4D.4

STATISTICS OF HURRICANE DAMAGE IN THE US

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If one normalizes for changes in population, wealth and value of the currency (Pielke et al. 2008), US damage from hurricanes has remained sensibly constant since 1900, as has the rate of US landfalls. Seasonally aggregated damage is reasonably well approximated by combinations of log-normal distributions (Katz 2002, Willoughby 2012a).

Downscaled Global Climate Model simulations support the idea that on a warmer globe the lifetime maximum intensities of the most intense hurricanes (those limited solely by thermodynamics) will increase as numbers of TCs remains constant, decrease slightly (Knutson et al. 2010, Bender et al. 2010), or increase slightly (Emanuel 2013). Examination of the most intense Atlantic Hurricanes since 1974, when geostationary satellite imagery first became available, reveals an abrupt increase in 1995, coincident with a cool-to-warm AMO transition. Other basins also show increases in extreme TCs (Kossin et al 2013, Elsner et al 2008), but given the relatively short record, the signal is less well defined. The most intense Atlantic hurricanes generally reach maximum intensity in the Caribbean, Gulf of Mexico, or over tropical North Atlantic. A significant fraction of these hurricanes reach US shores when they are still major hurricanes (maximum winds > 50 m s^{-1}), but 2-3 Saffir- Simpson categories weaker than their maximum.

Approximately ⅔ of US damage occurred during the most damaging 10% of hurricane seasons. The “fat tails” of the cumulative distributions (Fig. 1) for both seasonally aggregated and individual-hurricane damage are well approximated by Pareto distributions: $\Pr\{d \geq D\} = P_0(D_0/D)^{\alpha}$, where d and D are damage values, D_0 and P_0 are the baseline damage and probability at the lower end of the tail such that $\Pr\{d \geq D_0\} = P_0$., and α is the Pareto exponent. The Pareto exponents for seasonally

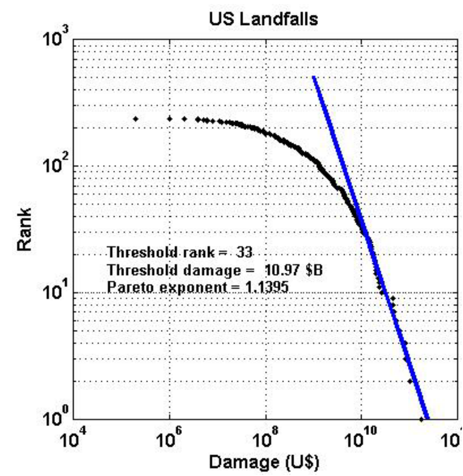

Fig. 1. Cumulative distribution of US normalized damage since 1900 plotted on log-log axes illustrating a Pareto fit (blue line) to the 33 most destructive TCs. Here α = 1.14. For seasonally aggregated damage, α = 1.37.

aggregated and individual hurricane damage are 1.37 and 1.14, respectively.

If the full range of damage obeys log-normal distributions, the Pareto distributions on the tails derive from Taylor expansions of the complementary cumulative distributions. The variances of Pareto distributions diverge when α < 2, and the means diverge when α < 1, but the underlying log-normal distributions are well behaved. Thus, extreme values obtained by extrapolation of Pareto distributions to low very probabilities (e.g., Willoughby 2012b) may be artifacts of the approximation.

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Intensities of TCs are thermodynamically limited (e.g. Emanuel 1999), and their size is limited by the requirement that the Rossby number must be

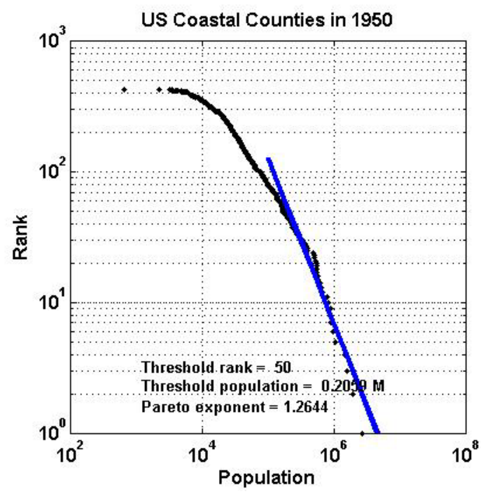

Fig. 2. Pareto distribution fitted to populations of the 436 US coastal counties from the 1950 Census.

significantly larger than unity (Shapiro and Willoughby 1983). Thus, they lack the self-similarity with increasing intensity that characterizes many other geophysical threats

A possible resolution of the conundrum lies in the distributions assets at hazard. It is well known among geographers and economists that sizes of "populated places" obey Zipf distributions (e.g., Ades and Glaeser 1995, Gabiax 1999) in which the sizes of the populated place are ranked from largest to smallest and S_n, the size of the nth populated place, is S_1/n, so that they obey a Pareto distribution with α = 1. If one assumes, following Pielke et al. (2008), that W_n, the wealth at risk in each of these populated places scales as S_n, this insight provides a possible explanation for the loss distribution's fat tail, inasmuch as it is inherited from the exposure distribution.

Fitting Pareto distributions (Fig. 2) to the 1900-2010 census populations of the 436 "coastal counties" (Pielke et al. 2008) yielded α = 1.145, 1.264, and 1.852 for 1900, 1950, and 2010, respectively. This result seems at variance with the demographic literature until one realizes that in the early 20th Century many coastal counties contained a single, dominant populated place. As the coastline became more settled, many counties developed multiple populated places and some populated places spanned multiple counties. As a result of the central limit theorem, this "Aggregation Effect" adjusted the Zipf distribution of county population toward a normal distribution, leading to larger values of α for the tail.

One way to test this insight is to generate a Zipf distribution, draw multiple samples from it, and examine the distribution of the sums of the elements in each sample. The sizes of the samples

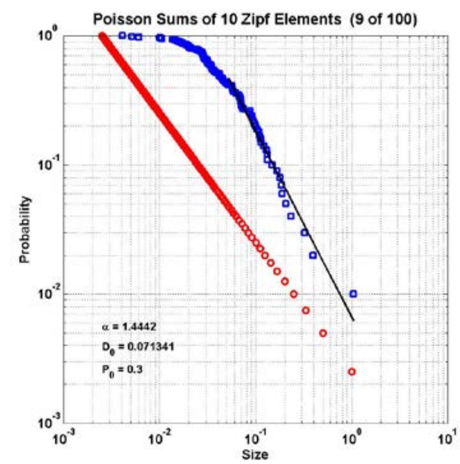

Fig. 3. Pareto distribution (blue squares, α = 1.44) generated by summing the elements contained in each of 100 Poisson samples (m=10) drawn from a Zipf distribution (red circles) with 400 elements. Each Zipf element is weighted by *w*, a uniformly distributed random factor , $0 \le w \le 1$; W_1 = 1.0 for the Zipf distribution.

can be fixed or drawn from a Poisson distribution, and the weighting used in summation can be unity, uniformly distributed, or normally distributed. As expected, sums of 4 to 8 elements yielded Pareto distributions whose exponents were in the 1.1—1.4 range that characterizes US damage, despite considerable random scatter (Fig. 4). In this example, α tends to approach a value of about 1.4 as the Poisson mean increases; although other sampling strategies produce different results.

These calculations show that the Pareto exponents characterizing tails of the distributions of random damage inflicted on a region where the sizes of populated places obey a Ziph distribution derive from the number of elements affected by each

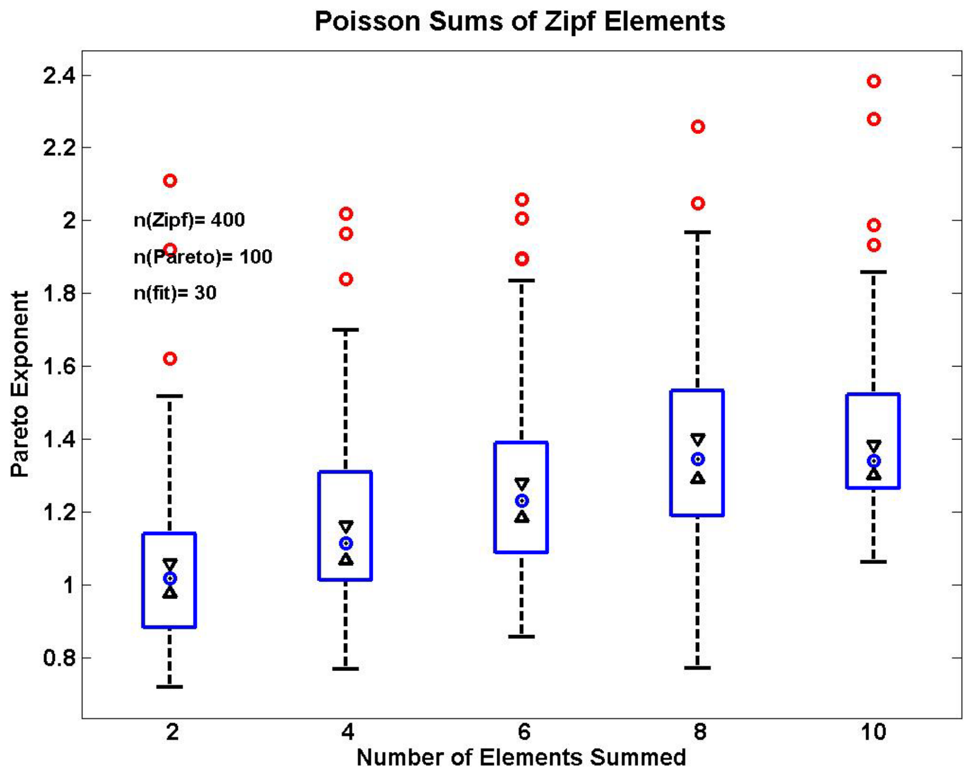

Fig. 4. Box and whisker plots of Pareto exponents produced by weighted Poisson sums of elements drawn from the Zipf distribution in Fig. 3. Target symbols indicate the means; edges of the boxes mark the 25th and 75th percentiles; ends of the whiskers include all elements except outliers, indicated by red circles. When the intervals between the centers of the triangular markers do not overlap, the medians of the data represented by the boxes differ significantly at the 5% level.

damaging event. For a selected P_0, the bounding probability of the tail, D_0, the bounding damage value is a function of the intensity of the damaging events and the vulnerability of the populated places. Large random variation for the Pareto exponent among realizations compromises the practical value of this insight for estimating real damage. It also poses a formidable challenge to detection of changes in damage as a result of factors such as climatic change, improved building standards or wiser land use.

Zipf distributions of assets at peril form the basis of the idealized “Zipfistan” catastrophe mode (Hernandez and Willoughby 2014). The Zipfistan model is a “toy” version of the full-scale commercial models used in windstorm underwriting (e.g., Watson and Johnson 2004). It is designed to provide qualitative insight into underlying model behavior, much in the spirit of analytical solutions for baroclinic instability (e.g., Phillips 1954), one-dimensional climate models (Budyko 1969, Sellers 1969), or even the Gaia Hypothesis (Watson and Lovelock 1983).

In the Zipfistan model, Zipf-distributed assets are scattered randomly along a straight coast and subjected to virtual hurricanes whose climatology is loosely based upon that of Hurricanes that strike the US Atlantic coast. Preliminary results show that the Zipfistan model can reproduce the tail of the distribution of the actual damage distribution and that large, random year-to-year fluctuations in damage present a substantial challenge to identifying the effects of climate change or mitigation measures in actual damage statistics.

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