CLIMATE CHANGE IMPACT ON U.S. HURRICANE RISK TO RESIDENTIAL BUILDINGS

BY

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DISSErTATION

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ABSTRACT

Hurricanes are one of the most disastrous natural hazards impacting the U.S. coastal regions causing a huge damage to property every year. The damages and losses during hurricanes can be attributed to the simultaneous occurrence of two major events - high intensity wind and heavy rainfall. Moreover, since hurricane is an atmospheric phenomenon, any changes in the present climate could impact both hurricane wind and rainfall, and the corresponding damages and losses.

Studies have shown that future climatic conditions could be different compared to present with an overall increase in the sea surface temperature. This increase is found to be non-uniform spatially based on the projections provided by Intergovernmental Panel on Climate Change (IPCC 2013). This could lead to varying effects on hurricane hazard and the corresponding losses across the different regions, resulting in some low risk regions observing a huge change in future hurricane risks whereas others observing only a slight change.

Additionally, if the hurricane-prone regions are inhabited by marginalized population, then the overall hurricane risk in those regions would be even higher. Many studies have found that some population groups are more vulnerable to the hazard impact compared to others. In other words, the differences in vulnerabilities of the different population groups could result in regions inhabited by marginalized population to be more sensitive to the hazard compared to others. Consequently, assessment of climate-dependent hurricane risk considering the population vulnerability of the region could provide a more holistic information in estimating the potential assistance needs of the impacted population.
Accordingly, in this research, a detailed analysis is performed to evaluate the regional hurricane risk across different U.S. coastal regions by considering the climate change impact on hurricane hazard, hurricane building damages and the corresponding losses. Residential buildings are selected for the damage and loss assessment since they are the most vulnerable structures to the hurricane hazard. Further, this research investigates climate change impact on hurricane risks considering the vulnerability of the impacted population.

It is found that the wind speeds for different locations across the U.S. south and east coast increase by around 30-50 mph in future climate (year 2100 under RCP 8.5) compared to the present climate (year 2005). The increase in wind speed led to an increase in the average individual building losses by almost 3.5 times in future compared to present. This in turn greatly increases future regional hurricane losses. However, different regions are found to have different degrees of increase in the future losses, with higher percentage increases found to be in the northeast coast compared to the southeast coast. In addition, it is also found that regional hurricane risks are greatly affected by the vulnerability of the impacted population.
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CHAPTER 1: INTRODUCTION

1.1 Research Motivation

In the United States, hurricanes are one of the most devastating natural disasters which cause a huge toll to properties and human lives. Since 1990, out of the top ten costliest catastrophes (inflation-adjusted) in the U.S., seven are due to hurricane damages (Insurance Information Institute 2017). The average annual hurricane loss from 1900 to 2017, normalized with respect to 2018 socio-economic conditions, is estimated to be around 17 billion U.S. dollars for the continental United States (Weinkle et al. 2018).

Hurricanes present such a hazardous situation as they are a combination of two extreme events - high wind speed and heavy rainfall. The simultaneous occurrence of these two events trigger a number of hazardous conditions which can lead to structural damage, tree fall, damage to crops and livestock, etc. Further, the interaction of these two events could result in combined losses to buildings much greater than if the individual events had occurred separately. This could be distinctively observed in residential buildings where high wind speeds damage the external structures through which rainfall can enter damaging the interiors and contents.

Due to the likelihood of hurricanes passing through various regions in the U.S. and their huge impacts on the building structures, wind load has been listed as one of the major loadings in the current building design load standard, ASCE 7-16. Further, the design in accordance with the code are meant to prevent the damages due to wind, which also inherently prevents the damages of the interior of building due to rain ingress from the impinging rain. The design wind load in ASCE was determined based on both hurricane and non-hurricane winds and is provided in the form of
wind speed maps for different occupancy categories of structures. The hurricane wind load adopted in the code is developed originally in Vickery et al. (2010), using the methodology described in Applied Research Associates (2001), Vickery and Wadhera (2008), and Vickery et al. (2000, 2009a, 2009b and 2010). This methodology utilizes Monte Carlo simulation to generate hurricanes based on a number of hurricane parameters. The statistics of the hurricane parameters are based on hurricane data from 1990 to 2006. In Vickery’s model, one of the hurricane parameters, hurricane central pressure, is modeled as a relative intensity parameter which is a function of sea surface temperature (SST). However, ASCE 7-16 does not consider any probable effect of changes in SST on the wind loads under future climatic conditions.

The United Nations Intergovernmental Panel on Climate Change (IPCC) reported that the period of 1983 to 2012 was the warmest 30-year period of the last 1400 years in the Northern hemisphere and this warming trend is expected to continue in future (IPCC 2013). IPCC has attributed the increase in temperature to both natural and anthropogenic processes. Based on the anticipated level of these processes in future, IPCC has projected four different climate change scenarios. All of these climate change scenarios show moderate to significant increases in mean sea surface temperature in future. The rapid increase in temperature is unprecedented, hence the consequence of climate change on damages and losses due to hazards that have some dependence on atmospheric temperature, like hurricanes, drought, crop yield, etc. has not been fully understood yet.

Studies based on the anticipated future climate have found an increase in hurricane wind speeds in future climate (Emanuel 2008, Knutson et al. 2010, Oouchi et al. 2006). Besides, studies have shown a positive relationship between rainfall rate and wind speed (Lonfat et al. 2004, Marks and
DeMaria 2003, Tuleya et al. 2007). This could cause increases in the future hurricane losses in residential buildings. Further, the impact of climate change on hurricane losses could vary by location. Even at present, hurricane hazard varies widely across different regions as could be observed from historical data. This is because hurricane hazard in a given location depends upon a lot of factors, including proximity to the ocean, temperature of neighboring ocean, Coriolis effect, etc. Besides, the IPCC projected climate change including the SST is distributed non-uniform spatially. Thus, the non-uniform SST in conjunction with the above listed factors could culminate into variable degree of changes in hurricane hazard and the corresponding losses across different locations in the U.S. Additionally, if these regions are inhabited by vulnerable population groups, then it might lead to a huge magnification of their overall regional hurricane vulnerability.

Many studies have found that some population groups are more vulnerable to the hazard impacts compared to others. For instance, studies have found that certain demographic groups, including people with low income, non-white race, children and old people, are known to suffer more severely following a hazardous event (Fothergill et al. 1999, Elliott and Pais 2006, Sastry et al. 2009, Hamama-Raz et al. 2014, Landry et al. 2007). More specifically, low-income population were found to be more adversely affected in terms of their education, health and other needs following a natural hazard (Kareem and Noy 2016). Similarly, non-white race was found to have difficulty evacuating following a hurricane, suffer higher job loss (Zottarelli 2008, Chaganti and Waddell 2015). Accordingly, the different vulnerabilities of the different demographic groups could further project in population-based regional hurricane risk, resulting in regions inhabited by marginalized population to be more sensitive to the hazard compared to others.
A holistic approach of assessing regional hurricane risk by considering population vulnerability can help identify the regions where people are most impacted by the hazard and thus help prioritize resources to those regions, which could be useful in pre-disaster planning phase. Such approach would be especially beneficial for large-scale hazards like hurricanes, since they require massive resource allocation, and hence need to be planned carefully. Further, since both hurricane hazard and demographic composition could vary spatially, this could result in huge variabilities in hazard risks across different regions. Accordingly, a comprehensive hurricane risk assessment considering potential impact of climate change and population vulnerability helps provide valuable guidance to prepare for future hurricane risk, by identifying the regions where people will be in the most need of assistance.

Thus, this research aims to investigate in detail the potential effect of future climate on the regional hurricane risk across the U.S. coast. Eight counties across the U.S. south and east coast are selected for the assessment of the hurricane risk. The impact of climate change on hurricane hazard, building damage and the corresponding monetary losses are thoroughly investigated across these counties. Currently, damages are investigated only for residential buildings since they are one of the most vulnerable structures to hurricane damage. Additionally, non-monetary hurricane impacts, including need of emergency shelter and job loss are also evaluated considering the vulnerability of the hazard-impacted population. It is noted that since the intent of this study is to investigate the impact of climate change on future hurricane risks only, any potential changes in building fragility, exposure, population, and building code changes in future are not considered at this time. Further, this study only considers the damage from wind and rain ingress; i.e., other
modes of hurricane damage, such as storm surge, flooding, are not considered. Accordingly, the following section discusses the objective and the major tasks of this research.

1.2 Research objectives and specific tasks

This study aims to investigate the potential change in the U.S. hurricane risk profile in future under climate change scenarios.

1.2.1 Research objectives

Below are the research objectives of this research.

Objective 1. Develop hurricane scenarios for present and future using a model capable of capturing the impact of climate on the hurricanes.

Objective 2. Develop a hurricane loss assessment framework for residential buildings.

Objective 3. Evaluate the impact of climate change on the regional hurricane risk across the U.S. coastal regions without considering population vulnerability.

Objective 4. Evaluate the impact of climate change on the regional hurricane risk across the U.S. coastal regions by considering population vulnerability.

1.2.2 Research tasks

Below are the specific tasks to realize the above research objectives.

• Tasks for Objective 1:
Task 1.1. Develop a model for storm system simulation incorporating sea surface temperature.

Task 1.2. Obtain the sea surface temperature data for present and future climate scenarios.

Task 1.3. Validate the hurricane simulation model.

• Tasks for Objective 2:

  Task 2.1. Develop a hurricane damage model considering effects from both hurricane wind and rainfall for residential buildings.

  Task 2.2. Develop a hurricane loss assessment model capable of capturing the wind and rain damages in residential buildings.

  Task 2.3. Validate the hurricane damage and loss models.

• Tasks for Objective 3:

  Task 3.1. Obtain prototype residential building structures and building inventory for selected locations.

  Task 3.2. Assess hurricane hazard and the corresponding damage in each residential building prototype for each region under the climate-dependent hurricane scenarios.

  Task 3.3. Evaluate regional losses for present and future climate scenarios by combining the hurricane losses in individual building prototypes for the corresponding scenarios.
• Tasks for Objective 4:

  Task 4.1. Develop a model for assessing hurricane impacts considering the differences in post-disaster response of different demographic groups.

  Task 4.2. Gather past hurricane data to develop the model, along with the data regarding the demographic composition for the selected counties.

  Task 4.3. Evaluate regional population vulnerability-considered hurricane impacts across the selected counties for present and future climate conditions.

1.3 Organization of Dissertation

This dissertation describes in detail the methodologies adopted to accomplish the tasks listed above, along with the findings of the study. The remainder of this dissertation consists of six chapters, followed by a list of references. Chapter 2 reviews the existing studies investigating the impacts of climate change on hurricane risk. Chapter 3 discusses the methodology adopted to develop climate-dependent hurricane risk model. Chapter 4 provides the findings of the effect of climate change on hurricane building damage. Chapter 5 discusses the findings of effect of climate on hurricane risk across the U.S. coast. Chapter 6 discusses the findings of population vulnerability-considered regional hurricane risk across the U.S. coast. Chapter 7 then summarizes the findings of this research and discusses the remaining future works.
CHAPTER 2: EXISTING STUDIES INVESTIGATING THE CLIMATE CHANGE IMPACT ON HURRICANE RISK

2.1 Climate change

The global mean surface temperature has increased since the late 19th century (IPCC 2013). The global surface temperature data shows a mean warming of 0.85°C (land and ocean combined) over the period from 1880 to 2012. The upper 75 m of ocean surface alone is found to have a mean warming of 0.11°C per decade over the period from 1971 to 2010. Further, this trend is expected to continue, with the future projected to have a much warmer climate compared to present (Andregg 2010, Bray 2010, Verheggen et al. 2014, Carlton et al. 2015, et al. 2016).

One of the leading bodies working on climate change is Intergovernmental Panel on Climate Change (IPCC). IPCC has developed several reports by assessing the numerous published climate change researches and can be considered as the most in-depth and state-of-the-art climate change studies which have been widely accepted and used in the scientific community. IPCC has published five assessment reports to date, with the fifth assessment report being the most current one. IPCC has attributed the warming to a number of natural and anthropogenic processes and substances that alter the earth’s energy balance. The anthropogenic substances include greenhouse

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gases (GHG) and short-lived gases and aerosols, among which GHG are known to contribute the most to the global surface warming.

The change in the Earth’s energy balance can be quantified using radiative forcing and is expressed in watts per square meter. Considering the anticipated radiative forcing, climate feedbacks and the storage of energy by the climate system, the fifth IPCC report has projected the rate and magnitude of global climate change for future in terms of four representative concentration pathways (RCP): RCP2.6, RCP4.5, RCP6.0 and RCP8.5. Each RCP is named as per the projected radiative forcing values expected in the year 2100. Consequently, the higher the radiative forcing, the higher is the surface temperature increase. If stringent mitigations are taken to lower the GHG emissions, it will result in lower radiative forcing corresponding to RCP2.6. However, without stringent mitigation, the climate change scenario is expected to be within RCP4.5 to RCP8.5.

For each of the RCP scenarios, the temperature was projected both for near-term and long-term future, for land as well as ocean surface. Figure 1 shows the projection of SST change for near-term future based on concentration-driven Coupled Model Intercomparison Project Phase 5 (CMIP5) simulations by IPCC (2013). The global mean surface temperatures (land and ocean combined) for 2081–2100 is projected to increase relative to 1986–2005 by 1°C (RCP2.6), 1.8°C (RCP4.5), 2.2°C (RCP6.0) and 3.7°C (RCP8.5). For the same time periods, the mean ocean temperature alone is projected to increase by 0.8°C (RCP2.6), 1.5°C (RCP4.5), 1.9°C (RCP6.0) and 3.1°C (RCP8.5).
2.2 Hurricane frequency

Since hurricane is an atmospheric phenomenon, future hurricane hazard could be impacted under climate change. One of the metrics of hurricane hazard is hurricane frequency. There have been many studies that have investigated the impact of future climate on hurricane frequency. Out of these, some studies have found an increasing trend of annual hurricane frequency for climate change scenario (Mann and Emanuel 2006, Mudd et al. 2013, Liu 2014) based on the analysis of HURDAT. However, various researchers have argued the completeness of HURDAT and insisted that a large portion of past hurricane data is missing owing to lower hurricane-reporting ship density as well as other observational and recording restrictions prior to satellite and aircraft...
reconnaissance era (Landsea et al. 2010, Knutson 2010), hence analysis of unadjusted HURDAT data to obtain frequency trend can be misleading.

Different methodologies have been devised to account for the missing data in HURDAT. Mann et al. (2007) adjusted for missing data by comparison of pre-aircraft reconnaissance era (1870–1943) to recent data from 1944-2006 to estimate number of TC (Tropical Cyclone) missed and found an undercount of 1.2 TC per year. After adjusting for the undercount, the frequency of TC was still found to have an increasing trend with time. On the other hand, Landsea et al. (2010) and Knutson et al. (2010) found no significant change when adjustment for missing TCs was done. Landsea et al. (2010) based their analysis on adjusting medium and long-term hurricanes based on ship density and other limitations in pre-satellite era. They also found that the increasing trend in hurricane data was mostly due to short duration TCs which they attributed to changes in hurricane observing and recording practices.

Further, various high-resolution models showed a decrease in frequency due to climate change (Bengtsson et al. 2007; Emanuel et al. 2008; Knutson et al. 2008; Knutson et al. 2015; Bender et al. 2010) but an increase in high intensity storms. For example, Bengtsson et al. (2007) suggested that even though the climate will be warmer in future, however the increase in the static stability and reduced vertical circulation could contribute to the reduction in number of storms. Knutson et al. (2015) using GFDL high resolution atmospheric model performed hurricane simulation for SSTs corresponding to 1980-2005 and late 21st century based on RCP4.5 scenario. It was found that tropical cyclones will be fewer in future climate, but frequency of intense category 4 and 5 storms will increase. Bender et al. (2010) found nearly a doubling of frequency for category 4 and 5 storms by the end of the 21st century, despite a decrease in the overall frequency of tropical
cyclones, using an operational hurricane-prediction model. Yoshida et al. (2017) based on high-resolution simulations from global atmospheric models found that for a 4K surface warming climate, the global number of TCs decrease by 33%. However, TCs were found to increase in the central and eastern parts of the extratropical North Pacific. Sugi et al. (2017) by using statistical downscaling of ensemble of many high-resolution global model experiments found that in future climate the frequency of very intense tropical cyclones will increase in most regions but decrease in the south western part of Northwest Pacific, the South Pacific, and eastern part of the South Indian Ocean. Thus, based on the review of the existing studies, it is found that climate change effect on hurricane frequency is still a contended subject.

2.3 Hurricane intensity

In addition to hurricane frequency, another parameter to measure hurricane hazard is hurricane intensity. Various studies have investigated how the increase in SST could impact hurricane intensity. For example, Emanuel (2005) had found that a degree Celsius increase in SST could increase the maximum wind speed of tropical cyclones by 5%. Emanuel (1988, 2008) had also used physics-based model and found an increase in the hurricane wind speed with an increase in the SST. Based on the averaged SST data for all the basins in the tropical cyclone season, Elsner et al. (2008) had found that a 1°C rise in SST increases the wind speed by 1.9 ± 2.9m/s in the value of 80th percentile and 6.5 ± 4.2m/s in the value of 90th percentile. NOAA (2019) had also found that tropical cyclone intensities globally will likely increase on average by 1 to 10% according to model projections for a 2°C global warming. Yoshida et al. (2017) based on high-resolution
simulations from global atmospheric models found that for a 4 K surface warming climate, lifetime maximum surface wind speeds and precipitation rates are amplified globally.

As stated in Section 2.1, future climate is expected to be warmer than the present climate. Accordingly, studies have assessed future hurricane intensity under climate change. For example, Oouchi et al. (2006) had developed tropical cyclones (TCs) using high resolution, global atmospheric model, based on which the increase in the maximum wind speeds for the future climate under IPCC A1B scenario in 2080-2099 to the present climate was found to be 7.3 m/s for the Northern Hemisphere and 3.3 m/s for the Southern Hemisphere. Murakami et al. (2012) had also found an increase in high intensity storms in future climate based on the analysis using atmospheric general circulation models. Nishijima (2012) performed risk assessment of typhoon event from simulation based on super-high resolution atmospheric general circulation model. It was found that at most locations of Japan, extreme wind events are most likely to occur in future than at present. Knutson et al. (2010) found that hurricane wind speeds may increase by 2–11% in the twenty-first century, globally. Knutson et al. (2015) performed hurricane simulation for SSTs corresponding to 1980-2005 and late 21st century based on RCP4.5 scenario using GFDL high resolution atmospheric model and GFDL hurricane model. The average cyclone intensity as well as precipitation rates is found to increase in future climates. Bengtsson et al. (2007) had also suggested that the increase in temperature and water vapor in future climate would provide more energy for the storms resulting in more intense storms.

Further, using statistical approaches, Mudd et al. (2014) had investigated the impact of climate change on hurricane intensity for the year 2100 under RCP 8.5 scenario. It was found that for ASCE 7-10 design category II wind speed, the majority of the Northeast U.S. coastline could see
an increase of about 15% in 2100 compared to the present climate corresponding to the year 2012. The increase in wind speed in future climate was also found in Mudd et al. (2014). Other studies (Mudd et al. 2017, Rosowsky et al. 2015) had found increases in both rainfall rate as well as the wind speed in 2100 under RCP 8.5 scenario compared to 2012. Accordingly, most studies agree that hurricane intensity will increase in the future climate.

2.4 Hurricane losses

The increase in hurricane intensity could result in the increase of hurricane losses under climate change. This has also been investigated in various studies. For example, Emanuel (2011) had evaluated the property losses for hurricanes land-falling U.S. Gulf and East coasts under constant climate as well as IPCC A1B scenario until 2100. The property loss calculation was based on empirical model which relates wind speed to fraction of the property loss. The accumulated loss since 2000 was found to almost double in 2100 for A1B scenario compared to constant climate conditions. Nordhaus (2010) had investigated the impact of global warming on hurricane losses and had estimated the U.S. hurricane losses to increase by 10 billion U.S. dollars due to the climate change corresponding to doubling of atmospheric CO2 concentrations. Choi and Fisher (2003) had investigated the impact of climate variability like El Nino on hurricane losses for North Carolina by performing regression analysis on historical data and found the climate variability to have a significant impact on hurricane losses. Hallegatte (2007) had generated synthetic hurricanes using model based on physical mechanism for the U.S. Atlantic and Gulf coasts. For future climate scenario based on a 10% increase in potential intensity, a higher percentage of intense hurricanes
were observed resulting in the increase of the annual hurricane damage by 54% in the future climate scenario. Bouwer (2013) had projected future extreme weather losses including losses due to TCs by analyzing results given in other studies. For TCs, the increase of average annual losses in 2040 compared to 2000 was found to be between 9% and 417%, with a median of 30%. However, it has been suggested that for the year 2040, the contribution of the increase in losses could be more due to increasing exposure rather than due to anthropogenic climate change. Li et al. (2016) had investigated the impact of increase in hurricane damages due to increase in hurricane wind speeds. For an annual 5% increase in wind speed, the annual probability of failure was found to increase by 10% in 50 years. Wang and Rosowsky (2017) had also simulated hurricanes under climate-dependent RCP 8.5 scenario for the year 2100 in Charleston, SC and evaluated the loss based on HAZUS software for present as well as the climate-dependent scenarios. The probability of exceedance of losses were found to be higher in the climate-dependent scenario.

Further, some studies have investigated and compared the climate change impact on hurricane losses across different regions. For example, Liu (2014) had used Vickery’s model (2000) to simulate hurricane for present and IPCC projected future climate scenarios and used HAZUS software directly to evaluate the regional hurricane losses for Orleans, Miami, Charleston and New York. The future hurricane scenarios were modeled considering only a change in intensity or change in both intensity and frequency. In the model considering only the change in intensity, the average increase in wind speed between RCP 8.5 scenario for the year 2100 and a no climate change scenario was found to be between 9-19m/s for a return period of 10 to 1700-year. The increase in 700-year return period hurricane losses were found to be 1.8, 0.8, 1.2 and 9.9 and for a 300-year return period was 3.8, 1.1, 2.6 and 9.3 for Orleans, Miami, Charleston and New York.
respectively. Bjarnadottir et al. (2014) had also compared the increase in hurricane damage cost in 2100 RCP 8.5 scenario for three locations- Miami-Dade, New Hanover and Galveston - due to change in hurricane frequency and/or wind speed. For a 10% increase in wind speed, an increase in annual damage cost was found to be 18%, 30% and 24% respectively in the above listed counties assuming a foreshore exposure. In summary, most of the existing studies have found that hurricane losses will increase in future climatic condition with varying degree of the increase by location.

2.5 Population vulnerability-considered hurricane impact

There are only a few studies that have investigated the potential effect of climate change on regional hurricane risks considering population vulnerability. Bjarnadottir, Li and Stewart (2010) had developed a metric to assess hurricane risk called coastal community social vulnerability index to quantify vulnerability of hurricane-prone areas under climate change. This metric was evaluated as a product of hazard and weighted vulnerability factors, which were scaled based on the method given in Davidson and Lambert (2001). The coastal community social vulnerability index is useful in comparing the overall population vulnerability-considered regional hurricane risks of different regions. In this study, the potential impact of climate change on future hazard is accounted by changing the present value of both wind and storm surge hazard from -5 to 15% at an increment of 5%. Accordingly, hurricane risk considering population vulnerability is not well investigated yet.
2.6 Limitations of existing works

From the review of the existing studies, it is noted that various studies have concluded that the anticipated increase in temperature will have an effect on the magnitude of future hurricanes, which will increase the degree of outer and interior damages in buildings. In most of these studies, hurricane losses are directly assessed for a given wind speed by using simple equations developed based on losses incurred during past hurricanes and expert judgment. However, this approach could potentially lead to loss of valuable information, especially for analysis performed under climate-dependent hurricane scenarios. Assessment of hurricane risk involves a lot of inherent uncertainties, and a detailed analysis considering the uncertainties could help get better estimates of the results.

Further, even though it is intuitive that during hurricanes, wind damage causes rain ingress leading to even more damage, the nature of this dependency has not been studied well. Besides, though both wind and rain ingress are the primary modes of hurricane damages, however most studies use a single fragility curve combining both modes for hurricane loss evaluation. However, since both wind and rain hazard can be affected under climate change, the nature of their dependency might as well be affected. This could affect the nature of the combined fragility curve in climate change scenarios.

Moreover, it is also noted that studies performing a thorough assessment of hurricane risks, especially across different locations are still lacking. However, since the spatial variation of climate change could impact hurricane risk across the different regions differently, some low-risk regions could observe a huge change in future hurricane risks whereas others could see only a
slight change. If this factor is not properly accounted, then regions with historically lower hurricane risks might not have enough preparedness to resist future hurricanes. In addition, if these regions are inhabited by marginalized population, then the overall hurricane risks inflicted on the people could be even higher.

Currently, there are extremely few studies that have investigated hurricane risk under climate change by considering population vulnerability. One of such studies as listed above is by Bjarnadottir et al. (2014). It is noted that though this study tries to account for the changing hazard, the hazard is not directly assessed as a function of potential future climatic condition. Further, the metric developed in the study is useful in comparing the vulnerability of a region relative to other regions; i.e., it can be used to rank different regions in terms of their vulnerability. However, the metric is not easily related to the parameters in real physical world and provides limited insight on the need of helps against hazard impacts. For example, the individual metrics cannot be directly interpreted in terms of financial implications for a region, such as emergency shelter needs, evacuation needs, medical needs.

Thus, a comprehensive hurricane risk assessment considering climate change could be valuable in long-term region-focused planning for disaster preparedness. Accordingly, this study investigates the changes in hurricane risk profile across the U.S. south and east coast under the anticipated climate change scenario, with consideration of population vulnerability. This study deviates from other studies in that it uses a state-of-the-art method to evaluate the overall loss in a building by performing a detailed analysis of hurricane damage for each individual building component under different climate scenarios. The analysis is performed for each predominant building in a selected county and the losses for all buildings are summed to get the overall regional loss. The aim of this
study is not only to understand the effect of climate change on hurricane losses for a whole region but also to investigate the variations in the effect on various types of buildings. Further, this study has also considered demographic composition of a region in evaluation of regional hurricane risk, in cases where applicable. The details of the methodology are explained in the following sections.
CHAPTER 3: CLIMATE-DEPENDENT HURRICANE RISK ASSESSMENT MODEL

3.1 Development of climate-dependent hurricane scenarios

A tropical cyclone (TC) is a rotating, organized system of clouds and thunderstorms that originates over tropical or subtropical waters and has a closed low-level circulation. (NOAA 2018b). TC that occurs in the Atlantic Ocean and northeastern Pacific Ocean is called a hurricane, if the one-minute maximum sustained wind speed of the cyclone is greater than 74 mph. TCs with lower intensity than hurricanes are called tropical storms.

Currently, there are various approaches used to model the tropical cyclones. These approaches can be broadly divided into two main categories based on the underlying modeling techniques – one using statistical methods and the other using physics-based mathematical equations. In statistical models, past data from HURDAT is analyzed to draw statistical inferences for TC parameters which is then used to simulate TCs. Models using this approach include CLIPER model (NOAA 2018b), Georgiou (1983), Georgiou, Davenport and Vickery (1983), Vickery (2000), etc. In physics-based models, various atmospheric processes like surface pressure, temperature, radiation, cloud, etc. are used as inputs to simulate TCs using complex mathematical equations. For example, NOAA’s GFDL model uses this approach. It is to be noted that though the physics-based models can capture various atmospheric processes, however they require rigorous computation making them extremely time consuming.

In this study, Vickery’s model (2000) is adopted for tropical cyclone simulation. This model considers the genesis of TCs from the ocean as well as development and progress with time until
the final dissipation. This is a statistical model, however also incorporates physics-based equation to limit central pressure within suitable range as dictated by atmospheric conditions and runs much faster than other physics-based models. Besides, this model uses SST as an input, thus making it easier to even incorporate climate change studies. This model has already been used in various research studies including building design load standards ASCE 7 (ASCE 2016) as well as hurricane hazard studies under climate change (Mudd 2014, Liu 2014). It is noted that even though the main focus of this proposed research is hurricane level winds since they cause the major devastating damage, however both forms of TCs (hurricanes and tropical storms) need to be considered in the origin and development phase since a tropical storm could intensify to a hurricane and a hurricane could weaken to a tropical storm.

The following sections detail the methodology adopted for the simulation of climate-dependent hurricane scenarios in this research. Section 3.1.1 introduces IPCC projections on climate change and the procedure of extracting the climate data for present and IPCC projected future scenarios. Section 3.1.2 discusses the methodology adopted for the hurricane simulation.

### 3.1.1 Climate change model

Climate is often described by various atmospheric parameters and the changes in these parameters could change future climate significantly compared to the present. One of the dominant and leading work in this field is done by IPCC. Their reports show that various driving forces, the most dominant being concentration of greenhouse gases in atmosphere can appreciably affect the climate. More elaborately, they predicted radiative forcing in future using climate model based on
changes in concentration of greenhouse gases due to the anticipated changes in human activities. Four different climate scenarios - RCP2.6, RCP4.5, RCP6 and RCP8.5 were presented based on the radiative forcing in the year 2100. Among these, RCP2.6 has the lowest difference between current and future climate and RCP8.5 has the highest difference. However, it is also noted that based on the warming to date, a recent study by IPCC (2018) has predicted that the future warming will likely exceed RCP 2.6 scenario.

In this research, climate is inputted in terms of SST in the hurricane model. Particularly, SST is used to simulate the central pressure difference and translation velocity of hurricanes. The changing climate is introduced in terms of SST. The analysis for the present climate is based on the year 2005. The year 2005 is also in conformance with the range of years considered for hurricane simulation in ASCE-16 (2016). Accordingly, for the present climate corresponding to the year 2005, the SST is obtained from COBE data set as provided in NOAA (Ishii et al. 2005, NOAA 2017a). COBE is one of the most comprehensive historical databases and was developed by obtaining historical in-situ observations from sources which include Kobe collection, ICOADS release 2, buoy data sets and weather reports. These were then processed for monthly mean SST starting from 1990 for a 1°longitude x 1°latitude across the ocean (Ishii et al. 2005), which are provided in NOAA (2017a). In this study, hurricane is simulated for the warmer months of May to November. Figure 2 shows the average of the monthly mean SST for these warmer months for the year 2005.
For the future climate, only IPCC RCP 8.5 is considered. The projected climate for the RCP 8.5 scenario is based on the results from Coupled Model Intercomparison Project (CMIP). The models under this project follow specific protocol so as to provide a consistency among various climate models running under this project. The latest protocol in conjunction with IPCC assessment report 5 is CMIP5. NOAA’s GFDL has run climate scenarios using the CMIP5 protocol under the radiative forcing as dictated by the RCP scenarios (NOAA 2017b). These values are also given as monthly mean for 1°longitude x 1°latitude across the ocean. These values are directly adopted in this study. As expected, these values are not uniformly distributed across the ocean. The difference between the average SST of future climate corresponding to RCP 8.5 scenario in the year 2100 and the present climate for the selected warmer months is shown in Figure 3. From the figure, it is clearly observed that the highest increase in SST in future is found to be near the ocean adjacent
towards the northeast side of the U.S. Further, it is also observed that SSTs are not provided for some grids as seen in Figure 3. For our analysis, these areas were assumed to have the same SST as the neighboring grids.

![Figure 3: Difference of SST (in Kelvin) between 2005 and 2100 based on IPCC projected RCP 8.5 scenario.](image)

### 3.1.2 Tropical cyclone simulation model considering climate impact

This study considers the genesis of TCs over ocean as well as its progress and development with time. The TCs are simulated by month, particularly for the warmer months from May to November that were found to comprise more than 98% of past TCs formed in the North Atlantic Ocean (NOAA 2018b). Their corresponding track and strength are assessed at each time step in terms of translation velocity, approach angle and central pressure difference. The time step for this study is
taken to be 6-hour interval. The following sections give the complete details of TCs genesis, their propagation over ocean as well as land, validation of the simulated TCs and finally the evaluation of corresponding wind and rainfall rate at desired locations.

### 3.1.2.1 TC genesis and propagation over ocean

To initiate and simulate the storms, the North Atlantic Ocean including the Gulf Coast is divided into a $5^\circ \times 5^\circ$ grid. Then, for each of the warmer months, TCs are randomly generated in each grid using Poisson distribution. As stated in the literature review, currently there is not a clear consensus among the scientific community on how climate change could impact hurricane frequency. Thus for this study, mean hurricane frequency is taken to be a constant and is obtained from historical data. Accordingly, the mean monthly TC genesis frequency is obtained by analyzing the data obtained from HURDAT. This frequency calculation is based only on the data after 1944 since various studies (Knutson et al. 2010, Landsea et al. 2010) have shown that the earlier data may be incomplete due to inadequate TC observing technologies.

The TCs are randomly initiated using the monthly frequency and then simulated for a given climate scenario using the SST data obtained as discussed in Section 3.1.1. The initial parameter values for translation velocity, approach angle and central pressure difference are randomly sampled from historical data, which describe the initial state of the randomly generated TCs. Then, the parameter values are updated for the next time-steps using statistical relationships to the relevant variables. These relationships are obtained by performing regression analysis on past storm data obtained from HURDAT (Landsea et al. 2015), which are explained below in detail.
The central pressure difference is related to central pressure difference in previous time steps as well as SST by using the method provided in Vickery et al. (2000), which is given below.

\[
\ln(l_{i+1}) = c_0 + c_1 \cdot \ln(l_i) + c_2 \cdot \ln(l_{i-1}) + c_3 \cdot \ln(l_{i-2}) + c_4 \cdot T_s + c_5 \cdot (T_{s(i+1)} - T_{s(i)}) + \epsilon
\]

where \( l \) is the relative intensity, \( T_s \) is sea surface temperature and \( \epsilon \) is a random error term. The subscript \( i \) represents the time step and since each time step is a 6-hour period, \( i - 1 \) and \( i - 2 \) represent 6-hour and 12-hour before the current time in the simulation. The relative intensity is defined as the ratio of central pressure difference for a given tropical cyclone to the maximum central pressure difference that climate conditions allow (Emanuel 1988, Darling 1991). Relative intensity is used for simulating central pressure since it helps to bound central pressure difference within the maximum allowable as dictated by the climate conditions (Darling 1991, Vickery et al. 2000).

The translation velocity \( V_t \) is evaluated by building upon the equation provided in Vickery et al. (2000). To better reflect the effect of climate, potential dependence of translation velocity on SST was investigated. It was found that translation velocity is negatively correlated to the SST at the center of the storm, i.e. as SST decreases translation velocity increases. A linear regression analysis between the two for all the past North Atlantic TCs yielded a negative correlation with a p-value almost zero, suggesting temperature could be a meaningful addition for evaluating translation velocity. The inclusion of temperature for evaluating translation velocity was also found in Mudd (2014). The following equation is used for the simulation of translation velocity (Mudd 2014).

\[
\ln(V_{t(i+1)}) = a_1 + a_2 \cdot \psi + a_3 \cdot \lambda + a_4 \cdot \ln(V_{t(i)}) + a_5 \cdot \theta_i + a_6 \cdot T_{si} + \epsilon
\]
where $\psi$ and $\lambda$ are the latitude and longitude of the storm center, $V_t$ is the translation velocity and $\theta$ is the approach angle. Similarly, approach angle is related to location, translation velocity and approach angle at previous time step using Eq. (3).

$$\Delta \theta = b_1 + b_2 \cdot \psi + b_3 \cdot \lambda + b_4 \cdot \ln(V_t) + b_5 \cdot \theta_i + b_6 \cdot \theta_{i-1} + \epsilon$$ (3)

This equation builds upon the model by Vickery et al. (2000). One difference is that $\ln(V_t)$ is used instead of $V_t$. This is because approach angle was found to be more highly correlated with $\ln(V_t)$ and its residual was closer to Gaussian distribution than $V_t$. Besides, dependence of approach angle on SST was also investigated. However, no significant relationship between the two was found.

The coefficients of the Eqs. (1), (2) and (3) are determined for each $5^\circ \times 5^\circ$ grid over the ocean by linear regression analysis. The updating of TC parameters using Eqs. (1), (2) and (3) is continued until the storm makes a landfall or dissipates in the ocean.

### 3.1.2.2 TC propagation over land

Once the TC landfalls, the TC decays. The decay of TC is modeled through central pressure difference using Eq. (4) (Vickery 2005).

$$\Delta P(t) = \Delta P_0 \cdot \exp(-\alpha \cdot t)$$ (4)

where $\Delta P(t)$ is the central pressure difference at time $t$ after landfall, $\Delta P_0$ is the central pressure difference at landfall, and $\alpha$ is the decay constant. The value of the decay constant $\alpha$ varies by region and are reported in existing studies (Liu 2012, Rosowsky et al. 1999, Vickery 2005). The values for the study region are obtained from Vickery (2005). The approach angle and translation
velocity are calculated for each time-step after landfall as well, using the Eqs. (2) and (3) without the SST terms. The coefficients for approach angle and translation velocity in land are calculated from the data in HURDAT similarly to the way they are calculated for TCs in ocean. If there are insufficient data to calculate coefficient for a given grid, then the coefficients from the neighboring grid is assumed to be used. The neighboring grid is taken to be the former grid from which the storm had traversed. The track and strength of TC at each time-step is simulated until the central pressure difference of the storm decays to less than 1 mb. Following this procedure, 40,000 years of the TCs for the year 2005 and 2100 are simulated. The simulation for year 2100 is done based on projected RCP8.5 climate scenario.

3.1.2.3 Validation

The simulated results for the parameters (frequency, central pressure difference, translation velocity and approach angle) of TCs landfalling U.S. have been compared with actual data obtained from HURDAT for validation of the model. These parameters are chosen for comparison since all the other storm parameters in this study are calculated as a function of these parameters. The values are compared for different locations along the coastline at time-step just before landfall. Figure 4 shows the location of considered mileposts. For the considered mileposts, the root mean square error between the simulated mean and actual mean is found to be 0.046, 1.23 KPa, 12.1° and 1.7 m/s (3.8 mph) for frequency, central pressure difference, approach angle and translation velocity, respectively. Figure 5 shows the means with one standard deviation above and below the means for each parameter from simulated result and actual data. It is noted that the number of
actual samples is quite low. The number of recordings is even lower for pressure parameter since the data is properly recorded only after around 1979. In spite of these limitations, the simulated values are found to match well with the historical values.

Figure 4: Location of mileposts for comparison of TC parameters.
Figure 5: Comparison of the simulated TC parameters with the actual TC parameters.

Note that even though this methodology generates TCs which include both tropical storms and hurricanes, only the TCs that make a landfall as hurricane (based on the sustained wind speed given in ASCE 7-16) are selected for damage and loss evaluation in the rest of the study.
3.1.2.4 Wind speed evaluation

The wind speed is evaluated using the hurricane parameters obtained from the tropical cyclone simulation. For this study, the gradient wind speed \( V_g \) at a distance \( r \) from the center of storm is calculated as given below (Georgiou 1983).

\[
V_g = \frac{1}{2} (V_t \cdot \sin \beta - f \cdot r) + \frac{1}{2} (V_t \cdot \sin \beta - f \cdot r)^2 + \frac{B \Delta P}{\rho} \cdot \left( \frac{R_{\text{max}}}{r} \right)^B \exp\left[ - \left( \frac{R_{\text{max}}}{r} \right)^B \right] \tag{5}
\]

where \( \beta \) is the heading angle, \( f \) is the Coriolis parameter, \( \rho \) is air density, \( \Delta P \) is the central pressure difference, \( B \) is pressure profile parameter, and \( R_{\text{max}} \) is radius to maximum wind speed. \( R_{\text{max}} \) can be calculated from \( \Delta P \) and \( \psi \), and \( B \) can be calculated using \( R_{\text{max}} \), \( f \), \( \Delta P \), and SST. These relationships have been studied for hurricanes that had made a landfall in U.S. in Vickery and Wadhera (2008), which are used in this study.

The gradient wind speed is then converted to the mean surface wind speed in two steps: first to the wind speed at 300 m and then to 10 m. This two-step conversion is necessary because conversion characteristic changes at 300m (Franklin et. al 2003). The first conversion is done by using conversion factors provided in Franklin et al. (2003). These factors were obtained from the tests to calculate mean vertical profile of wind speed using data from dropwindsonde tests and are given as a function of distance with respect to \( R_{\text{max}} \). The wind speed at 300 m \( (V_{300}) \) is converted to 10 m \( (V_{10}) \) using Eq. (6) (Franklin et al. 2003, Pita et al. 2012).

\[
V_{10} = V_{300} \cdot \frac{\ln \left( \frac{10}{z_0} \right)}{\ln \left( \frac{300}{z_0} \right)} \tag{6}
\]
where $z_0$ is the surface roughness length. The surface length is taken from HAZUS, which provides these values at census tract level. The mean surface wind is finally converted to gust wind speed using the conversion factor of 1.46 as provided in ESDU model (ESDU 1983).

### 3.1.2.5 Rainfall evaluation

Besides intense wind, another characteristic of hurricane is heavy rainfall. Rainfall is the major cause of interior and content damage (Crandell 1998, Stegman 1993, Stubbs and Perry 1993, Van de Lindt et al. 2007) and thus rainfall evaluation is equally important for loss assessment. More specifically, not only the rainfall through a horizontal plane but wind driven rain, i.e. the rainfall flowing through a vertical plane is needed to properly quantify the amount of rain entering through the breaches.

The rainfall through a vertical plane is obtained based on the rainfall through a horizontal plane and the effect that wind has on changing the direction of rain. The relationship developed by Straube and Burnett (2000) is used for this conversion in terms of the rainfall rates in the two directions, which is given in Eq.(7).

$$RR_v = RR_h(r) \cdot V_m \cdot DRF$$  \hspace{1cm} (7)

where $RR_h(r)$ is the vertical rainfall rate, i.e. rainfall rate through a horizontal plane at a distance $r$ from the storm center location, $V_m$ is the horizontal sustained wind at the height of interest and $DRF$ is the driving rain factor. The $DRF$ for hurricane level winds is taken to be 0.185 as calculated in Pita et al. (2012).
The rainfall rate through a horizontal plane is calculated based on R-Cliper model. R-Cliper model is developed based on analysis of satellite-based rainfall data recorded in Tropical Rain Measuring Mission. The detail of the model is provided elsewhere (Lonfat et al. 2004, Marks and DeMaria 2003; Tuleya et al. 2007). The vertical rainfall rates are calculated by using Eq. (8).

\[
RR_h(r) = \begin{cases} 
T_0 + (T_m - T_0) \cdot \left( \frac{r}{r_m} \right) & r < r_m \\
T_m \cdot \exp \left( - \frac{r-r_m}{r_e} \right) & r \geq r_m
\end{cases}
\]  

(8)

where \( r_m \) is the radial extent of the inner-core rain rate \( T_m \), \( r_e \) is the measure of radial extent of the tropical system rainfall, and \( T_0 \) is the rainfall rate at \( r=0 \). The above parameters, \( T_0, T_m, r_e, r_m \), are suggested to be functions of maximum wind speed of storm at each time in Tuleya et al. (2006). These relationships are directly used in this study.

### 3.2 Hurricane loss model for residential buildings

In this study, hurricane loss is evaluated for residential buildings since they are one of the most susceptible structures to hurricane damage and their damage affects people’s lives considerably in many different aspects. The overall loss in a residential building can be categorized into three specific types of losses: structural, interior and content loss. The structural loss is attributed to wind damage of external components of a building whereas the interior and content losses are attributed mainly to damage due to rain ingress. The following sections detail the methodology adopted in this study to evaluate the hurricane damage and loss in individual buildings.
3.2.1 Damage model for individual structural components

The first step to evaluate the hurricane loss is to assess the damage due to wind. As noted above, high intensity wind is the primary cause of structural damage during hurricanes. In this study, the extent of structural damage for individual structural components in a building is estimated in terms of damage ratio. The structural component-types at the most risk during wind loading are identified based on past observations (FEMA 2013, Cope 2004), which include roof-sheathing, roof cover, windows and doors, roof to wall connections, and wall, as shown in Figure 6. Since each component-type can have multiple components (for e.g. there could be multiple windows), the damage in each component of the component-type is assessed; and the final output is recorded in terms of damage ratio which provides the proportion of damage to the component-type.

![Figure 6: Vulnerable structural component-types in a residential building (Cope 2004).](image)

To introduce the variability in material strength and workmanship, the resistances are probabilistically modeled. Statistics of individual strength capacities of the structural components
for prototype buildings (see Section 3.3.2 for details of prototype buildings) are mostly obtained from HAZUS (FEMA 2013). These statistics are based on different experimental tests, analytical models and expert judgment. The capacities of the components used in this study are provided in Table 1. For the window, both damage due to wind pressure as well as wind-borne debris is considered. The debris damage model given in Cope (2004) is utilized.

*Table 1: Strength of vulnerable structural components considered in this study.*

<table>
<thead>
<tr>
<th>Structural component</th>
<th>Distribution</th>
<th>Mean</th>
<th>COV</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sheathing Panel (6d)</td>
<td>Lognormal</td>
<td>54.6psf</td>
<td>0.11</td>
<td>6&quot; center, 12&quot;edges (nailing pattern)</td>
</tr>
<tr>
<td>Sheathing Panel (8d)</td>
<td>Lognormal</td>
<td>103psf</td>
<td>0.11</td>
<td>6&quot; center, 12&quot;edges (nailing pattern)</td>
</tr>
<tr>
<td>Sheathing Panel (8d)</td>
<td>Lognormal</td>
<td>133psf</td>
<td>0.11</td>
<td>6&quot; center, 6&quot;edges (nailing pattern)</td>
</tr>
<tr>
<td>Cover</td>
<td>Normal</td>
<td>70psf</td>
<td>0.4</td>
<td></td>
</tr>
<tr>
<td>Window/Sliding Glass Door Pressure</td>
<td>Normal</td>
<td>40psf</td>
<td>0.2</td>
<td></td>
</tr>
<tr>
<td>Entry Door Pressure</td>
<td>Normal</td>
<td>50psf</td>
<td>0.2</td>
<td></td>
</tr>
<tr>
<td>Roof-to-wall connection</td>
<td>Normal</td>
<td>1200lb</td>
<td>0.2</td>
<td>Strap-up lift resistance</td>
</tr>
<tr>
<td>Wooden wall (connections of wall)</td>
<td>Normal</td>
<td>2142lb</td>
<td>0.25</td>
<td>Damage due to damage of connection</td>
</tr>
<tr>
<td>Concrete wall</td>
<td>Normal</td>
<td>47.2psf</td>
<td>0.2</td>
<td>Damage evaluated based on yield theory</td>
</tr>
</tbody>
</table>

The wind load is calculated based on ASCE 7-16 (ASCE 2016), with some modifications to reflect the actual loading condition as well as to realize the probabilistic nature of wind loading. The method introduced by Cope (2004) is adopted. For example, Eqs. (9) and (10) are used to calculate the wind load in a structural component (ASCE 2016).

\[
q_h = 0.00256 K_z \cdot K_{zt} \cdot K_d \cdot V^2
\]  

(9)
\[ p = RF \cdot q_h \cdot GCp - P_i \]  \hspace{1cm} (10)

where \( K_z \) represents velocity exposure coefficient and is calculated based on formula given in ASCE 7-16 and \( K_{zt} \) represents topographic factor and assumed to be 1. \( RF \) represents the reduction factor and has a value of 0.8. The \( RF \) is introduced to negate the safety factor embedded in the pressure coefficients of the ASCE 7 wind load equation (Cope 2004). \( V \) represents 3-sec gust wind speed. \( GCp \) represents product of external pressure coefficient and gust effect factor. To reflect the uncertain nature of wind load, pressure coefficients \( (GCp) \) for roof and wall are assumed to follow a normal distribution with mean equals to the nominal value given in the code and COV of 0.1. \( P_i \) is the internal pressure and is calculated based on the external damage to the structure. Thus, velocity pressure \( (q_h) \) is obtained from (9), which is inputted into Eq. (10) to get wind pressure \( (p) \) for a given structural component.

Further, since the direction of orientation of the building is not known, a given wind speed is applied through eight angles at increments of 45°; and the final damage ratio is taken as the average of damage ratios for all directions. The pressure coefficient zone is remapped as a function of wind direction and the directionality factor \( K_d \) is taken as 1. The complete details of these modifications can be found in Cope (2004). Thus, for each hurricane scenario, the corresponding wind speed at a given time and given angle of incidence is used to calculate the wind load in all the components. This is then compared with the wind resistance of the component to determine the initial failure of components. The initial failure statuses are updated by considering the interdependence of the component failures. For example, if the sheathing has already failed, the roof cover also fails by default. Then, the internal pressure is recalculated as the average of the external pressure at the
location of broken doors and windows. The comparison of load and resistance is repeated to record any further damage due to the change in internal pressure. This process is repeated three times, after which the damage is typically found to be constant. The damage in a component type is recorded in terms of damage ratio which indicates the average damage considering all the components and all the directions of the same type in the building.

3.2.2 Damage model for interior and content

In addition to structure, interior and content also comprise the major asset of a building. Various post-storm surveys (Crandell 1998, Stegman 1993, Stubbs and Perry 1993, Van de Lindt et al. 2007) have conceded that rain ingress is the major cause of damage to interior and content. However, at present majority of loss studies either calculate overall loss as a function of wind speed using empirical formulas without differentiating the different modes of loss (Emanuel 2011, Huang et al. 2001) or in some studies calculate interior and content loss as a function of damage in other structural components (Gurley et al. 2005). Recently, a few studies (FEMA 2013, Pita et al. 2012) evaluate interior loss based on rainfall depth. Accordingly in this study, a detailed assessment is done to evaluate interior and content damage by assessing the amount of rain ingress inside a building.

3.2.2.1 Rain ingress

As stated above, to evaluate the interior and content damage, the amount of rain ingress in a building needs to be determined. This rain enters through the openings or breaches caused due to
wind damage in structural components. Further, there could also be pre-existing breaches due to deficiencies like vents, uncaulked windows, doors, etc. This study considers both form of breaches to evaluate rain ingress. The deficiencies considered for this study included window deficiency, door deficiency, wall deficiency, bathroom vent, dryer vent, kitchen vent and outlet. The average deficiency area provided in American Society of Heating, Refrigerating and Air-Conditioning Engineers Handbook (ASHRAE 2001) is used for the calculation of rain ingress. From these breaches, wind driven rain (WDR) can enter the building either impinging directly or in the form of surface runoff from nearby undamaged envelope surface.

To calculate the amount of rain ingress, an empirical relationship developed by Baheru (2014) is used in this study. The relationships are provided in terms of two sets of coefficients - rain admittance factor ($RAF$) and surface runoff coefficient ($SRC$) at different locations and wind directions. These coefficients are based on a wind tunnel test and for low rise buildings in suburban terrain, the pictorial representation of which is shown in Figure 7. The $RAF$ is representative of impinging rain and $SRC$ is a representative of surface runoff. The values for $RAF$ was provided for both gable and hip roofs and for winds flowing at $0^\circ$, $45^\circ$ and $90^\circ$. The values for $SRC$ was provided only for gable roof and thus the same values are used for hip roof for this study. Based on these coefficients, the rain ingress due to a particular damaged component is calculated as

$$Vol_t = (RAF \cdot A_o \cdot RR_v + SRC \cdot A_{SR} \cdot RR_v) \cdot t$$ (11)

where $RR_v$ is the horizontal rain rate i.e. rain rate passing through a vertical plane, $A_o$ is the area of opening, $A_{SR}$ is the area for surface runoff and $Vol_t$ is the total volume of water accumulated
due to the opening during time interval $t$. The depth of water is then calculated by dividing the volume accumulated from all the breaches by the floor area.

![Diagram](image)

Figure 7: Rain ingress test performed to get RAF and SRC values: (a) Test wind direction, (b) RAF values when the wind direction is 0º (Baheru 2014).

3.2.2.2 Interior and content damage ratio

As stated above, many studies agree that the major cause of interior damage is rain ingress, thus the interior damage in this study is evaluated based solely on rain ingress. This study utilizes a similar relation as given in Pita et al. (2012) and HAZUS (FEMA 2013) to model interior damage. The interior damage is assessed in terms of interior damage ratio, which is calculated using Eq. (12).
\[
IDR = \begin{cases} \frac{1}{t_d} \cdot d_w & \text{if } d_w < t_d \\ 1 & \text{if } d_w \geq t_d \end{cases}
\]

where IDR is interior damage ratio, \(d_w\) is the depth of water and \(t_d\) is the threshold depth of water that represents complete interior damage. In this study, the value of threshold depth \(t_d\) is assumed to be 1 inch, which is the same value used in Pita et al. (2012). This value was validated in this study by examining four historical hurricane losses - Hurricane Andrew, Hugo, Erin and Opal. For this validation, the hurricane loss data were obtained from existing studies (Crandell 1998, Bhinderwala 1995, FEMA 2013).

Similarly, content damage is calculated as a function of depth of water. Content comprises of furniture, goods, appliances, clothes, etc. inside a building. Content damage has been found to be highly correlated to interior damage of building and hence assumed to be accrued at a certain rate of interior damage in various studies (FEMA 2013, Gurley et al. 2005). In this study, content damage ratio is related to interior damage ratio using the relationship provided in Gurley et al. (2005), which is then used to relate content damage ratio to the depth of water.

### 3.2.3 Loss ratio for individual buildings

In this study, the losses in the buildings are assessed in terms of loss ratio which is defined as the value of the loss divided by the insured value of the building. Since loss ratio is independent of the actual cost of the building, it helps better visualize the proportion of damage and losses to individual buildings as well as compare the severity of the hurricane losses in one building to
another regardless of their individual values. The loss ratio \( LR \) is obtained from damages of individual components using Eq. (13).

\[
LR = \sum_{l=1}^{n} (DR_l \cdot RCR_l)
\]

(13)

where \( DR_l \) represents damage ratio in the \( l^{th} \) component, \( RCR_l \) represents replacement cost ratio for the \( l^{th} \) component, and \( n \) is the number of all the considered individual components which include the structural components like sheathing, windows, doors, etc. as well as interior and content. The replacement cost ratio is defined as the cost of replacing the component divided by the insured value of the building including the contents. The replacement costs from Gurley et al. (2005) are used for this study.

### 3.2.4 Validation

The damage and loss models are validated with the actual loss data from past hurricanes. The loss data for two past hurricanes used for this analysis are: (1) Hurricane Andrew for South Florida and (2) Hurricane Hugo for South Carolina. The actual losses in the regions following the hurricanes are provided in existing studies (FEMA 2013, Bhinderwala 1995), which were originally obtained from insurance claim data. In the records, loss ratio is defined as the total claim paid divided by the insured value of the structure and its contents. The corresponding wind speed obtained via a reconnaissance aircraft and the ratios of buildings falling under the subcategories of building types are also provided in the same literatures. By considering the ratios of buildings under the subcategories, the mean loss ratios of individual subcategories obtained from the simulated model are combined to determine the total mean loss ratios. The total mean loss ratios of buildings in the
two affected regions given wind speeds are plotted together with the corresponding loss data, which are shown in Figure 8. It is shown that the predicted loss ratios are in good agreement with the loss ratios from the data.

Figure 8: Comparison of mean hurricane loss ratio of simulated model to actual loss data from (left) Hurricane Andrew and (right) Hurricane Hugo.
3.3 Regional hurricane loss model for the U.S. coast

One of the intents of this research is to assess regional hurricane losses under climate change scenarios. This assessment is done at county level, and the counties are selected such that they are dispersed throughout the U.S. south and east coast. The following sections provide the details of the methodologies of the climate-dependent regional hurricane loss assessment.

3.3.1 Selection of study regions and building inventory

Eight U.S. coastal counties are selected for hurricane risk assessment, which are listed below and presented in Figure 9. These counties contain cities which have been historically found to be hurricane prone. For example, Chatham County contains Savannah city, Harris County contains Houston city, etc.

- New Orleans, LA
- Mobile, AL
- Miami-Dade, FL
- Chatham, GA
- Charleston, SC
- Norfolk, VA
- New York, NY
The regional loss is calculated for 1 and 2 story wooden or masonry-walled buildings. The process adopted in evaluating the regional hurricane loss in the selected coastal counties is described below in detail.

### 3.3.2 Prototype structures

The first step in evaluating the regional hurricane loss is assessing the building inventory in the region. Residential building inventory in a region contains a wide array of building types. In this study, for simplification, prototype structures are selected to represent the damage and loss characteristics of the overall housing inventory. The prototypes are chosen by considering the wind-resistant characteristics of different residential building types and the composition of the residential building types in the region. The following wind-resistant structural variations were
found common amongst the residential buildings in the U.S. coastal regions (FEMA 2013, Vickery et al. 2006, Gurley et al. 2005, Cope 2004) and hence considered for this study.

- Type of wall: masonry or wood-framed
- Type of roof: hip or gable
- Roof cover: shingle or tile
- Roof nailing: 6d with 6/12” nailing pattern, 8d with 6/12” nailing pattern or 8d with 6/6” nailing pattern
- Number of stories: one-story or two-story

The percentage of each structural variation in the different regions are listed in HAZUS software (2018), which are used in this study.

The one-story buildings are assumed to have a plan area of 1800 sqft (167.2 m²) with a height of 9 ft (2.7 m) and the two-story buildings are assumed to have the same plan area with a height of 17 ft (5.2 m). The buildings have a roof pitch of 4/12 and roof sheathing nailing pattern is 6/12, i.e. the spacing is 6” (15.2 cm) on the edges and 12” (30.5 cm) for intermediate supports. The overall configuration of the buildings is similar to as given in Cope (2004).

### 3.3.3 Regional hurricane loss model

Using the methodologies given in Section 3.1 and 3.2, climate-dependent hurricane scenarios are simulated and the loss ratios evaluated for the prototype buildings listed in Section 3.3.2. The regional hurricane loss for the county, assessed in terms of annual aggregated loss (AAL) is
evaluated from the hurricane loss ratios, $LR$ (see Eq. (13), of the individual prototypes using Eq. (14).

$$AAL = \sum_{j=1}^{m} \sum_{i=1}^{n_{th}} \left( \sum_{k=1}^{n_{h}} (LR_{ijk}) \cdot n_{ij} \right) \cdot IV_{j}$$

where $IV_{j}$ is the median insured value of residential buildings in the $j^{th}$ zone, $n_{ij}$ is the number of the $i^{th}$ building type in the $j^{th}$ zone and $nb$ is the number of building prototypes, $nh$ is the total number of hurricane per year, and $LR$ represents the proportion of hurricane loss in a building to its insured value. $n_{ij}$ in a given region is obtained from FEMA (2013) and Census (2018). Each zone mostly comprises of 10 census tracts. Figure 10 shows the census tracts in one of the counties considered in this study – Miami-Dade County. In our study the counties have 8 to 79 zones, depending upon the size of the county. For this study, the insured external structure and interior value is taken to be 50% of the median building value given in Census (U.S. Census Bureau 2005). This percentage value is based on a study done by Davis and Palumbo (2008) which estimated the external structure and interior value to be around 40-76% of the total building value with the remaining percentage attributed to value of land for buildings in Miami-Dade County. Further, content insured value is assumed to be 50% of the total value of external structure and interior (Bhinderwala 1995).
Figure 10: Census tracts in Miami-Dade county.
3.4 Population vulnerability-considered hurricane impact model for the U.S. coast

This study also investigates the regional hurricane risks by considering the population vulnerability. Non-monetary hurricane impacts are considered for the investigation, which are short term need of emergency shelter immediately after hurricane, long term need of emergency shelter after a month following a hurricane event and job loss. Accordingly, in this section a population vulnerability-considered regional hurricane impact model is developed which incorporates the discrepancies in the behavior of the different demographics against the hurricane impacts. The following sections detail the existing studies that have investigated hazard risk considering demographic factors, followed by the details of the proposed model.

3.4.1 Existing studies investigating hazard impact considering demographic factors

Inequity in the disaster impact experienced by different demographic groups has been noted in many studies (Fussell and VanLandingHam 2009, Peacock et al. 2014, Kareem and Noy 2016, Zottarelli 2008). Fussell and VanLandingHam (2009) have found that among the displaced residents, African-American residents returned to the city at a much slower pace than white residents based on the analysis of Hurricane Katrina survey data. Similarly, Elliot and Pais (2006) have found a strong difference on pre-hurricane evacuation based on people’s race and socio-economic status by analyzing Hurricane Katrina data. For example, most of the African-American population were found to evacuate only after the hurricane and low-income group were found to not evacuate at all. Zottarelli (2008), Chaganti and Waddell (2015) found that African-Americans
suffered more job loss than Whites following hurricane Katrina. Peacock et al. (2014) have found that housing in higher-income neighborhoods suffered less damage and recovers more quickly based on the data from Hurricane Andrew and Hurricane Ike. Kareem and Noy (2016) analyzed results of 38 papers (Rodriguez-Oreggia et al. 2013, Mogues 2011, Hou 2010, Jakobsen 2012, Reardon and Taylor 1996), which investigated impact on poverty by a wide variety of natural disasters including floods, rainfall, tropical cyclones, droughts, earthquakes in Asia, Africa, Central America, South America and Oceania. Using meta-regression analysis of the data reported on these papers, Kareem and Noy have concluded that disasters have economic impact on people’s lives and the poor households have a tendency of smoothing consumption by reducing consumption of non-food items like health and education. Thus, the above studies along with many others suggest that certain demographic groups, including low-income people, children and old-age people, non-white race, have a higher vulnerability to hazard impact compared to others.

Accordingly, some studies have tried to account the hazard impact by considering the differences in the vulnerabilities of the affected population. For example, Cutter (2003) has introduced a metric to measure the vulnerability of the population in a region called Social Vulnerability Index (SoVI) which is a summation of the normalized vulnerability factors. SoVI has been used in studies to integrate social vulnerability into hazard impact assessment. For instance, Boruff, Emrich and Cutter (2005) have evaluated erosion hazard vulnerability of the U.S. coast as a summation of SoVI and coastal vulnerability index, where the coastal vulnerability index is a function of physical indicators of hazard (mean tidal range, mean wave height, coastal slope, rate of relative sea level rise, shoreline erosion and accretion rates, geomorphology). Schmidtlein, Shafer, Berry and Cutter (2011) have performed a regression analysis between the loss due to earthquake and PGA, distance
and SoVI for historical earthquakes. Similarly, Emrich and Cutter (2011) have presented the overall vulnerability for southern United States using bivariate maps that include both SoVI and vulnerabilities for climate sensitive hazards (drought, flooding, hurricane winds and sea level rise). Although SoVI has been incorporated into hazard vulnerability analysis for a more comprehensive assessment in many studies, SoVI has a limitation of not allowing relative weights for individual factors (Cutter et al. 2003). In other words, each factor is assumed to have an equal contribution on the overall vulnerability. This assumption can lead to inaccurate results if some factors indeed have a higher influence on the social vulnerability than others. It is also noted that most of the above-mentioned studies integrate hazard and social vulnerabilities by adding or multiplying the two without considering their relative weights.

Besides the studies using SoVI, other studies have also considered both hazard and population vulnerability on the evaluation of the overall impact. In these studies, a metric is introduced which assesses impact as a product of scaled hazard and vulnerability parameters (Davidson and Lambert 2001, Hernandez et al. 2018, Bjarnadottir, Li and Stewart 2010). For example, Davidson and Lambert (2001) have proposed a metric called hurricane disaster risk index to compare hurricane disaster in the U.S. coastal counties, considering factors for both hazard and population vulnerability along with exposure and recovery capability. All the considered factors are scaled to get a dimensionless value and multiplied considering their weightage to obtain the risk index. However, it is noted that in the above studies it is difficult to assess the parameters of the scaling function and the weights, and the results can be sensitive to those parameters.

The afore-mentioned studies introduce various metrics to measure impact by considering population vulnerability. These metrics are useful in comparing the vulnerability of a region
relative to other regions; i.e. they can be used to rank different regions in terms of their vulnerability. However, the metrics are not easily related to the parameters in real physical world and provide limited insight on the need of helps against hazard impacts. For example, the individual metrics cannot be directly interpreted in terms of financial implications for a region, emergency shelter needs, evacuation needs, medical needs. Without the real physical parameter to relate the metric, it is difficult to ascertain the influence of the different hazard and vulnerability factors on the metric, which resulted in a lack of the comprehensive assessment of the weights in the above studies. Moreover, the hazard and vulnerability terms are simply multiplied or added together in the metrics in the above studies. However, two cases with a same value of metric obtained by combining (1) low hazard and high vulnerability and (2) high hazard and low vulnerability may not have the same consequence in real world. Further, the influence of the vulnerability and hazard factors might be different depending on the impact, therefore a single metric evaluated in the above studies might not be the representative of all the aspects of the hazard impacts.

Some other studies have specifically considered the vulnerability of the population for a specific hazard impact by employing a factor to increase the hazard impact for the vulnerable population group. Sutley et al. (2017a) have developed odd ratios for different demographic groups based on past earthquakes, that indicate how the demographic groups were impacted relative to the baseline population group following the earthquake. By multiplying the odd ratios of all the individuals in the county to their respective baseline hazard impact, Sutley et al. (2017b) have obtained the overall hazard impacts at county-level in terms of injuries, fatalities, PTSD and dislocated households. Similarly, FEMA (2003) has also provided coefficient for each individual
demographic group for assessing the need of emergency shelter following a seismic event, based on the study done by Harrald et al. (1994). These coefficients have also been used to evaluate the need of emergency shelter for hurricane events (FEMA 2013). Khazai et al. (2012) have also presented a model to evaluate the demand for emergency shelter following earthquake damage using a multi-criteria decision model that considers inhabitability of building, shelter accessibility analysis and socio-economic factors. This model has been integrated into MAEVIZ earthquake loss estimation model, where the user can assign weights to the selected indicators. Although the above studies have tried to assess different hazard impacts considering both hazard and population vulnerability, however these studies have some inherent assumptions which could impact the final result. For example, the relative weights for a lot of factors in these studies are based on expert judgment. Further, the different demographic factors could be correlated, and it is not clear how the above studies consider the correlation between the demographic factors.

From the review of the existing studies, it is noted that many studies agree that certain demographic groups are more vulnerable to the hazard impacts. Accordingly, there have been efforts made to account for the hazard impact considering both hazard and the population vulnerability. However, in most of the existing studies, hazard and population vulnerability are integrated to obtain a metric which is useful to compare different regions in terms of their overall vulnerability but does not provide much insights on the regional need of helps against specific hazard impacts. In a few studies that have looked at the specific hazard impacts considering the population vulnerability, majority of factors are based on expert judgment or have not considered correlation of the demographic factors, as noted in the above paragraph. Further, most of the existing studies only focus on hazard for present climatic scenario, but for climate-dependent hazards like hurricanes,
these assessments might not be able to capture the long-term impacts. Accordingly, this study has developed a methodology to assess regional hurricane hazard impact considering demographic composition based on a comprehensive analysis of past hurricane impact record. This methodology also considers hurricane building damage in hazard impact assessment, making it capable of accounting for the changing hurricane scenarios under the climate change conditions. The details of the methodology are explained in the following sections.

3.4.2 Population vulnerability-considered hurricane impact model

This study analyzes past hurricane survey data to develop population vulnerability-considered hurricane impact model by not only considering the direct hurricane risk but also the demographics of the affected population. The direct hurricane risk considered in this study is hurricane building damage. Hurricane building damage is selected since it is representative of the consequence of the hazard on the built environment; and is reflective of the hurricane risk on peoples’ lives. Further, other studies have also found building damage to be one of the prime indicators of various types of hurricane risks. The demographic factors considered in this study are gender, age, income and race. Accordingly, the hurricane impact model developed in this study incorporates both building damage and the demographic factors to assess the following hurricane impacts – need of emergency shelter immediately after hurricane (NESi), need of emergency shelter after a month following a hurricane event (NESm) and job loss (JL). Assessment of NESi and NESm helps plan for emergency shelters in hurricane prone regions; whereas JL helps gauge the financial implications of hurricane events.
The hurricane impact model in this study is developed by statistically analyzing the behavior of different demographics following a hurricane event. For this, the data from Hurricane Katrina Survivors poll (Gallup/CNN/U.S.A Today/Red Cross Poll # 2005-45) is used, which was conducted over the phone by Gallup organization between the dates of September 30, 2005 to October 9, 2005. Hurricane Katrina is one of the most devastating natural hazards that affected various regions in the U.S.; and has been rigorously studied, with considerable amount of records in the public domain. The Hurricane Katrina Survivors poll used in this study has records of the building damage state, the demographic composition (gender, age, income and race), and a measure of the hurricane impact for each of the surveyed individual; making it suitable to develop a population vulnerability-considered hurricane impact model considering both the hazard consequence (building damage) and the demographics. Further, 1,510 people were surveyed in this poll who had residence prior to the hurricane in Louisiana, Mississippi, and Alabama; thus, the data is representative of the hazard-impact behavior of people living in different regions across the U.S. southeast coast.

The composition of the different demographic groups in the total surveyed population as well as in the portion of the surveyed population impacted by NESi, NESm and JL are shown in Figure 11. A comparison of demographic compositions of the total surveyed population and the hazard impacted population shows that some demographic groups are more vulnerable to the hurricane impact than others. For example, in the total surveyed population, the non-white race comprises 60.3%. However, the proportion of non-white race is higher in the portion impacted by NESi, NESm and JL, i.e. 80.3%, 82.1% and 75.6%, respectively, suggesting that non-white races are more vulnerable than white race to the hurricane impact. Accordingly, the population
vulnerability-considered hurricane impact model developed in this section tries to account for the behaviors of different demographic groups on the hurricane impact. Besides the demographic factors, the survey data also has records of the building damage state of each interviewee classified into four categories - completely destroyed, damaged and unlivable, damaged but livable and no damage.

Logistic regression is used to develop the hurricane impact model considering the building damage and the demographic composition of the individuals affected by the hazard. Logistic regression can incorporate binary data for dependent variable and both categorical and continuous data for independent variable, making it suitable for this analysis. Besides, logistic regression has the advantage of providing the detailed statistical information that helps in understanding the extent of influence of the independent variables on the output, compared to other approaches like Support Vector Machine (SVM), neural network, etc. Logistic regression has also been employed by other studies to investigate the impact of demographic factors on hurricane impacts. For example, Elliot and Pais (2006) have analyzed Hurricane Katrina survey data using logistic regression to assess how race and class affect the source of emotional support (e.g. family and friends, religious faith, formal organization, etc.) after disaster. Hamama-Raz et al. (2015) have used logistic regression to assess the impact of gender in psychological reactions to Hurricane Sandy. Landry et al. (2007) have used logistic regression on Hurricane Katrina data to investigate evacuees’ preference to return to their pre-disaster residence based on their income, college education, race, age, etc. Riad et al. (1999) have used logistic regression to predict evacuation decisions following hurricanes with consideration of evacuees’ race, gender, damages, ownership, social support, etc.

The general form of logistic regression is as given below.
\( l(y) = \beta_0 + \sum_{i=1}^{n} \beta_i \cdot x_i \)  

(15)

where \( l(y) \) is the log-odds of the dependent variable \( y \), \( \beta_i \)'s are the coefficients, \( x_i \) represents each considered independent variable and \( n \) is the total number of the independent variables. For this study, each \( x_i \) is either a function of each of the considered demographic factors or the building damage state of the surveyed individual. Among the four demographic factors (gender, age, income and race) used in this analysis, income and age are taken as continuous variables whereas gender and race are taken as categorical variables. The building damage state is taken as ordinal variable. Out of the five above-mentioned variables, the final model consists only of the variables selected based on the best fit according to AICc (Akaike information criterion with correction). The variables that are not selected are also found to be insignificant for a \( p \)-value of 0.1. It is noted that the \( p \)-value of each variable is used to test the null hypothesis that the coefficient for the variable is 0, with lower \( p \)-value suggesting a lower probability of the coefficient being 0. The polynomial degrees of the variables also are selected in accordance with the best fit for AICc. Thus, using the methodologies as described above, the final population vulnerability-considered hurricane impact model is developed for each of the considered hurricane impact and is listed in Eq. (16), Eq. (17) and Eq. (18). The coefficients of these equations are provided in Table 2.

\[
l(NESi) = \beta_0 + \beta_{DS} \cdot DS^2 + \beta_{AG} \cdot AG^4 + \beta_{BR} \cdot BR + \beta_{HR} \cdot HR + \beta_{OR} \cdot OR + \beta_{IN} \cdot IN
\]  

(16)

\[
l(NESm) = \beta_0 + \beta_{DS} \cdot DS^4 + \beta_{BR} \cdot BR + \beta_{HR} \cdot HR + \beta_{OR} \cdot OR
\]  

(17)

\[
l(JL) = \beta_0 + \beta_{DS} \cdot DS^5 + 0.33637^* \cdot G + \beta_{BR} \cdot BR + \beta_{HR} \cdot HR + \beta_{OR} \cdot OR + \beta_{IN} \cdot \log(IN)
\]  

(18)

where \( l(NESi) \) is the log-odds of the need of emergency shelter immediately following a hurricane, \( l(NESm) \) is the log-odds of the need of emergency shelter a month after hurricane
event, \( l(JL) \) is the log-odds of job loss as a result of hurricane, \( AG \) is the age of the impacted individual; \( G \) is a function of the gender with 0 representing male and 1 representing female; \( BR \), \( HR \) and \( OR \) represent African-American race, Hispanic race and the remaining other races (except African-American, Hispanic and White race), respectively, with 1 representing that race and 0 representing not, \( IN \) is the income (in 10000\$) for the impacted individual; and \( DS \) represents the damage state of the building inhabited by the individual. As stated above, the survey data records the building damage state into four categories - 1 (completely destroyed), 2 (damaged and unlivable), 3 (damaged but livable) and 4 (no damage). Since this analysis considers the hurricane impacts only in the event of building damage, thus only data with damage states 1, 2 and 3 are considered.

*Table 2: Coefficients of the logistic regression for the various hurricane impacts.*

<table>
<thead>
<tr>
<th>Factor</th>
<th>NESi</th>
<th>NESm</th>
<th>JL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept ( (\beta_0) )</td>
<td>-0.41411*</td>
<td>-3.3564***</td>
<td>0.79848**</td>
</tr>
<tr>
<td>Gender ( (\beta_G) )</td>
<td>N/A</td>
<td>N/A</td>
<td>0.3404*</td>
</tr>
<tr>
<td>Damage state ( (\beta_{DS}) )</td>
<td>-0.09044***</td>
<td>-0.02521***</td>
<td>-0.00937***</td>
</tr>
<tr>
<td>Age ( (\beta_{AG}) )</td>
<td>-2.48E-08</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>African-American ( (\beta_{BR}) )</td>
<td>0.96729***</td>
<td>0.77211</td>
<td>0.52122**</td>
</tr>
<tr>
<td>Hispanic ( (\beta_{HR}) )</td>
<td>0.54961</td>
<td>-98.399</td>
<td>0.8899</td>
</tr>
</tbody>
</table>
From Table 2, it is suggested that damage state is a significant predictor for all the considered hurricane impacts with a p-value of 0.001. Income level is also suggested to be significant for NESi and JL with a p-value of at least 0.05. For the race, the reference category is taken to be the White. It is suggested that compared to the White race, all the other races are significantly more vulnerable to the hurricane impacts, with most of them having a p-value of at least 0.05. Besides building damage state, income and race, gender is found to be significant only for JL for a p-value of 0.1. Age is found to be insignificant in predicting the vulnerability of the population for any of the considered hurricane impact.

It is noted that log-odds $l(y)$ in logistic regression is a linear combination of the independent variables. In logistic regression, the probability of occurrence of $pr(y)$ could be determined in terms $l(y)$ as given below.

$$pr(y) = \frac{1}{1+e^{-l(y)}} = \frac{1}{1+e^{-\left(\beta_0 + \sum_{i=1}^{n} \beta_i x_i\right)}}$$

(19)
From Eq. (19), it is observed that as \( l(y) \) increases, \( pr(y) \) also increases. Thus, a positive coefficient in Eq. (16) to Eq. (18) indicate that an increase in the value of the independent variable leads to an increase in the log-odds and correspondingly the probability of the considered hurricane impact, and vice-versa. In the above equations, it is noted that \( DS \) has a negative coefficient for all the considered population hurricane impacts. Since \( DS = 1 \) indicates the highest damage degree and \( DS = 3 \) indicates the lowest damage degree in this study, this suggests that as the degree of damage increases, the probability of hurricane impact increases. Similarly, the income level has a negative coefficient suggesting that as income increases, the probability of both NESi and JL decrease. For the race, the reference category is taken to be the white, thus a positive coefficient for any other race indicates the probability of hurricane impact to be higher for that race compared to the White race, and vice versa. In the above equations, all the other races are found to have a positive coefficient, therefore all the other races are found to be more vulnerable to hurricane impact compared to the White race. In the function for gender, \( G \) has a value of 1 for female and 0 for male. Since the coefficient for \( G \) is positive for JL, it indicates that the probability of JL increases when \( G \) is 1, suggesting that females were more vulnerable to JL than males.

Thus, using the methodology described above, the demographic factors that have the most influence on hurricane impacts are identified and the degree of their influence is also quantitatively assessed. Further, the population vulnerability-considered hurricane impact model includes the hazard parameter in terms of building damage, making it possible to extend the model to climate-dependent hurricane scenarios. This analysis is next used to evaluate regional hurricane impact considering the relative weights of each demographic factors and the hazard parameter, as described in the Section 3.4.3.
3.4.3 Population vulnerability-considered regional hurricane impact

The population vulnerability-considered hurricane impact model developed in the above section helps assess the hurricane impact on each individual, based on the demographic factors and the building damage state of the individual’s residence. This model can be used to assess regional hurricane impact by considering regional demographic composition. Mean proportion of population affected by the hurricane impacts is used as a metric of the regional hurricane impacts for this study. In this section, the regional hurricane impacts are evaluated for fixed damage states for the selected counties (Harris, New Orleans, Mobile, Miami-Dade, Chatham, Charleston, Norfolk, New York) to study regional variability in population vulnerability.

The four demographic factors considered in the hurricane impact model developed in Section 3.4.3 are gender, age, income and race. Thus, for the regional hurricane impact assessment, these demographic factors are obtained from the census data (Census 2010) for each of the selected counties. The most recent and detailed census data is available for the year 2010, thus it is used in our study. The values of the demographic factors for this census data are provided at census tract level. Figure 11 shows the demographics of the selected counties as reported by the census data.
To assess the average value of the proportion of the hazard-impacted population, Monte-Carlo simulation is employed. The average proportion of the hazard-impacted population is obtained from 500 simulations. For each simulation, 480 individuals are randomly sampled per each zone based on the demographic composition of the county. The hurricane impact is evaluated for each selected individual by considering their demographic composition and a fixed damage state.

The average value of the proportion of the hazard-impacted population given fixed damage state is shown in Table 3. In addition, these results are compared with the regional hazard impacts.

Figure 11: Demographic composition of the considered counties.
evaluated by a simple hurricane impact model which considers only the building damage; so as to investigate the influence of the population vulnerability on the regional hurricane impact. It is found that the proportion of population affected by hurricane impact for a fixed damage state differs across the counties if demographic composition is considered while it remains same for all counties when the demographic composition is not considered. The hurricane impact is found to be estimated mostly lower when the demographic composition is considered than when it’s not in this study. This is attributed to the overestimating tendency of the simple hurricane impact model developed using the survey data which has a higher portion of vulnerable demographic groups compared to the considered counties. In other words, when the underlying demographics’ vulnerabilities of the individual counties are not accounted, the proportion of population affected by the hurricane impact for a given damage state is the same as that of the surveyed population with higher vulnerability in this comparative study, therefore resulting in a higher value. The lower hurricane impact for less vulnerable demographic group is accounted in the model developed in Section 3.4.2, leading to a lower proportion of population affected by hurricane impact for the counties considered in the study. Nonetheless, it is also noted that some counties have a higher proportion of certain vulnerable demographic groups than the survey data, leading to a higher proportion of affected population when demographic composition is considered than when it’s not. For example, in the population vulnerability-considered hurricane impact model for JL, Hispanic population are found to be the most vulnerable. Thus, JL value for Miami-Dade which has a higher proportion of Hispanic population than the survey data when demographic composition is considered.
Table 3: Average proportion of hazard-impacted population for fixed damage states.

<table>
<thead>
<tr>
<th>Building damage only</th>
<th></th>
<th></th>
<th></th>
<th>Building damage + Demographic composition</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NESi</td>
<td></td>
<td></td>
<td></td>
<td>NESi</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>DS1</td>
<td>DS2</td>
<td>DS3</td>
<td>DS1</td>
<td>DS2</td>
<td>DS3</td>
<td>DS1</td>
</tr>
<tr>
<td>All counties</td>
<td>0.39</td>
<td>0.34</td>
<td>0.21</td>
<td>0.06</td>
<td>0.04</td>
<td>0.01</td>
<td>0.73</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>NESi</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Among the selected counties, Orleans is found to have the highest values for proportion of people with NESi and NESm and Miami-Dade is found to have the highest values for proportion of people with JL, indicating them to suffer the most from hurricane impact for the same amount of building damages. The lowest values of NESi, NESm and JL are found for Charleston, Miami-Dade and
Charleston, respectively. The hurricane impact normalized against the simple model result is shown in Figure 12. From the figure, relative vulnerabilities of the different regions attributed to their demographic composition can be easily observed. Further, it is also observed that even for the same county, the different hurricane impacts are affected variously when demographic composition is considered. This is because the different demographic factors have various levels of influence on the different hurricane impacts. This shows the importance of considering the appropriate relative weights of the factors corresponding to each hurricane impact.

![Figure 12: Ratio of people affected by hazard for a fixed damage state (DS1) in the county compared to the results of the simple hurricane impact model.](image)

The discrepancies in the hurricane impact among the counties are found to be mainly attributed to the differences in racial composition and income level among the counties. This can also be inferred from Table 2. Further, it is noted that the income ranges are comparable for most of the counties considered in this study, and thus race is found to be the most influential cause of the differences in the hurricane impact across the counties. For example, from Section 3.4.2, it is found...
that all other race groups are vulnerable compared to White race. This led to the lower values of NESi and JL in Charleston due to its predominant white population. Similarly, the high value of NESi and NESm in Orleans is attributed to high African-American population and high value of JL in Miami-Dade is attributed to high Hispanic population. The low value of NESm in Miami-Dade is suspected as a modeling error. The surveyed Hispanic population were found not to need emergency shelter after a month, which is one of the predominant races in Miami-Dade. However, it is noted that Hispanic population forms a small percentage of the total surveyed population groups, the NESm in counties like Miami-Dade which has a huge Hispanic population might not be properly predicted by the developed model.
CHAPTER 4: EFFECT OF CLIMATE ON HURRICANE BUILDING DAMAGE

To assess the impact of climate change on hurricane building damages due to different hazard modes, building damages due to wind and rain are assessed for hurricanes in present and future climate scenarios. For this, Miami-Dade County is used, which is divided into 52 zones for which the wind speed and rainfall rate under each hurricane scenarios are assessed. This is then used to evaluate the corresponding damages in the building prototypes described in Section 3.3.2. The following sections detail the findings of the investigation.

4.1 Effect of climate on individual building hurricane losses attributed to wind and rainfall

As stated in Section 3.2, damages and losses due to the different mechanisms of hurricane damage – rain ingress and wind is assessed in this study. Accordingly, Figure 13 summarizes the result of this investigation with a prototype wooden building with gable roof and 6d nails as an example. As expected, it was found that for a given climate scenario, structural loss ratio increases with the increase in wind speed. Furthermore, the loss due to rain ingress, as indicated by the shaded portion in the figure, is found to be also positively dependent on wind speed. This increase in loss due to rain damage could be because of two conditions that must be met for rain to enter a building, which includes breaches in the building and rain. Breaches in a building are mostly caused due to wind damage and thus increase in wind speed increases the frequency and extent of the damage allowing more rain to enter. Further, rainfall rate is also positively correlated with the maximum wind speed.
of a storm system. Thus, this combined effect of increase in breaches as well as the rainfall rate with increasing wind speed seem to lead to an increase in interior and content loss.

It is also found that the structural loss ratio for present and future climate overlap whereas the total loss ratio is higher in future climate. Thus, it is suggested that the discrepancy in total loss is a result of the discrepancy in the rainfall rate for the two considered climate scenarios as rainfall is expected to be higher in future. This discrepancy highlights the importance of the inclusion of rain ingress in the assessment of hurricane loss, especially investigating the impact of changing climate.

**Figure 13:** Mean loss ratio for a prototype 1-story wooden building with gable roof and 6d nails.

It is also observed that the major cause of hurricane loss is rain ingress compared to wind damage. This can be observed more clearly by the ratio of mean interior and content loss to mean structural loss for each prototype buildings. Figure 14 presents the mean and the variation of these ratios of
the 48 prototypes based on present as well as future climate scenario. It is concluded that the mean interior and content loss is higher than the mean structural loss for all the building types. Further, the variation of this ratio among different building types is similar for present and future climates. From the figure, it is found that below a certain wind speed, the ratio is very high. This is suspected to be because at low wind speed, there is negligible structural damage while rain could still have ingressed through the already existing vents. Once appreciable structural damage is made, for example after 120 mph, the loss due to rain ingress for present climate is found to be around 3 times to the loss due to wind damage with the value ranging approximately between 1.9 to 4 for one standard deviation below and above mean, respectively. For future climate under RCP8.5 scenario, the ratio is even higher with the mean around 3.2 to 3.9 times and the one standard deviation below and above mean within the range of 2.4 to 5.3. Furthermore, the difference in the ratios between the two climates is observed to decrease as wind speed increases. This could be because of high structural loss term as well as the smaller difference in rainfall losses between the two climate scenarios for higher wind speeds.
Figure 14: Mean and standard deviation of the ratio of mean interior and content loss to mean structural loss of 48 building prototypes.

4.2 Variable effect of climate on hurricane damages to different building types

Figure 15 shows the mean damage ratio for the considered structural components at different wind speeds for a prototype building. The wind speed corresponds to the maximum wind speed at the location for the hurricane scenarios.
Figure 15: Mean damage ratio in a one-story gable-roofed, wooden-walled building with 8d-6/6 nails and shingle roof cover.

Figure 16 shows the mean loss ratio calculated at 10 mph interval for present climate scenario for the selected prototype buildings. Among the one-story buildings, masonry-walled, hip-roofed building with 8d-6/6-nails and shingle-roof cover is found to have the best performance and the wooden-walled, gable-roofed with 6d-6/12-nails and tile-roof cover found to have the worst performance. It is found that once appreciable damage is done, the loss ratios between the two differ significantly. This discrepancy in the loss ratios shows that constructing buildings with structural components with higher strength for wind-resistance could appreciably reduce the losses in hurricane-prone areas.
Figure 16: Mean loss ratio of selected one-story buildings.

The discrepancy in the loss ratios is observed to increase under future climate conditions. Evaluation of the average annual aggregated loss ratio for the different climate scenarios suggested that the intensity of hurricane losses vary depending upon the building type. Figure 17 shows the loss ratios for the four prototype buildings in Figure 7, for example. The difference in the loss ratios between the best performing one-story building and the worst performing one-story building is 0.0097 for present climate scenario and 0.0342 for RCP 8.5 scenario. This shows how climate change is bound to have unequal effect on different structural types with risk magnified for more vulnerable structures.
Figure 17: Effect of climate change on damage of different types of buildings located in Miami-Dade County.

The discrepancy in the projected losses observed in the figure has an important implication in planning and design of any structure which is expected to serve for a considerable number of years. These losses are a measure of the expected risk in structure based on which future planning can be done. The results of the investigation on the projected losses suggest that the hurricane risk for a structure increases over time. Therefore, basing the planning just on past data and assuming stationary climate can expose the structure to unexpected and undesirable level of risk.
CHAPTER 5: EFFECT OF CLIMATE ON REGIONAL HURRICANE RISK ACROSS THE U.S. COAST

5.1 Effect of climate on regional average hurricane wind speeds across the U.S. coast

Currently, one of the common approaches to measure hurricane risk is in terms of hurricane wind speed. For example, ASCE 7-16 provides a wind map for each risk category with the objective of having uniform risk for structures designed in accordance with the code. This implies that areas with higher design wind speeds have higher risks. Therefore, a comparison is made between the annual maximum spatially-averaged wind speeds corresponding to different annual exceedance probabilities for present and future climate scenarios for each study location, which is shown in Figure 18. The future climate scenario corresponds to the worst condition i.e. RCP 8.5 for this comparison.

Figure 18: Annual maximum wind speed corresponding to different annual exceedance probabilities for the selected U.S. coastal locations: Figure on left is for present climate and Figure on right is for future climate corresponding to year 2100 under RCP 8.5 scenario.
For the present climate, it is found that higher wind speeds correspond to areas adjacent to ocean with higher SST as observed from Figure 18 and Figure 2. For example, towards the east of Miami-Dade as we move along the north, SST is found to decrease and so is the wind speed; i.e. the SSTs as well as the wind speeds are in decreasing order in the following locations - Miami Dade, Chatham, Charleston, Norfolk and New York.

In the future climate scenario, the wind speed is found to increase in all the selected locations. The difference in wind speeds between the present and future climate for the selected locations for the annual exceedance probability of 0.0001-0.02 is found to be between 30 to 50 mph. However, it is observed that the increase in wind speed is not uniform across the different locations. For example, even though Miami-Dade is found to have a higher wind speed than Mobile at present, the future wind speed of Mobile and Miami-Dade are comparable. Similar cases are also found between Orleans and Chatham, Charleston and Harris, New York and Norfolk, etc.

The increase in the wind speed is also analyzed in terms of relative increase in average ratio of future to present wind speeds for the exceedance probability of 0.0001-0.02, which is shown in Figure 19. The increase in future wind speed is found to be 1.24 to 1.45 times the present wind speed with the lowest increase in Harris and the highest in New York. It is to be noted that the highest increase in SST is also found in the ocean adjacent to New York from Figure 3.
Thus, it can be suggested that the increase in hurricane risk in terms of wind speed under the climate change will be variable across the different locations with a higher ratio between the future and present wind speeds in areas adjacent to ocean with higher SST change.

It is noted again that currently ASCE 7-16 does not consider the climate change impact on hurricane wind speeds. However, design of building structures without consideration of the potential effect of climate change could result in higher hurricane risk in future climate. A few ways to incorporate climate change impact in design hurricane wind speeds could be

- Re-analyzing the hurricane wind speeds considering projected climate change
• Using current analysis for hurricane wind speeds but increasing the wind speed by a percentage

• Using current analysis for hurricane wind speeds, but at a lower annual exceedance probability than considered at present

Design of structures based on the increased wind speed could help in mitigation of the long-term hurricane risk under climate change scenarios.

5.2 Effect of climate on regional hurricane-induced building damages across the U.S. coast

One component of risk is the extent of impact of hazard on human lives. The impact on properties, especially buildings in which people reside, would certainly be a major part of the hazard impacts on human lives. Further, the impact of the hazard would be different depending upon the building type. Thus, assessing hurricane risk for a specific building type is important for risk management planning. Annual loss ratio could be a good metric to evaluate the hurricane risk on different types of buildings. Annual loss ratio estimates the annual hurricane loss incurred in a building and is normalized with the value of the building, hence it solely measures the level of damage incurred upon the building.

Figure 20 shows the comparison of the annual loss ratios across different locations for a building prototype (6d 6/12 nailed gable roof 1-story wooden house for example). Similar trend is also found among other prototypes. From the figure, it is found that risk in terms of loss ratio also increases non-uniformly across the different locations. For the present climate scenario, the loss
ratios in buildings across Miami-Dade are the highest and the loss ratios in New York are the lowest. For the future climate scenario, New York still has the lowest loss ratio, however the highest loss ratio is found to be in Mobile. This non-uniform increase in loss ratios is noted throughout all the study locations. For example, both Charleston and Harris are at comparable risks at present; however, in the future climate scenario, Charleston is at a higher risk. Thus, the locations that have similar level of expected building damage at present could experience a huge difference in the level of expected building damage in future.

Figure 20: Exceedance probability of annual loss ratio for a 6d 6/12 nailed gable roof 1-story wooden house for present climate (left) and future climate (right).

Further, from Figure 18 and Figure 20, it is observed that the risk level measured in terms of wind speed does not always match to the risk level in terms of loss ratio. For example, for the future climate scenario, the wind speeds in Miami-Dade and Mobile are almost equal for all the above-considered exceedance probabilities (0.0001-0.02), while Mobile is generally found to have higher building damage. For example, the percentage of houses with loss ratios greater than 50% is 1.1
times higher in Mobile than Miami-Dade. Similarly, New York is always found to have higher wind speeds in future climate than Norfolk for the annual exceedance probability of 0.0001-0.02; however, higher percentage of buildings are found to be damaged in Norfolk than New York. For example, the percentage of buildings with annual loss ratio greater than 10% is 8.2 times higher in Norfolk than New York.

The mismatch in the ranking of the risk level based on the annual maximum wind speeds compared to the ranking based on the building loss ratios may be attributed to a number of factors. For example, the frequency of hurricanes in a given location, the relative difference in intensity of less intense hurricanes to the most intense hurricanes, the rate of decay of hurricane once it landfalls, the hurricane radius, etc. are not reflected in maximum wind speed. Thus, even though the annual maximum wind speeds play a huge role in the determination of annual loss ratios, the contribution of other hurricane parameters on the hurricane losses could change the hurricane risk level compared to when assessing the risk based on wind speed alone. The impact of other hurricane parameters on the total hurricane loss is also pointed out by other researchers; for example, Wang and Rosowsky (2012) have stated that not only hurricane wind speed but hurricane radius is also useful to predict regional loss. Hence, even though maximum wind speed is one of the simplest yet reliable metric that could be employed for hurricane risk assessment; however, the risk assessed as such could be slightly different compared to the risk that measures the impact on the building. Thus, in cases where detailed analysis is required, loss ratios could provide a more holistic information regarding the potential impact of the hazard on the buildings.
5.3 Effect of climate on regional hurricane losses across the U.S. coast

For a comprehensive risk assessment, it is important to measure the economic burden inflicted upon a society and the people living in it in the event of a hazard. Thus, regional hurricane losses for present and future climate scenarios are determined by combining the losses in individual buildings. The regional loss is measured in terms of monetary value and not only depends on the level of damage of the buildings but also on the value of the buildings, the number of buildings in the area, etc. Thus, using Eq. (14), average AAL is calculated across the different locations, and shown in Figure 21. Since the counties selected in this study are of variable sizes, the regional loss is normalized with respect to the population as it helps better quantify the risk incurred upon the people.

![Figure 21: Comparison of regional hurricane loss across the selected locations.](image-url)
From the figure, it is seen that losses increase in the future case scenario. However, the increases in losses are not balanced across the regions, which led to the changes in the relative rankings of regional hurricane losses in the future. For example, Miami-Dade has the highest regional losses in present climate, however Charleston has the highest regional losses in RCP 8.5 scenario. It is to be noted that Charleston did not have the highest risk for RCP 8.5 scenario among the regions in terms or wind speed or loss ratio. Similarly, Chatham has lower regional loss compared to Orleans for present climate but higher regional loss in RCP 8.5 scenario. Similar discrepancies were found when comparing other locations as well.

Furthermore, ranking of risk level based on regional loss among the different locations was found to be inconsistent with those based on wind speed and annual loss ratio. For example, for the present scenario, the wind speed as well as loss ratio in Orleans is less compared to Mobile; however, the regional losses are found to be higher in Orleans. For the future RCP 8.5 scenario, similar situations are observed among Miami-Dade and Charleston, Chatham and Orleans, Mobile and Miami-Dade, etc. This discrepancy occurs since regional hurricane loss not only depends on the hazard and corresponding damage but also on many other factors including building value, density, composition of buildings in the region, etc. This discrepancy emphasizes the need of using various metrics for risk assessment for different risk management context.

The increase in regional losses is also quantified in terms of the ratio of future losses to present losses as shown in Figure 22. Since this is a ratio, it also normalizes for the value of building, number of buildings, population, etc. making it easier to compare among the different locations.
It is found that Miami-Dade has the lowest ratio (4.1 for RCP8.5 scenario) and New York has the highest ratio (25.3 for RCP8.5 scenario). It is to be noted that the ratio of increase is highest towards the Northeast side and it decreases along the South. This trend is very similar to the difference between future and present SST, i.e. the SST increase in future is highest towards the Northeast side and it decreases along the south as can be observed in Figure 2. Thus, even though the model used for the TC simulation considers SST at each time step after the genesis, however it can be said that the SST of ocean nearer to the landfalling area is more dominant regarding the hurricane intensity. This implies that the areas nearer the warmer oceans will observe a higher ratio increase of losses in the future climate. It is also to be noted that, locations like New York already have lower loss causing the denominator in the ratio to be smaller which could also be partly
responsible for the ratio to be higher in the county. Similar trend is observed in Figure 19 in terms of the increase in ratios for maximum wind speed, although the difference of ratios between the different locations is not as pronounced as in the above figure.

To further investigate how the increase in the SST of adjacent ocean could impact hurricane losses in future climate, ratio of future to present losses versus increase in SST in neighborhood ocean is evaluated. For this investigation, a $10^\circ \times 10^\circ$ grid is drawn around the considered location as shown in Figure 23, and the SST of the ocean that falls in this grid is averaged out. For example, in Figure 23, the SST of the dotted portion is averaged out for the SST of the adjacent ocean for Norfolk, VA.

![Figure 23: Grid to calculate SST of adjacent ocean.](image)

The ratio of future to present losses vs the SST of adjacent ocean for the eight considered locations is plotted as shown in Figure 24. It can be seen that with increase in SST of the neighborhood
ocean, the ratio increases. To further quantify this increase, an exponential curve is fitted through the points. The exponential curve fitted is of the form as given in Eq. (20).

\[ f = a \cdot e^{b \cdot x} \]  

(20)

where \( a = 1.251 \) (0.7084, 1.793) and \( b = 0.436 \) (0.3657, 0.5064), where the values in the bracket indicate 95% confidence interval for \( a \) and \( b \). A positive value of \( a \) and \( b \) indicates that with increase in SST of the neighborhood ocean, the ratio of the losses also increases. It is also noted that the 95% confidence interval bound is also greater than 0, suggesting with more certainty that with the increase in SST of adjacent ocean, the ratio of losses increase.

Figure 24: Increase in future losses with increase in SST of the ocean.
CHAPTER 6: EFFECT OF CLIMATE ON HURRICANE RISK ACROSS THE U.S. COAST BY CONSIDERING POPULATION VULNERABILITY

6.1 Effect of climate on the average number of affected people across the U.S. coast

To investigate the climate change impact on hurricane risk further, the average number of people affected by the hazard impacts, NESi, NESm and JL, are assessed for the selected counties for both present and future climate scenarios. This investigation helps understand not only which counties will be more vulnerable to the hazard impacts in the future climate, but also which hazard impact will be affected the most in climate change. Monte Carlo simulation is employed to assess the annual average number of affected people.

The assessment is conducted with 40,000 simulations. For the assessment, the average proportion of affected population is calculated first for individual simulated hurricanes similarly in Section 3.4.3. For each simulated hurricane, 480 individuals are randomly sampled per each zone based on the demographic composition of the county. Out of 480 individuals, each 10 individuals are assigned with a same building type. Building damage state for each individual is assessed using the methodology described in Section 3.2. The hurricane impact is evaluated for each selected individual by considering their demographic factors and building damage state. The average proportion of affected population is then multiplied by the number of regional population to obtain average number of affected people. Considering all hurricanes in each year of simulation, annual average number of affected people is calculated.
Figure 25 shows the annual average number of people affected by NESi, NESm and JL for both present and future climates. It is noted that the selected counties are of different sizes; thus, this evaluation is done at census tract level to normalize the size of the county. It is found that the number of people affected by hazard increases in the future climate for all the considered hurricane impacts. The increase in the risk is found to be more along the counties towards the north side than the south side. For example, the increase in future climate compared to present climate is found to be in the range of 4.5-5.6 times for Harris, Orleans, Mobile and Miami-Dade, 9.9-12 times for Chatham and Charleston, 39.6-45.1 times for in Norfolk and 303-461 times for New York. The higher increases along the north side is attributed to higher SST increase of the adjacent ocean in climate change scenario. Besides, counties like Norfolk and New York have a much lower value of hurricane risk at present which could have caused the ratio to be higher in future climate. The highest value of NESi, NESm and JL in this study are found to be 13.5, 1.78 and 31.4 for present climate and 61.2, 8.99 and 142.4 for future climate, respectively in Mobile, Mobile and Miami-Dade County. The lowest values of NESi, NESm and JL are found to be 0.005, 0.0003, 0.01 for present climate and 1.58, 0.14, 3.51 for future climate, all of which were found to be in New York.

Further, the ratio of NESm to NESi, which provides the proportion of population in need of emergency shelter after a month compared to immediately, is found to be within the range of 0.049-0.132 for present climate and 0.054-0.147 for future climate scenarios. It is noted that for all the counties, the ratio is found to be higher in future climate scenario compared to present scenario; suggesting that in the future, a higher proportion of population with NESi will continue living in emergency shelter following a month after hurricane. The highest ratio of NESm to NESi was found in Mobile and the lowest in Miami-Dade.
It is also observed that the counties are influenced variously for the different hurricane impacts. For example, consider the hurricane impacts in Mobile and Miami-Dade for future climate scenario. The numbers of people impacted by NESi, NESm and JL in Mobile is found to be 1.03, 2.78 and 0.998 times of that in Miami-Dade. Similar discrepancies when comparing the different hurricane impacts are found in other counties as well. This is because even though all the considered hurricane risks are a function of the demographic factors and the building damage state; the degree of influence of the various factors differ for the different risks. This shows the importance of considering the relative weights of the factors in accordance with the considered hurricane impact.
Figure 25: Average number of people affected by the hurricane impacts, NESi, NESm and JL, for present and future climate scenarios.
6.2 Effect of climate on annual exceedance probability of hazard impact across the U.S. coast

To investigate the varying effect of climate on the hazard impacts in different intensities, the annual exceedance probability is determined for the proportion of affected population in present and future climates. The annual exceedance probability for NESi is shown in Figure 26 as an example. It is noted that similar trend is found for the other hurricane impacts. As expected, NESi increases for all the considered locations in the future climate compared to present climate. For example, for an exceedance probability of 0.01, the proportion of people impacted with NESi increased in the range of 0.002 - 0.33 from present to future climate across the considered counties.

It is also observed that climate change has varying degree of impacts across the different locations. For example, Harris and Chatham have similar exceedance probabilities for NESi in present climate; however, Chatham is found to have much higher exceedance probabilities for NESi than Harris in the future climate. Similar discrepancies are also observed between many other counties, e.g. Chatham and Charleston, Miami-Dade and Charleston, etc.
Further, to investigate the influence of population vulnerability on hazard risk assessment, NESi evaluated based on the current model is compared with that of a simple hurricane impact model that does not consider population vulnerability for future climate scenario. Figure 27 shows the annual exceedance probability for proportion of people with NESi evaluated based on the simple hurricane impact model. As expected, it is observed that the annual exceedance probabilities for a given proportion of population with NESi based on the simple hurricane impact model is higher, for all the counties. This is because of the overestimating tendency of the simple hurricane impact model that was developed using the data with high portion of vulnerable demographic groups. Further, the discrepancy is more pronounced when the proportion of impacted population is higher. A comparison of Figure 26 and Figure 27 shows how population vulnerability influences NESi in the different counties variously. For example, when population vulnerability is not considered (Figure 27), Mobile has the highest exceedance probabilities for the entire range of the proportion of population impacted with NESi. However, once the population vulnerability is considered

Figure 26: Annual exceedance probability for proportion of people with NESi: (left) present climate and (right) future climate (RCP 8.5).
(Figure 26), Orleans has higher exceedance probabilities when the NESi level is higher than 0.033. Similarly, Chatham has higher vulnerability compared to Charleston when exceedance probability is greater than 0.061 for the case where population vulnerability is considered, even though their vulnerability is comparable when only building damage is considered.

**Figure 27:** Annual exceedance probability for proportion of population with NESi in future climate when only building damage is considered.
CHAPTER 7: CONCLUSION AND FUTURE WORKS

Hurricanes are one of the most destructive natural hazards to the built-environment of many nations, including the United States. Since it is a phenomenon influenced by various atmospheric conditions, the occurrence patterns of hurricanes are expected to change in future climate. Climate studies have confirmed that the future climate could be very different that the present climate, with an overall increase in the atmospheric temperature. Accordingly, this study investigates whether the future climate can have a substantial effect in hurricane risks across the U.S. coast. For this, effect of climate change on hurricane hazard and residential building damages is first investigated, which is then extended to assess regional hurricane risks across the U.S. coast.

To evaluate the hurricane risk in buildings, the two modes of hurricane damage- wind and rain ingress are assessed. From the investigation, it is found that both modes of hurricane damages and losses increase in future under the climate change scenarios. Between the two modes of losses, the rain ingress losses were found to be higher than the structural loss. Also, the discrepancy between the two is greater in future than in present. It is also seen that some buildings (e.g. masonry-walled, hip-roofed buildings) fare better than others in sustaining hurricane winds. Further, the more vulnerable a building is at present, the more increase in losses is expected in the future. This shows an advantage in consideration of more robust building designs which have a huge impact in building performance now and more so in future.

The study is then extended to assess hurricane risk across the U.S. south and east coast under the climate change scenarios in terms of three different metrics - wind speed, building loss ratio and monetary regional loss. From the risk assessment, it is found that in all the three metrics employed
to measure risk, the future hurricane risk increases for all the selected locations. However, it is observed that the ratios of future to present hurricane risks are hugely variable across the different locations. The ratio is highest in New York based on both wind speed and hurricane loss and it decreases for locations towards the south. This variation in the ratio is similar to the trend of the variation in the difference of future and present SSTs; i.e. the difference of future and present SSTs is found to be highest adjacent to the ocean near New York and decreasing along the south. In addition, this study also investigates the impact of climate change on hurricane risk by considering population vulnerability. It is found that the population vulnerability of a region can also have substantial effect on hurricane risk, and the combination of the two could lead to a much higher impact on future hurricane risks for regions inhabited by marginalized population.

Thus, based on the analysis of this study, it is observed that there is a huge difference in hurricane risk between present and future climate and between different locations of the U.S. east and south coast. This shows the necessity of consideration of hurricane risk both spatially as well as temporally for comprehensive risk assessment. Further, the use of various risk metrics could provide valuable information regarding the different aspects of the risk which could be useful in proper planning and risk mitigation. In addition, considering population vulnerability of a region to assess hurricane risk could provide a more holistic information regarding hurricane risk.

It should be noted that this study is based on certain assumptions. For example, building fragility, exposure, building stock, population density, building density, demographic composition, number of people, etc. can change over time, subsequently affecting the losses. However, because the main intent of this study was to compare annual losses at present with those in the future under changing hurricane scenarios for a given building inventory, the losses evaluated here do not reflect the
changes in the aforementioned factors. Also, only the direct impact on buildings due to wind and rain was considered in this study and impacts from storm surge and flooding were not included in the damage and loss calculations. Considering these damage modes may further aggravate the changing trend in losses and possibly the discrepancy between the present and future climates. Such loss modes could be included for a more holistic loss evaluation in future investigations.

Also, any possible change in hurricane genesis frequency has not been incorporated at this time since with the limited amount of past hurricane records, it was difficult to ascertain the impact of climate change on frequency. Further, there is not a clear consensus among the existing literatures regarding the climate change impact on hurricane frequency. Thus, the hurricane risk assessment results should be used to understand the discrepancies in risk spatially and temporally, rather than as the absolute measure of hurricane risk.
REFERENCES


