14th International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP14
Dublin, Ireland, July 9-13, 2023

Probabilistic Modeling of North Atlantic Ocean Hurricane Spawn Considering Climate Change

Susmita Bhowmik
PhD Student, Glenn Dept. of Civil Engineering, Clemson University, Clemson, USA

Weichiang Pang
Professor, Glenn Dept. of Civil Engineering, Clemson University, Clemson, USA

Michael Stoner
Research Assistant Professor, Glenn Dept. of Civil Engineering, Clemson University, Clemson, USA

ABSTRACT: Hurricanes are a significant natural hazard, which cause significant damage and financial losses in the coastal areas of the United States almost every year. For example, the devastating nature of North Atlantic Ocean (NAO) storms can easily be understood from the 2005 Hurricane Katrina, which was the most damaging NAO storm in modern history, causing more than 1,800 deaths and a financial loss of at least 161.3 billion USD. It has been found that the formations of hurricanes depend heavily on climate conditions, which implies a direct relationship between the changes in climate extremes and the occurrences of hurricanes or tropical cyclones. There are several environmental factors widely accepted as favorable conditions for the formation of tropical cyclones: (1) warm sea surface temperature (SST), (2) high relative humidity (RH), (3) low vertical wind shear (WS), (4) high counter-clockwise relative vorticity (RV), and (5) low air temperature (AT) at the top of troposphere. This paper presents a new modeling approach to study the effects of climate change on hurricane genesis over the North Atlantic Ocean. The proposed method utilizes a probabilistic model for simulating the formation of hurricanes based on the data of four climate variables (SST, RH, WS, and AT) and the Coriolis effect. For modeling purposes, the NAO was divided into 5-deg x 5-deg grid cells and the annual spawn rate for each cell was computed from historical data. The daily SST, WS, RH, and AT recorded during the formation of 677 NAO storms from 1982 to 2021 were fit to Weibull, lognormal, Beta, and general extreme value probability distributions respectively. The likelihood of a tropical cyclone to spawn in each day and cell was assumed to be proportional to the cumulative joint occurrence probability of the four climate variables for which historical spawns were observed. The historical record of climate variables was re-simulated and calibrated using exponential coefficients for each of the climate variables, calculated by matching the mean annual spawn rate for a mapped grid over the NAO. To explore the impact of climate change on hurricane genesis, simulations were run according to the Intergovernmental Panel on Climate Change (IPCC) fifth assessment report, using the climate variables from one of Representative Concentration Pathways (RCP 4.5) in the year 2060. It has been found that the number of storms per year is increasing in this RCP scenario. Based on the RCP 4.5 scenario, the wind speeds along the coastal areas of the U.S. in the year 2060 are found to be significantly larger than the wind speeds in the current U.S. building code (ASCE 7-22).

1. INTRODUCTION

Tropical storm or hurricane is one of the major natural hazards that poses significant risk to the coastal area of the United States. The formations of hurricanes depend heavily on climate conditions, which implies a direct relationship between the changes in climate extremes and the occurrences of natural hazards such as hurricanes or tropical cyclones. It can be observed from HURDAT2, a database of historical hurricane and tropical cyclone records maintained by the Hurricane Research Division (HRD) of the United States National Oceanic and Atmospheric Administration (NOAA) (Jarvinen et al., 1984, Landsea, et al. 2014) that with the progression of time, there is an increasing trend in the number of storms in the North Atlantic Ocean (NAO). Figure 1 shows the annual number of tropical cyclones spawned in the NAO from 1851 to 2021 hurricane seasons. The average storm frequency over the entire period is 11.32 storms/year with a standard deviation of 5.66 storms/year. The highest monthly genesis rate is found in September whereas the dominant season is from late summer to autumn (July to October) with 85% of tropical cyclones occurring in this period.

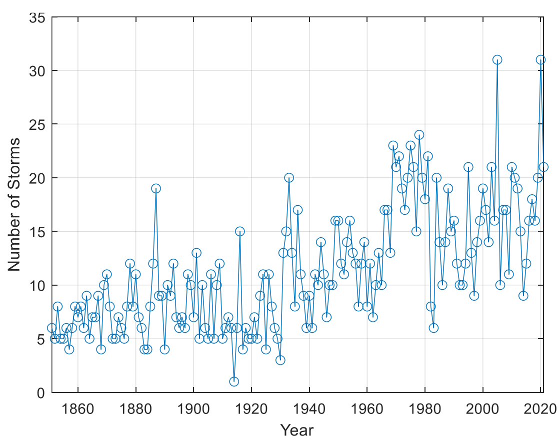

Figure 1:Annual number of storms spawned in the Atlantic Ocean from 1851 to 2021 hurricane seasons.

It is widely known that NAO storms can cause severe damage to the coastal regions and adjacent areas. The devastating nature of NAO storms can easily be understood from the 2017 Hurricane Karina, which is the most damaging NAO storm in modern history causing a death toll of 1,836, affecting Louisiana and Mississippi the most, that caused a financial loss of at least USD 161.3 billion. The second costliest U.S. tropical cyclone is the Hurricane Harvey, responsible for at least 68 direct deaths in Texas, and a USD 125 billion of financial loss (Blake & Zelinsky, 2018). Previous studies exhibit that the most destructive hurricanes in the United States will occur more frequently than they used to occur in the past with climate change. Figure 1 shows an increasing trend of annual storm frequencies over the years; however, it is necessary to consider that the starting year of aircraft reconnaissance is 1944 and starting of polar orbiting satellite coverage is 1966. The average number of storms since the launch of satellites (i.e. from 1966 to 2021) is 16.82 storms/year with a standard deviation of 5.12 storms/year.

1.1. Climate Change

Climate change refers to a long-term change in the Earth system in terms of weather phenomena. Burning fossil fuels, converting land from forest to agriculture, and deforestation are the major human activities that cause climate change. A comprehensive assessment report is prepared by the Intergovernmental Panel on Climate Change (IPCC) on current state of climate, its risk, and effects and ways to mitigate human-induced climate change. The sixth IPCC assessment report (AR6) issued in 2021 reveals that the range of global average combined land and sea surface temperature has increased from 0.8^0C to 1.3^0C from the period 1850-1900 to 2010-2019 (Zhongming et. al., 2021). As the formations of natural hazards like hurricanes or tropical cyclones depend on the climate states, climate change has a profound influence on natural hazards. A positive correlation has been found between SST and storm frequency based on historical data (Mann & Emanuel, 2006). A study shows that 1^0C increase in sea surface temperature can result in the frequencies of Category 4 and 5 hurricanes (Saffir–Simpson classification) to double (Bender et. al., 2010).

1.2. Current Storm Genesis Models

The consequences of climate change on storm activity are important issues in the present time. Previous studies simulate storms considering several climate variables, i.e., SST, RH, VWS, absolute vorticity, El Nino-Southern Oscillation (ENSO), Southern Oscillation Index (SOI), and so on (Vickery et. al., 2009; Vickery et. al., 2000; Villarini et. al., 2010; Tippett et. al., 2011; Lee et. al., 2018; Yonekura & Hall, 2011;

Jing & Lin, 2020; Zhang et. al., 2018). Few studies consider only SST as a climate variable without assessing climate change effects (Vickery et. al., 2009; Vickery et. al., 2000; Zhang et. al., 2018). On the other hand, the genesis model is developed considering only ENSO indices by Yonekura & Hall (2011). Several studies use the Poisson regression method to model storm genesis considering several climate variables (SST, RH, VWS, and absolute vorticity) and storm location based on statistical modeling (Villarini et. al., 2010; Tippett et. al., 2011; Lee et. al., 2018). Lately, the Poisson regression model is developed without considering storm location as a predictor, rather using clustering grids with similar environmental fields instead of regular grids to model tropical cyclones (TCs) (Jing & Lin, 2020). However, storm location is not taken into account in such models, whereas historical storm locations can be a useful predictor for storm genesis. The authors found that these Poisson regression models underestimated the storm frequencies during hurricane season (August to October) despite applying complex clustering algorithms.

2. MODELING APPROACH

2.1. Stochastic Hurricane Simulation Model

In this study, a stochastic hurricane simulation program (Liu 2014) was utilized to generate simulated hurricane tracks. The simulation framework is shown in Figure 2. The hurricane simulation model consists of several modules, which includes hurricane formation (genesis) model, tracking model, intensity (central pressure) model, central pressure filling rate (decay) model, wind field model and boundary layer model. The statistical model of each module is calibrated using historical hurricane data (HURDAT2). The Monte Carlo simulation technique is applied to simulate the spatial and temporal evolutions of the storm states from the initial formation of the storm to final dissipation. In the hurricane simulation model, the state of a storm is described by seven parameters. These seven parameters are: (1) latitude and (2) longitude of the storm eye, (3) storm forward speed (V_t), (4) heading angle (θ), (5) central pressure (P_c), (6) storm size expressed as radius to maximum wind (R_{max}), and (7) pressure profile parameter (also known as Holland B parameter).

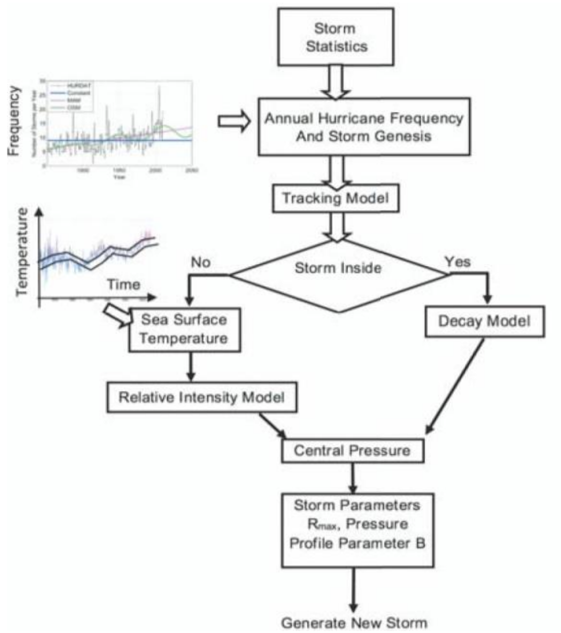

Figure 2:Stochastic hurricane simulation framework.

To study the effect of climate change, two hurricane simulation models were created:

- **Baseline model** – this model assumes (1) the annual genesis of tropical cyclones observed from 1851 to 2021 remains stational and unchanged into the future, and (2) the SST, one of the key parameters affecting storm intensity (central pressure), remains at the current level.
- **Climate change model** – this model assumes (1) the annual spawn rate of tropical cyclones changes according to the projected climate conditions of the IPCC RCP 4.5 scenario for the year 2060, and (2) the storm intensity changes based on the SST of the RCP 4.5 scenario.

3. BASELINE GENESIS MODEL

In the baseline model, the number of storms in each year in HURDAT is first fitted to a negative binomial distribution with parameters *R* and P, which are determined using maximum likelihood estimation. Equation (1) shows the probability mass function of this distribution, where the random variable x indicates the annual number of storms.

$$f(x) = \binom{x+R-1}{x} P^R (1-P)^x \qquad (1)$$

The annual number of storms in baseline model is randomly selected from the negative binomial distribution fit using historical data.

4. CLIMATE CHANGE GENESIS MODEL

Existing research works generating storm formations do not consider several important factors, such as storm locations, seasonal variability, and so on, which can be used to find more accurate genesis model. This paper presents a new modeling approach to study the effects of climate change on hurricane genesis over the NAO. The proposed method utilizes a probabilistic model for simulating the formation of hurricanes based on climate variables.

There are several environmental factors widely accepted as favorable conditions for the formation of tropical cyclones: (1) warm sea surface temperature (SST), (2) high relative humidity (RH), (3) low vertical wind shear (WS), (4) high counter-clockwise relative vorticity (RV), and (5) low air temperature (AT) at the top of troposphere (at 100mb elevation). The WS is computed using the wind vectors between 200mb and 850mb elevations.

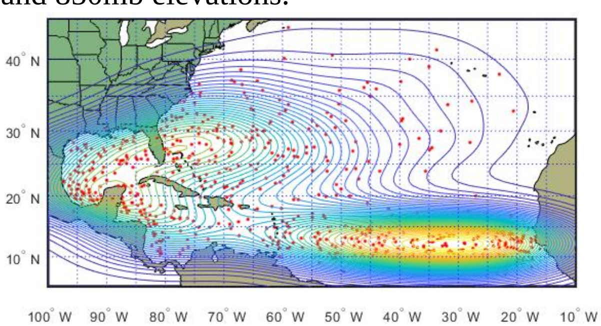

Figure 3: Study domain and initial spawn locations of tropical cyclones observed from 1982 to 2021.

For modeling purposes, the NAO was divided into 5-deg x 5-deg grid cells and the annual spawn rate for each cell was computed from historical data (Figure 3). While HURDAT2 contains storm tracks information starting from 1851, climate data for full coverage of the NAO are only available starting from 1982. Therefore, the climate data and initial spawn locations of 677 storms from 1982 to 2021 are utilized in this study.

For predicting the spawn potential of a tropical cyclone, the efficiency (*eff*) of each grid cell modeled as a "heat engine" is computed using the following equation:

$$eff = \frac{SST - AT}{SST} \qquad (2)$$

For each grid cell, the daily averaged SST, WS, RH, and *eff* are organized into two groups of data: (1) no formation of tropical cyclone (NoSpawn), and (2) initial formation of a tropical cyclone (Spawn). As can be seen in Figure 4, SST greater than about 25^{0}C, low WS, high RH and high *eff* are conditions conducive to the formation of tropical cyclones.

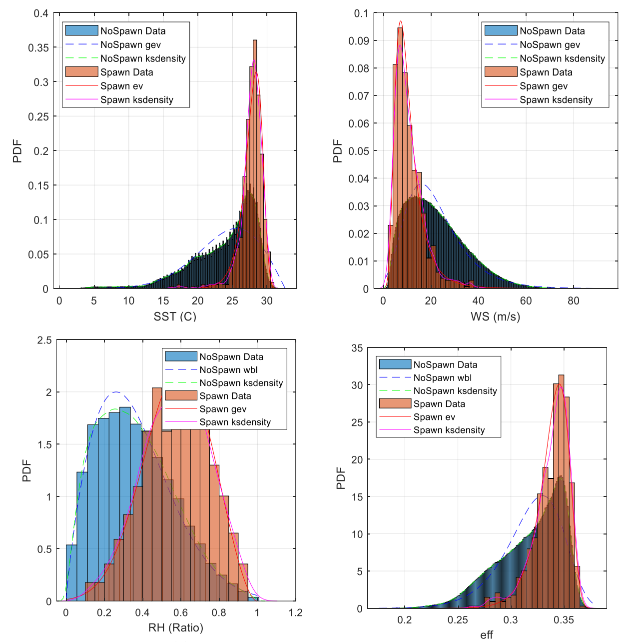

Figure 4: Probability density functions of SST, WS, RH, and eff for No-Spawn and Spawn day-cells.

The daily SST, WS, RH, and *eff* recorded in the cells during the formation of 677 NAO storms from 1982 to 2021 were fit to Weibull, lognormal, Beta, and general extreme value probability distributions (Figure 5). Note that low WS is favorable to formation of tropical cyclones. Thus, the exceedance probability function is used to quantify the spawn probability conditioned on WS.

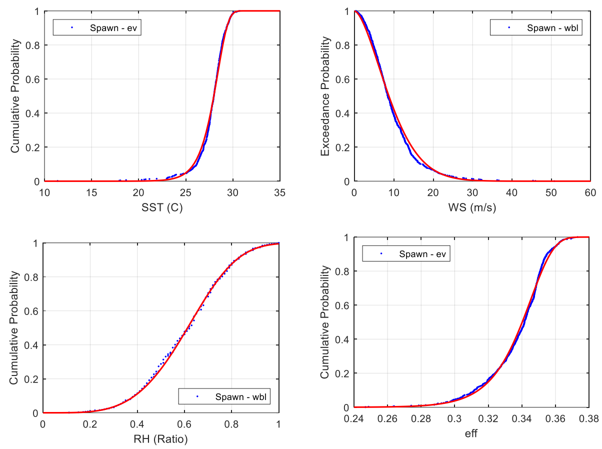

Figure 5: Cumulative distribution functions of SST, WS, RH, and eff for Spawn day-cells.

The probability of a tropical cyclone to spawn in each day and a cell is assumed to be proportional to the cumulative joint occurrence probability of the four climate variables for which historical spawns were observed. In addition, the Coriolis parameter (cor) is also utilized to compute the day-cell spawn probability.

$$P_{spawn} = F(SST)^{n1} \times [1 - F(WS)]^{n2} \times \dots F(RH)^{n3} \times F(eff)^{n4} \times F(cor)^{n5} \quad (3)$$

Where cor = $2\Omega \times \sin(\phi)$. Ω is the rotation rate of the Earth (7.2921×10^{-5} rad/s). ϕ is the latitude of the cell. F(.) is the cumulative distribution function (CDF). n_1 to n_5 are exponents for SST, WS, RH, *eff*, and *cor* parameters, respectively. P_{spawn} is the probability of the formation of a tropical cyclone in a cell in a day given the climate conditions.

A set of best-fit exponents were determined for each cell by matching the observed mean annual spawn rate and the simulated mean annual storm rate (Figure 6). The process of fitting exponents:

1) Assign initial values for n_1 to n_5 (e.g. all equal to unity) for Cell *j*.
2) Use the daily averaged SST, WS, RH, and *eff* of historical observations (Figure 7) along with the assumed exponent values to compute the daily spawn probability, P_r, of Cell *j* using Eqn. (3).
3) Use a uniform random number generator (0 to 1) to simulate spawn or no spawn for each cell in a day over the entire year.
4) Repeat steps 2 to 3 for N realizations or simulation years and compute the mean annual spawn rate for Cell *j*.
5) Adjust the values of n_1 to n_5 and repeat Steps 1 to 4 until the mean annual rate matches or converges to the historical observed spawn rate.

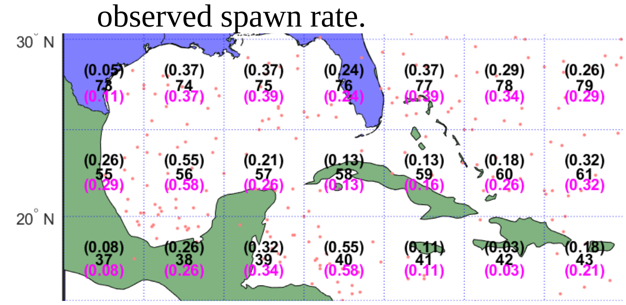

Figure 6: Annual spawn rates of selected cells, top bracketed values are from simulation, bottom bracketed values are from historical data, middle values are cell numbers.

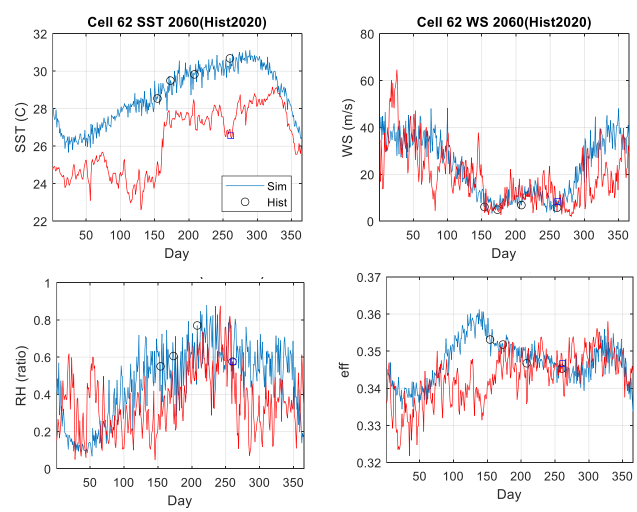

Figure 7: Daily averaged SST, WS, RH and eff time histories for year 2020 (red) and RCP 4.5 year 2060 (blue).

5. RESULTS AND DISCUSSION

5.1. Storm Frequencies

Figure 8 compares the monthly number of storms observed from 1982 to 2021 and that simulated using the best-fit exponents and historical climate data (baseline model) for June, July, October, and November. As can be seen, the distributions of the simulated monthly spawn rates match the observations well.

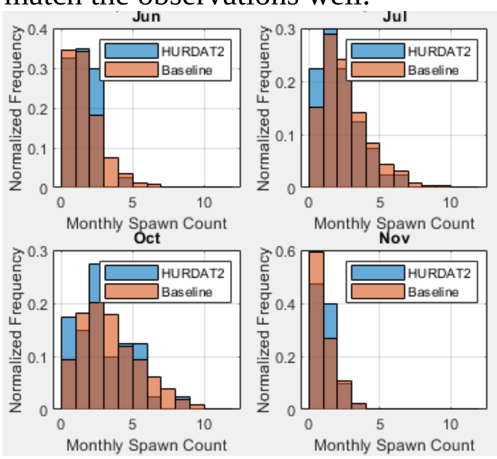

Figure 8: Histograms comparing the distributions of monthly number of storms in NAO between the baseline model and historical observation (1982 to 2021).

Figure 9 shows the simulated monthly number of storms for the RCP 4.5 scenario for year 2060. The simulation results show that the storm spawn rates in June and July in 2060 are significantly higher than the past observations.

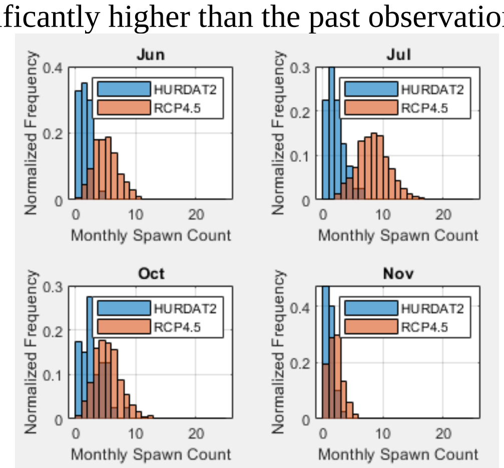

Figure 9: Histograms comparing the distributions of monthly number of storms in NAO between the climate change genesis model (RCP 4.5 2060) and historical observation (1982 to 2021).

Figure 10 shows the mean monthly spawn rates of the new baseline genesis model match that recorded in HURDAT2 well. Thus, further confirms the validity of the new genesis model using climate parameters to consider estimate tropical cyclone spawn rates. The mean monthly spawn rate in July increases from the current rate of 2 in a year to as high as 8 in a year (Figure 10).

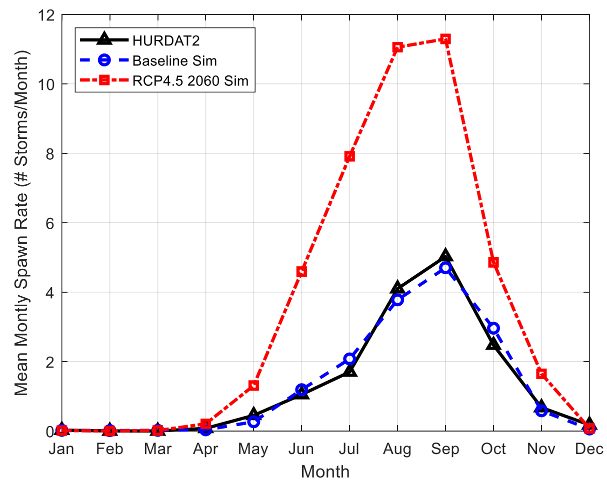

Figure 10: Comparison of mean monthly spawn rates of (1) HURDAT2, (2) baseline model, and (3)climate change model for RCP 4.5 year 2060.

5.2. Poleward Shift

Figure 11 shows the starting locations of storms for 40 simulation years or realizations of 2060 assuming the climate conditions of RCP 4.5. Due to rise in SST, in addition to more storms, it appears that storms may also shift toward the north pole forming in higher latitude region (compare Figure 11 to Figure 3).

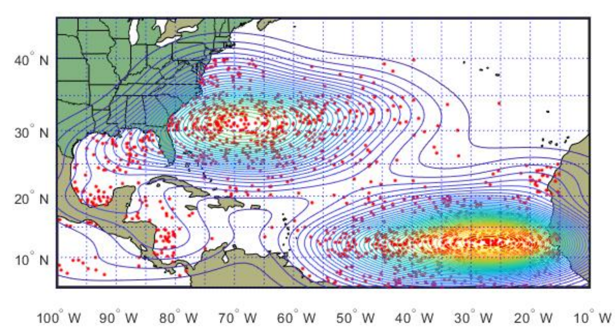

Figure 11: Initial locations of tropical cyclones simulated for RCP 4.5 year 2060.

5.3. Wind Speed Return Period Curves

The stochastic hurricane simulation program was utilized to simulate 10,000 years of storm tracks each for the baseline model and the climate change model. A coastal site in Charleston, South Carolina (latitude 32.7313°, longitude -80.0631°) was selected for quantifying and comparing the hurricane wind hazards under the two climate conditions (i.e. baseline and RCP 4.5 2060 climate models). Figure 12 shows the site of interest and examples of simulated tracks passing near the site.

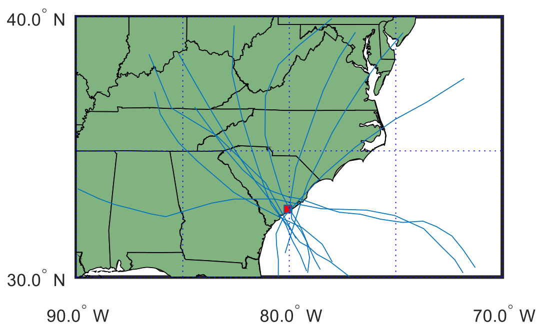

Figure 12: A site in Charleston, South Carolina and selected simulated hurricane tracks.

A tropical storm with its track more than 250 km away from a site typically does not produce significant level of wind speed (e.g. not more than 40 mph or 18m/s). To reduce computational time in calculating wind speeds, all storms that pass within 250 km from the site of interest were pre-selected. The Georgiou (1985) wind field model is used to compute the peak wind speed at the site of interest for each of the storms that come within 250 km of the site. A boundary layer model was used to convert the wind speed at the top of the boundary layer to the surface 10-m elevation 3-s gust.

Figure 13 shows the hurricane wind hazard curves of the site for the baseline and climate change models. Also shown in the figure is the US design wind speeds specified in ASCE 7-22 for various return periods at the site of interest (square markers). The peak wind speed versus mean recurrence interval (MRI) or return period curve of the baseline model matches the values of the ASCE 7-22 reasonably well. This serves as a confirmation of the validity of stochastic hurricane simulation program. The wind speed MRI curve of the RCP 4.5 2060 model is to the left of the baseline model. This means the future hurricane hazard is significantly higher than the current level.

For reference purpose, the peak wind speed of the most devastating hurricane that hit the region, the 1989 Hurricane Hugo, at the site was estimated at 120 mph (54 m/s) (3s gust, 10m elevation, open terrain). According to the wind hazard curve of the baseline model, the return period of Hurricane Hugo for the site is approximately 125 years. However, under the RCP 4.5 scenario, in year 2060, the Hurricane Hugo would be a 25-year return period storm.

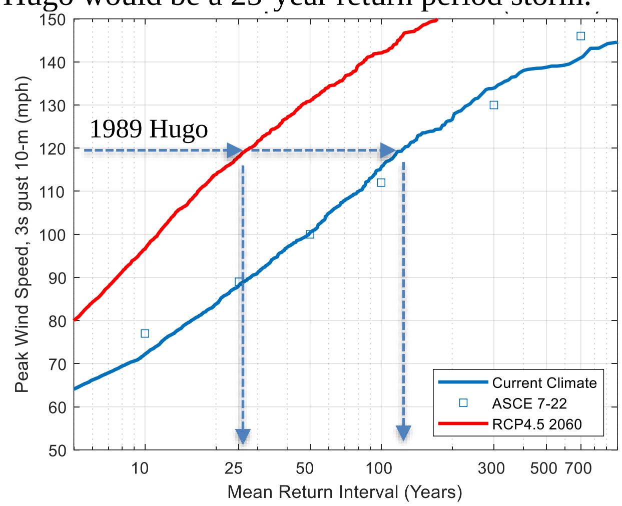

Figure 13: Peak wind speed (3s gust at 10m elevation, open terrain) versus mean recurrence interval for baseline model, RCP 4.5 year 2060, and ASCE 7-22 wind speeds (1mph = 0.447 m/s).

6. CONCLUDING REMARKS

This paper presents a new modeling approach to study the effects of climate change on hurricane genesis over the North Atlantic Ocean (NAO). The proposed method utilizes a probabilistic model for simulating the formation of hurricanes based on four climate variables (SST, RH, WS, and AT) and Coriolis effect. For modeling purposes, the NOA was divided into 5-deg x 5-deg grid cells and the annual spawn rate for each cell was computed from historical data. The daily SST, WS, RH, and AT recorded for all NAO storms from 1982 to 2021 were fit to Weibull, lognormal, Beta, and general extreme value probability distributions. The daily spawn probability of a tropical cyclone in each cell is assumed to be proportional to the cumulative joint probability of the four climate variables for which historical spawns were observed.

To explore the impact of climate change on hurricane genesis, two simulations were created: (1) a baseline model represent the current climate condition, and (2) a climate change model represents the IPCC RCP 4.5 scenario in the year 2060. It has been found that the annual storm frequency in year 2060 under the RCP 4.5 is higher than the current annual storm rate. Based on the RCP 4.5 scenario, the wind speeds along the coastal areas of the U.S. in year the 2060 are found to be significantly larger than the wind speeds specified in the current U.S. building code (ASCE 7-22). The presented climate genesis model is a preliminary model and the authors are working on further refinement to improve and validate this model.

7. REFERENCES

Bender, M. A., Knutson, T. R., Tuleya, R. E., Sirutis, J. J., Vecchi, G. A., Garner, S. T., and Held, I. M. (2010), Modeled impact of anthropogenic warming on the frequency of intense Atlantic hurricanes. Science, 327(5964) 454-458.

Blake, E. S. and Zelinsky, D. A. (2018). National Hurricane Center Tropical Cyclone Report: Hurricane Harvey, National Hurricane Center.

Fitzpatrick, P. J. (1997) Understanding and forecasting tropical cyclone intensity change with the typhoon intensity prediction scheme (TIPS), Weather and Forecasting, 12(4), 826-846.

Jarvinen, B. R., Neumann, C. J. and Davis, M. A. S. (1984). A tropical cyclone data tape for the North Atlantic Basin, 1886-1983: Contents, limitations, and uses, National Oceanic and Atmospheric Administration (NOAA) Technical Memorandum.

Jing, R. and Lin, N., (2020) An environment-dependent probabilistic tropical cyclone model, Journal of Advances in Modeling Earth Systems, 12(3) (2020).

Landsea, C., Franklin, J. and Beven, J. (2014) The revised Atlantic hurricane database (HURDAT2), https://www.aoml.noaa.gov/hrd/hurdat/newhurdat-format.pdf, Last accessed: March 14, 2022.

Lee, C. Y., Tippett, M. K., Sobel, A. H. and Camargo, S. J., (2018) An environmentally forced tropical cyclone hazard model, Journal of Advances in Modeling Earth Systems, 10(1) 223-241.

Liu, F, (2014). "Projections of Future US Design Wind Speeds Due to Climate Change for Estimating Hurricane Losses", PhD Dissertation, Clemson University, Clemson, South Carolina, USA. https://tigerprints.clemson.edu/all_dissertations/1305

Mann, M. E., and Emanuel, K. A., (2006). Atlantic hurricane trends linked to climate change, Eos, Transactions American Geophysical Union, 87(24) 233-241.

Tippett, M. K., Camargo, S. J. and Sobel, A. H. (2011) A Poisson regression index for tropical cyclone genesis and the role of large-scale vorticity in genesis, Journal of Climate, 24(9) 2335-2357.

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. and Twisdale, L. A. (2000). Simulation of hurricane risk in the US using empirical track model, Journal of Structural Engineering, 126(10) 1222-1237.

Villarini, G., Vecchi, G. A. and Smith, J. A., (2010), Modeling the dependence of tropical storm counts in the North Atlantic basin on climate indices, Monthly Weather Review, 138(7) 2681-2705.

Yonekura, E. and Hall, T. M., (2011) A statistical model of tropical cyclone tracks in the western North Pacific with ENSO-dependent cyclogenesis, Journal of Applied Meteorology and Climatology, 50(8) 1725-1739.

Zhang, X., Zhong, S., Wu, Z. and Li, Y. (2018) Seasonal prediction of the typhoon genesis frequency over the Western North Pacific with a Poisson regression model, Climate Dynamics, 51(11) 4585-4600.

Zhongming, Z., Linong, L., Xiaona, Y., Wangqiang, Z., and Wei, L., (2021) AR6 Climate change 2021: The physical science basis.