Climate Change Effects on the Performance of Single-Family Residential Buildings in the US Gulf Coast

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ABSTRACT: The US Gulf Coast is often struck by severe hurricane events. These natural events can cause massive economic and life losses. Based on the projected increase in global sea surface temperature and in population residing along the US Gulf Coast region, the intensity of future hurricanes is expected to increase with time in conjunction with an increase in vulnerability, leading to a significant increase of the risk for future catastrophic hurricane events. Therefore, there is an urgent research need for hurricane risk assessment and mitigation techniques that can quantify the effects of climate change. This paper presents a comprehensive statistical model to account for the effects of climate change on hurricane wind hazard. The model is based on a linear regression of historical hurricane characteristics versus historical sea surface temperature at the time and location of the hurricanes. The proposed model is validated by comparing the simulated hurricane wind speed distributions at any given site along the US Gulf Coast with the wind speed data from the National Institute of Standards and Technology. The validated wind speed model is used, in conjunction with the future climatological scenarios proposed by the 5th Assessment Report of the Intergovernmental Panel on Climate Change, to forecast future hurricane wind speed distributions along the US Gulf Coast. These wind speed distributions are used within a multi-layer Monte Carlo simulation implementation of the Performance-Based Hurricane Engineering framework to estimate potential hurricane-induced losses for a single-family residential building located near Miami, FL. The loss analysis results show that the expected hurricane-induced losses could increase by up to 35% under the projected worst-case scenario in 2060 when compared to the expected losses corresponding to the 2015 climatological conditions.

1. INTRODUCTION

The US Gulf Coast is often struck by severe tropical storms that are locally known as hurricanes. These natural events usually cause extensive economical and life losses, with recent examples such as Hurricane Katrina (2005) with $160 billion losses and Hurricane Harvey (2017) with $125 billion losses normalized to 2017 US dollar (NOAA, 2018). The increasing rate of residential population (NOAA, 2013) contributes to increasing the vulnerability of the region to hurricanes.

The global warming phenomena known as climate change are responsible for increasing the air temperature at the troposphere level of the earth, increasing the sea water level, increase in the sea water temperature, and intensified extreme weather events including hurricanes (IPCC, 2013). Climate scientists generally agree that climate change will most likely results in the intensification of future hurricanes. Thus, significant research efforts have been directed toward understanding the relation between hurricane hazard and climate change. Grinsted et al. (2013) related the Atlantic hurricane records of hurricane-induced storm surges to global temperature and concluded that the frequency of Katrina-like hurricane could double during the 20th century due to global warming.

Significant work has been also done to assess the effects of intensified hurricane actions on structures and infrastructures in a warmer climate, often based on the climate projection scenarios suggested in the reports issued by the Intergovernmental Panel on Climate Change (IPCC) (IPCC 2007, 2013). Bjarnadottir et al. (2011) developed a performance-based framework that accounts for the effects of climate change on residential buildings and concluded that, if the average hurricane wind speed increases about 5% over a 50-year period, the annual regional damage to housing units in the coastal areas of Miami-Dade County in Florida could increase up to \$120 million annually. Cui and Caracoglia (2016) developed a framework for estimating lifetime costs of tall buildings due to hurricane-induced damage under the climate change scenarios provided in the IPCC 5th assessment report (AR5) (IPCC, 2013). Their model was based on simulating the hurricane track path from its origin to its dissipation to derive the wind speed distributions at different locations under different global climate conditions. They concluded that, under a worst-case scenario, the hurricane-induced losses on tall buildings could increase as much as 30% from 2015 to 2115.

This paper presents a simulation model based on the indirect statistics approach (Unnikrishnan and Barbato, 2017) to describe the hurricane wind hazard (expressed as hurricane wind distribution at a given location) as a function of climatological conditions. The developed model is validated through a comparison with the wind speed distributions provided by the National Institute of Standards and Technology (NIST, 2016) at different mileposts along the US Gulf Coast and Florida East Coast and representing historical conditions. The validated model is used in conjunction with the projection scenarios from the IPCC AR5 (IPCC, 2013) to predict the wind hazard for future climatological conditions in the US Gulf Coast. Finally, a Multi-layer Monte-Carlo Simulation (MMCS) implementation of the Performance-Based Hurricane Engineering (PBHE) framework (Barbato et al., 2013) is used to predict the changes in the losses of a single-family house in different location along the US Gulf Coast when considering different climatological conditions.

2. HURRICANE INTENSITY MEASURES MODELED AS FUNCTION OF CLIMATOLOGICAL CONDITIONS

Wind hazard is described in this study in terms of a vector of intensity measures (IM). Among the different IMs proposed in literature (Unnikrishnan and Barbato, 2013), the following IMs are selected here: hurricane frequency, ν_h; maximum hurricane wind speed, V_{max}; radius of maximum wind speed, R_{max}; and hurricane translational speed, V_t. These IMs are highly correlated with the sea surface temperature (SST) (Bjarnadottir et al., 2011; Emanuel, 2011; Vickery et al., 2006, 2009). This relation can be explained by considering that the energy that fuel hurricanes derive from evaporation of warm water from the sea surface. In the present study, an indirect statistics approach is used to model the wind speed distribution (i.e., the wind speed statistics are obtained indirectly based on the site-specific statistics of fundamental hurricane parameters considered as IMs) at any given location (Unnikrishnan and Barbato, 2017).

The changes in hurricane frequency were determined based on the yearly number of hurricanes affecting the US Gulf Coast during the 1851-2017 period expressed as function of the yearly global SST, T_y. The hurricane data were derived from the HURDAT2 database (Landsea et al., 2017), whereas the temperature data were obtained from the NOAA database (NOAA, 2017). Figure 1 reports these data for the entire US Gulf Coast together with a linear regression line. It is observed that the slope of the regression line is almost zero (p-value = 0.93). Thus, it is assumed that changes in T_y do not affect the overall hurricane frequency in the US Gulf Coast. Using the same approach, it was determined that climate change has only minimal or negligible effects on the hurricane annual frequency at different locations along the US Gulf Coast, as identified by the marine milepost used in the NIST database (NIST, 2016). In this analysis, a hurricane was considered to affect a specific site at a given milepost if either its landfall or its path are within a specified radius (referred to as influence radius, r_{inf}, hereinafter) from the site of interest. This radius of influence was obtained by matching the historical hurricane frequency with the hurricane frequency provided by the NIST database (NIST, 2016).

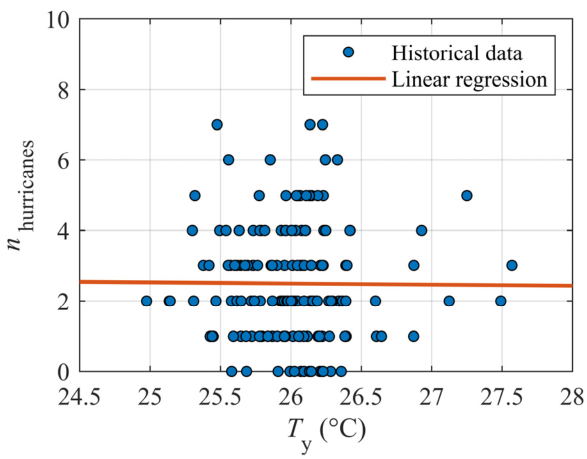

Figure 1. Number of hurricanes per year in the US Gulf Coast region during the 1851-2017 period plotted as function of T_{y}.

Observations based on the historical data reported in in the literature suggest that the remaining IMs considered in this study are better correlated with the temperature at the time and location of the hurricanes, T (Cui and Caracoglia, 2016; Emanuel, 2005) than with the yearly global SST, T_{y}. Therefore, a linear regression model is developed here to obtain the statistical parameters of T as a function of T_{y}. The data for this regression are derived for the years 1988-2017 from the NOAA database (NOAA 2017). Based on the results of a Kolmogorov-Smirnov test (Soong, 2004), the normal distribution was identified as the distribution with the best fit to the historical data of T. The distribution mean, μ_T, is given as:

$$\mu_T\left(T_{\text{y}}\right) = a_0 + a_1 \cdot T_{\text{y}} \quad \left(T_{\text{y}} \geq 25.5°\text{C}\right) \tag{1}$$

in which $a_0 = -26.36\ ^{\text{o}}\text{C}$ and $a_1 = 2.07$. For these data, the standard deviation calculated for the entire US Gulf Coast region is equal to $\sigma_T = 1.22\ ^{\text{o}}\text{C}$ and is assumed to a constant (i.e., not dependent on T_{y}).

For $V_{\max}$, $R_{\max}$, and V_{t}, the following linear regression model is used

$$\mu_p(T) = b_{0p} + b_{1p} \cdot T \quad \left(T \geq 24°\text{C}\right) \tag{2}$$

in which μ_p is the mean of the variable $p = V_{\max}, R_{\max}, V_{\text{t}}$, and b_{0p} and b_{1p} are the corresponding regression parameters. These regression models are based on data from 1988 to 2017 (for which the temperature T at the time and location of the hurricane is available) from the HURDAT2 database (Landsea et al., 2017) and the tropical cyclone extended best track dataset (Demuth et al., 2006). The standard deviation of p is identified with the symbol σ_p. The best fit distribution for each parameter was also selected based on the results from a two-sided Kolmogorov-Smirnov test (Soong, 2004). In particular, a translated Weibull distribution (with a location parameter = 33.4 m/s) was selected to model $V_{\max}$, a truncated normal distribution (defined only for positive values of the random variable) was selected for $R_{\max}$, and a log-normal distribution was selected for V_{t}. While the values of $V_{\max}$ and $R_{\max}$ were given explicitly in the databases, the values of V_{t} were calculated using the hurricane positions at different times along the hurricane paths. For $\mu_{V_{\text{t}}}$, the slope of the regression was found to be very close to zero (p-value = 0.77); thus, $\mu_{V_{\text{t}}}$ is considered constant and independent of T. It is also noted that, based on historical records for the hurricanes in the Atlantic basin during the years 1988-2017 (Demuth et al., 2006), a correlation factor of

$\rho_{R_{\max},V_{\max}} = -0.30$ was obtained and used to generate correlated random samples of $V_{\max}$ and $R_{\max}$.

The obtained values of the regression parameters are reported in Table 1. The values of the standard deviations were found to be dependent on the ranges of T and are reported in Table 2.

Table 1. Regression parameters for the mean of different IMs as functions of T.

Regression parameter	$V_{\max}$ [m/s]	$R_{\max}$ [km]	V_t [m/s]
b_{0p}	-30.86	104.40	6.68
b_{1p}	2.99	-2.55	0.00

Table 2. Standard deviations for different IMs as functions of different T ranges.

T ranges (°C)	$V_{\max}$ [m/s]	$R_{\max}$ [km]	V_t [m/s]
$24 \le T < 26$	6.12	10.73	4.28
$26 \le T < 28$	9.50	16.52	
$T \ge 28$	12.83	14.40	

3. CALCULATION OF WIND SPEED AT SITE FOR GIVEN HURRICANE IMS

For a given site and given hurricane IMs, the wind speed V at the site can be calculated based on the Willoughby's hurricane wind profile for the rotational component V_r (Willoughby et al., 2006). The location of the hurricane eye that produces the highest wind speed at the site is randomly sampled within a circular region of radius $r_{\inf}$ centered on the site as a function of the relative distance, r, and the bearing angle, θ (i.e., the angle formed by the line between the hurricane eye and the site with respect to the South-North line). The distribution for r was derived for different mileposts along the US Gulf Coast and East Coast of Florida based on the hurricane frequency from NIST for the 1851-2017 period (NIST, 2016). Using a Kolmogorov-Smirnov test (Soong, 2004), a generalized extreme value distribution with positive values and maximum value equal to $r_{\inf}$ was determined for all mileposts along the coast. For the bearing angle θ, a uniform distribution between 0 and 2π was assumed. It is further assumed that, if the hurricane eye location generated by this procedure is on land, the wind speed at the site of interest is negligible. This constraint is imposed by identifying the geographical location of sampled hurricane eye by using the spherical geometry formulations (Todhunter, 2006) and comparing the obtained geographical coordinates with a digitized map of the region.

Once the rotational component V_r at the site is known, the Georgiou's model (Georgiou, 1986) is used to calculate the maximum wind speed (expressed as 1-minute wind speed at a height of 10 meters on open terrain) as follows:

$$V = \frac{1}{2}(V_t \sin\alpha - f \cdot r) + \sqrt{\frac{1}{4}(V_t \sin\alpha - f \cdot r)^2 + V_r^2} \tag{3}$$

in which f is the Coriolis parameter at the location of $V_{\max}$ and α is the hurricane heading direction, the distribution of which is derived from the literature (Vickery et al., 2000).

4. SIMULATION OF HURRICANE WIND SPEED AT LOCATION OF INTEREST

A Monte-Carlo simulation approach is used to determine the wind speed distribution at the site of interest. Here, the simulation scheme is briefly described step-by-step:

- Select the site of interest.
- Select the number of samples needed, n_s.
- For $i = 1 : n_s$
  - Set T_y: use historical data for past years or sample a temperature increment based on IPCC AR5 (IPCC, 2013) and sum it to $T_{2005} = 26.32$ °C for future years.
  - Sample the number of hurricanes per year, n_h, from a Poisson distribution with ν_h

equal to the NIST hurricane frequency for the site of interest.

- If $n_\mathrm{h} = 0 \rightarrow V = 0$ m/s
- Else: for $j = 1 : n_\mathrm{h}$
  - Find the location of the hurricane eye that corresponds to the highest wind speed at the site by sampling r and θ.
  - If the location of the hurricane eye is on land $\rightarrow V = 0$ m/s.
  - Else:
    - Calculate μ_T from Eq. (1) and sample T.
    - Calculate $\mu_{V_{\max}}, \mu_{R_{\max}}, \mu_{V_\mathrm{t}}$ from Eq. (2) and sample $V_{\max}, R_{\max}, V_\mathrm{t}$.
    - Sample the parameters needed to define the Willoughby's hurricane wind profile and calculate V_r.
    - Sample α and calculate V at the site.
  - End
- End

- Build the desired wind speed distribution (using directly the empirical cumulative distribution function or fitting an analytical function to the sampled data).

5. MODEL VALIDATION

The developed simulation model for wind hazard was validated by comparing its simulated data with the data provided by the NIST database (NIST, 2016) for selected milepost along the US Gulf Coast and East Coast of Florida. The NIST data is based on hurricane data for the 1887-1963 period, for which the average yearly SST was $T_{1871\text{-}1963} = 25.94\,^\circ\mathrm{C}$ (NOAA, 2017). Wind speed distributions were generated using 1,000,000 samples for coastal mileposts from the Texas border to the border between Florida and Georgia at intervals of 50 nautical miles with an input $T_\mathrm{y} = 25.94\,^\circ\mathrm{C}$.

Figure 2 compares the mean wind speeds obtained from the proposed simulation model and the NIST database. For both sets of estimates, a 95% confidence interval is also provided. However, the confidence interval for the simulation results is so small that it is almost invisible at the scale used in this figure. It is observed that all mean wind speed estimated obtained from the simulation results fall within the confidence intervals of the mean wind speeds obtained from the NIST database. The normalized average differences between the two sets of mean wind speeds is -0.60%, which indicates an excellent agreement between the two sets of data.

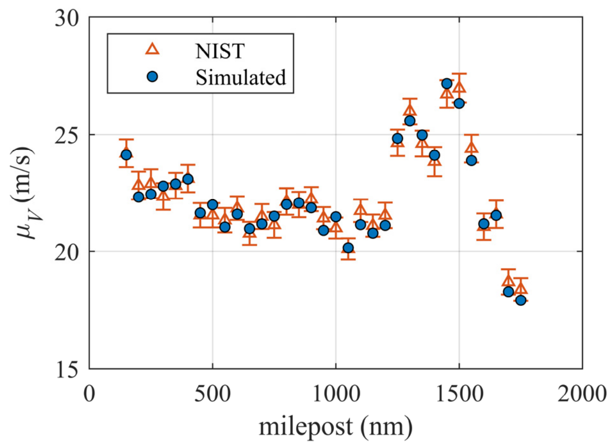

Figure 2. Comparison of simulation and NIST wind speed means at different mileposts.

Figure 3 compares the standard deviations of the wind speeds obtained from the proposed simulation model and the NIST database. As for the mean wind speeds, a 95% confidence interval is also plotted; however, the confidence interval for the simulation results is too small to be visible.

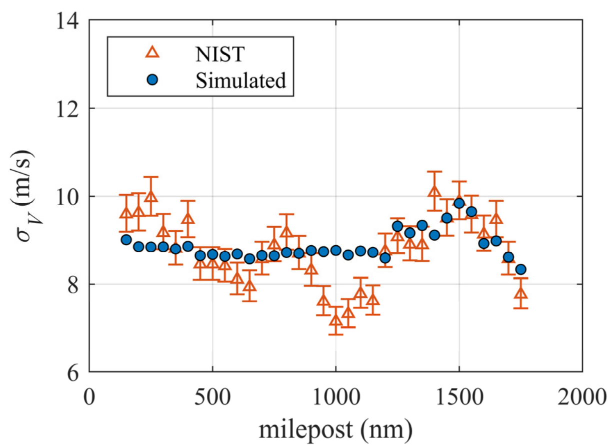

Figure 3. Comparison of simulation and NIST wind speed standard deviations at different mileposts.

It is observed that the wind speed standard deviation estimates obtained from the simulation results and from the NIST database are generally in good agreement, even though some of the simulation values are outside the 95% confidence interval of the NIST values. The normalized average differences between the two sets of wind speed standard deviations is +0.88%, which still indicates an excellent agreement between the two sets of data. It is also observed that the modified root mean squared error (Peng et al., 2014) is equal to 0.60 m/s for the mean and 0.38 m/s for the standard deviation. Based on these results, it is concluded that the proposed simulation method is able to reproduce wind speed distributions based on historical data at different locations along the US Gulf Coast region.

6. FUTURE WIND SPEED PROJECTIONS

The proposed simulation model is used in conjunction with the four projection scenarios from the IPCC AR5 (IPCC, 2013) to derive the wind speed distributions along the US Gulf Coast region for the 2020-2060 period. The IPCC AR5 provides the mean and 95% confidence interval for four different projection scenarios for the increase in yearly SST, ΔT_{y}, for the period of interest with reference to the year 2005. Hence, the temperature for future years is calculated as:

$$T_{\mathrm{y}} = T_{2005} + \Delta T_{\mathrm{y}} \tag{4}$$

where ΔT_{y} is sampled from a normal distribution fitted on the projection scenarios and $T_{2005} = 26.32\ ^{\circ}\mathrm{C}$. The simulated wind speed means and standard deviations for the mileposts along the US Gulf Coast and the East Coast of Florida for year 2015 (based on the measured yearly SST) and year 2060 (for all four projection scenarios) are reported in Figure 4 and Figure 5, respectively.

The results of the hurricane wind simulations show that the average wind speed mean for all the mileposts of under consideration is expected to increase between 2015 and 2060 by 3.65% for RCP 2.6, 6.73% for RCP 4.5, 6.04% for RCP 6.0, and 11.09% for RCP 8.5. The corresponding average increases of the wind speed standard deviations are 4.64% for RCP 2.6, 7.92% for RCP 4.5, 7.23% for RCP 6.0, and 11.89% for RCP 8.5.

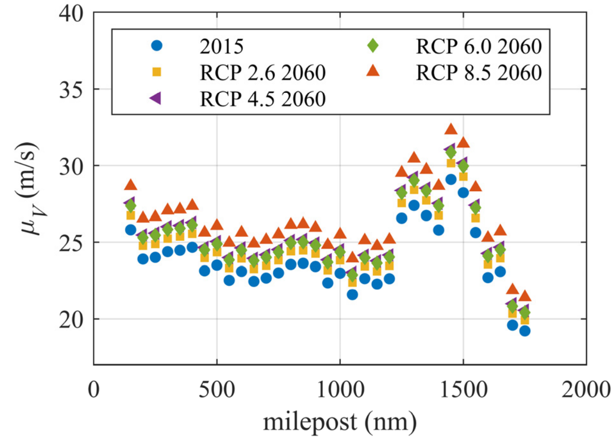

Figure 4. Wind speed means for year 2015 and 2060 under different projection scenarios.

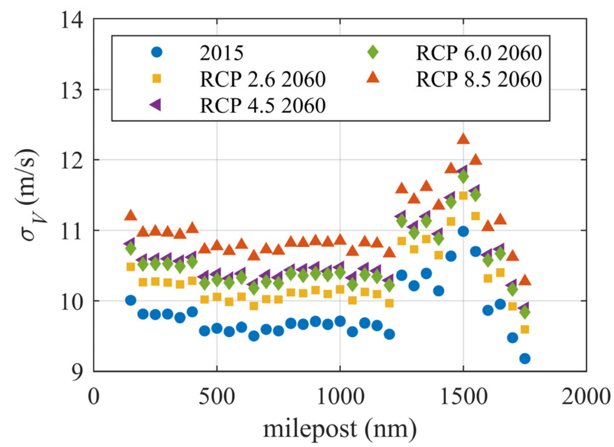

Figure 5. Wind speed standard deviations for year 2015 and 2060 under different projection scenarios.

7. LOSS ESTIMATION UNDER CHANGING CLIMATE CONDITIONS.

A typical single-family wooden-frame house is used as benchmark structure for a loss analysis based on a multi-layer Monte-Carlo simulation implementation of the Performance-based Hurricane Engineering (PBHE) framework (Barbato et al., 2013). The general scheme of the building is given in Figure 6. For this building, the strength properties and cost statistics of all building components are taken from Unnikrishnan and Barbato (2017). The benchmark house was analyzed at different locations along the US Gulf Coast region (corresponding to the mileposts for which the wind speed distributions were derived in the hazard analysis phase) and for the four IPCC AR5 climate change projection scenarios using 1,000,000 samples for each considered case. It is noteworthy that, due to reduced computational cost of the proposed simulation method, all simulations for all cases were completed in a couple of hours on a personal computer.

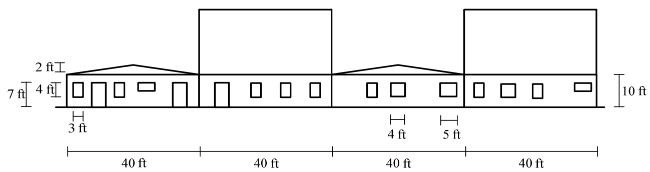

Figure 6. Unfolded scheme for the benchmark house.

Figure 7 compares the expected annual losses due to hurricane winds for the benchmark structure at different locations and for different climate change scenarios in year 2060 with the expected annual losses for the same structure under the climatological conditions corresponding to year 2015.

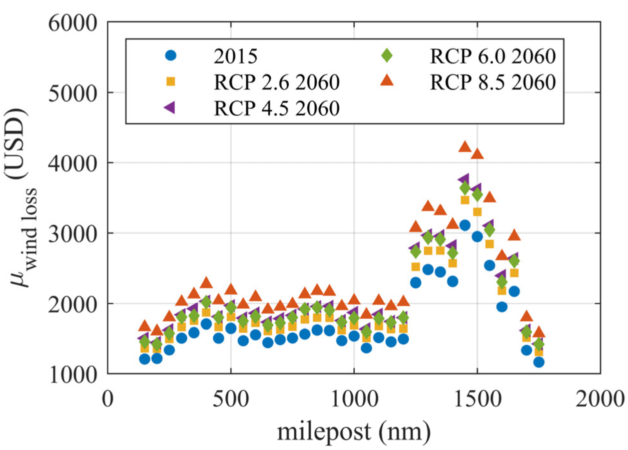

Figure 7. Hurricane wind-induced expected annual losses for the benchmark house under different changing climate conditions.

It is observed that the expected increase in mean annual hurricane wind-induced losses (averaged over all considered locations) is equal to 11.21% for RCP 2.6, 21.04% for RCP 4.5, 18.59% for RCP 6.0, and 34.66% for RCP 8.5. This increase is clearly more than proportional to the mean wind speed increase.

8. CONCLUSIONS

In this research work, the effects of climate change on hurricane wind risk for buildings in the US Gulf Coast region was investigated. A simulation procedure to derive wind speed distributions under changing climate conditions was presented. The proposed model was validated by comparing the simulation results with hurricane wind speeds from the NIST database. This model was used in conjunction with the IPCC AR5 climate change projection scenarios to predict changes in hurricane wind speed distributions and expected losses for single-family wooden-frame houses. The results indicate that, between 2015 and 2060, the average hurricane wind speed for the region is expected to increase by 3.65% to 11.09%, and the expected annual losses for the benchmark house are expected to increase by 11.21% to 34.66%.

9. REFERENCES

Barbato, M., Petrini, F., Unnikrishnan, V. U., and Ciampoli, M. (2013). “Performance-Based Hurricane Engineering (PBHE) framework.” *Structural Safety*, 45, 24–35.

Bjarnadottir, S., Li, Y., and Stewart, M. G. (2011). “A probabilistic-based framework for impact and adaptation assessment of climate change on hurricane damage risks and costs.” *Structural Safety*, 33(3), 173–185.

Cui, W., and Caracoglia, L. (2016). “Exploring hurricane wind speed along US Atlantic coast in warming climate and effects on predictions of structural damage and intervention costs.” *Engineering Structures*, 122, 209–225.

Demuth, J. L., DeMaria, M., and Knaff, J. A. (2006). “Improvement of advanced microwave sounding unit tropical cyclone intensity and size estimation algorithms.” *Journal of Applied Meteorology and Climatology*.

Emanuel, K. (2005). “Increasing destructiveness of tropical cyclones over the past 30 years." *Nature*, 436(7051), 686–688.

Emanuel, K. (2011). "Global warming effects on U.S. hurricane damage." *Weather, Climate, and Society*, 3(4), 261–268.

Georgiou, P. N. (1986). "Design wind speeds in tropical cyclone-prone regions." *Ph.D. Dissertation*, University of Western Ontario, London, Ontario, Canada.

Grinsted, A., Moore, J. C., and Jevrejeva, S. (2013). "Projected Atlantic hurricane surge threat from rising temperatures." *Proceedings of the National Academy of Sciences*, 110(14), 5369–5373.

IPCC (2007). *Climate Change 2007 - The Physical Science Basis.* Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

IPCC (2013). *Climate Change 2013 - The Physical Science Basis*. Cambridge University Press, Cambridge, England (UK).

Landsea, C., Franklin, J., and Beven, J. (2017). "The revised Atlantic hurricane database (HURDAT2)." <http://www.aoml.noaa.gov/hrd/hurdat/hurdat2.html>.

NIST (2016). "Extreme wind speed data sets: Hurricane wind speeds." *National Institute of Standards and Technology*, <http://www.itl.nist.gov/div898/winds/hurricane.htm>.

NOAA (2013). "National coastal population report: Population trends from 1970 to 2010." *NOAA State of the Coast Report Series*, 22.

NOAA (2017). "NOAA high resolution SST data." <http://www.esrl.noaa.gov/psd/>.

NOAA (2018). "Costliest U.S. tropical cyclones tables updated." *NOAA Technical Memorandum NWS NHC-6*, 3.

Peng, X., Yang, L., Gavanski, E., Gurley, K., and Prevatt, D. (2014). "A comparison of methods to estimate peak wind loads on buildings." *Journal of Wind Engineering and Industrial Aerodynamics*, 126, 11–23.

Soong, T. T. (2004). *Fundamentals of probability and statistics for engineers*. Wiley, Chichester, West Sussex, England (UK).

Todhunter, I. (2006). *Spherical Trigonometry: For the Use of Colleges and Schools*. Mamillan and co., London, England (UK).

Unnikrishnan, V. U., and Barbato, M. (2013). "Performance-based hurricane risk assessment with application to wind and windborne debris hazards." *Proceedings of the 11th International Conference on Structural Safety and Reliability, ICOSSAR 2013*, (1), 1273–1279.

Unnikrishnan, V. U., and Barbato, M. (2017). "Multihazard Interaction Effects on the Performance of Low-Rise Wood-Frame Housing in Hurricane-Prone Regions." *Journal of Structural Engineering*, 143(8), 04017076.

Vickery, P. J., Masters, F. J., Powell, M. D., and Wadhera, D. (2009). "Hurricane hazard modeling: The past, present, and future." *Journal of Wind Engineering and Industrial Aerodynamics*, 97(7–8), 392–405.

Vickery, P. J., Skerlj, P. F., Lin, J., Twisdale, L. A., Young, M. A., and Lavelle, F. M. (2006). "HAZUS-MH Hurricane Model Methodology. II: Damage and Loss Estimation." *Natural Hazards Review*, 7(2), 94–103.

Vickery, P., Skerlj, P., and Twisdale, L. (2000). "Simulation of hurricane risk in the US using empirical track model." *Journal of Structural Engineering*, 126(10):1222-1237.

Willoughby, H. E., Darling, R. W. R., Rahn, M. E., Willoughby, H. E., Darling, R. W. R., and Rahn, M. E. (2006). "Parametric Representation of the Primary Hurricane Vortex. Part II: A New Family of Sectionally Continuous Profiles." *Monthly Weather Review*, 134(4), 1102–1120.