

Article

North Atlantic Hurricane Winds in Warmer than Normal Seas

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Abstract: Tropical cyclones devastate coastlines around the world. The United States and surrounding areas experienced catastrophic extreme events in recent hurricane seasons. Understanding extreme hurricanes and how they change in a warming ocean environment is of the utmost importance. This study makes use of the historical, positive relationship between average summer sea surface temperatures (SSTs) and maximum hurricane wind speeds across the North Atlantic Basin from 1854–2018. Geographically weighted regression shows how the relationship between hurricane winds and SSTs varies across space. Each localized slope is used to increase historical wind speeds to represent winds in a three-degree Celsius warmer-than-average sea surface. The winds are then used to estimate the maximum intensity of the thirty-year hurricane (one with a 3.3% annual probability of occurrence) across the hexagonal grid using extreme value statistics. Viewing the results spatially allows for geographic patterns to emerge in the overall risk of major hurricane occurrence in warm SST environments. This study showcases the difference in the historical extreme compared to the potential future extreme in the hopes to better inform those charged with making important, life-saving decisions along the U.S. and neighboring coasts.

Keywords: tropical cyclones; climate change; risk; spatial statistics

1. Introduction

Harrowing winds, torrential downpours, and rising storm surges are all characteristics of the extreme hurricane, the tropical tempest designed to transfer massive amounts of energy from our planet's equator to the poles. Millions of people around the globe feel the effect of these impressive phenomena as they barrel through oceanscapes, often striking land with fierce repercussions. In 2017 and 2018, only five events, i.e., Hurricanes Harvey, Irma, Maria, Florence, and Michael, took the souls of nearly 3500 people throughout the Caribbean Islands and the United States' Gulf and East coasts [1–4].

Hurricane Harvey ranks second only to Hurricane Katrina for the costliest hurricane to ever strike the United States, causing an estimated \$125 billion in damage [5]. Hurricanes Maria and Irma rank third and fifth in the list at \$90 and \$50 billion, respectively [5]. There are a wide variety of reasons why damage amounts are so high and why death tolls are so catastrophic, and one reason is because more people live in harm's way along the coasts, with over three times as many people living along coastlines compared to the global average [6]. Many of the fastest growing urban areas around the world are located on or near coastal zones [7,8], presenting a growing risk to and heightened costs from the adverse effects of extreme hurricanes. A notion plaguing the tropical cyclone research community offers another potential reason the costs are increasing: changing hurricane frequency and intensity.

Hurricane scientists around the world have been attempting to assess the frequency and intensity of hurricanes in a changing climate for over three decades [9–12]. The approaches to gain insight into this include empirical [13], numerical [14,15], and statistical [16,17], all having their rightful place in

the pursuit of understanding. The models show some disagreement due to varying approaches, but strong influences on the variability of hurricanes from multi-decadal and interannual forces, such as the Atlantic Multidecadal Oscillation [18] and the El Niño Southern Oscillation [19], are generally agreed upon. They show general agreement because the basic physics of hurricane development focuses on the importance of heat in the intensification of the system [20]. Many of these studies attempt to understand the impact of heat on extreme hurricanes.

Under some numerical simulations, the frequency of very intense tropical cyclones and storm-related precipitation are projected to increase in warmer sea surface temperatures (SSTs) [12]. In some statistical simulations, the frequency of tropical cyclones is expected to increase in the far North Atlantic, and the expected intensity for given time periods is expected to increase throughout the Basin with warmer SSTs [16]. Other studies show climate change has impacted the average and extreme rainfall amounts in recent events but did not impact the maximum sustained wind speed [21].

Hurricane risk estimates are prolific in the literature, also using a variety of calculation methods. Risk can be defined many ways, but here, it is defined as the statistical probability of something happening (i.e., a certain magnitude wind speed) in a given location. Simpson and Lawrence [22] offered one of the first return period calculations using an empirical approach, which has been utilized in papers since [23]. More sophisticated statistical approaches exist to calculate risk, including generalized Pareto probabilities [24] and quantile regression [25]. Some emphasize the importance in the spatial variability of hurricane risk and utilize methods appropriate to calculate changes across space, i.e., extreme value theory [26] and geographically weighted regression [16,17].

It is important to consider the geographic variability of climate change impacts to the average and extreme behavior of hurricanes because the risk of impact is not the same everywhere [16]. Focusing on individual events, or on the Basin as a whole, can be problematic when wondering how hurricanes will be impacted by climate change because we know the influences of climate change are also not ubiquitous [27]. The definition of an extreme hurricane is also highly variable and is dependent upon what locations are “used to” [28]. Each location along our coast or throughout the North Atlantic Basin has its “normal” extreme hurricane based on the local, historical climatology.

The purpose of this study is to compare the spatial variability of extreme hurricane risk in a world with ocean temperatures similar to the climatology (the mean) to a world where ocean surface temperatures are higher than the climatology. Said another way, it is meant to compare the historical “normal” extreme to the extreme expected in conditions warmer than “normal”. In our present climate, ocean temperatures are increasing [29]. Trenberth et al. [30] describe the role ocean heat content played in the development of the 2017 hurricane season, where the National Oceanic and Atmospheric Administration (NOAA) report the accumulated cyclone energy was 225% of the normal [30]. In this study, the expected maximum intensity of a hurricane along the U.S. Coast and throughout the North Atlantic Basin in an ocean environment with more available heat is provided using a combination of extreme value statistics and geographically weighted regression (GWR). The goal is to better understand future hurricane risk.

The Importance of Geography

Hurricanes are not the same everywhere. It is difficult for scientists to understand how every hurricane will change in a warming climate because every hurricane is unique in its formation, and every landfalling end point has a unique resiliency and adaptation strategy (and in some cases, the unique is the nonexistent). The geography of hurricane risk is important. When appropriately estimating the spatial variability in the risk of extreme hurricane winds, proper attention and resource allocation can be paid to those areas most at risk [16].

Ellis et al. [28] describe the importance of understanding the relative risk of tropical cyclones in a given spot. Every location analyzed has its own definition of an extreme hurricane based on the localized 50 year return level. Extreme hurricanes in the Northeastern USA, such as Boston or New York City, are high level Category 1 events on the Saffir–Simpson Hurricane Wind Scale (38.9 and

37.9 ms⁻¹, respectively), whereas extremes in places known for hurricanes, such as Miami, FL, and New Orleans, LA, are Category 4 and 3 events, respectively [28]. This difference in relative risk is important for societal preparedness [31] and for understanding how risk will change in an environment with oceans warmer than the historical average.

Hurricane Sandy was a post-tropical cyclone with wind speeds in the Category 1 range when it made landfall near Brigantine, New Jersey, on 29 October 2012 [32]. Hurricane Irma destroyed virtually all structures on the island of Barbuda when it made landfall as a Category 5 hurricane and made landfall six more times in various places landing, finally, near Marco Island, Florida, as a Category 3 event on 10 September 2017 [33]. Hurricane Maria was a raging Category 5 hurricane when it made landfall in Puerto Rico on 20 September 2017 [34]. Hurricane Harvey was a rapidly intensified Category 4 when it struck Houston on 25 August 2017 [1], and Hurricane Florence, a rapidly weakening Category 1 as it made landfall near Wrightsville Beach, NC, on 14 September 2018 [4]. This storm synopsis is provided to suggest the wind category of the storm is arguably irrelevant when related to the magnitude of damage in a given place. Category 1 events through Category 5 events all have the capacity to destroy locations, kill people, and cause irreparable damages. In all reports, similar statements are made regarding the rarity of these events in the given locations. A Category 1 hurricane to the New Jersey coast is not dissimilar from the Category 4 in Houston or the Category 3 in Florida. The risk often boils down to this: what are the locations most familiar with and, thus, what have they been preparing for? The preparation for the “normal” in the past may not be enough for the “normal” in the future.

2. Materials and Methods

2.1. The Data

Estimating the climatological, or “normal”, conditions of the North Atlantic is a necessary first step to describing the difference in a warmer world. All analyses use two data sources. The National Hurricane Center’s Best Track HURDAT2 data set [35] and NOAA’s Extended Reconstructed Sea Surface Temperature (ERSST) V5. HURDAT2 includes the six-hourly information on the location and maximum winds of all known tropical cyclones in the North Atlantic from 1851–2018. The six-hourly values are spline interpolated to hourly-values to increase the resolution of the data [36]. Only hurricanes (maximum sustained 10 meter, 1-minute averaged winds ≥ 33 ms⁻¹) are considered for this study. The data are available at <https://www.nhc.noaa.gov/data/?#hurdat>. There are known problems with the HURDAT2 data, including observational bias post-satellite era. It is likely more extreme hurricanes were missed in earlier parts of the record [37], suggesting intensity estimates for extreme hurricanes prior to the satellite era are likely unreliable. However, reanalyses to these data have been underway for the last few decades (e.g., [38]) to assess necessary changes to the earlier parts of the record. At present, HURDAT2 is the best approximation of known hurricane data in the North Atlantic back to 1851 and should not be discounted due to likely inconsistencies, particularly where extreme hurricanes are concerned, as these are the events causing the largest losses of life and money.

The NOAA ERSST V5 data are the newest version of ERSST data and are available as monthly SST averages from 1854 to the present. The data are on a $2 \times 2^\circ$ grid with spatial completeness enhanced with statistical methods. The SSTs are derived from the latest International Comprehensive Ocean-Atmosphere Data Set 3.0, with additional supplementary data sources enhancing resolution. The NOAA ERSST V5 data are provided by the NOAA/OAR/ESRL PSD, in Boulder, CO, USA, from their website at <https://www.esrl.noaa.gov/psd/data/gridded/data.noaa.ersst.v5.html>.

North Atlantic hurricane climatology is described in a wide variety of articles [39–42]. Figure 1 displays all hurricane events included for analysis color coded by levels of the Saffir–Simpson Scale.

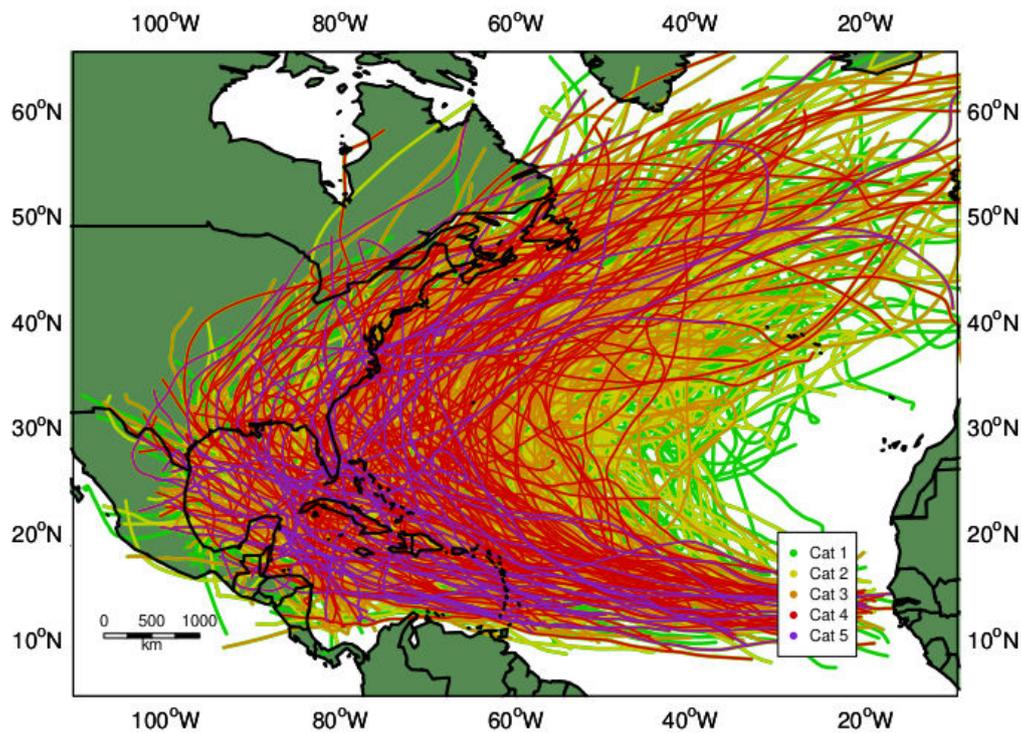


Figure 1. North Atlantic Hurricane Tracks from 1854–2018. Hurricanes are color coded by Saffir–Simpson Category at maximum sustained wind intensity. Category 1, $33\text{--}42\text{ ms}^{-1}$, green. Category 2, $43\text{--}49\text{ ms}^{-1}$, yellow. Category 3, $50\text{--}58\text{ ms}^{-1}$, orange. Category 4, $59\text{--}69\text{ ms}^{-1}$, red. Category 5, $\geq 70\text{ ms}^{-1}$, purple. Category 5 events are rare and geographically limited, while Category 1 events are common and ubiquitous throughout the Basin.

All results in this study are displayed using a hexagonal tessellation because hexagons are a geometric representation of a circle (similar to the shape of a hurricane), and hurricane characteristics and risk have been successfully shown using them in the past [16,17,43]. Each of the 36 hexagons has an area of $626,147\text{ km}^2$, which is a little less than the size of Texas. This size is chosen to ensure a large enough sample of maximum sustained winds (i.e., $n \geq 30$), while having it small enough to allow for any patterns in geographic variability to emerge.

Figure 2a shows the number of hurricane events per equal-area hexagon overlaid on a map of the North Atlantic Ocean Basin, and Figure 2b shows the number of major hurricanes (maximum sustained wind speeds $\geq 50\text{ ms}^{-1}$). The maximum number of 220 wind speed events is off the coast of the Carolinas in the open Atlantic, likely due to the recurving nature of hurricanes as they interact with the Bermuda High. Everywhere along the United States coastline, the countries of Central America, and the Caribbean, have all been frequented by hurricanes in the past and will continue to receive them into the future. Major hurricanes are experienced almost everywhere except the far eastern extent of the Basin. The maximum frequency of major hurricanes shifts to the south toward the Florida peninsula compared to all hurricane events. The concern over the warming ocean environment questions the changing frequency and intensity of future major, or extreme, hurricanes.

Figure 3a shows the mean observed wind speed per hexagon, and Figure 3b shows the maximum observed wind speed. The mean, or average, of the climate is a good representation of the “normal” type of hurricane a location can expect to experience within the hexagonal region, or what the people living in the locations are likely most used to because they experience those conditions more often than others. Figure 3a is the “normal” hurricane expectation (i.e., the climatological mean), where Figure 3b is the extreme (i.e., the climatological maximum). Historically, the most extreme wind speeds throughout the Basin are experienced in the Gulf of Mexico, Caribbean Sea, and in the North

Atlantic approaching the Florida Straits. Both graphics utilize the same color scale to showcase the incredible difference between the average and the maximum, highlighting the importance for a model to utilize an approach useful for estimating the risk of extreme behavior of hurricanes and not the climatological average.

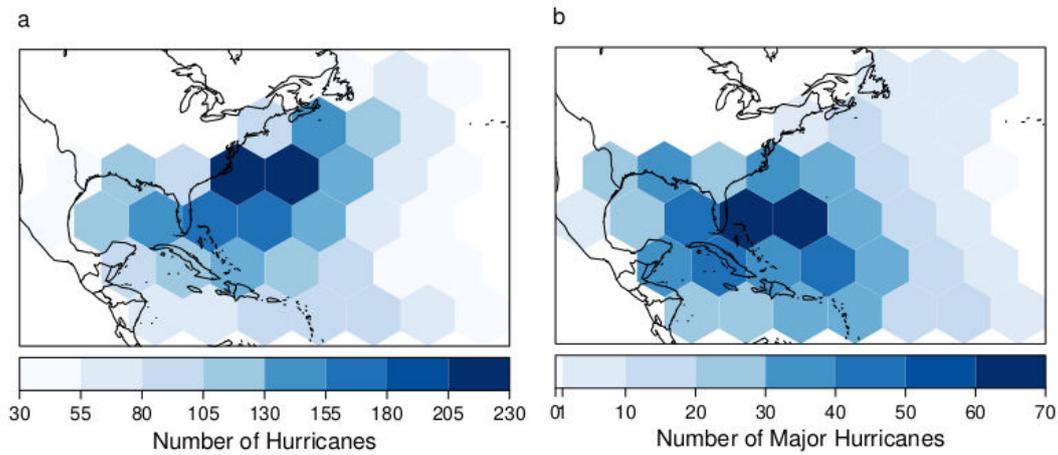


Figure 2. (a) Number of hurricanes with winds $\geq 33 \text{ ms}^{-1}$ in equal-area hexagons from 1854–2018. (b) Number of major hurricanes with winds $\geq 50 \text{ ms}^{-1}$.

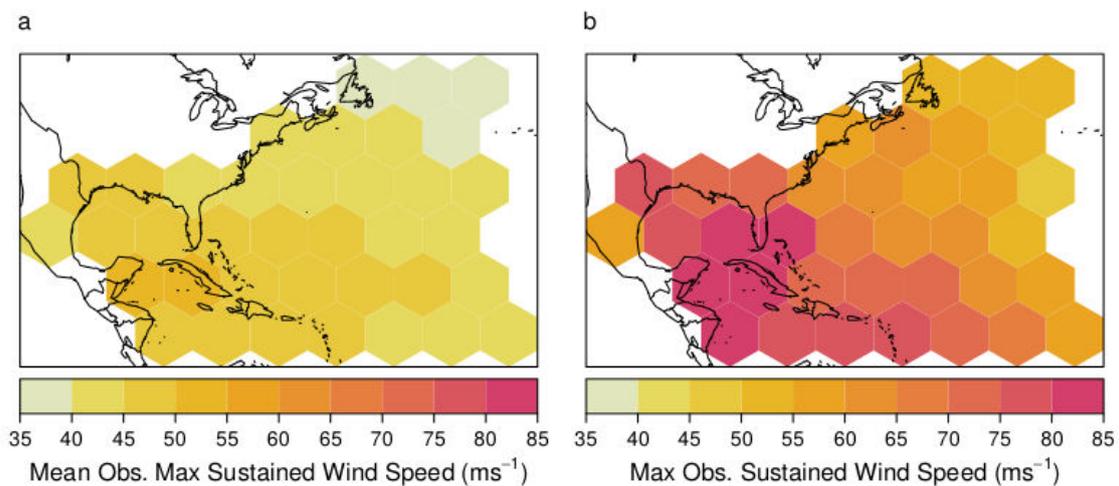


Figure 3. (a) Mean observed maximum sustained wind speeds per hexagon in ms^{-1} . (b) Maximum observed sustained wind speeds per hexagon in ms^{-1} . Note the identical scale between the graphics.

The maximum potential intensity equation offered by Emanuel [9,20,44] and further expanded upon in the decades since suggests, all else being equal, a hurricane thrives in an environment with greater surface ocean temperature. One accepted theory describing the formation of hurricanes is similar to the Carnot heat engine; more energy in = more energy out [20]. Theoretically, more energy available at the surface of the ocean allows for easier evaporation, higher water vapor content, and more convective potential within the developing system, and some have argued SST provides an upper boundary of intensity of a tropical cyclone, but it is not, alone, enough to estimate the maximum intensity of a hurricane [45]. A large number of variables play a role in whether a hurricane will actually form in an environment of high ocean heat. At varying levels of the atmosphere, these include, but are not limited to, vertical wind shear, relative/specific humidity, air temperature near the tropopause, vorticity, and divergence aloft. An additional oceanic variable is the amount of available energy in the upper portion of the ocean, known as upper ocean heat content. Trenberth et al. [30] found record high ocean heat content levels present during the life cycle of Hurricane Harvey in 2017,

which led to exacerbated rainfall and rapid intensification. In this study, these additional variables are largely ignored, purposefully, in an attempt to highlight the importance of higher ocean surface heat in the geographic variability of hurricane risk. The model assumes these characteristics are not changing in response to changing ocean heat.

Figure 4 shows the difference between the mean August–October SST in degrees Celcius and the maximum value experienced in those months throughout the duration of the record. This time period is chosen because it represents the part of the year with the most energy available for hurricane intensification [16]. In all locations in the Gulf of Mexico and Caribbean Sea, the maximum SST experienced is higher than the average, and in some places by as much as 6 degrees Celsius. Models utilizing average conditions, like those in Trepanier [16], offer conservative estimates of the sensitivity of extreme hurricanes to SST. The areas of greatest increase between the maximum and the average are nearest to the coastline, which exacerbates the potential threat of extreme hurricanes to coastal citizens. The increased temperature from the average most certainly plays a role on the intensification of hurricanes [30], and if the higher heat is available near the coast, it could lead to rapid intensification.

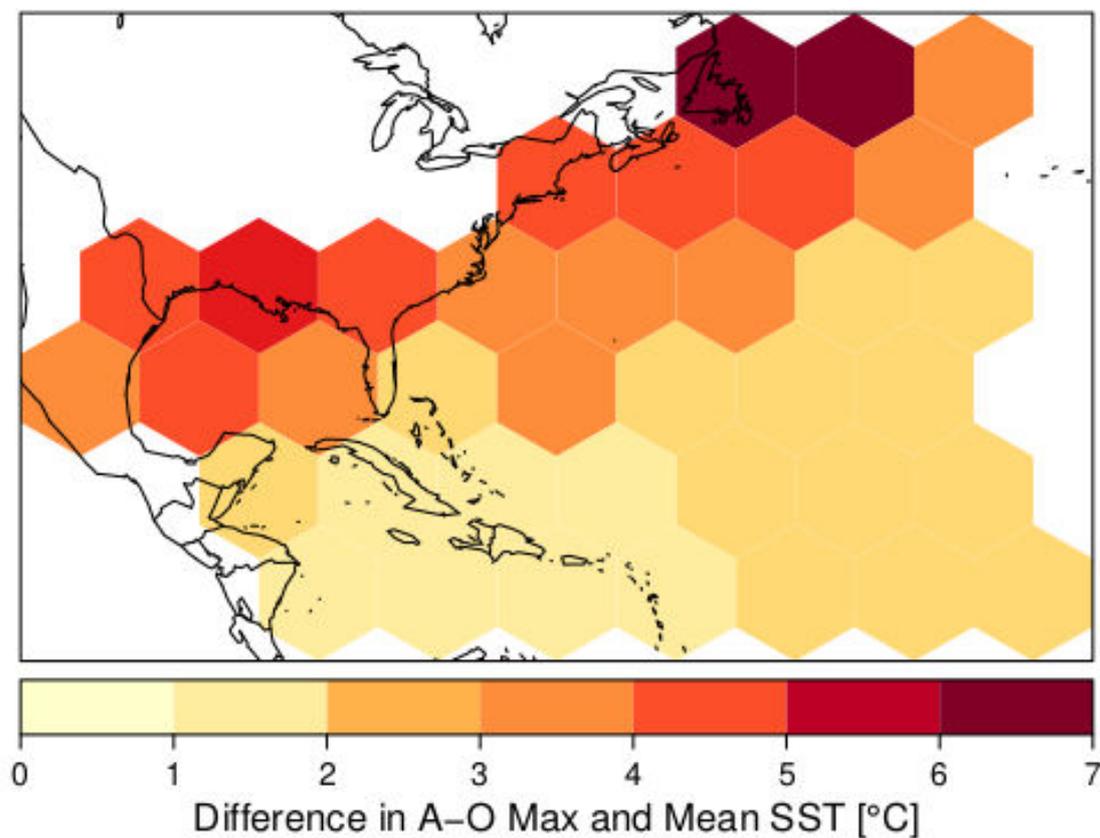


Figure 4. Difference between mean August–October sea surface temperatures (SST) ($^{\circ}\text{C}$) and maximum August–October SST ($^{\circ}\text{C}$).

2.2. Calculating the Expected Extreme

A wide variety of hurricane return frequency estimation methods are present in the literature. The empirical approach finds how many events exist in a given time period [23], the numerical approach creates simulations based on physical and mathematical relationships between variables [46], and the statistical approach utilizing extreme value theory focuses in on the rarest of events and uses extrapolation methods to estimate how often the most intense hurricane will come [24,26,47,48]. The average, or “normal”, event is more easily estimated due to its prolific occurrence in a given spot. The maximum, or most extreme, hurricane is difficult to statistically estimate because the sample size in

any given location is often very low. Extreme value analysis is helpful with this problem as it requires an estimation of a wind speed greater than what has been observed and provides a framework for this extrapolation [49].

Probabilistic extreme value theory deals with the stochastic behavior of the maximum and the minimum of independent and identically distributed random variables [50]. Distributional properties of extremes, as well as of exceedances over specified thresholds are determined by the upper tails of the underlying distribution [51]. Three extreme limit distributions exist [52]. Extreme value distributions are typically broken into three families: Type 1 (Gumbel-type distribution) has an infinite upper tail (though not as high as the Fréchet distribution), Type 2 (Fréchet-type distribution) has a higher infinite upper tail, and Type 3 (Weibull-type distribution) has a finite upper tail [51]. According to Coles [49], the families can be combined into a single family known as the generalized extreme value (GEV) distribution. The model has three parameters, a location parameter μ , a scale parameter σ , and a shape parameter ξ . A major limitation to the GEV distribution is it restricts the data to annual maxima only, and it may ignore data that could be potentially useful in describing the extreme tail behavior [53]. Models based on a threshold approach were developed as a response to this limitation. When an entire time series of data are available, modeling exceedances over a threshold results in a better use of the data [49]. This is known as the generalized Pareto distribution (GPD) model and is used here.

Following Trepanier [16] and Trepanier and Scheitlin [50], wind speed exceedances (i.e., wind speeds over a given threshold u) $W - u$ are modeled as samples from a GPD, so that for an individual hurricane with maximum wind W ,

$$\begin{aligned} \Pr(W > v | W > u) &= \left(1 + \frac{\xi}{\sigma}[v - u]\right)^{-1/\xi} \\ &= \text{GPD}(v - u | \sigma, \xi) \end{aligned} \tag{1}$$

where $\sigma > 0$ and $\sigma + \xi(v - u) \geq 0$. The frequency of storms with intensity reaching at least u follows a Poisson distribution [40] with a threshold crossing rate, λ_u . Thus, the number of hurricanes per year with winds exceeding v is a thinned Poisson process with mean $\lambda_v = \lambda_u \Pr(W > v | W > u)$. This is the peaks-over-threshold (POT) method. That is, to estimate the return period for a given return level, values below a certain threshold are removed before analysis so as to not bias the results toward the mean [49,53]. The estimated model is characterized for a given u by σ , ξ , and λ_u .

The return period for any v has an exponential distribution with mean $r(v) = 1/\lambda_v$ since the number of storms exceeding any wind speed v is a Poisson process. By substituting for λ_v in terms of both λ_u and the GPD parameters then solving for v as a function of r the corresponding return level for a given return period can be estimated as

$$\text{rl}(r) = u + \frac{\sigma}{\xi} \left[(r \cdot \lambda_u)^\xi - 1 \right]. \tag{2}$$

For a more complete description of the statistical theory supporting this model please refer to Kotz and Nadarajah [51] and Coles [49], and for more applications of this theory with hurricane data using hexagonal tessellations see Trepanier [16] and Trepanier et al. [17].

2.3. Relationship to SST

The relationship between extreme hurricane winds and SST is not geographically ubiquitous [16]. SST significantly effects the σ parameter, or the type of wind speeds a given location will likely experience, as well as significantly effecting the estimated 30-year return level (i.e., the expected maximum intensity of a hurricane, on average, every 30 years, or an event with a 3.3% annual probability of occurring). The effect of SST is most noted in the Caribbean Sea (σ) and in the Gulf of Mexico (the 30-year return level) [16]. Estimating the variability in the sensitivity of hurricane wind speeds to SST is done with GWR.

GWR allows the relationship between two variables to vary across the study area [54,55]. It is easier to identify where the explanatory variable (SST) contributes the strongest to a change in the response variable (extreme hurricane winds). The relationship between the response (y) and the explanatory (x) can be expressed mathematically as

$$y = X\beta(g) + \epsilon \quad (3)$$

where g is your set of geographic coordinates, here the set of hexagons.

$\hat{\beta}(g) = (X^T W X)^{-1} X^T W y$ where W is a weights matrix given by $W = \exp\frac{-D^2}{h^2}$ where D is a matrix of pairwise distances between the hexagons, and h is the bandwidth [55]. The weights matrix is proportional to the influence a hexagon j has on its neighboring hexagons i in determining the localized relationship between x and y . Weights are determined using the bisquare scheme. The bandwidth controls the amount of smoothing. The procedure for choosing the bandwidth is an iterative optimization procedure where improvements are made to the bandwidth choice based on previous bandwidth values. It is considered the cross-validation bandwidth [36,56].

3. Results

The model provides an estimate of how often any magnitude hurricane will occur in a given location. The extreme value model is estimated at each of the 36 hexagons throughout the Basin. The threshold u in the extreme value model is set at the 50th percentile of the wind speed distribution in each hexagon. When the threshold is at this level, it allows for each geographic location to describe its own unique hurricane risk, while still providing enough data values for the model to be robust. Any higher than the 50th percentile, and many locations, particularly in the northern ocean, end with sample sizes too small to fit the model. This type of estimation is conducted in Trepanier [16]. Figure 5 shows the historical 50th percentile threshold choice in a model using HURDAT2. One location over the Greater Antilles Islands stands out at nearing Category 3 intensity for the median value, while the majority of locations in the main development region are in the Category 2 range. Locations on the eastern seaboard expect high level Category 1 events. This graphic suggests the extreme behavior of hurricanes is geographically dependent.

One concern within the scientific community focuses on what maximum wind speeds will look like in future extreme events. To maintain this focus, observed per-event maximum wind speeds are chosen to represent this value in each hexagon for the model. This allows for the relative risk of hurricanes to be represented while also considering the geographically varying influence of SST. The strength of SSTs explanatory power of maximum wind speeds in a hurricane is offered by the R^2 value from the model. The values range from 0.46 (46% variability explained) near land to 0.79 in the open Atlantic. The closer to land, the more varying influences can impact the maximum wind (e.g., land interaction, local changes in SST, rapidly changing wind shear).

The strength of the local relationship between the observed per event maximum wind intensity and the average (“normal”) August–October SST is shown in Figure 6a, and the significance of the relationship is shown in Figure 6b. Local significance is estimated by dividing the coefficient value by its standard error (the t -value). Regions where $t \geq 2$ show statistically significant relationships between the variables. Only in the far North Atlantic do areas show insignificant relationships between the variables. Residuals of the model were tested for normality using the Shapiro Wilk’s Test, and the model proves to be an adequate representation of the relationship.

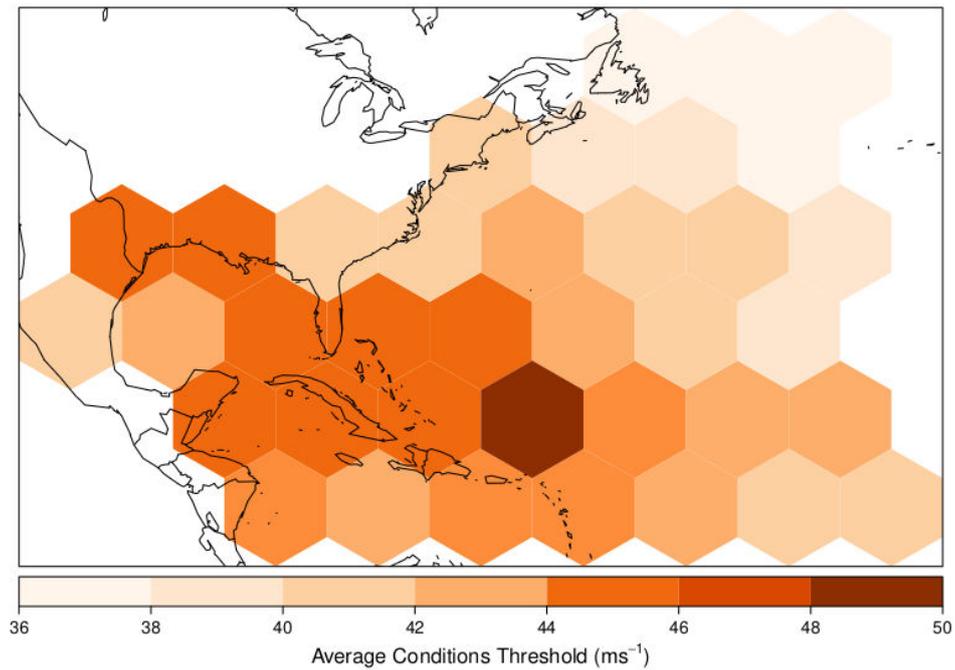


Figure 5. The historical 50th percentile wind speed used as the extreme value model threshold in ms^{-1} .

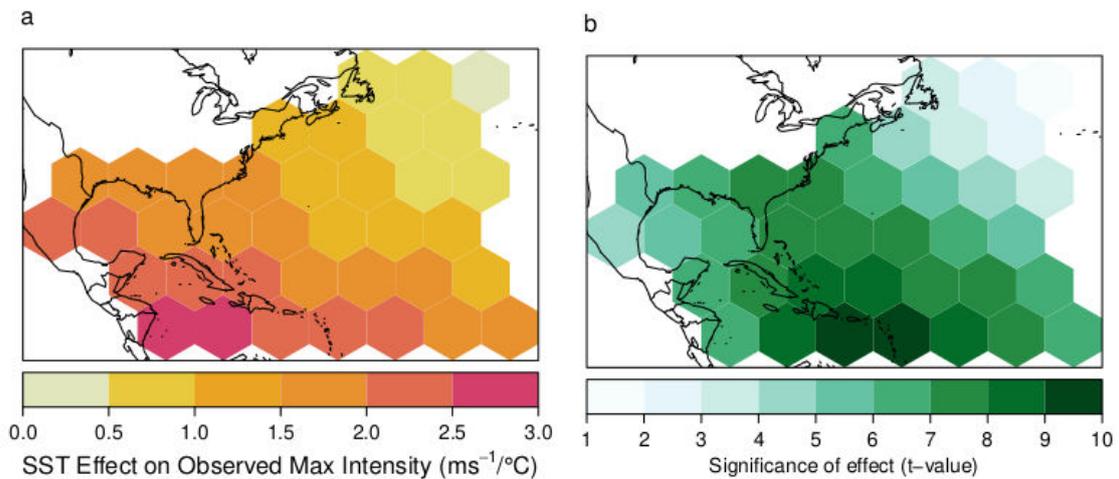


Figure 6. (a) Strength of the local relationship between the observed per event maximum wind intensity and the average (“normal”) August–October SST in $^{\circ}\text{C}$. (b) Significance of the relationship.

The range of sensitivity varies from a 0.5 ms^{-1} increase per $^{\circ}\text{C}$ in the far North Atlantic and over Mexico, to a 2.5 ms^{-1} increase per $^{\circ}\text{C}$ in the southwestern Caribbean Sea. This means, all else being equal, that an increase of three degrees Celsius in SST compared to the average conditions used in the model would equate to an increase in your maximum hurricane winds of 7.5 ms^{-1} in parts of the Caribbean. This increases the category, and thus, expected damages of the system.

This relationship leads to this question, what do the new return frequencies look like in a world with warmer sea surfaces? One could simply increase the winds by the local slope. However, a more sophisticated technique would be to utilize the extreme value analysis as the definition of extreme (50th percentile wind speeds) will change in each location based on the new distribution of wind speeds, but the societal expectation of wind speeds is still based on the historical experience. The extreme value approach can offer return frequency estimates for higher winds to better prepare for the future expectation.

The individual per-hexagon slopes representing the relationship between wind and SST are used to calculate wind speed changes in an SST environment with three-degree Celsius increases from the average. One and two degree increases are also estimated but are not included here, for brevity purposes. The expected increases in a three-degree warmer environment scale down to one and two degree increases with this model so increases at this level can be inferred from Figure 6a. The difference between the maximum and average is offered in Figure 4. As an example, if the slope of the relationship suggests a two ms^{-1} increase in wind for every one degree Celsius SST increase, then a three-degree SST increase would equate to winds being six ms^{-1} higher than the historical record.

Three-degree increases are not unprecedented. SSTs have been higher than average during the past three decades than at any other time since 1880 and are continuing to rise [57]. Trepanier [16] show the variable most sensitive to changes in SST is the ξ parameter, representing the extreme tail behavior of the hurricane wind distribution in a given spot. This means the wind intensity of the event is most affected by changing SSTs compared to, say, frequency of the events. Alexander et al. [58] used global climate models to assess the mean, variability, and extreme SSTs in the northern oceans and found annual SST trends are all positive ranging, with a general shift in the mean, suggesting that many SSTs of the future will always be warmer than the warmest years from 1976–2005. Using a three degree increase to SSTs locally compared to the average is a conservative estimate of SST increases in the future.

These changed wind speeds are then used to estimate the thirty-year return level of a hurricane in the warmed sea environment. Thirty years is chosen because it represents the typical homeowner's mortgage duration. It is a short enough period of time when people would be present to experience an extreme, while not being so short that the expected return level is not indicative of the extreme in a location. The model is calculated using the historical threshold, as this is what the local populations are most familiar with. The intent is to model the new wind speeds over the historical threshold to maintain the "normal" expectation.

The extreme value approach is used on the observed wind data and the simulated wind data in warmer SSTs (Figure 7a,b, respectively), and the difference between the two in Figure 7c. The tracks of the 2017 Hurricanes Maria, Irma, and Harvey and 2018 Hurricane Michael are superimposed on the last figure with wind speeds color coded by the Saffir–Simpson Scale.

In Figure 7a, the average return level is shown. This is the return level we would expect once, on average, every thirty years (or a 3.3% annual chance), if we consider the historical climatology of SSTs and hurricane wind speeds in the Basin. Upper-level Category 4 hurricanes are expected throughout the Caribbean Islands, near the Florida Peninsula, and near the Yucatan Peninsula in these historical conditions.

Figure 7b shows the expected return level for the same time period and using the same graphic scale in an environment with all else being equal and SSTs being three degrees warmer than the climatological average. In these warmer conditions (which are very similar to the SST conditions present in the 2017 hurricane season), wind speeds reaching Category 5 intensity are expected throughout the Caribbean, over all major islands, over Florida, and Louisiana. Category 4 wind speeds now cover north Florida (evidenced in reality by Hurricane Michael in 2018), spread throughout the main development region and up the eastern coast of the United States. Category 3 winds are now experienced much farther north than previously experienced.

Figure 7c shows the areas with the largest differences in return level. Areas in the main development region, Gulf of Mexico, and near Florida have increases from 1 up to 8 ms^{-1} . This means the locations with the highest populated areas can expect even more devastating wind speeds than historically typical in years where SSTs are warmer than the climatological average and the remaining atmospheric conditions are conducive to formation. Hurricanes Harvey, Irma, Maria, and Michael are shown with Category depiction to show the relationship between these high wind speeds and the new return levels in warmer than normal seas. A Wilcoxon t-test suggests a significant

statistical difference between population means of the historic return level and the return level in warmer than normal SST conditions.

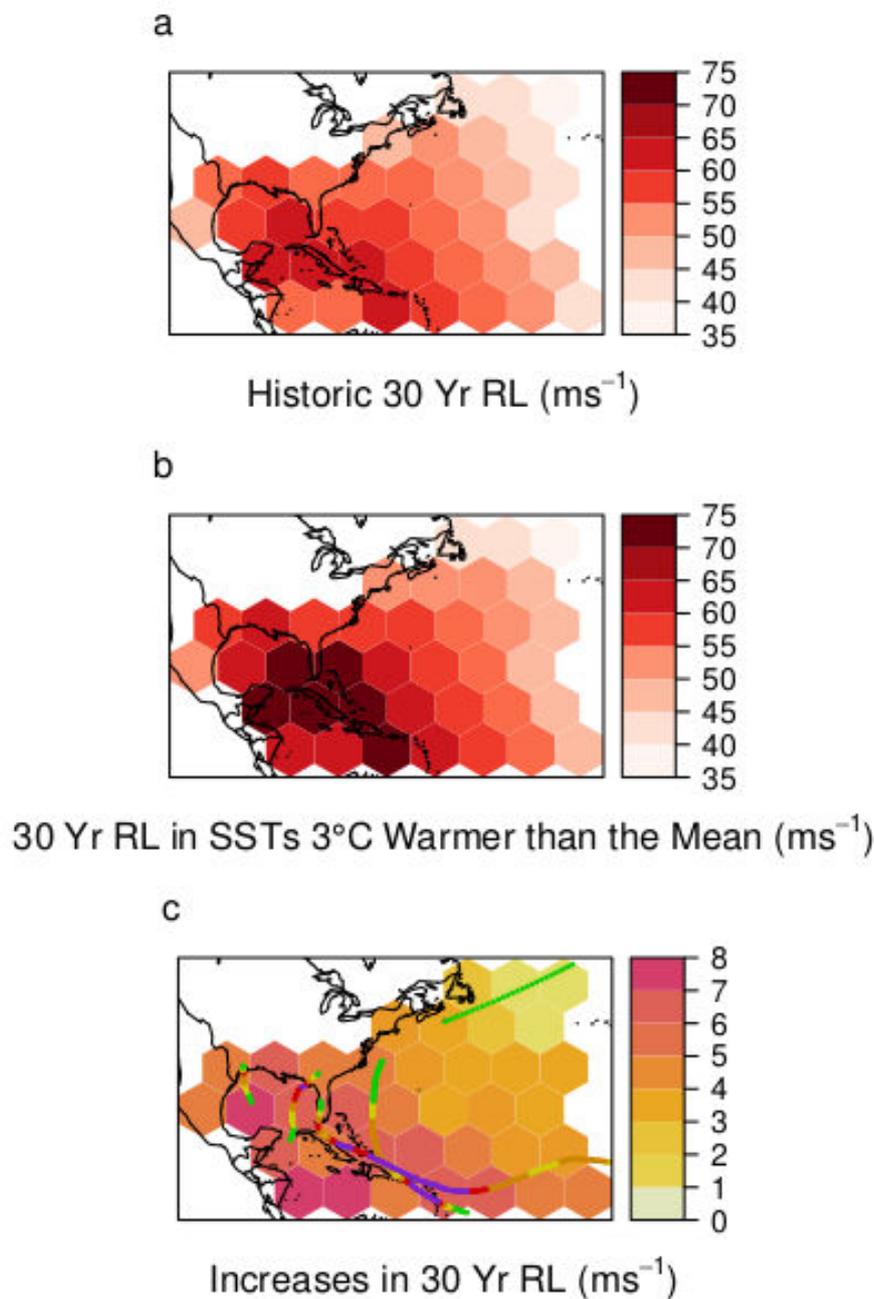


Figure 7. (a) The calculated return level (in ms^{-1}) for 30 years or 3.3% annual probability of occurrence using historic data and the average relationship between maximum wind and SSTs. (b) The calculated return level for 30 years using the increased maximum wind speeds based on local sensitivity to SST. (c) The difference between historic and future return levels. Tracks from Hurricanes Harvey, Irma, and Maria from 2017 and Hurricane Michael from 2018 are included and color coded based on the Saffir–Simpson Wind Scale described in Figure 1.

4. Discussion and Concluding Remarks

The Where Matters

Extreme hurricane winds are changing. This is evidenced in the most recent hurricane seasons and is supported by the geographic and statistical approach offered in this study. Each hexagon

represents the location's individualized extreme wind event in warmer than normal seas based on the local relationship with SSTs. The geographic variability in hurricane wind risk is evident.

The official Category of the hurricane does not matter. A Category 1 to a place that normally never experiences hurricanes can be just as detrimental as the Category 5 in a place that receives hurricanes often. Hurricanes Sandy, Irma, Maria, Harvey, and most recently, Florence and Michael are proof of this. All of these events were ranging in characteristics, categories, and landfall locations, and all caused incredible damages in each place. The relative risk of a hurricane is dependent upon the location's historical climatology and overall preparedness.

This study aims to support the idea that past hurricane climatology will not be the same as future hurricane climatology. Future hurricanes will have more extreme wind speeds when the heat content of the ocean's surface is higher, and the other variables are conducive to formation. Currently, SSTs are showing no signs of decreasing anywhere but in the far extreme North Atlantic (likely due to glacial melting) [57]. All else being equal, future hurricanes will have higher wind speeds, and thus, higher Categories than what each location has historically experienced. This is supported by numerical modeling approaches, where frequency, intensity, and intensification all shift to higher values under future increases in SST anomalies [46].

The impacts of this result on emergency preparedness are immense. Hurricane Sandy proved that New Jersey and surrounding locations were underprepared, even when the threat had been made apparent by research scientists in the year before [59,60]. Hurricane Michael made landfall in a location along the north Florida coastline as a Category 5 system and was the strongest system ever experienced in this location [61]. This rarity led to a general under-preparedness, and 1584 of the 1692 buildings in Mexico Beach, Florida, were destroyed. One might argue it is impossible to prepare for a Hurricane Michael or Maria. Quite unfortunately, the research here suggests hurricanes in warmer sea environments will be closer to these extremes than throughout the historical climatology, as evidenced in the higher return levels over the same time period. It is of the utmost importance emergency officials consider the anticipated changes to the "normal" extreme in the locations for which they are responsible for preparing.

In order for the results of this paper to be applicable, SSTs must be warmer than the historical average. While this has been the case for the last three decades [57], in future years with anomalously cool SSTs, the maximum intensity of the hurricane should be lower than expected. There are major climatological mechanisms controlling the status of SSTs in the North Atlantic. The El Niño Southern Oscillation (ENSO) can be characterized by SST anomalies, suggesting large scale influence on SSTs by ENSO [18]. Multidecadal changes in intense North Atlantic hurricane formation have been attributed to changes in the Atlantic SST structure (the Atlantic Multidecadal Oscillation) [62]. These influencing factors are not considered here as possible forcings leading to changing SSTs. SSTs are simply made warmer due to the recent observed high values of SSTs throughout the main development region and not because of large-scale oscillation patterns.

Emanuel [63] states hurricane potential intensity, low-level vorticity, and vertical wind shear strongly covary and are highly correlated with SST, particularly in the period where reanalysis data are most reliable. Vecchi et al. [64] show the different expected trends in absolute versus relative SST and discuss the resultant influence on Atlantic hurricane activity. Relative SST, at this point, did not yet have a distinct difference from natural climate variability, and thus, was not expected to influence localized hurricane intensity differently in the future than it had in the past. However, a recent study suggests warming in SSTs is typically underestimated in reconstruction data sets (including the one utilized in this study) when compared to instrumental records (e.g., buoys) [65], suggesting that studies relying on these data sets are typically under-representing the level of actual warming occurring in the oceans. Thus, this study is necessary because localized increases in SST exist throughout hurricane prone regions, and, when other conditions are conducive, will lead to increases in power availability within the hurricane and will increase the risk of extreme hurricane behavior locally.

SST warming is not discussed as being caused by anything specific. Research exists suggesting anthropogenic influences are the cause [21] by considering pre and post industrial era tropical cyclones. The purpose of this study is not to point a finger at human activity, but instead, to showcase the necessity of accepting a warming SST climate and its influence on tropical cyclone intensity. Every location in the North Atlantic and Gulf of Mexico will feel increased hurricane wind intensity when warm seas are present and a hurricane is capable of forming (i.e., other conditions are conducive). Emergency officials in each location along the United States Gulf and Eastern seaboard need to educate, plan, and prepare for an increasingly windy future.

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Abbreviations

The following abbreviations are used in this manuscript:

ENSO	El Niño Southern Oscillation
GPD	Generalized Pareto Distribution
GWR	Geographically Weighted Regression
NOAA	National Oceanic and Atmospheric Administration
SST	Sea Surface Temperature

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