Estimated return periods for Hurricane Katrina

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[1] Hurricane Katrina is one of the most destructive natural disaster in U.S. history. The infrequency of severe coastal hurricanes implies that empirical probability estimates of the next big one will be unreliable. Here we use an extreme-value model together with interpolated best-track (HURDAT) records to show that a hurricane of Katrina's intensity or stronger can be expected to occur, on average, once every 21 years somewhere along the Gulf coast from Texas through Alabama and once every 14 years somewhere along the entire coast from Texas through Maine. The model predicts a 100-year return level of 83 ms^{-1} (186 mph) during globally warm years and 75 ms^{-1} (168 mph) during globally cool years. This difference is consistent with models predicting an increase in hurricane intensity with increasing greenhouse warming.
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1. Introduction

[2] On Sunday, August 28, 2005, Hurricane Katrina's winds increased to 78 ms^{-1} in the central Gulf of Mexico making it one of the strongest hurricanes ever recorded in this part of the world. Early morning the next day (7 a.m. LDT) the eye of Katrina crossed over Plaquemines Parish in Louisiana with winds estimated near 65 ms^{-1}. It is useful to know the return period of a storm of Katrina's magnitude and how it might vary under climate change. Probability estimates of extreme hurricanes are available in the literature [*Darling*, 1991; *Rupp and Lander*, 1996; *Heckert et al.*, 1998; *Chu and Wang*, 1998] but they do not address the question of variability under different climate regimes [*Jagger et al.*, 2001]. Here we use a model from extreme value theory to estimate the return period of Katrina-like hurricanes along the Gulf coast. The model, described in detail by *Jagger and Elsner* [2006], is an application from *Coles* [2001]. The analysis is useful in putting the near-coastal strength of Hurricane Katrina into historical perspective.

2. Data

2.1. Data Description and Sources

[3] Extreme value theory relies on asymptotic arguments for the behavior of the maximum value observed in a data set [*Palutikof et al.*, 1999]. Here maximum sustained (1-minute average) wind speed estimates near the coast are interpolated from the best-track data set (HURDAT) maintained by the U.S. National Hurricane Center (NHC). Limiting our analysis to near-coastal hurricanes allows us to use data back to 1899. The best-track data set is the official record of tropical cyclones for the Atlantic Ocean, Gulf of Mexico and Caribbean Sea, including those that have made landfall in the United States. It consists of the 6-hourly position and intensity estimates of tropical cyclones back to 1851 [*Jarvinen et al.*, 1984; *Neumann et al.*, 1999]. For storms and hurricanes prior to 1931, the 6-hr positions and intensities are interpolated from once daily (12 UTC) estimates. For hurricanes in the period 1931–1956, the 6-hr positions and intensities are interpolated from twice daily (00 and 12 UTC) observations. Here we use the latest version of data set as of February 2005, which includes reanalysis of all known storms prior to 1911.

[4] The best-track data set does not contain a complete list of hurricane events by landfall location so we develop an objective technique for estimating near-coastal wind speeds. First we divide the coast into 3 regions including the Gulf coast, Florida, and East coast. The combined coastal region of 1, 2, and 3 is referred to as the entire coast. Second, a cubic spline interpolation is used to obtain positions and wind speeds at 1-hr intervals from the 6-hr values for all tropical cyclones in the best-track [*Kossin*, 2002]. The spline interpolation guarantees we do not miss storms passing quickly through a near-coastal region. The spline interpolation in this context is preferable because it captures rapid changes in intensity better than linear interpolation. Also with spline interpolation the values at the 6-hr observations remain the same. Third, for each hurricane, we note the maximum wind in each of 2 regions affected by a given hurricane: Gulf coast and entire coast. Fourth, for recent hurricanes where landfall intensities have been reevaluated by experts (e.g., Hugo in 1989 and Charley in 2004), we use these values instead of the 1 hr interpolated best-track values. A comparison of the power dissipation index (cubed of the wind speed integrated over the lifetime of the storm [*Emanuel*, 2005]) using 6 hr observations and 1 hr spline interpolations shows that there is only a 1% difference providing support for our choice of interpolation for capturing the maximum wind speed of a hurricane in a region.

[5] We also obtain monthly global near-surface air temperature anomalies (1961–1990 base period) from the Intergovernmental Panel on Climate Change (IPCC) online from the Climatic Research Unit (CRU) [*Folland et al.*, 2001]. We average the global temperature anomalies over the months of August–October. The anomalies are accurate to ±0.05°C for the period since 1951, but are about 4 times as uncertain during the previous century. We treat the global temperatures as a binary factor by subdividing the record into years of above and below average.

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2.2. Hurricane Data Assumptions

[6] Considering only tropical cyclones with at least tropical-storm force winds (>18 ms^{-1}) over the period 1899–2004, we have N = 875 entries from 383 tropical cyclones for the entire coast. Each entry $i = 1, \ldots, N$ is a pair consisting of the year y_i and the maximum wind w_i, denoted as D. Also, associated with each entry is a row vector of global air temperature x_{y_i}. We consider D a sample from a spatial point process, $\mathcal{D}$, over the two dimensional space composed of the integers and positive reals. Using the idea of a spatial point process we define quantities useful for the present analysis. For instance, the activity for year y of all tropical cyclones with maximum winds exceeding u is the number of points, $N(y, u)$ from a realization of $\mathcal{D}$ inside the region ($y \times (u, \infty]$). Thus, $N(y, u)$ represents a family of random variables on the positive integers, and $N(y, H)$ is the annual number of hurricanes for year y, where H = 33 ms^{-1} corresponding to hurricane intensity. We can view the problem of finding the maximum yearly wind speed by fixing the threshold, u, and noting that the distribution of the yearly maxima can be determined from the distribution of $N(y, u)$ and the distribution of the maximum winds given that the maximum winds exceed u. If u is large enough, then for practical purposes, $N(y, u)$ takes only values of zero and one, so based on a conditioning argument the probability that the maximum wind W exceeds a value v is $\Pr(N(y, u) = 1)\Pr(W > v|W > u)$. This is called the peaks-over-threshold method [*McNeil and Saladin*, 2000; *Coles and Pericchi*, 2003].

[7] Additional assumptions are necessary. First, we assume that the occurrence of a hurricane within a coastal region is independent of future hurricane occurrences in the same region. Second we assume that hurricane intensity is independent such that the intensity of a previous hurricane has no bearing on the intensity of a future hurricane. Thus, while the interpolated hurricane intensities along a particular hurricane track are not independent, the maxima from one hurricane to the next are. Then, the two dimensional spatial process describing set D is a two dimensional Poisson process with an associated mean measure Λ_A. For example, if $A = [1901, 2000] \times [33,\infty]$ then Λ_A is the expected number of hurricanes in the 20th century occurring within the region. Since D is a Poisson process, the number of hurricanes observed during this century has a Poisson distribution with a mean value of Λ_A. Another feature of the Poisson process is that the probability of a single event B occurring in a smaller region contained in A is just λ_B/λ_A, thus if a single hurricane occurs in year y then $\Pr(W > v|W > u) = \Lambda(y, [v, \infty])/\Lambda(y, [u, \infty])$. We also assume that the maximum wind speed has a continuous distribution so our process has an associated intensity λ where $\Lambda([a, b] \times [c, d]) = \sum_a^b \int_c^d \lambda\,(y, w)\,dw$. So our count $N(y, u)$ is a Poisson random variable with mean $\int_u^\infty \lambda(\mathrm{y},\mathrm{u})\,\mathrm{du}$. Finally, we assume that a tropical cyclone occurrence in a given year is a function of the set of yearly climate variables, and the wind speed, w so that the intensity in each coastal region, λ, can be expressed as $\lambda(y, w) = \lambda(x_y, w)$.

[8] We model hurricane intensification and occurrence separately. Using a generalized Pareto distribution (GPD), we specify the probability that the maximum wind speed of a near-coastal hurricane W will be greater than some value v given that it exceeds some threshold intensity u. The GPD is used because it describes the behavior of individual extreme events. The frequency of hurricanes at intensity u or higher is assumed to follow a Poisson distribution. With u at hurricane intensity, *Elsner et al.* [2004] find no significant rate shifts in hurricane activity along the Gulf coast during the 20th century. The above formulation allows us to obtain an annual return rate on the extreme winds, which is meaningful for the businesses of insurance and risk management.

[9] The probability that the maximum observed wind speed exceeds some value v given that it exceeds the threshold u is

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

$$= \mathrm{GPD}(v - u|\sigma_u, \xi) \quad (2)$$

where $\sigma_u > 0$ and $\sigma_u + \xi(v - u) \geq 0$. Since this model is true for any u we have $\sigma_u = \sigma_0 + \xi \cdot u$ and $\xi_u = \xi$. The parameters σ_u and ξ are referred to as the scale and shape parameters respectively. For negative shape parameters the GPD has an upper limit of $W_{\max} = u + \sigma_u/|\xi|$.

[10] The GPD describes the maximum wind distribution for each hurricane whose winds exceed u but not the frequency of hurricanes at that intensity. From our assumptions, the number of hurricanes in year y whose maximum winds exceed u has a Poisson distribution with mean (or exceedance) rate $\lambda_u = \Lambda(y, [u, \infty])$. Thus by combining the probability and the rate with our assumption that they are independent we get the number of hurricanes per year with winds exceeding v, N_v has a Poisson distribution with mean

$$\lambda_v = \lambda_u \cdot P(W > v|W > u). \quad (3)$$

The threshold u is set to 41 ms^{-1}. A plot of the mean excess, where excess is the difference between a threshold value and the observed speed for speeds exceeding the threshold, shows a straight line fit starting at a threshold between 39 and 46 m^{-1}. Estimates of the scale and shape parameters of the extreme value distribution are not significantly different for different choices of threshold within this range. Additional details on the choice of threshold are provided by *Jagger and Elsner* [2006].

3. Results

[11] Figure 1 shows a return level plot of extreme hurricane winds for the Gulf coast region from our model. A map of the region is shown as an inset. The return level (ordinate) has units of wind speed in ms^{-1} and knots (kt) and the return period (abscissa) is given in years. The return level is exceeded on average once every return period. The middle curve is the expected return level for a given return period and the thin lines are the 95% confidence limits. The curves asymptote to finite levels as a consequence of the negative value for the GPD shape parameter. The model

shows a 5-year return level of 54 ms^{-1}, a 50-year return level of 77 ms^{-1} and a 500-year return level of 88 ms^{-1}. Model estimates are consistent with empirical estimates that show three hurricanes over the past 106 years in the region with maximum sustained winds of at least 71 ms^{-1} including Hurricane Ethel in 1960 (71 ms^{-1}), Hurricane Carla in 1961 (77 ms^{-1}), and Hurricane Camille in 1969 (85 ms^{-1}).

[12] Using the 2-hourly NHC updated positions and intensities, within the Gulf coast region, we estimate Katrina's strongest wind speed to be 71 ms^{-1} (dot in Figure 1). This corresponds to a return period of 21 years. Thus assuming the future will be similar to the past, we can expect to see a hurricane of Katrina's strength or stronger somewhere in this region (of course not necessarily affecting the city of New Orleans) on average once every 21 years. The 95% confidence limits on this estimate are 10 and 50 years (Table 1). We extend the model to include the entire U.S. coast from Texas to Maine and find a return period of 14 years for hurricanes of Katrina's strength or stronger with a 95% interval range from 9 to 30 years.

[13] The above results are based on the assumption that hurricane events are independent. The increase in power dissipation and frequency of strong Atlantic hurricanes over the past 30 years suggests that things might be changing [*Emanuel*, 2005; *Trenberth*, 2005; *Webster et al.*, 2005]. Local SST plays a direct role in powering hurricanes by providing moist enthalpy and instability. Warmer Atlantic SST caused by a faster thermohaline circulation leads to more and stronger hurricanes. We therefore rerun the extreme value model for the entire coast separating years of above from years of below average global temperature (Figure 1b). The model predicts an expected 100-year return level of 81 ms^{-1}. However, the expected value ranges from 83 ms^{-1} during globally warm years to 75 ms^{-1} during globally cool years. The magnitude of the difference in return levels is consistent with a numerical modeling study predicting a 3–10% increase in maximum sustained surface winds for CO_2-induced hurricane intensification sustained over 80 years [*Knutson and Tuleya*, 2004]. Since we find no substantial difference in the return periods for weaker hurricanes, we conclude an increase in the average number of hurricanes per year for warm years, with the increase coming at the higher return levels. Although statistically we find changes in return levels conditioned on global near-surface air temperature, the causality is through regional SST [*Elsner et al.*, 2006]. Changes in North Atlantic SST and hurricane activity are known to co-vary in aperiodic multidecadal cycles [*Goldenberg et al.*, 2001; *Henderson-Sellers et al.*, 1998].

Table 1. Return Periods[a]

Region	2.5%	Mean	97.5%
Gulf Coast	10	21	50
Entire Coast	9	14	30

[a]Values are in years and represent the mean and 95% confidence limits for a storm of Katrina's strength or stronger to approach the near-coastal waters of the United States. Values are derived from an extreme-value model of U.S. hurricanes using data over the period 1899–2004.

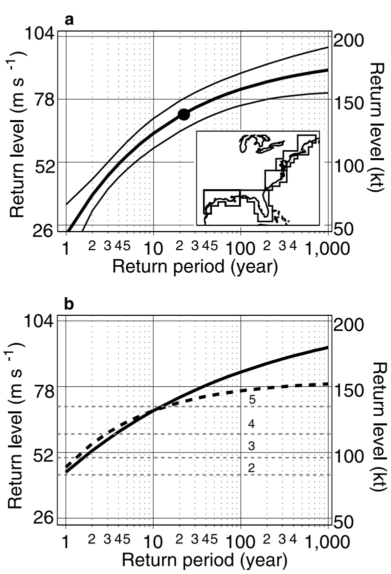

Figure 1. Exceedance probability curves. Near-coastal hurricanes along the Gulf coast (Texas to Alabama). (a) The curves are based on an extreme value model and asymptote to finite levels. Parameter estimates are made using the maximum likelihood approach. Thin lines are the 95% confidence limits. The return level is the expected maximum hurricane intensity over *p*-years. The map inset shows the Gulf coast and entire coast regions. The dot indicates the return level of Hurricane Katrina when it entered the Gulf coast region. Near-coastal hurricanes along the entire U.S. coast (Texas to Maine). (b) The solid (dashed) line is for years with global temperatures above (below) normal. The dashed horizontal lines correspond to the minimum speed of the corresponding Saffir/Simpson hurricane scale. Similar results are obtained using Atlantic sea-surface temperature in place of global air temperature.

4. Summary

[14] Here we employ a model described by *Jagger and Elsner* [2006] and based on data from the period 1899–2004. Since Katrina occurred in 2005, we use the model to estimate an out-of-sample return period for Katrina-like storms. Scientifically, the assessment of hurricane return periods using the model goes beyond empirical methods of storm counting by intensity category.

[15] Understanding the role climate plays in modulating hurricane destructiveness is crucial to society, particularly as coastal populations continue to swell [*Pielke et al.*, 2005]. The recent increase in strong hurricanes over the Atlantic is indeed troubling. Although Hurricane Katrina caused catastrophic damage we can expect another hurricane at that strength or stronger somewhere along the U.S. coast with an annual probability somewhat higher than 7%. Although the annual probabilities for hurricanes weaker than Katrina do not change between globally warm and globally cool years, for hurricanes stronger than Katrina, we find that the increase in the 100-year return level from cold to warm years amounts to 11%.

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