

Sensitivity of limiting hurricane intensity to ocean warmth

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[1] The strongest hurricanes are getting stronger as the oceans heat up especially over the North Atlantic. Sensitivity of hurricane intensity to ocean heating is an important variable for understanding what hurricanes might be like in the future, but reliable estimates are not possible with short time-series records. Studies using paired values of intensity and sea-surface temperature (SST) are also limited because most pairs represent hurricanes in an environment less than thermodynamically optimal. Here we overcome these limitations using spatial grids and a model for the limiting hurricane intensity by region and estimate the sensitivity to be $7.9 \pm 1.19 \text{ m s}^{-1} \text{ K}^{-1}$ (s.e.) for hurricanes over seas hotter than 25°C across the North Atlantic. Results indicate the potential for stronger hurricanes during the 21st century as oceans continue to warm over this part of the world. **Citation:** Elsner, J. B., J. C. Trepanier, S. E. Strazzo, and T. H. Jagger (2012), Sensitivity of limiting hurricane intensity to ocean warmth, *Geophys. Res. Lett.*, 39, L17702, doi:10.1029/2012GL053002.

1. Introduction

[2] Tropical cyclones can have devastating human and economic impacts making accurate assessments of future changes of considerable value. Estimates of the sensitivity of hurricane intensity to ocean heat are needed to better understand how fierce hurricanes might become in the future. Maximum intensities are increasing especially over the warming Atlantic, but reliable estimates of sensitivity are not possible with time-series data. Sensitivity estimates for the most intense hurricanes are made using quantile regression [Elsner *et al.*, 2008], but the variation of SST over time is rather small making it difficult to get a precise value using only the past few decades. Studies using paired values of intensity and SST [Evans, 1993; DeMaria and Kaplan, 1994; Emanuel, 2000, 2007] are also limited since most pairs represent hurricanes in an environment less than thermodynamically optimal. Here we overcome these limitations by using a spatial tessellation of the hurricane data and a statistical model for the limiting intensity to obtain robust

estimates of the sensitivity of hurricane intensity to sea-surface temperature (SST).

2. Spatial Tessellation

[3] We use hexagons to tessellate the North Atlantic where hurricanes occur [Elsner *et al.*, 2012]. The hexagons are constructed in two steps. First the set of hurricane (33 m s^{-1} or stronger) locations (tenths of a degree latitude/longitude) are projected onto a Lambert conformal conic projection (true at 30°N and 60°N and centered at 60°W) planar coordinate system. For each hurricane the raw best-track estimates are six hours apart so we interpolate them to one hour intervals using splines and spherical geometry. Details of the procedure including R code for the interpolation are given in Elsner and Jagger [2012].

[4] Next a rectangular domain encompassing the set of hurricane locations is gridded into equal-area hexagons. The area of each hexagon is a compromise between large enough to have a sufficient number of hurricanes passing through to reliably estimate model parameters and small enough that regional variations are meaningful. Here we use an area of 428.5 thousand square kilometers (slightly larger than the state of California). We then count the number of hurricanes and determine the highest per hurricane intensity in each hexagon. We remove hexagons having fewer than 15 hurricanes and average the August–October SST over the period 1981–2010 in the remaining hexagons. The SST values are NOAA’s extended reconstructed version 3b data set for the North Atlantic Ocean. The data are provided by the NOAA/OAR/ESRL PSD in Boulder, CO, USA.

3. Frequency and Intensity

[5] Figure 1a shows the spatial tessellation of the North Atlantic and the color shading indicates the number of hurricanes in each hexagon over the period 1981–2010. We only consider grids having at least 15 hurricanes (at least one hurricane every other year on average). Figure 1b shows the highest hurricane intensity within each of the 24 hexagon grids. Intensity is given by the maximum sustained near-surface wind speed estimated within the hurricane eyewall less 60% of the forward speed [Emanuel *et al.*, 2006]. We restrict our analysis to the North Atlantic using the period 1981–2010 because data records over this region and time are most reliably consistent. Areas across the central Atlantic have the highest number of hurricanes, while areas farther south especially the Caribbean and Gulf of Mexico have seen the strongest hurricanes.

[6] As two examples we show histograms of the highest per hurricane intensity for grids labeled c and d in Figures 1c and 1d. The bar width is 5 m s^{-1} and the range is 25 to 75 m s^{-1} .

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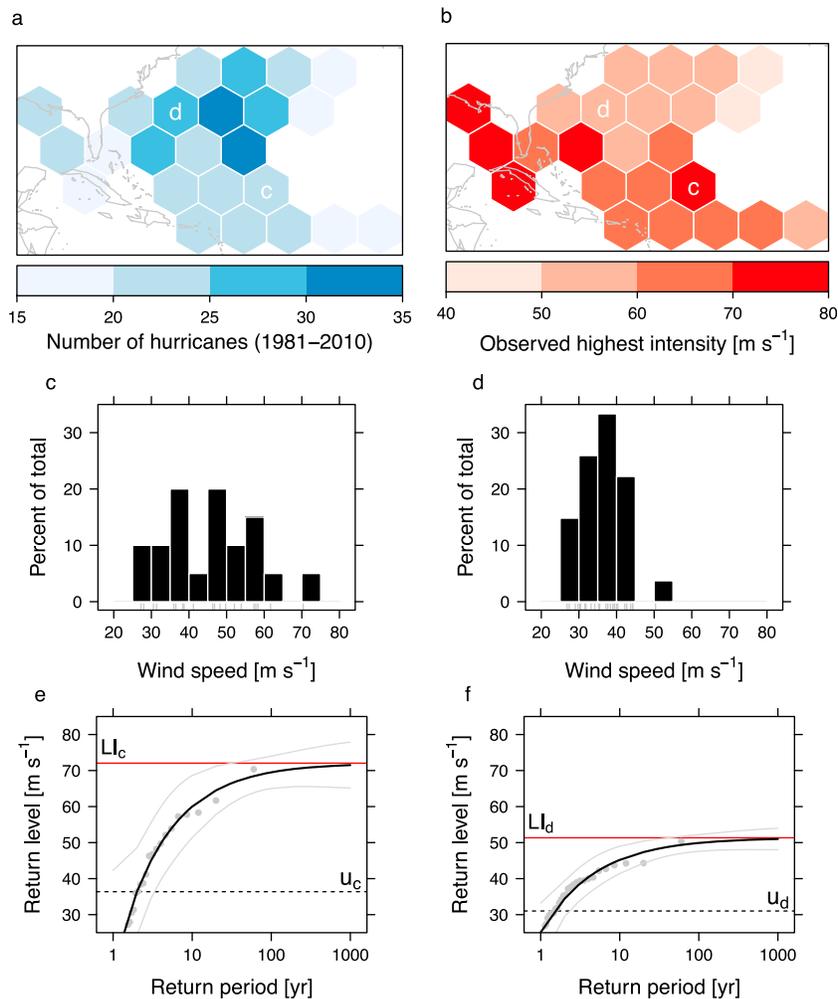


Figure 1. Hurricane frequency and intensity over the period 1981–2010. (a) Number of hurricanes in equal-area hexagons and (b) highest intensity of all hurricanes in each hexagon grid. (c, d) Histogram of per hurricane maximum wind speeds from grids c and d. Bin width is 5 m s^{-1} . (e, f) Statistical model (solid line) for the data in grids c and d. The thin gray lines are the 95% confidence limits on the model curve. The gray points are empirical estimates. The dotted line is the threshold intensity (u) and the red line is the limiting intensity (LI).

Grid c has 20 hurricanes and grid d has 27. The 75th percentile intensity is 54.7 m s^{-1} in grid c compared to 40.2 m s^{-1} in grid d. Grid c has fewer, but stronger hurricanes compared with grid d. The set of highest intensities in each grid provides the data and extreme-value theory provides the rationale for a statistical model to estimate each grid's limiting intensity.

4. A Model for the Limiting Intensity

[7] The statistical model (solid curve) is shown in Figures 1e and 1f for the data in grids c and d. The method of maximum likelihood is used to estimate the model parameters. The uncertainty on the model parameters is captured by the 95% confidence limits (thin gray lines) on either side of the model curve. The gray points are empirical estimates of the return level as a function of return period. The empirical estimates generally fall well within the confidence limits indicating the model is a reasonable fit to the data. The dotted

line is the 25th percentile intensity (threshold) and the red line is the limiting intensity (LI) given the data and the model. The LI amounts to 72.1 m s^{-1} for the set of hurricanes in grid c and 51.3 m s^{-1} for the hurricanes in grid d.

[8] The statistical model combines a generalized Pareto distribution (GPD) with a Poisson distribution to give an estimate of the limiting intensity from a set of per hurricane fastest wind speeds [Jagger and Elsner, 2006]. A GPD describes the set of fastest winds above some high intensity threshold. Some years will contribute no values to the set and some years will contribute two or more. The threshold choice is a compromise between having enough values to estimate the distribution parameters with sufficient precision, but not too many that the intensities fail to be described by a GPD. Here we set the threshold u to the 25th percentile wind speed in each grid.

[9] Specifically, given a threshold wind speed u we model the excesses, $W - u$, as samples from a GPD family so that for an individual hurricane with maximum winds W , the

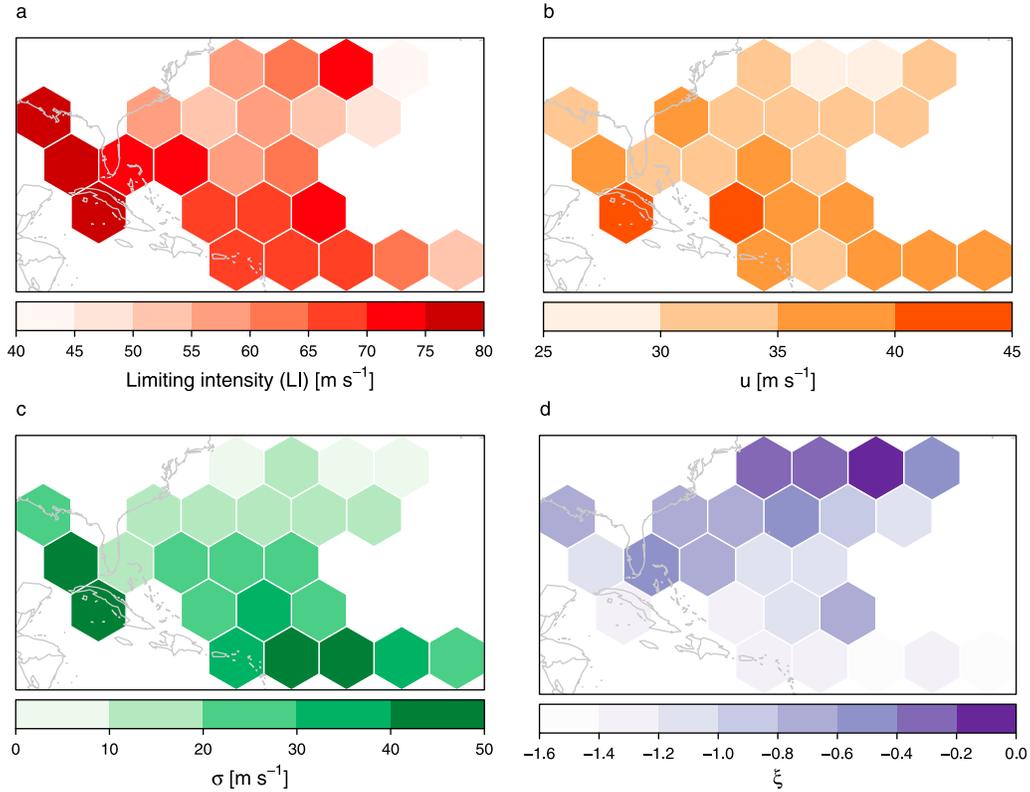


Figure 2. (a) Limiting intensities and (b–d) model parameters. Limiting intensities are highest in grids over the western Caribbean Sea and Gulf of Mexico. Higher LIs are associated with higher threshold and higher scale values.

probability that W exceeds any value v given that it is above the threshold u is given by

$$p(W > v | W > u) = \begin{cases} \exp(-(v-u)/\sigma) & \text{when } \xi = 0 \\ \left(1 + \frac{\xi}{\sigma}[v-u]\right)^{-1/\xi} & \text{otherwise} \end{cases} \quad (1)$$

where $\sigma > 0$ and $\sigma + \xi(v-u) \geq 0$. The parameters σ and ξ are scale and shape parameters of the GPD, respectively. Thus we can write $p(W > v | W > u) = \text{GPD}(v-u, \sigma, \xi)$. The probability depends on the scale and shape parameters. The scale parameter controls how fast the probability decreases for values near the threshold. The decay is faster for smaller values of σ . The shape parameter controls the length of the tail. For negative values of ξ the probability is zero beyond a certain intensity. With $\xi = 0$ the probability decay is exponential and only goes to zero asymptotically.

[10] The frequency of hurricanes with intensities at least u is described by a Poisson distribution with a rate, λ_u , called the threshold-crossing rate. Thus the number of hurricanes per year with wind speed levels 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 and the resulting model is characterized by σ , ξ , and λ_u for a given threshold u .

[11] Since the number of hurricanes exceeding any wind speed v is described by a Poisson process, the return period for any v has an exponential distribution, with mean $r(v) = 1/\lambda_v$. 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 is described by

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

For values of ξ less than zero, the model provides a limiting intensity (LI) given by

$$LI = u - \left(\frac{\sigma}{\xi} \right). \quad (3)$$

The limit is highest for large values of σ and small values of ξ . A more complete description of the statistical theory supporting this model is given in *Coles* [2001]. Examples of its application in the field of hurricane climatology are provided in *Jagger and Elsner* [2006] and *Malmstadt et al.* [2010].

5. Spatial Maps of Model Parameters

[12] Models are fit to the intensity values in each grid and the parameters mapped in Figure 2. Eighteen of the 24 hexagon grids have 20 or more hurricanes. Threshold (u) values range from 26 m s^{-1} in grids along the far northern part of the basin to 44 m s^{-1} for the grid near Hispaniola. Wind speeds exceeding the threshold are used in the statistical model. The scale parameter (σ) is the spread of intensities above the threshold and controls how fast the

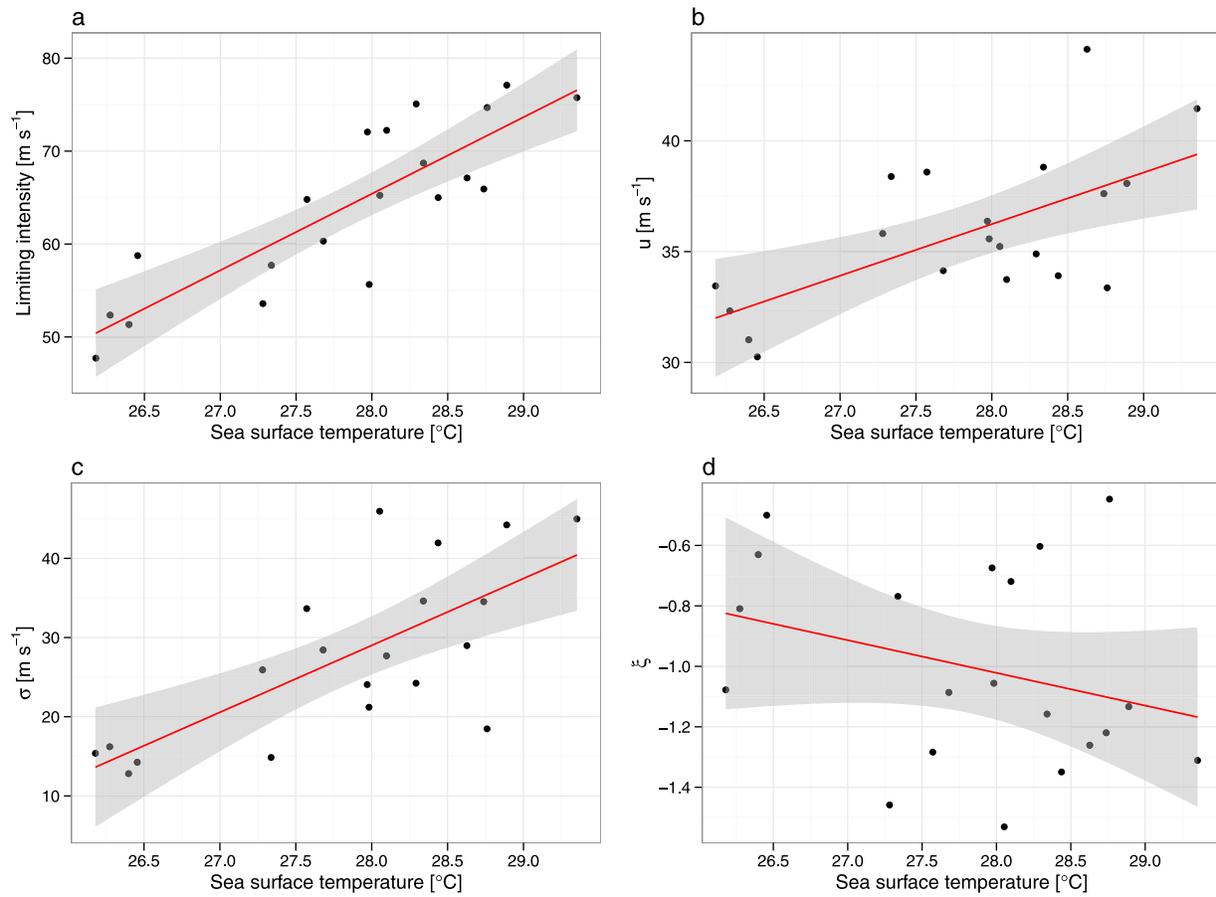


Figure 3. Scatter plots of (a) limiting intensity and (b–d) model parameters versus SST for grids having SST values greater than 26°C . A best-fit linear regression line (blue) represents the sensitivity of hurricane intensity to SST. The 95% confidence interval about the sensitivity is shown as a gray band.

cumulative probability function decays for values near u . Larger values indicate slower decay. Spreads are largest in grids over the Caribbean, Gulf of Mexico, and tropical central Atlantic and smallest in grids farther north. The shape parameter (ξ) describes the tail behavior with negative values indicating a LI given by equation (3). LIs are highest over the western Caribbean and Gulf of Mexico where the ocean surface is hottest.

6. Relationship to Sea-Surface Temperature

[13] We average the SST values within each of the hexagons from the period 1981–2010 during the months of August–October and then separately regress each of the model parameters onto them. Since the number of hurricanes used in estimating the model parameters varies with grid we use a weighted regression instead of ordinary least squares. The translation speed of hurricanes moving through the four northern grids where the average SST is colder than 25°C is significantly (t -test p -value $< .05$) faster (11.2 m s^{-1}) than the speed of hurricanes elsewhere (6.4 m s^{-1}). Thus these grids are removed from further analysis. Results are shown in Figure 3. Each point represents the LI–SST pair for a particular hexagon. The LI (Figure 3a) shows a significant

trend with increasing SST indicating a sensitivity of $7.9 \pm 1.19 \text{ m s}^{-1} \text{ K}^{-1}$ (s.e.). The value is reasonably close to an inferred estimate of $8.7 \text{ m s}^{-1} \text{ K}^{-1}$ from *DeMaria and Kaplan* [1994] (Figure 1).

[14] The sensitivity results from an increase in both the threshold and scale with increasing SST over the range between 25 and 30°C . Four grids having SST less than 25°C are removed because hurricanes are not operating as heat-engines over waters this cold. The shape parameter is largely independent of ocean temperature. In moving over a warmer part of the ocean the threshold shifts to higher values and there is a greater spread of values above the increasing threshold. Uncertainty about the sensitivity estimate assumes the regression residuals are spatially uncorrelated. We test this using Moran's I and a contiguity neighborhood for each grid and find no evidence of residual spatial correlation (p -value = .44 under the null hypothesis of no correlation). We also find no relationship between LI and latitude.

[15] Choosing a higher threshold value u leads to fewer observations and implies inefficient parameter estimates with large standard errors. Choosing a lower threshold leads to more observations but induces biased parameter estimates as observations not belonging to the tails are included in the estimation process. We find that lowering the threshold to

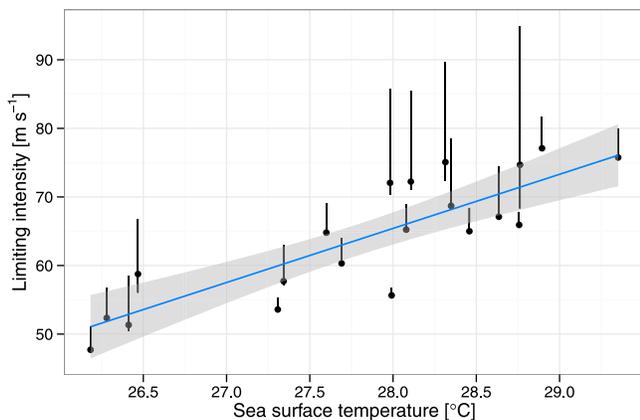


Figure 4. Scatter plots of limiting intensity versus SST. The 80% confidence interval (10% on the upper limit) on the points are based on a bootstrap resampling of the wind speed values in each grid.

the 15th percentile increases the sensitivity estimate to $8.1 \text{ m s}^{-1} \text{ K}^{-1}$ and raising it to the 35th percentile increases it to $8.3 \text{ m s}^{-1} \text{ K}^{-1}$, neither of which is statistically different from the estimate using the 25th percentile threshold.

[16] To obtain an estimate of the uncertainty on the LI in each hexagon we use a bootstrap resampling of the wind speeds. The set of per hexagon per hurricane wind speeds are resampled with replacement 100 times and the model parameters and LIs are re-estimated for each sample. The bootstrap sample of LIs is sorted from highest to lowest and the LI of the 10th highest (90th percentile) and 10th lowest (10th percentile) are used as a confidence interval. Results are shown in Figure 4 and indicate that the uncertainty around the estimate of LI does not change the evidence of a sensitivity on the order of $5\text{--}10 \text{ m s}^{-1} \text{ K}^{-1}$. Restricting ξ to values greater than -1 or by using the method of L moments to estimate model parameters might reduce the uncertainty on the LI for grids with relatively few hurricanes.

[17] Finally we test the variability of the above results to changes in grid area and to changes in the minimum number of hurricanes used to fit the extreme value model (see Tables 1 and 2). Smaller grids require more of them to cover the hurricane tracks resulting in fewer hurricanes per grid. The sensitivity ranges from a minimum of $5.61 \text{ m s}^{-1} \text{ K}^{-1}$ using grid areas of $395,534 \text{ km}^2$ to a maximum of $8.41 \text{ m s}^{-1} \text{ K}^{-1}$ using grid areas of $514,195 \text{ km}^2$. The standard errors generally decrease with increasing areas so all sensitivity estimates are significant against the null hypothesis of no sensitivity. Furthermore, requiring each grid to have

Table 1. Sensitivity of LI to SST for Increasing Grid Sizes^a

Grid Area [km^2]	395,534	428,496	467,450	514,195
Minimum Number of Hurricanes	15	15	15	15
Number of Grids	21	20	20	15
Sensitivity [$\text{m s}^{-1}/\text{K}$]	5.61	7.89	7.69	8.41
Standard Error [$\text{m s}^{-1}/\text{K}$]	1.837	1.188	1.143	1.263
p -value	0.006	<0.001	<0.001	<0.001

^aThe p -value is evidence in support of the null hypothesis that the sensitivity is zero.

Table 2. Sensitivity of LI to SST for Increasing Number of Minimum Hurricanes per Grid^a

Minimum Number of Hurricanes	15	17	19	21
Grid Area [km^2]	428,496	428,496	428,496	428,496
Number of Grids	20	18	15	11
Sensitivity [$\text{m s}^{-1}/\text{K}$]	7.89	7.47	7.27	7.75
Standard Error [$\text{m s}^{-1}/\text{K}$]	1.188	1.279	1.542	1.788
p -value	<0.001	<0.001	<0.001	0.002

^aThe p -value is evidence in support of the null hypothesis that the sensitivity is zero.

minimum number of hurricanes ensures that the model parameters are stable. Increasing this number from 15 to 21 does not significantly change the sensitivity estimates.

7. Discussion

[18] Most hurricanes exist in environments that are less than thermodynamically optimal for reaching their maximum potential intensity. Here we introduce LI as a theoretical construct based on the family of extreme-value distributions. LI represents a statistically best estimate of the most intense hurricane for a given grid and it is not constrained to be the highest wind observed. Variation in LI with SST across the spatial domain allows us to estimate hurricane sensitivity. All the code to reproduce the results is available at (<http://rpubs.com/jelsner/1040>).

[19] It is well known that other factors play a role in modulating hurricane intensity. While it is likely that some of these might influence LI especially those related to ambient moisture and upper-level temperature, these factors are difficult to extract independently of the hurricane activity. Thus we feel that it is reasonable to estimate the sensitivity of LI to SST in isolation as a first-order approximation while recognizing that the estimate might need to be adjusted when additional factors are found significant. The results are strictly valid only over the range of seasonal mean SST greater than 25°C .

[20] Finally strong hurricanes leave a cold wake [Schade, 2000] that can last for days to a month thus it is possible that our sensitivity estimate is a bit too conservative but we are unable at this time to estimate the degree of this bias. In this regard it might be better to use the maximum SST in each grid instead of the average as done here. The methodology will be applied to cyclone data arising from high-resolution general circulation models from the Climate Model Inter-comparison Project (CMIP5) and comparisons made between observed and modeled sensitivity of LI.

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