Maximum wind speeds and US hurricane losses

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[1] There is academic, commercial, and public interest in estimating loss from hurricanes striking land and understanding how loss might change as a result of future variations in climate. Here we show that the relationship between wind speed and loss is exponential and that loss increases with wind speed at a rate of 5% per m s^{-1}. The relationship is derived using quantile regression and a data set comprising wind speeds of hurricanes hitting the United States and normalized economic losses. We suggest that the "centercepts" for the different quantiles account for exposure-related factors such as population density, precipitation, and surface roughness, and that once these effects are accounted for, the increase in loss with wind speed is consistent across quantiles. An out-of-sample test of this relationship correctly predicts economic losses from Hurricane Irene in 2011. The exponential relationship suggests that increased wind speeds will produce significantly higher losses; however, increases in exposed property and population are expected to be a more important factor for near future losses. **Citation:** Murnane, R. J., and J. B. Elsner (2012), Maximum wind speeds and US hurricane losses, *Geophys. Res. Lett.*, *39*, L16707, doi:10.1029/2012GL052740.

1. Introduction

[2] In part due to the uncertainty of climate change on the risk of extreme events, there is significant interest in understanding society's risk and designing adaptation measures [*Intergovernmental Panel on Climate Change*, 2012]. One of the more objective and relevant measures of the impact of extreme events is the record of loss. Hurricanes striking the United States cause many of the largest insured losses from natural hazards [*Bevere et al.*, 2012]. However, actual economic losses produced by hurricanes (and other extreme events) are difficult to collect [*Cutter et al.*, 2008]; in fact, recent economic losses for US hurricanes as summarized by the National Hurricane Center are often assumed to equal twice the insured loss as reported by the Insurance Services Office plus storm-by-storm adjustments [*Pielke et al.*, 2008]. For example, National Flood Insurance Program (NFIP) losses were included in the economic loss estimates for Hurricane Irene in 2011 [*Avila and Cangialosi*, 2011]. Here we exploit a record, starting in 1900, of normalized economic loss from hurricanes striking the US coastline. To our knowledge this is the longest and best record of publicly available hurricane loss data and it is primarily extracted from reports in the Monthly Weather Review.

[3] We expect a plot of damage of single structure versus wind speed to have an S-shaped profile with no loss at low wind speed and complete loss at a high wind speed [*Vickery et al.*, 2006]. The losses to contents, appurtenance structures, and additional living expenses or business interruption can be more complicated, but they are commonly estimated to be a function of the loss to a structure. Estimates of total insured losses from a hurricane include all these loss types.

[4] When comparing losses from landfalling hurricanes the historical losses should be normalized to account for changes in population, wealth, and inflation [*Neumayer and Barthel*, 2011; *Pielke et al.*, 2008; *Pielke and Landsea*, 1998]. Most recent analyses of historical losses from weather-related disasters provide essentially no evidence of statistically significant trends once the data have been normalized [*Bouwer et al.*, 2007; *Miller et al.*, 2008; *Bouwer*, 2011]. This observation holds for specific weather-related hazards such as floods [*Downton et al.*, 2005], tornadoes [*Brooks and Doswell*, 2001], bushfires [*Crompton et al.*, 2010], and hurricanes [*Pielke et al.*, 2008; *Pielke and Landsea*, 1998], as well as for earthquakes [*Vranes and Pielke*, 2009]. Studies that find increasing trends [e.g., *Nordhaus*, 2010; *Barthel and Neumayer*, 2012] have been criticized for using incomplete normalizations [*Bouwer*, 2011] or include caveats that the data spans a relatively short number of years or do not properly account for changes in insurance uptake and/or reporting [*Barthel and Neumayer*, 2012]. There is evidence that damage can be reduced through better construction codes [*Gurley and Masters*, 2011]. Regardless of the existence of an upward trend in loss as a result of climate change, it is clear that losses increase with the intensity of a hurricane [*Kantha*, 2006; *Pielke and Landsea*, 1998] and with increases in population and wealth in areas subject to extreme events.

[5] The relationship between loss and a hurricane's size, forward motion, precipitation, and wind speed, and other important factors such as building construction and occupancy, surface roughness, and storm surge, is complex and difficult to model explicitly. As a simple alternative, loss (L) is often estimated from wind speed at landfall (V) using a power law relationship where L = αV^{β} and β ranges between 3 and 9 [*Bouwer and Botzen*, 2011; *Howard et al.*, 1972; *Nordhaus*, 2010]. In this study we find that a simple exponential relationship between aggregate normalized economic losses and wind speed at the time of United States landfall provides a better fit to the data.

2. Data

[6] In our analysis we use normalized economic losses and wind speeds at landfall. These are available online from the

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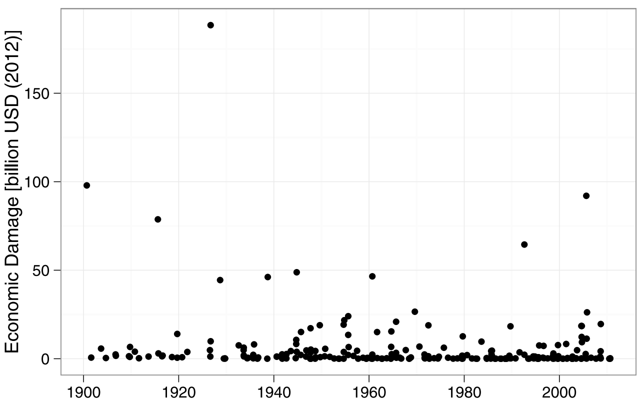

Figure 1. Time series of normalized losses. Note that the largest normalized economic loss is associated with the 1926 Miami hurricane. Losses from http://www.icatdamageestimator.com/all-storms?StormName=ALL&State=ALL&Year=ALL&Category=ALL&hurdatNumber=&searchInSearchParam=&currentSearchText=.

ICAT Damage Estimator (http://www.icatdamageestimator.com). (ICAT is an insurance company that provides hurricane and earthquake insurance to businesses and homeowners in the United States.) Economic losses produced by a storm in the year it made landfall are extracted from Monthly Weather Review reports and storm reports from the National Hurricane Center. The economic losses are normalized for changes in population, wealth and for inflation using the approach outlined by *Pielke et al.* [2008].

[7] There is no significant trend in the time series of normalized losses used in the regression (Figure 1). The frequency distributions of loss (log scale) and wind speed are shown in Figure 2. The loss data range over nearly six orders of magnitude whereas wind speeds vary by less than an order of magnitude. Several factors contribute to the variability in loss including: population density in the area affected by the storm, the nonlinear response of damage to wind speed, and the amount of precipitation and flooding. This variability can be seen in scatter plots of wind speed versus loss (Figure 3) for the whole U.S. coastline and for three landfall regions (Gulf coast, Florida, East Coast). The regions are based on an analysis showing that landfalls in Florida depart from a Poisson rate process and are clustered [*Jagger and Elsner*, 2012].

3. Results

[8] We model the log (base 10) of normalized loss as a function of wind speed using quantile regression [*Koenker and Bassett*, 1978]. The fits for the 0.10, 0.25, 0.50, 0.75 and 0.90 quantiles are shown as colored lines in scatter plots (Figure 3). Regression results are shown in Table 1. Interestingly, within the uncertainty of the estimates, a slope of $\sim$5% per m s^{-1} based on an exponential relationship seems appropriate for most quantiles and regions (Table 2). Higher quantiles with lower slopes have a large uncertainty and appear to be associated with East Coast storms (Table 2). However, a test of significance using the Wald approach [*Hendricks and Koenker*, 1991] indicates little evidence to reject the null hypothesis of equal slopes for the different regions (Table 3). The relative constancy in slopes suggests the possibility of an inherent relationship that causes losses to increase by about 5% for each m s^{-1} increase in wind speed.

[9] Conveniently, the regression centiles can be used to define a confidence interval for a loss from a land falling storm. Losses from Hurricane Irene in 2011 are not used for the quantile regression and are used as an out-of-sample test. The NHC reports that Hurricane Irene struck land in NC, NJ, and NY in 2011 with winds of 39, 31, and 28 m s^{-1}, respectively, and caused insured losses of \$4.3 B and NFIP losses of \$7.2 B. The NHC assumes economic losses are twice the insured loss (excluding NFIP) and thus the total economic loss from Irene is estimated at \$15.8 B. Our model predicts a median economic loss of \$490 M for a wind speed of 39 m s^{-1} and \$140 M for a wind speed of 28 m s^{-1}. The 90th centile loss for the landfall with 39 m s^{-1} winds is \$11 B with a 90% confidence interval of \$5 to \$24 B. The 90th centile loss for the landfall with 28 m s^{-1} winds is \$7.5 B with a 90% confidence interval of \$2 to \$28 B. This fit is surprisingly good considering the large flood losses from Irene relative to many other U.S. hurricanes. Typically, the ratio of flood loss to total insured

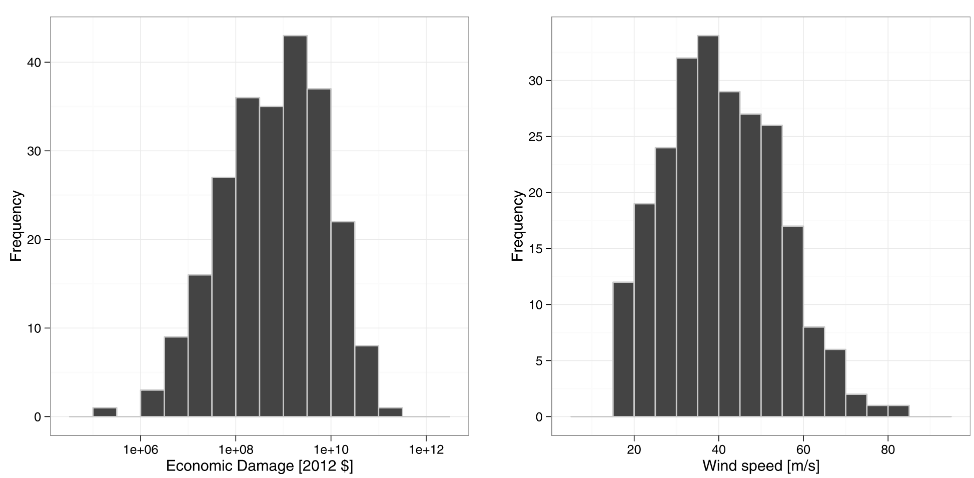

Figure 2. Frequency distribution of (right) wind speeds and (left) damage loss (log scale).

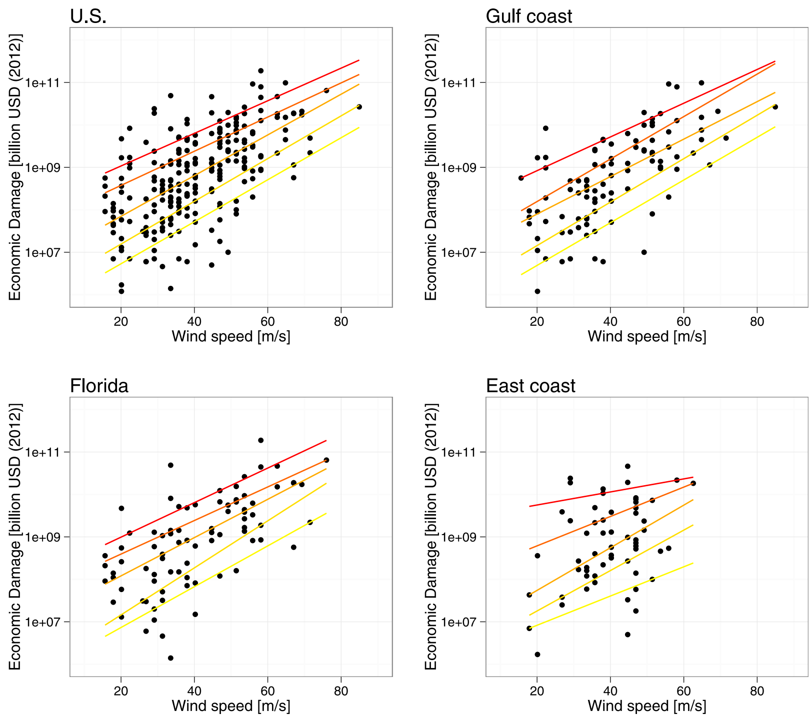

Figure 3. Quantile fits of damage as a function of wind speed. Statistics for the fits at the 0.10, 0.25, 0.50, 0.75, and 0.90 centiles are given in Table 1.

loss from hurricanes is much smaller than that produced by Hurricane Irene.

4. Discussion

[10] Previous estimates of how aggregate damage and loss increase with wind are generally based on a power law relationship [*Bouwer and Botzen*, 2011; *Howard et al.*, 1972; *Nordhaus*, 2010]. However, it can be difficult to confirm a power law relationship with small sets of data [*Clauset et al.*, 2009]. Using Kolmogorov-Smirnov statistics [*Clauset et al.*, 2009] we find a low p-value (0.08) that suggests the power-law relationship provides a poor fit to the data. In addition, we find a significant variation in quantile slopes for the model based on the power-law relationship and no significant variation in quantile slopes for the exponential relationship (Figure 4). Regardless, the strong dependence of loss on wind speed highlights the strong correlation between maximum wind speeds and the overall amount of loss.

[11] We suggest that the centercepts (the quantile losses for the mean wind speed) for the different quantiles represent the expected loss associated with a combination of essentially random factors such as storm: size, shape, precipitation, location (and associated surface roughness), surge, and rate of decay over land. Once these factors are accounted for, the loss caused by a storm will be dominated by wind speed and the response should be relatively consistent across quantiles. Thus, although it is not possible to determine a priori into which quantile a storm might fall, it is possible to determine how loss will vary with a storm's maximum wind speed at landfall.

[12] The 5% per m s^{-1} relationship derived using the exponential relationship can be used to estimate how loss might vary with a change in wind speed. *Elsner et al.* [2008] show that the strongest storms are getting stronger at a rate

Table 1. Statistics From Quantile Regressions[a]

Quantile	Damage at Mean Wind Speed ($\log_{10}$)	Slope % m^{-1} s^{-1}
0.10	7.722 (7.467, 7.902)	5.0 (3.9, 6.4)
0.25	8.228 (8.156, 8.397)	5.1 (4.5, 5.9)
0.50	8.820 (8.739, 8.948)	4.9 (3.7, 5.4)
0.75	9.400 (9.297, 9.551)	4.0 (3.2, 5.3)
0.90	9.820 (9.746, 9.978)	3.8 (2.8, 4.6)

[a]Values in parentheses are the 95% confidence intervals.

Table 2. Same as Table 1 but for Coastal Regions

Quantile	Damage at Mean Wind Speed ($\log_{10}$)	Slope % m^{-1} s^{-1}
	Gulf Coast	
0.10	7.745 (7.403, 8.023)	5.0 (3.6, 6.4)
0.25	8.230 (8.103, 8.390)	5.1 (4.7, 5.9)
0.50	8.825 (8.639, 8.950)	4.4 (3.7, 5.7)
0.75	9.244 (9.123, 9.594)	5.0 (3.0, 6.5)
0.90	9.755 (9.673, 9.993)	4.0 (2.7, 5.9)
	Florida	
0.10	7.857 (7.461, 7.968)	4.8 (3.5, 6.8)
0.25	8.306 (8.105, 8.601)	5.5 (3.3, 6.6)
0.50	9.012 (8.797, 9.088)	4.5 (3.7, 5.2)
0.75	9.411 (9.294, 9.651)	4.0 (3.4, 5.4)
0.90	9.834 (9.691, 10.107)	4.1 (2.5, 5.0)
	East Coast	
0.10	7.332 (6.686, 7.938)	5.7 (2.2, 11.4)
0.25	8.188 (7.963, 8.428)	4.8 (2.9, 7.3)
0.50	8.724 (8.516, 8.943)	5.0 (1.2, 8.3)
0.75	9.467 (9.333, 9.762)	3.5 (0.7, 5.6)
0.90	10.053 (9.767, 10.319)	1.5 (−1.2, 6.4)

Table 3. Analysis of Variance for Equality of Quantile Regression Slopes

Region	Df	Residual Df	F-Value	P-Value
United States	4	1186	1.315	0.263
Gulf coast	4	481	0.871	0.481
Florida	4	406	0.592	0.669
East coast	4	291	0.659	0.621

of $\sim$0.1 m s^{-1} y^{-1}. At the end of 10 years, assuming this trend is maintained, there will be a 1 m s^{-1} increase in hurricane wind speeds, and thus we would expect a 5% increase in loss independent of any change in exposure.

[13] Commercial catastrophe risk models (cat models) for US hurricanes generate real-time and post-event insured loss estimates; the results appear sporadically through press releases from the model vendors. These model results are generated using wind fields adjusted for terrain effects, exposure data, proprietary vulnerability functions, and policy information such as deductibles and limits for structure, contents, and other terms such as business interruption [*Grossi and Kunreuther*, 2005]. The models estimate damage and loss to individual policies that are, in turn, aggregated to determine the total loss from an event.

[14] The storm catalogs in the cat models can be altered to represent future climate scenarios, and loss can then be estimated while other factors, such as exposure, are held constant. For example, one study found that with fixed exposures (the location and distribution of population, and the location, value and construction characteristics of property, were unaltered) future insured annual average losses (in 2004 dollars) might increase by 45% to 118% in response to a uniform 4% to 9% increase in hurricane wind speeds [*Association of British Insurers*, 2005]. Other work suggests that an 18% increase in intensity with fixed exposure would increase damage by 64% [*Pielke*, 2007]. Our exponential relationship shows suggests that a 10% increase in intensity would result in economic losses $\sim$10% higher for a storm with wind speeds of 20 m s^{-1} and $\sim$30% higher for storms with winds of 60 m s^{-1} (both scenarios assume constant exposure).

[15] The exponential relationship between wind speed and loss is a simple yet powerful way to estimate losses from US hurricanes. The relationship is specific to the United States, other regions would have different exposure characteristics. Further analysis is required to determine if similar relationships would apply for other coastlines. The relationship provides support for the view that changes in exposure will likely dominate increases in future losses and

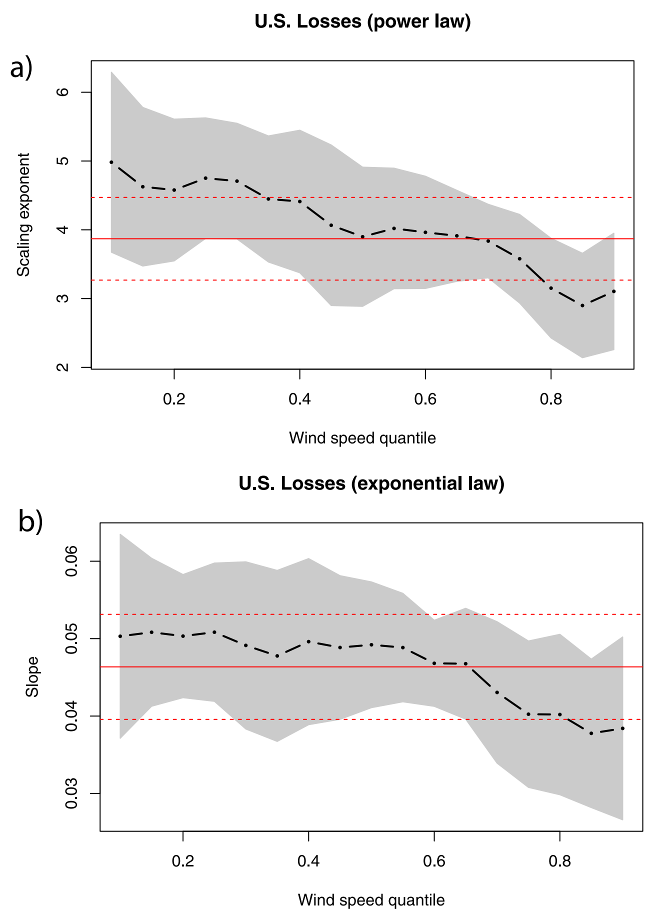

Figure 4. Quantile slopes for economic damage as a function of wind speed. (a) Power law. (b) Exponential law. Slopes for the power law indicate a decreasing trend for increasing quantile losses whereas there is insufficient evidence to reject the null hypothesis of no difference in the slopes for the exponential law.

emphasizes the importance of proper building codes and code enforcement.

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