes to improve computational efficiency.

4.2.3.2 HSOFS Mesh

We use the Hurricane Surge On-demand Forecast System (HSOFS) mesh, which was developed jointly by the National Ocean Service, Riverside Technology, and AECOM
(Riverside Technology & AECOM, 2015). It spans the Gulf of Mexico and the U.S. Atlantic Coast, extending into the Atlantic Ocean to the approximate longitude of 65W Figure 4.2. Nearshore, the mesh generally extends on to land up to a topographic height of 10 m. Because it was developed with the intent of operational use, it does not have the local resolution of more geographically-focused ADCIRC meshes, however it is one of the only meshes with national inundation coverage, i.e., it allows overland flooding to be modeled across the entire coastline of the eastern and southern U.S. It has a total of 1,813,443 vertices and 3,564,104 triangular elements, with an overland grid resolution that ranges from 150 to 500 m.

Version 50.99 of ADCIRC was previously used to verify this mesh for astronomical tides and 10 major tropical and extratropical storms (i.e., Hurricanes Ike, Katrina, Dennis, Charley, Hugo, Floyd, Isabel, Sandy, and the Great New England Hurricane and Perfect Storm of 1938 and 1991, respectively). Storm surges were modeled primarily using high fidelity wind data developed by Ocean Weather, Inc. (OWI) (Hurricane Sandy and Hurricane Floyd were modeled using HWRF and Hwind data, respectively). The National Oceanic and Atmospheric Administration (NOAA) Coast Survey Development Laboratory Skill Assessment Software (Zhang et al., 2010,0) and high water marks were used to determine that maximum storm surge heights were modeled with an RMSE of 0.26 m, demonstrating the suitability of the HSOFS mesh for research applications.

ADCIRC is run with the HSOFS mesh for each WRF simulation to model the storm surge of hurricanes given present day and end of century climate scenarios. The simulations are executed using the high performance computing facilities at the Texas Advanced Com-
The Advanced Circulation (ADCIRC) Model, the Hurricane Surge On-demand Forecast System (HSOFS) mesh. Bathymetry is shown in meters below mean sea level. Dark green regions are used to depict areas that are above sea level, i.e. overland.
4.2.3.3 Surge Inundation Metrics

To quantify the storm surge risk modeled by ADCIRC, we use two metrics to describe storm surge inundation volume and extent. Because our interest is storm surge impacts to the built environment, we focus on inland geographical regions, i.e., those elements of the HSOFS mesh that are initially entirely above the reference sea level (geoid) defined in ADCIRC. Each ADCIRC simulation produces a global maximum water surface elevation file, which describes the peak storm surge height at each node of the mesh over the duration of the storm. For each inland (i.e., initially dry) element, we calculate its inundation volume using its (triangular) area and the peak storm surge height computed for each of its three nodes (i.e., vertices of each triangular element):

\[ V_e = A_e \times \left( D_1 + D_2 + D_3 \right) / 3, \]  

(4.1)

where \( V_e \) is the element volume, \( A_e \) is the element area, and \( D_i \) is the water depth at node \( i \). (When computing \( A_e \), we use the World Geodetic System to account for the projection of the area onto the spherical earth.) We sum each of these element inundation volumes to compute a measure of total inundation volume for each simulation. A similar approach was used in Fossell et al. (2017).

If all three nodes of an inland element have a peak water elevation above zero (i.e., if the element inundation volume is >0), we consider its area to have been “wetted” by the
simulated storm:

\[ A_w = \begin{cases} 
A_e, & \text{if } D_1 \geq 0 \text{ and } D_2 \geq 0 \text{ and } D_3 \geq 0 \\
0, & \text{otherwise.}
\end{cases} \]  

(4.2)

Here \( A_w \) is the wetted area. We sum each of these wetted element areas to compute a measure of total inundation extent for each simulation.

Both of these metrics allow storm surge to be quantified and compared across simulations, while accounting for the variable spatial resolution of the unstructured mesh. In contrast to more routinely used metrics, such as root mean square difference, regions with high spatial resolution are not weighted more heavily than those that are coarser. Additionally, uncertainties introduced by the description of the atmospheric characteristics, the numerical approximation of the WRF model, the deviations of the simulated hurricanes from observed data, the prescribed boundary conditions and wind field representation within ADCIRC, and the numerical approximation of the ADCIRC model all compound and propagate in complex ways that are difficult to quantify without formal analysis. The use of these inundation metrics serves to reduce the sensitivity of our results to these uncertainties by effectively smoothing error with integration (Oden, 2011; Smith, 2013).
4.3 Results

4.3.1 Simulated Storm Surge

4.3.1.1 Maximum Storm Surge Levels

The combined maximum storm surges of all 21 storms simulated for the present day climate scenario (CTRL) is shown in Figure 4.3A. The largest storm surges occur along the Gulf Coast, specifically near Texas, Mississippi, and the Florida panhandle. The highest surges were caused by Hurricane Ike that produced up to 9.8 m near the Galveston area. Maximum storm surges are less severe along the Atlantic coastline, with the largest levels attained near the Outer Banks of North Carolina and Chesapeake Bay in Virginia.

The combined maximum storm surges of all 21 storms simulated for the end of century climate scenario (PGW) is shown in Figure 4.3B. Hereafter, hurricanes from these simulations are referred to as Hurricane(P). The largest storm surges occur in the same areas along the Gulf coast seen in the CTRL scenario, although the levels are greater. Water levels >5.0 m are seen in Texas and Mississippi. These large surges are caused by Hurricane Ike(P) and Hurricane Isidore(P), respectively. The surge caused by Hurricane Isidore(P) in Mississippi increases by 2.30 m from the CTRL scenario, while the surge caused by Hurricane Ike(P) in Texas increases surge by just 0.01 m. A greater extent of the Gulf side of Florida is affected by higher storm surges, including Tampa Bay, which is not inundated in the CTRL simulation. Along the Atlantic coast, North Carolina and Virginia remain affected, and substantial increases in storm surges are also seen near South Carolina and
Figure 4.3: (A) A composite of the maximum storm surge levels of all 21 present day (CTRL) simulations. (B) A composite of the maximum storm surge levels of all 21 end of century (PGW) simulations.

New York.

Overall, there is an increase in maximum storm surge levels from the CTRL to the PGW simulations. Figure 4 shows a more pronounced increase along the Gulf coast of more
than 1.0 m. Notable increases are seen near Mississippi, the Gulf Coast of Florida, the Carolinas, and New York. However, there are parts of Albermarle Sound and Pamlico Sound in North Carolina and the eastern side of Chesapeake Bay that show lower surges (i.e., decreases ranging from about 0.5 to 1.0 m) in the PGW simulations. Few studies have implemented this methodology to deterministically assess climate change impacts to storm surges, however our results are consistent with Yates et al. (2014), who used the PGW method to assess climate change impacts to Hurricane Sandy over the 21st century and found significant increases to flood heights and inundation extent along the New Jersey and Long Island coasts. Additionally, Little et al. (2015) developed a novel flood index and demonstrated substantial and positively skewed changes to coastal flood risk along the east coast by the end of century, and Yin et al. (2020) used a fully coupled global weather and climate modeling system to simulate storm surge risk along the U.S. Atlantic Coast under elevated CO2 levels and also found increased storm surge risk.

4.3.1.2 Inundation Volume

The total volume inundated in each simulation, along with the relative change from the CTRL to the PGW simulations, is summarized in Table 1. Volumes are arranged in descending order based on the CTRL simulations, i.e., in order of decreasing severity for the present day scenario. Values for the CTRL simulations range from 0.01 to 22.81 km$^3$, and have a mean value of 2.55 km$^3$. Six storms (i.e., Hurricane Gustav, Hurricane Isaac, Hurricane Irene, Hurricane Rita, Hurricane Isidore, and Hurricane Ike) have inundation volumes above this mean. Notably, the inundation volume computed for Hurricane Ike is
22.81 km$^3$, which is substantially (more than five times) larger than the next largest volume of 4.13 km$^3$ (Hurricane Isidore). Figure 4.5A reflects the widespread flooding caused by Hurricane Ike near coastal Texas, and specifically near Galveston Bay and the Houston Ship Channel. Storm surge levels in this region exceed 5.0 m. Most (all but six) of the 21 CTRL simulations cause inundation volumes >1 km$^3$. 

Figure 4.4: Difference (PGW-CTRL) between maximum storm surge levels over the 21st century.
For the PGW simulations, the inundation volumes range from 0.01 to 30.13 km$^3$, and the mean value increases to 3.56 km$^3$. Six storms again have inundation volumes above this mean [Hurricane Dennis(P), Hurricane Isaac(P), Hurricane Irene(P), Hurricane Rita(P), Hurricane Isidore(P), and Hurricane Ike(P)]. The inundation volume computed for Hurricane Ike(P) remains the largest, and increases to 30.13 km$^3$. Figure 4.5B illustrates more intense flooding than that seen in the CTRL simulation (Figure 5A), with high storm surge levels extending further inland and inundating Galveston Island. The inundation volume for Hurricane Ike(P) (30.13 km$^3$) is again substantially larger than the next largest volume [7.87 km$^3$ for Hurricane Isaac(P)]. However, Figure 4.6 shows that the changes are mostly limited to the states of Texas, Louisiana and some parts of Mississippi, where Ike (P) generally causes increases in water levels >1 m.

The inundation volumes of 14 storms increase across the climate scenarios (CTRL to PGW), with relative increases ranging from +3 to +161%. The largest relative increase occurs for Hurricane Frances(P). The inundation volume of Hurricane Alex does not change, while the inundation volume decreases for 6 storms, with Hurricane Ivan(P) decreasing the most, relatively (-25%). Across all simulations, the average change to inundation volume is an increase of 36%.

4.3.1.3 Inundation Area

The total area wetted in each simulation is summarized in Table 2. Areas are arranged in descending order based on the CTRL simulations, i.e., in order of decreasing severity for the present day scenario. Values for the CTRL simulations range from 69 to 16,224
km$^2$, and have a mean value of 3,457 km$^2$. Hurricane Ike is again worthy of note, and has the largest wetted area (16,224 km$^2$; Figure 4.5A). The next largest wetted area is less than half of this (6,174 km$^2$ for Hurricane Rita). Hurricane Isidore, Hurricane Irene, and Hurricane Sandy complete the set of the five storms with the largest wetted areas. All but three of the CTRL simulations cause wetted areas >1,000 km$^2$.

Figure 4.5: (a) Maximum storm surge levels of the Hurricane Ike CTRL simulation. (b) Maximum storm surge levels of the Hurricane Ike PGW simulation
Figure 4.6: Difference (PGW-CTRL) between maximum storm surge levels over the 21st century for Hurricane Ike. The storm tracks for the CTRL (green) and PGW (orange) simulations are also included.

For the PGW simulations, wetted areas range from 69 to $17,546 \text{ km}^2$, and the mean value increases to $4,044 \text{ km}^2$. Hurricane Ike(P) again produces the largest wetted area, however there is not as great a difference between the two largest wetted areas. Hurricane Isaac(P) produces the second largest wetted area, $10,457 \text{ km}^2$ (Figures 4.7A,B). The redistribution of water is illustrated in Figure 4.8. Hurricane Sandy(P), Hurricane Isidore(P), and Hurri-
Figure 4.7: (a) Maximum storm surge levels of the Hurricane Isaac PGW simulation. Storm surges are lower, but affect portions of Louisiana and southwest Florida. (b) Maximum storm surge levels of the Hurricane Isaac CTRL simulation. Portions of northwest Florida are inundated with storm surges over 2 m.

cane Irene(P) complete the set of the five storms with the largest wetted areas for the PGW simulations.

The wetted areas of 13 storms increase across the climate scenarios (CTRL to PGW), with relative increases ranging from +1 to +244%. The largest relative increase occurs for Hurricane Isaac(P). The wetted area of Hurricane Alex does not change, and has the smallest wetted area under both climate scenarios. The wetted area decreases for seven storms, with relative decreases ranging from -2 to -28%. Hurricane Jeanne(P) has the
Figure 4.8: Difference (PGW-CTRL) between maximum storm surge levels over the 21st century for Hurricane Isaac. The storm tracks for the CTRL (green) and PGW (orange) simulations are also included.

largest relative decrease. Across all simulations, the average change in wetted area is +25
4.3.2 Storm Characteristics

The storm characteristics of each simulation are summarized in Table B.1. This is a subset of the complete set of storm characteristics (i.e., including damage potential and rainfall rates) analyzed in Gutmann et al. (2018). On average, from the CTRL to the PGW simulations, the wind speeds and radii of the 33 ms\(^{-1}\) winds increase by +5.33 and +1.46%, respectively, and the translation speeds and central pressures decrease by -4.53 and -0.42%. Of note, the wind speeds are averaged over the entire duration of the hurricane and the averages thus include wind speed values that occur overland (averaging wind speeds over the 24-h period prior to landfall was explored but did not impact the results of this study). Additionally, the values are instantaneous wind speeds, differing from the oft reported 1-min averages. The values of the storm characteristics for each simulation are illustrated in Figure 4.9(CTRL) and Figure 4.10(PGW), arranged from top to bottom in order of increasing inundation volume. The changes in the storm characteristics are illustrated in Figure 4.11, arranged from top to bottom in order of increasing change to inundation volume.

4.4 Discussion

4.4.1 Impact on Inundation Volume and Extent

Our results indicate that we can generally expect remarkably greater severity of storm surges at the end of the century, as the volume and extent of inundation increase for most hurricanes examined here. The inundation volumes increase for 14 of 21 hurricanes, and
Figure 4.9: Average hurricane characteristics of each simulated storm arranged from top to bottom by increasing inundation volume of the CTRL simulations. Magnitudes of hurricane characteristics that theoretically contribute positively to larger surges (e.g. higher wind speeds, larger radii, and slower translation speeds) are depicted by darker hues.

The inundation volumes of three hurricanes (Hurricane Isaac, Hurricane Dennis, and Hurricane Frances) more than double over the century. Hurricane Ike produces the most severe storm surges for both climate scenarios, however the other storms do not change in severity uniformly. For example, the wetted area of Hurricane Isaac, which is near the mean for the present day climate scenario, substantially increases and its surge becomes the second most severe by this metric.
Figure 4.10: Average hurricane characteristics of each simulated storm arranged from top to bottom by increasing inundation volume of the PGW simulations. Magnitudes of hurricane characteristics that theoretically contribute positively to larger surges (e.g. higher wind speeds, larger radii, and slower translation speeds) are depicted by darker hues.

Hurricane Alex produces the smallest inundation volume and wetted area, and neither metric changes over the century. The hurricane tracks of both the CTRL and PGW simulations of this storm make landfall close to the Texas and Mexico border (see Figure 5 of Gutmann et al. (2018)), close to the boundaries of the ADCIRC model domain. The simulations are likely impacted by limitations in the hydrodynamics modeling in this region.

The calculations of inundation volume and wetted area broadly indicate that in the future
Figure 4.11: Differences (PGW - CTRL) in average hurricane characteristics arranged from top to bottom by increasing inundation volume. Decreases in translation speed and pressure contribute positively to larger surges so signs are reversed in this figure accordingly (e.g. decreases in translation speed are defined as positive changes).

we can expect hurricanes to produce relatively more high storm surge levels in concentrated areas rather than smaller storm surges that are more wide spread, as inundation
volumes generally increase more substantially than wetted areas. For example, Hurricane Jeanne and Hurricane Rita both produce decreases in wetted areas, but increases in inundation volume. On the other hand, we also find that storms that produce increases in wetted areas do not necessarily cause increases to inundation volumes. Hurricane Lili(P) shows a small increase in area (+1%) but decreases in inundation volume (-4%). In these cases, the heights of storm surges may decrease, while a larger area is impacted. The relationship between inundation volume and wetted area must be closely examined for specific impacted regions, as both are greatly impacted by local topography, but in general we expect that coastal inundation will increase in the future.

The potential societal impacts of these findings are vast. Increased inundation increases the number of people and property threatened by storm surge, particularly as coastal populations and the associated urban development grow (Neumann et al., 2015). Beyond increased fatalities, this can have long lasting consequences for the under- and uninsured, and agencies, such as the Federal Emergency Management Agency (FEMA), which provide disaster assistance and already substantially contribute to the national deficit. Increased inundation also poses a greater threat to infrastructure. Transportation networks may face greater obstructions during and after a storm, impeding evacuation efforts and access to medical care and other resources. Widespread flooding can also flood power equipment and limit the mobility of power restoration crews, which can cause and extend the power outages that often accompany hurricanes, resulting in large economic and social losses. Increased inundation can also have a number of environmental impacts, for example by exacerbating other hazards, such as inland flooding caused by obstructions to drainage systems, and saltwater intrusion which can have catastrophic consequences for
agriculture and the biogeochemical cycles of coastal ecosystems.

4.4.2 Influence of Storm Characteristics

We examine the relationships between storm surge inundation and storm characteristics to gain more insight into the impacts of climate change. The coastal research community generally agrees on the influences of individual storm characteristics to storm surges. Higher intensity hurricanes, i.e., those with larger maximum wind speeds and lower minimum pressures, produce larger storm surges, all other things being equal. Slower-moving hurricanes produce more storm surges inland, while faster-moving storms cause higher water levels along the coast (Rego & Li, 2009). Larger storms, particularly those that translate over mildly sloping beaches, e.g., Hurricane Katrina, are expected to produce higher surges than smaller storms that translate over steeper continental shelves (Irish et al., 2008). Given this, six hurricanes in our study have storm characteristics that change over the century in precisely the directions that would theoretically result in increased storm surges. They are Hurricane Isabel, Hurricane Jeanne, Hurricane Ike, Hurricane Dolly, Hurricane Sandy, and Hurricane Irene Figure 4.11. Simulations of five of the six named storms do produce increases in inundation (Hurricane Isabel is the exception). However, the magnitudes of the increases greatly vary by storm, ranging from +6 to +63%, and a number of hurricanes without this “perfect storm” of changes produce more substantial increases in surge. Hurricane Sandy is notable on this list, because it was historically one of the costliest storms, and much of the cost was associated with the flooding caused by the storm surge. This storm has substantial intensification of the simulated pressure, how-
ever the changes in the other storm characteristics are mild in comparison to those of other storms.

Figure 4.11 further illustrates the variation in the influences of individual storm characteristics on storm surge inundation. As the storms are ordered by increasing changes to volume inundation, we expect to see systematic changes to the storm characteristics. However, we do not see such changes. In particular, wind speed does not strongly nor directly relate to the severity of surges. Furthermore, the five hurricanes that produce inundation volumes with the largest increases do not share similarities in the directions of change to their storm characteristics. In fact, Hurricane Frances, which produces the largest increase in inundation volume, decreases in both wind intensity and radius. It does decrease in translation speed (and central pressure), but only by 3%, which is lower than the average decreases of translation speeds for the full set of storms studied here. This could suggest that changes in translation speed play a more significant role in storm surge generation than previously indicated. However, in contrast, Hurricane Ophelia has the largest decrease in translation speed (44%), yet produces a significant decrease of inundation volume. It is evident that more research is needed to better understand the role of translation speed on storm surge generation in combination with other storm characteristics in both present day and future climate scenarios.

Upon closer examination of the two other storms whose inundation volumes double over the century, i.e., Hurricane Dennis and Hurricane Isaac, there is generally no discernible pattern emerging in the hurricanes that produce substantial increases in inundation volume. Six storms produce decreases in inundation volumes. For example, the inundation vol-

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ume of Hurricane Gustav, which was one of the more severe hurricanes of the CTRL simulations (2.74 km$^3$), decreases by 11%. The wind speed, translation speed, and radius decrease, while the central pressure increases, i.e., each characteristic decreases in severity with the exception of translation speed. This is similar to the behavior observed in the storm characteristics of Hurricane Frances, however the impacts on storm surge are much different.

These results demonstrate that there is no single storm characteristic for which changes induced by climate can predict impacts to storm surge severity. Even when considered in conjunction, the resulting influences are difficult to anticipate. Our results may be influenced by moderate differences in tracks of the CTRL and PGW simulations, which can have important implications for landfall location and angle of approach. Perpendicularly landfalling storms tend to produce more wide spread surges than those that make landfall diagonally, however this is rare (Hall & Sobel, 2013; Ramos-Valle et al., 2020). Also, in some areas, track fluctuations lead to landfalls of areas with different physical characteristics of the coastline and shelf that can either amplify or diminish surge magnitude (Azam et al., 2004; Mori et al., 2014). It is unlikely that the moderate differences in tracks observed in this study would significantly impact computed inundation volumes (Resio et al., 2009); however, the impact of local topography and bathymetry, including how these may also be impacted by climate change, should be investigated further.
The methodology presented here offers a framework with which climate change impacts to storm surge inundation can be systematically assessed; however, there are several limitations. Here, we focus exclusively on storm surge, i.e., we do not simulate astronomical tides, waves, or sea level rise. While this reduces the introduction of uncertainties related to the timing of hurricane landfall, resolution of short period waves, and projections of local sea level rise, these phenomena can have important impacts on total water levels (Atkinson et al., 2013; Bilskie et al., 2014; Dietrich et al., 2011; Rego & Li, 2010). As a result, in the future, coastal inundation may become more extreme than the results of this study suggest.

Additionally, we do not account for coastal morphodynamics and land use change. Coastal morphodynamics and hydrodynamics are coupled processes, with each directly impacting the other (Roelvink et al., 2009). As such, climate change impacts including sea level rise and increases to tropical cyclone intensity and frequency will likely cause morphological changes to the U.S. coastline, with important implications for coastal flood risk (Ozkan et al., 2020; Passeri et al., 2015; Roelvink et al., 2020). Furthermore, land use is also changing with population growth and urban development (Lawler et al., 2014). This can significantly impact the climate and coastal flood risk, as was recently observed during Hurricane Harvey (Kalnay & Cai, 2003; Zhang et al., 2018).

The tracks, landfall locations, and intensities of several simulated hurricanes differ slightly from those reported in the HURDAT database (Gutmann et al., 2018), which are also sub-
ject to error (Landsea & Franklin, 2013). These differences impact the locations and magnitudes of flooding simulated (Sebastian et al., 2014; Weisberg & Zheng, 2006). These differences also make it difficult to systematically verify our simulations with observational data, e.g., from high water marks and tide gauges (exemplary hydrographs of Hurricane Ike, the simulations of which had good agreement with HURDAT data, are shown in Figure 12). As the main objective of this study is to investigate climate induced changes to storm surges, we have not included extensive verification exercises here, though preliminary analyses show reasonable reproduction of observed peak storm surge levels and timing. The use of the inundation metrics described in section 2.2.3.2 reduces the sensitivity of our assessment to the slight storm variations.

Finally, although the HSOFS mesh extends inland with resolution ranging from 150 to 500 m, it is not able to resolve fine details, such as roads and infrastructure close to the coastline. While we believe that the mesh is suitable for describing general locations and patterns of storm surge along the coastline, it cannot be used to explicitly simulate, e.g., neighborhood-level impacts or coastal protection measures.

4.5 Conclusions

In this study, we simulate the storm surges of 21 hurricanes to understand the potential impacts of climate change to coastal inundation. While this small sample of storms is not large enough for statistical analysis of changing coastal flood risk, it makes feasible the use of high fidelity, high resolution atmospheric and hydrodynamics models to investigate the
Figure 4.12: Time series of water levels recorded at NOAA tide gauges that lie within 100 km of Hurricane Ike at landfall (blue) and data from the present day (red) and end of century (yellow) WRF-ADCIRC simulations. Note that several gauges failed prior during peak storm conditions.

potential impacts for a broad range of events. We assess the changes to storm surges produced by hurricanes under present day and end of century climate conditions, and find that storm surges will likely become more severe by 2100. On average, storm surge inundation volume and extent both increase over the century, with notable increases along the Gulf Coast (Texas, Louisiana, Mississippi, and the West Coast of Florida), the Carolinas, and New Jersey (i.e., within Delaware Bay and the New York-New Jersey Bight). The inundation volume increases for 14 of the 21 modeled storms, and the average change across all 21 storms is +36%. The inundation extent increases for 13 storms, and the average change
across all storms is +25%. Storms that increase in inundation volume generally increase in inundation extent; however, there are three exceptions to this. Hurricane Jeanne and Hurricane Rita both increase in volume, but decrease in area. Hurricane Lili increases in area, but decreases in volume. Our assessment of inundation broadly demonstrates that in the future, hurricanes may produce larger storm surge levels in more concentrated areas as opposed to surges with lower magnitudes that are more widespread.

We find that neither the changes to nor magnitudes of storm surge inundation are predictable by any single hurricane characteristic. Even when storm characteristics are considered together, the resulting influences to storm surge is difficult to assess. The hurricanes with the largest increases to inundation volume are not those whose storm characteristics change in expected ways; their intensities and sizes do not always increase, and their forward speeds do not always decrease. We find that hurricanes with characteristics that do change in ways expected to produce larger storm surges do in fact increase inundation volume and extent. However, the increase in inundation is generally not as large as might be expected. This indicates that even as climate change research advances and more is learned about potential impacts to hurricanes, implications for storm surge will be difficult to predict without probabilistic assessments or numerical experiments, such as those conducted here. Ultimately, the changes to storm surge inundation are caused by the complex interplay between the spatio-temporal distribution of storm characteristics and the geographical properties of the nearshore.

This work provides a fundamental first step in coastal hazard assessment under climate change by improving our understanding of the storm surge component. The atmospheric
model used here can also simulate rainfall, so there is potential to explore inland and compound flood risk as the state of numerical modeling of these coupled hazards advances. Additionally, as more is learned and uncertainties are reduced in our understanding of climate change impacts to waves and sea level rise, we are better equipped to assess climate change impacts on total flood risk. Particularly as computational advances are made toward resolving the spatial scales necessary to model fluid/structure interactions, this will have significant implications for our understanding of climate change impacts to the built environment.
DATA AVAILABILITY STATEMENT

The WRF data used in this study are available through the NCAR Research Data Archive: Rasmussen & Liu (2017). High Resolution WRF Simulations of the Current and Future Climate of North America. Research Data Archive at the National Center for Atmospheric Research, Computational and Information Systems Laboratory. https://doi.org/10.5065/D6V40SXP The ADCIRC data files supporting the conclusions of this article will be made available by the authors without undue reservation, upon request.

AUTHOR CONTRIBUTIONS

JC: performed ADCIRC simulations, data analysis and interpretation of all elements, design and creation of figures, and lead contributor to the writing. TM: concept development, provided guidance for analysis of all elements, and major contributor to the writing. EG: aided in project concept development, performed WRF analysis, contributed to interpretation, and aided in writing. All authors contributed to the article and approved the submitted version.

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CHAPTER 5: CONCLUSION

Storm surge will always be a constant threat for people living in coastal regions, and it will likely be an even bigger danger in the future as the climate changes. Although it is the leading cause of death in hurricane related hazards, its most devastating impacts are highly preventable. Timely and proper evacuations can potentially save lives of coastal residents, but for longer term efforts to mitigate surge impacts, we must be able to increase resilience of not only the population but also the coastal areas themselves. In the present time, the efforts of NHC to separate surge risk messaging from the SSHWS categories is a great stride in the right direction, and the decrease in fatalities due to storm surge in the last decade may be largely due to this. The public response to messaging is more complex than just obeying orders because coastal residents also depend on other factors such as experience, socio-economic bias, confidence in authorities, or their geographic location.

We have also seen that the problem goes beyond just solving challenges in storm surge risk communication. While improving risk communication can improve risk perception, it is not always sufficient in the long term. The storm surge hazard however occurs frequently and a better way to mitigate against it is through building systems to minimize the vulnerability of residents. For example, the construction of structures that can minimize surge can also help protect property in the long term. But beyond that, we must look at ways that can develop capacity of communities to recover quickly and build up their resilience. This problem is systematic and solutions do not necessarily fit in one box of physical science or social science, but rather require a multidisciplinary approach.
Storm surge resilience can also be improved though contributions in understanding the physics of it through modeling. This can be done several ways, but most importantly, we need to understand the relationship of hurricane properties to storm surge. Ensemble models are a great tool for this because they give us more information. Unlike most studies, this work simulated several different hurricanes instead of just one. There was no calibration in the model parameters to fit a single event. This enabled us to look at the system in groups by simulating multiple hurricanes or multiple variations of a single hurricane to generate new knowledge about their behavior as a whole.

The quality of meteorological inputs affects storm surge models substantially. Uncertainty in wind intensity can come from different sources, namely the natural variability as storms evolve and measurement or recording error and bias. It is important to learn how much this impacts storm surge estimates by exploring uncertainty propagation in storm surge models. This study has shown that wind uncertainty results in a substantial range in storm surge and can significantly vary from storm to storm, and region of landfall. Coastal planners and managers who intend to use results from the surge models should be made aware of these ranges of surge heights and should not take these values as absolute. They should have buffers in place to accommodate these uncertainties in the models.

Another way to reduce uncertainties is through the implementation of better wind models. However, this is severely limited to the technology and resources that are available. Hurricane wind itself is generally subject to a lot off natural variability, and it is generally difficult to predict its behavior let alone project how much surge it will cause without performing numerical simulations. We have proposed a more systematic way of creating
ensembles from wind uncertainties that can reduce computational time and cost.

Although we have applied this methodology to wind intensities, the same method can be used to explore other hurricane properties such as pressure, size, and translation speed. The method can also be used to explore the impacts of joint probabilities of multiple hurricane properties by exploring joint probability distributions.

We have simulated several hurricanes to investigate how hurricane properties when taken in combination affect the generation of storm surge. It is generally accepted that hurricanes with high wind intensities, low central pressures, large sizes, and slow translational speeds result in large storm surges. Through simulating several storms, we find that this is not always the case due to specific storm tracks and local topography. Most importantly, this shows that simply knowing the general meteorological parameters does not result in knowing how much surge will be produced. To fully understand their relationship, sensitivity analyses using numerical modeling are still necessary.

Numerical models are also increasingly important in learning how changes to hurricanes in the future affect storm surge. We have found that we can expect that surge heights will be higher and concentrated in smaller areas. Although not included in our work, changes in precipitation and the addition of sea level rise can create a more complete picture of how widespread coastal and compound flooding will become over the next 100 years. The addition of these variables can create a more realistic picture of what to expect so stakeholders can better plan for these impending hazards.

Lastly, much of the scientific and engineering community is moving towards machine
learning approaches and the use of big data to predict physical processes like storm surges due to the potential for faster results. However, we believe that numerical modeling remains central to storm surge prediction, and at minimum more statistical methods should be used in conjunction. There are still many uncertainties about the long term impacts of global warming, and climate scientists still debate exactly how it will affect hurricanes. Machine learning largely relies on data that is already available and has been produced in the past, so effective resilience efforts will rely heavily on physics based numerical models to understand the relationship of hurricanes and surges in the future.
APPENDIX A: LIST OF HURRICANES INCLUDED IN ENSEMBLE GENERATION
Table A.1: Hurricanes Included and Their Corresponding Landfalls Used in Chapter 3.

<table>
<thead>
<tr>
<th>Year</th>
<th>Storm Name</th>
<th>Highest SSHWS</th>
<th>Date, Time</th>
<th>Landfall Pressure</th>
<th>Landfall Intensity</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>Gordon</td>
<td>1</td>
<td>Sept 18, 0300</td>
<td>991</td>
<td>55</td>
<td>Florida Big Bend</td>
</tr>
<tr>
<td>2001</td>
<td>Gabrielle</td>
<td>1</td>
<td>Sept 14, 1200</td>
<td>983</td>
<td>60</td>
<td>near Venice, FL</td>
</tr>
<tr>
<td>2002</td>
<td>Kyle</td>
<td>1</td>
<td>Oct 11, 1200</td>
<td>1011</td>
<td>35</td>
<td>near McClellanville, SC</td>
</tr>
<tr>
<td>2003</td>
<td>Claudette</td>
<td>1</td>
<td>July 15, 1530</td>
<td>996</td>
<td>80</td>
<td>Matagorda Island, TX</td>
</tr>
<tr>
<td>2004</td>
<td>Gaston</td>
<td>1</td>
<td>Sept 18, 0300</td>
<td>991</td>
<td>55</td>
<td>Florida Big Bend</td>
</tr>
<tr>
<td>2005</td>
<td>Cindy</td>
<td>1</td>
<td>Sept 14, 1200</td>
<td>983</td>
<td>60</td>
<td>near Venice, FL</td>
</tr>
<tr>
<td>2006</td>
<td>Ernesto</td>
<td>1</td>
<td>Sept 18, 0300</td>
<td>991</td>
<td>55</td>
<td>Florida Big Bend</td>
</tr>
<tr>
<td>2007</td>
<td>Humberto</td>
<td>1</td>
<td>Sept 14, 1200</td>
<td>983</td>
<td>60</td>
<td>near Venice, FL</td>
</tr>
<tr>
<td>2008</td>
<td>Hanna</td>
<td>1</td>
<td>Sept 18, 0300</td>
<td>991</td>
<td>55</td>
<td>Florida Big Bend</td>
</tr>
<tr>
<td>2012</td>
<td>Isaac</td>
<td>1</td>
<td>Sept 14, 1200</td>
<td>983</td>
<td>60</td>
<td>near Venice, FL</td>
</tr>
<tr>
<td>2016</td>
<td>Hermine</td>
<td>1</td>
<td>Sept 18, 0300</td>
<td>991</td>
<td>55</td>
<td>Florida Big Bend</td>
</tr>
<tr>
<td>2017</td>
<td>Nate</td>
<td>1</td>
<td>Sept 14, 1200</td>
<td>983</td>
<td>60</td>
<td>near Venice, FL</td>
</tr>
<tr>
<td>2019</td>
<td>Barry</td>
<td>1</td>
<td>Sept 18, 0300</td>
<td>991</td>
<td>55</td>
<td>Florida Big Bend</td>
</tr>
<tr>
<td>2008</td>
<td>Dolly</td>
<td>2</td>
<td>Sept 14, 1200</td>
<td>967</td>
<td>75</td>
<td>South Padre Island, TX</td>
</tr>
<tr>
<td>2014</td>
<td>Arthur</td>
<td>2</td>
<td>Sept 14, 1200</td>
<td>974</td>
<td>80</td>
<td>Shackleford Banks, NC</td>
</tr>
<tr>
<td>2002</td>
<td>Isidore</td>
<td>3</td>
<td>Sept 26, 0600</td>
<td>984</td>
<td>55</td>
<td>west of Grand Isle, LA</td>
</tr>
<tr>
<td>2004</td>
<td>Jeanne</td>
<td>3</td>
<td>Sept 26, 0400</td>
<td>950</td>
<td>105</td>
<td>east of Stuart, FL</td>
</tr>
<tr>
<td>2012</td>
<td>Sandy</td>
<td>3</td>
<td>Oct 29, 2330</td>
<td>945</td>
<td>70</td>
<td>near Brigantine, NJ (ETS)</td>
</tr>
<tr>
<td>2004</td>
<td>Charley</td>
<td>4</td>
<td>Aug 13, 2045</td>
<td>942</td>
<td>125</td>
<td>near Punta Gorda, FL</td>
</tr>
<tr>
<td>2004</td>
<td>Frances</td>
<td>4</td>
<td>Sept 05, 0430</td>
<td>960</td>
<td>90</td>
<td>Hutchinson Island, FL</td>
</tr>
<tr>
<td>2005</td>
<td>Dennis</td>
<td>4</td>
<td>July 10, 1930</td>
<td>946</td>
<td>105</td>
<td>Santa Rosa Island, FL</td>
</tr>
<tr>
<td>2008</td>
<td>Gustav</td>
<td>4</td>
<td>Sept 01, 1500</td>
<td>954</td>
<td>90</td>
<td>near Cocodrie, LA</td>
</tr>
<tr>
<td>2008</td>
<td>Ike</td>
<td>4</td>
<td>Sept 13, 0700</td>
<td>950</td>
<td>95</td>
<td>Galveston Island, TX</td>
</tr>
<tr>
<td>2017</td>
<td>Harvey</td>
<td>4</td>
<td>Aug 26, 0300</td>
<td>937</td>
<td>115</td>
<td>San Jose Island, TX</td>
</tr>
<tr>
<td>2018</td>
<td>Florence</td>
<td>4</td>
<td>Sept 14, 1115</td>
<td>956</td>
<td>80</td>
<td>Wrightsville Beach, NC</td>
</tr>
<tr>
<td>2003</td>
<td>Isabel</td>
<td>5</td>
<td>Sept 18, 700</td>
<td>957</td>
<td>90</td>
<td>Drum Inlet, NC</td>
</tr>
<tr>
<td>2004</td>
<td>Ivan</td>
<td>5</td>
<td>Sept 16, 0650</td>
<td>946</td>
<td>105</td>
<td>near Pine Beach, AL</td>
</tr>
<tr>
<td>2005</td>
<td>Katrina</td>
<td>5</td>
<td>Aug 29, 1110</td>
<td>920</td>
<td>110</td>
<td>near Buras, LA</td>
</tr>
<tr>
<td>2005</td>
<td>Rita</td>
<td>5</td>
<td>Sept 24, 0740</td>
<td>937</td>
<td>100</td>
<td>between Johnson’s Bayou, LA and Sabine Pass, TX</td>
</tr>
<tr>
<td>2005</td>
<td>Wilma</td>
<td>5</td>
<td>Oct 24, 1030</td>
<td>950</td>
<td>105</td>
<td>near Cape Romano, FL</td>
</tr>
<tr>
<td>2016</td>
<td>Matthew</td>
<td>5</td>
<td>Oct 08, 1500</td>
<td>963</td>
<td>75</td>
<td>McClellanville, SC</td>
</tr>
<tr>
<td>2017</td>
<td>Irma</td>
<td>5</td>
<td>Sept 10, 1300</td>
<td>931</td>
<td>115</td>
<td>Cudjoe Key, FL</td>
</tr>
<tr>
<td>2018</td>
<td>Michael</td>
<td>5</td>
<td>Oct 10, 1730</td>
<td>919</td>
<td>140</td>
<td>Florida Panhandle, FL</td>
</tr>
<tr>
<td>2019</td>
<td>Dorian</td>
<td>5</td>
<td>Sept 06, 1230</td>
<td>956</td>
<td>85</td>
<td>landfall at Cape Hatteras, NC</td>
</tr>
</tbody>
</table>

100
APPENDIX B: SUMMARY OF WRF HURRICANE CHARACTERISTICS
Table B.1: Summary of average hurricane characteristics of each simulated storm. Adapted from (Gutmann et al. (2018)). Data is illustrated in Figures 4.9 to 4.11, where $\Delta = PGW - CTRL$

<table>
<thead>
<tr>
<th>Year</th>
<th>Storm Name</th>
<th>Wind Speed (ms$^{-1}$)</th>
<th>Radius of 33ms$^{-1}$ wind (km)</th>
<th>Translation Speed (ms$^{-1}$)</th>
<th>Central Pressure (hPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>CTRL</td>
<td>PGW</td>
<td>$\Delta$</td>
<td>CTRL</td>
</tr>
<tr>
<td>2002</td>
<td>Isidore</td>
<td>23</td>
<td>25</td>
<td>+2</td>
<td>84</td>
</tr>
<tr>
<td>2002</td>
<td>Lili</td>
<td>25</td>
<td>25</td>
<td>0</td>
<td>46</td>
</tr>
<tr>
<td>2003</td>
<td>Isabel</td>
<td>32</td>
<td>34</td>
<td>+2</td>
<td>114</td>
</tr>
<tr>
<td>2004</td>
<td>Frances</td>
<td>34</td>
<td>33</td>
<td>-1</td>
<td>82</td>
</tr>
<tr>
<td>2004</td>
<td>Ivan</td>
<td>35</td>
<td>36</td>
<td>+1</td>
<td>106</td>
</tr>
<tr>
<td>2004</td>
<td>Jeanne</td>
<td>29</td>
<td>30</td>
<td>+1</td>
<td>67</td>
</tr>
<tr>
<td>2005</td>
<td>Dennis</td>
<td>32</td>
<td>32</td>
<td>0</td>
<td>56</td>
</tr>
<tr>
<td>2005</td>
<td>Emily</td>
<td>34</td>
<td>36</td>
<td>+2</td>
<td>62</td>
</tr>
<tr>
<td>2005</td>
<td>Ophelia</td>
<td>38</td>
<td>42</td>
<td>+4</td>
<td>58</td>
</tr>
<tr>
<td>2005</td>
<td>Rita</td>
<td>36</td>
<td>35</td>
<td>-1</td>
<td>61</td>
</tr>
<tr>
<td>2005</td>
<td>Wilma</td>
<td>26</td>
<td>30</td>
<td>+4</td>
<td>121</td>
</tr>
<tr>
<td>2006</td>
<td>Ernesto</td>
<td>27</td>
<td>25</td>
<td>-2</td>
<td>52</td>
</tr>
<tr>
<td>2008</td>
<td>Dolly</td>
<td>31</td>
<td>35</td>
<td>+4</td>
<td>35</td>
</tr>
<tr>
<td>2008</td>
<td>Gustav</td>
<td>30</td>
<td>28</td>
<td>-2</td>
<td>84</td>
</tr>
<tr>
<td>2008</td>
<td>Hanna</td>
<td>26</td>
<td>27</td>
<td>+1</td>
<td>72</td>
</tr>
<tr>
<td>2008</td>
<td>Ike</td>
<td>37</td>
<td>42</td>
<td>+5</td>
<td>111</td>
</tr>
<tr>
<td>2010</td>
<td>Alex</td>
<td>27</td>
<td>27</td>
<td>0</td>
<td>117</td>
</tr>
<tr>
<td>2010</td>
<td>Earl</td>
<td>34</td>
<td>42</td>
<td>+8</td>
<td>93</td>
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<tr>
<td>2011</td>
<td>Irene</td>
<td>40</td>
<td>43</td>
<td>+3</td>
<td>106</td>
</tr>
<tr>
<td>2012</td>
<td>Isaac</td>
<td>28</td>
<td>32</td>
<td>+4</td>
<td>51</td>
</tr>
<tr>
<td>2012</td>
<td>Sandy</td>
<td>32</td>
<td>33</td>
<td>+1</td>
<td>146</td>
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APPENDIX C: MAXIMUM SURGE HEIGHTS OF HURRICANE ENSEMBLES
Figure C.1: Maximum storm surge elevations from Hurricane Isabel simulation of the Best Track Data, an increase 20% wind intensity from BT, a decrease of 20% wind intensity from BT, wind ensemble members #1, #2, and #3. Hurricane track is shown in dotted lines.
Figure C.2: Maximum storm surge elevations from Hurricane Isabel simulation of wind ensemble members #4, #5, #6, #7, and #8. Hurricane track is shown in dotted lines.
Figure C.3: Maximum storm surge elevations from Hurricane Katrina simulation of the Best Track Data, an increase 20% wind intensity from BT, a decrease of 20% wind intensity from BT, wind ensemble members #1, #2, and #3. Hurricane track is shown in dotted lines.
Figure C.4: Maximum storm surge elevations from Hurricane Katrina simulation of wind ensemble members #4, #5, #6, #7, and #8. Hurricane track is shown in dotted lines.
Figure C.5: Maximum storm surge elevations from Hurricane Rita simulation of the Best Track Data, an increase 20% wind intensity from BT, a decrease of 20% wind intensity from BT, wind ensemble members #1, #2, and #3. Hurricane track is shown in dotted lines.
Figure C.6: Maximum storm surge elevations from Hurricane Rita simulation of wind ensemble members #4, #5, #6, #7, and #8. Hurricane track is shown in dotted lines.
Figure C.7: Maximum storm surge elevations from Hurricane Ike simulation of the Best Track Data, an increase 20% wind intensity from BT, a decrease of 20% wind intensity from BT, wind ensemble members #1, #2, and #3. Hurricane track is shown in dotted lines.
Figure C.8: Maximum storm surge elevations from Hurricane Ike simulation of wind ensemble members #4, #5, #6, #7, and #8. Hurricane track is shown in dotted lines.
Figure C.9: Maximum storm surge elevations from Hurricane Sandy simulation of the Best Track Data, an increase 20% wind intensity from BT, a decrease of 20% wind intensity from BT, wind ensemble members #1, #2, and #3. Hurricane track is shown in dotted lines.
Figure C.10: Maximum storm surge elevations from Hurricane Sandy simulation of wind ensemble members #4, #5, #6, #7, and #8. Hurricane track is shown in dotted lines.
Figure C.11: Maximum storm surge elevations from Hurricane Matthew simulation of the Best Track Data, an increase 20% wind intensity from BT, a decrease of 20% wind intensity from BT, wind ensemble members #1, #2, and #3. Hurricane track is shown in dotted lines.
Figure C.12: Maximum storm surge elevations from Hurricane Matthew simulation of wind ensemble members #4, #5, #6, #7, and #8. Hurricane track is shown in dotted lines.
REFERENCES

Accuweather (2020). 'I wasn’t prepared' Residents reflect on Hurricane Sally.


Carroll-Smith, D. L. (2018). “If it happened in...” a pseudo-global warming assess-
ment of tropical cyclone tornadoes. PhD thesis, University of Illinois at Urbana-Champaign.


mississippi. part ii: Synoptic description and analysis of hurricanes katrina and rita. 


Fussell, E. (2015). The long-term recovery of new orleans’ population after hurricane...


Holland, G. & Bruyère, C. L. (2014). Recent intense hurricane response to global climate


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dimensional circulation model for shelves, coasts, and estuaries. report 1, theory and methodology of adcirc-2dd1 and adcirc-3dl.


Moghimi, S., Van der Westhuysen, A., Abdolali, A., Myers, E., Vinogradov, S., Ma, Z.,


National Hurricane Center (n.da). About the national hurricane center.
National Hurricane Center (n.db). Automated Tropical Cyclone Forecast (ATCF) System.
National Hurricane Center (n.dc). Experimental Peak Storm Surge Forecast: Dorian adv46.
National Hurricane Center (n.dd). Tropical Cyclone Reports.
National Ocean Service (n.d). How long is the U.S. shoreline?
National Weather Services (2020).


Rasmussen, R. & Liu, C. (2017). High resolution wrf simulations of the current and future climate of north america, research data archive at the national center for atmospheric research, computational and information systems laboratory.


NCAR’s experimental real-time convection-allowing ensemble prediction system. *Weather and Forecasting*, 30(6), 1645–1654.


The Saffir-Simpson Team (2019). *The Saffir-Simpson Hurricane Wind Scale*.

on tides and storm surge during hurricane matthew. *Ocean Modelling*, 137, 1–19.


the rainfall and flooding caused by hurricane harvey in houston. *Nature*, 563(7731), 384–388.