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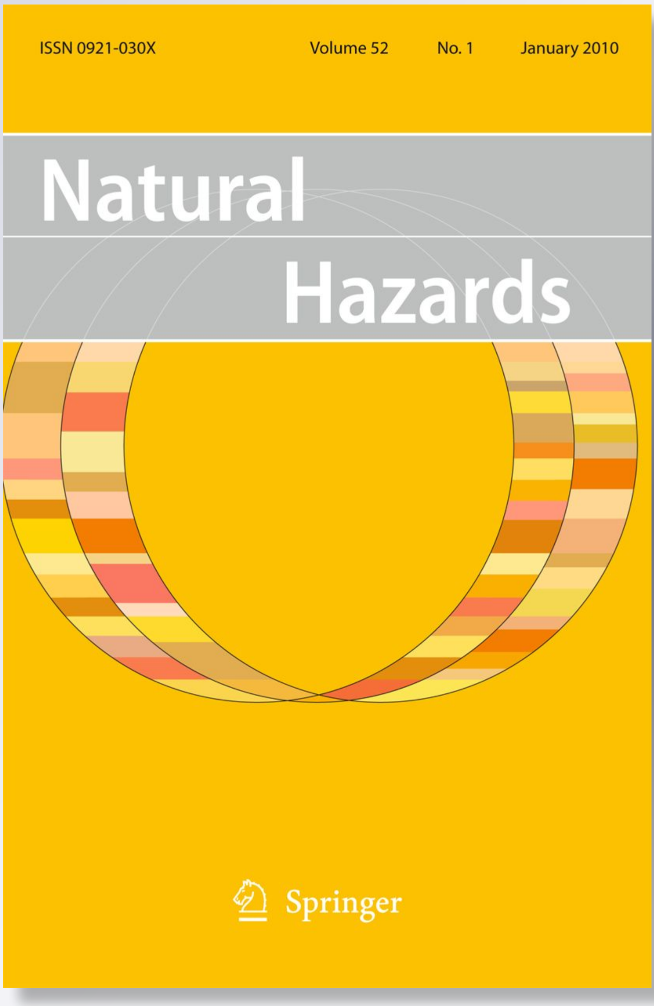

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ORIGINAL PAPER

Climate and solar signals in property damage losses from hurricanes affecting the United States

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Abstract The authors show that historical property damage losses from US hurricanes contain climate signals. The methodology is based on a statistical model that combines a specification for the number of loss events with a specification for the amount of loss per event. Separate models are developed for annual and extreme losses. A Markov chain Monte Carlo procedure is used to generate posterior samples from the models. Results indicate the chance of at least one loss event increases when the springtime north–south surface pressure gradient over the North Atlantic is weaker than normal, the Atlantic ocean is warmer than normal, El Niño is absent, and sunspots are few. However, given at least one loss event, the magnitude of the loss per annum is related only to ocean temperature. The 50-year return level for a loss event is largest under a scenario featuring a warm Atlantic Ocean, a weak North Atlantic surface pressure gradient, El Niño, and few sunspots. The work provides a framework for anticipating hurricane losses on seasonal and multi-year time scales.

Keywords Hurricanes · Property damage · Loss model · Environment · Risk compound Poisson · MCMC

1 Introduction

Climatologists have constructed statistical models using climate variables to anticipate the level of coastal hurricane activity (Elsner and Jagger 2006) and to account for changes in hurricane intensity (Jagger and Elsner 2006; Elsner et al. 2008). Thus, we speculate that it

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might be possible to detect climate signals in historical damage losses caused by hurricanes. The purpose of the present paper is to show evidence that specific climate and solar signals are indeed detectable in records of damage losses from hurricanes along the US coastline (Jagger et al. 2010).

Elucidating a connection between environmental conditions and economic threats from natural hazards is an important new and interesting line of inquiry (Leckebusch et al. 2007). Although others have discovered climate signals in damage losses using bivariate relationships including El Niño and wind shear (Katz 2002; Saunders and Lea 2005), this paper is the first to look at the problem from a multivariate perspective. The work is based on a recent study that uses pre-season environmental variables to anticipate insured losses before the start of the hurricane season (Jagger et al. 2008). Here, we examine the multivariate relationship between a set of pre-determined environmental variables and damage losses from hurricane winds.

Our loss modeling strategy is to combine separate models of event counts with event losses. For modeling annual losses, we use a compound Poisson distribution with the Poisson distribution on the annual number of loss events with a log-normal distribution for each loss amount. The annual loss is therefore represented as a random sum of independent losses, with variations in total loss decomposed into two sources, one attributable to variations in the frequency of events and another to variations in loss from individual events. For modeling extreme losses over longer time spans, we use an exceedance model with a Poisson distribution for the annual number of losses exceeding a given threshold and a generalized Pareto distribution (GPD) for the excess loss of each exceedance.

We begin in Sect. 2 by examining the normalized damage loss data. In Sect. 3 we consider the environmental data associated with climate patterns and solar activity. In Sect. 4, we justify our decision to model small and large losses separately. In Sect. 5, we develop a model for annual losses and in Sect. 6 we develop a model for extreme losses. Summary and conclusions are provided in Sect. 7.

2 Damage losses from hurricanes

We obtain normalized damage loss data from the work of Pielke et al. (2008). The normalization attempts to adjust loss amounts to what they would be if the hurricane struck in the year 2005 by accounting for inflation and changes in wealth and population, plus an additional factor to account for a change in the number of housing units that exceeds population growth between the year of the loss and 2005. The methodology produces a longitudinally consistent estimate of economic losses from past tropical cyclones affecting the US Gulf and Atlantic coasts. A favorable assessment of the adjustment methodology using two case studies is given in Changnon and Changnon (2009).

Economic damage loss is the direct loss associated with a hurricane's impact. It does not include losses due to business interruption or other macroeconomic effects including demand surge and mitigation. Details and caveats for two slightly different normalization procedures are provided in Pielke et al. (2008). Here we focus on the data set from the Collins/Lowe methodology, but note that both data sets are quite similar. Results presented in this study are not sensitive to the choice of data set as we demonstrate throughout.

We extend the data set in time by adding the estimated economic damage losses from the three tropical cyclones during 2006 and 2007. The damage loss estimates are those reported in the *National Hurricane Center* (NHC) storm summaries and derived by the NHC by the *American Insurance Services* and the *Property Claim Services*. This is the same primary data source used in the normalization methods described in Pielke et al. (2008). There were six tropical cyclones that caused at least some damage in the United States during this two-year period, but loss levels were quite small, especially when compared with the losses experienced in 2004 and 2005. In fact loss levels for three of the six tropical storms were below the $25 million reporting threshold (Alberto in 2006; Barry and Gabrielle in 2007).

Tropical storm Ernesto in 2006 struck southern Florida and North Carolina. Total direct damage losses are estimated at $500 mn (million). We estimate that 4/5ths of those losses occurred in North Carolina where the storm was stronger at landfall. The total property damage loss from tropical storm Erin is estimated at $35 mn and the total loss from hurricane Humberto is estimated at $50 mn. Both Erin and Humberto hit the state of Texas. The NHC suggests that Humberto's damage total was low due to its small size and the fact that it impacted a relatively unpopulated area. In addition, the large losses in the same area from Hurricane Rita in 2005 may have moderated the amount of damage that could have been done by Humberto. We make no attempt to normalize the losses from Ernesto, Erin, and Humberto.

We keep separate the losses from a storm that makes multiple landfalls over different regions. For example, in 1992 Hurricane Andrew produced a $52 bn (billion) loss in southeast Florida and a separate $2 bn loss in Louisiana. When multiple landfall events are included, the updated data set contains 221 loss events from 210 separate tropical cyclones over the period 1900–2007. Figure 1 shows the distribution and time series of the damages from all loss events. The histogram bars indicate the percentage of events with losses in groups of $10 bn. The distribution is highly skewed with 88% of the events having losses less than or equal to $10 bn and 95% of the events having losses less than $20 bn.

The greatest loss occurred with the 1926 hurricane that struck southeast Florida creating an estimated damage loss adjusted to 2005 dollars of $129 bn. The Galveston hurricane of 1900 ranks second with an estimated loss of $99 bn, and hurricane Katrina of 2005 ranks third with an estimated total loss of $81 bn. Years with more than one loss have more than one point on the plot. There is large year-to-year variability but no obvious long-term trend, although here the data are not disaggregated into loss amount and the number of loss events.

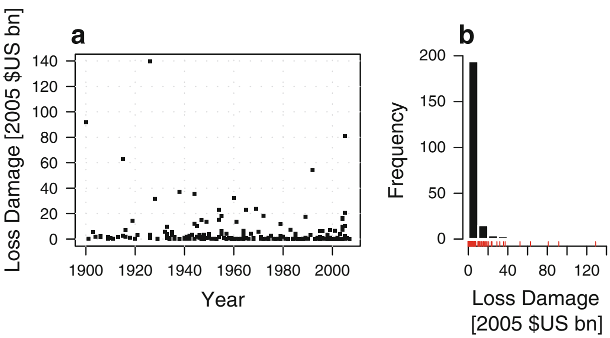

Fig. 1 Hurricane damage losses. **a** Time series plot of per storm damage losses from hurricanes in the United States (excluding Hawaii). Some years have more than one loss event. The number of loss events is increasing over time. **b** The distribution of per storm damage losses. The actual values are located as red tic marks above the abscissa. The loss distribution is positively skewed with relatively few events generating most of the damage losses

Table 1 Damage loss exceedances ($US adjusted to 2005)

Exceedance $US (2005)		Number of events (CL)	Number of events (PL)
1	Million	219	219
10	Million	207	207
100	Million	169	169
1	Billion	98	94
10	Billion	28	27
100	Billion	1	1

Values are the number of events exceeding various loss thresholds. Data from 1900–2007, inclusive

CL is for the Collins and Lowe data set and *PL* is for the Pielke and Landsea data set

Table 2 Cumulative losses by Saffir-Simpson hurricane intensity category in billions of $US adjusted to 2005

Category (Saffir/Simpson)	Cumulative losses (CL)	Cumulative losses (PL)
0	1,103.9	1,125.1
1	1,063.1	1,084.5
2	1,022.7	1,045.6
3	941.4	964.4
4	533.1	557.3
5	79.4	79.3

Data from 1900–2007, inclusive

CL is for the Collins and Lowe data set and *PL* is for the Pielke and Landsea data set

The damage loss exceedances are shown in Table 1. Of the 221 loss events from 1900 to 2007, 169 exceeded $100 mn in losses and 28 of these exceeded $10 bn. The two events producing losses less than $1 mn include Gustav in 2002 and Dean in 1995. The distribution of losses is similar in the Collins/Lowe (CL) data and the Pielke/Landsea (PL) data, although the Collins/Lowe data has somewhat larger losses. The CL method differs from the PL method by including a normalization factor for changes in the number of housing units exceeding population growth.

Another way to examine the data is to look at cumulative losses by hurricane intensity. Table 2 shows losses in billions of US dollars from 1900–2007, inclusive by intensity categories. Category 0 is the minimum tropical storm threshold of 17 m s^{-1}, and category 1 is the minimum hurricane threshold of 33 m s^{-1}. From this table, we can see that cyclones of tropical storm intensity or higher accounted for of $1,103.9 bn 2005 adjusted $US while cyclones of hurricane intensity or higher accounted for $1,063.1 bn. Here again we see the similarity in the two data sets and that category 4 and 5's, although rare, have historically accounted for nearly 50% of all damage losses.

Figure 2 shows the annual number of loss events and their distribution. There are five years with 6 loss events, with the most recent being 2005. The annual rate of loss events is 1.94 per year with a variance of 2.48 $(\text{events/year})^2$. There is a distinct upward trend in the number of loss events attributable to some extent to an increase in coastal population. As population increases so do the number of loss events from the weaker tropical cyclones. Indeed, prior to 1950 the number of loss events from tropical storms was 6% of the total number of events. This increases to nearly 38% from 1950 onward. It is noted that although the per storm damage losses have been adjusted for increases in coastal population, the number of loss events have not. An early tropical cyclone making landfall in an area void of a built environment did not generate losses, so there is nothing to adjust. Additional

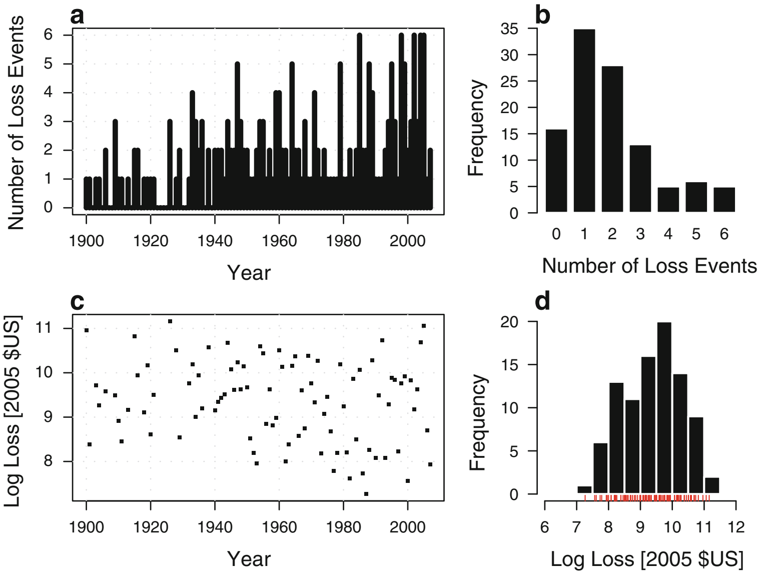

Fig. 2 Number of loss events and the amount of loss per event (normalized to 2005 dollars). **a** Time series and **b** distribution of the number of loss events. The number of loss events is increasing over the time period. **c** Time series and **d** distribution of the amount of damage losses. The amount of losses is on a logarithmic (base 10) scale. There is no trend over time in the amount of normalized losses

descriptive characteristics of severe Atlantic hurricanes in the United States are provided in Changnon (2009).

In this study, we primarily focus on the largest losses from the set of strongest tropical cyclones. There is positive skewness in per storm loss amounts, so we transform them using logarithms. We use base 10 logarithms, so a billion dollar loss has a value of 9 making it is easy to mentally convert back to actual losses.

3 Climate and solar variables

Statistical relationships between US hurricane activity and climate are well established (Elsner et al. 2004; Murnane et al. 2000). More importantly for the present work, recent studies have modeled the wind speeds of hurricanes at or near landfall (Jagger et al. 2001; Jagger and Elsner 2006). Results show exceedance probabilities of strong hurricanes vary appreciably with the El Niño cycle (ENSO), the North Atlantic Oscillation (NAO), and sea-surface temperature (SST). Recent work also shows a linkage between US hurricane activity and sunspot numbers (SSN) (Elsner and Jagger 2008; Elsner et al. 2010).

The ENSO is characterized by basin-scale fluctuations in sea-level pressure between Tahiti and Darwin. Although noisier than equatorial Pacific ocean temperatures, pressure values are available back to 1900. The Southern Oscillation Index (SOI) is defined as the normalized sea-level pressure difference between Tahiti and Darwin (in units of standard deviation). Negative values of the SOI indicate an El Niño event. The relationship between ENSO and hurricane activity is strongest during the hurricane season, so we use a

August–October average of the SOI as a climate factor. The monthly SOI values (Ropelewski and Jones 1987) are obtained from the *Climatic Research Unit* (CRU).

The NAO is characterized by fluctuations in sea level pressure (SLP) differences. Index values for the NAO (NAOI) are calculated as the difference in SLP between Gibraltar and a station over southwest Iceland (in units of standard deviation), and are obtained from the CRU (Jones et al. 1997). The values are averaged over the pre- and early-hurricane season months of May and June (Elsner et al. 2001) as this is when the relationship with hurricane activity is strongest (Elsner and Jagger 2006).

SST values are a blend of modeled and observed data. Raw (unsmoothed and not detrended) monthly values dating back to 1871 (in units of °C) over the North Atlantic basin (0 to 70°N) are obtained from the NOAA-CIRES *Climate Diagnostics Center*. For this study, we average the SST values over the peak hurricane season months of August through October.

For SSN, we use the monthly total sunspot number for September (the peak month of the hurricane season). Sunspots are magnetic disturbances of the sun surface having both dark and brighter regions. The brighter regions (plages and faculae) increase the intensity of the ultraviolet emissions. Increased sunspot numbers correspond to more magnetic disturbances. Sunspot numbers produced by the *Solar Influences Data Analysis Center* (SIDC), *World Data Center for the Sunspot Index*, at the *Royal Observatory* of Belgium are obtained from the US *National Oceanic and Atmospheric Administration*.

In summary, normalized historical damage losses from hurricane events over the period 1900–2007 will be modeled using the above climate and solar data. These covariates are chosen based on previous studies relating climate factors to the variability in US hurricane activity. We make no attempt to search for new covariates.

Time series' of the covariates are plotted in Fig. 3. The SOI and NAO variables have no obvious long-term trend. The SST variable, on the other hand, indicates warming from 1900 to about 1940 followed by cooling until about 1980 then warming since. This pattern has been called the Atlantic multidecadal oscillation. The SSN variable shows an obvious 11-year cycle and increasing amplitude of the cycle through 1960 with a declining amplitude since.

Upper and lower quartile values of the SOI are 0.40 and −0.90 SD, respectively with a median (mean) value of −0.18 (−0.16) SD. Years of above (below) normal SOI correspond to La Niña (El Niño) events and thus a higher probability of at least one US hurricane. The upper and lower quartile values of the NAO are 0.40 and −1.09 SD, respectively with a median (mean) value of −0.39 (−0.33) SD. Years of below (above) normal values of the NAO correspond to a weak (strong) NAO phase and thus to higher (lower) probability of US hurricanes. The upper and lower quartile values of the Atlantic SST anomalies are 0.22 and −0.16°C, respectively. Years of above (below) normal values of SST correspond to higher (lower) probability of hurricane activity. The upper and lower quartile values of the September SSN are 91.7 and 17.1, respectively with a median (mean) value of 50.2 (62.0). Years of below (above) normal SSN correspond to a lower (higher) probability of US hurricanes. The largest correlation among the covariates occurs between SSN and SST at a value of +0.18.

As an initial look at losses relative to variations in the covariates, here we compare conditional distributions of per storm damage losses. Table 3 lists the damage amounts at the median and upper 99th percentile value for the damage loss data sets and the damage ratio as the amount of damage during above normal years to the amount during below normal years. It can be seen that during seasons characterized by La Niña conditions (above normal values of SOI), the median losses are greater by a factor of more than two

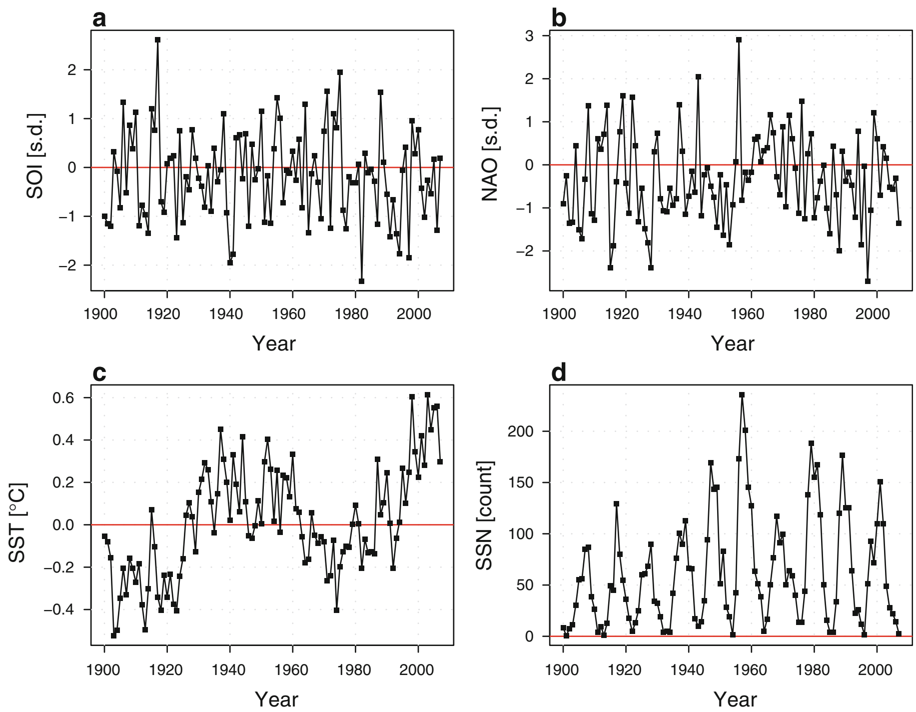

Fig. 3 Time series of the four variables (covariates) used to model damage losses from hurricanes. The variables include the Southern Oscillation Index (SOI), an index of the North Atlantic Oscillation (NAO), North Atlantic sea-surface temperature (SST) and sunspot number (SSN). A description of the variables is given in the text

Table 3 Loss amounts from hurricanes in billions of $ US adjusted to 2005 along with conditional damage ratios

Quantile	CL		PL	
	50%	99%	50%	99%
Damage	0.544	79.377	0.530	79.830
SOI	2.340	0.588	2.257	0.580
NAO	0.845	0.363	0.868	0.320
SST	0.437	1.271	0.477	1.211
SSN	0.282	0.437	0.309	0.430

The damage loss ratio is the respective quantile amount of loss per storm during above normal years to the amount during below normal years independently for each covariate

CL is for the Collins and Lowe data set and *PL* is for the Pielke and Landsea data set

compared with years with El Niño conditions. However, extreme losses are higher during years featuring El Niño conditions. During seasons with below normal springtime NAO conditions, the damages tend to be greater at the median level and even more so at the extremes.

Seasons characterized by higher than average SST show smaller loss amounts at the median levels compared with seasons characterized by lower SST. There is, however, a modest increase in loss amounts during warm years over loss amounts during the cold years at the upper tails of the distribution. During seasons with below normal sunspots, damage losses tend to be greater at the median level and similarly so at the extremes. These results are expected from what we know about how these environmental factors influence US hurricane activity (Elsner and Jagger 2006; Jagger and Elsner 2006). We note that the CL and PL loss data sets give nearly the same results.

4 Large and small losses

Figure 4 shows distributions of losses by the Saffir-Simpson category of storm intensity. The logarithm of the losses by category are plotted as red horizontal tick marks. The median loss in each category is shown by a black horizontal line. The distribution is shown by the gray area. Wider areas correspond to more frequent loss events at that amount of loss. The distributions tend to be fairly symmetric on the log scale.

The range of damage losses tends to be greater for the lower category storms. For instance, at the 80% interval of losses the range is from 6.8 to 9.0 for category 0 storms, and from 7.2 to 9.1 for category 1 storms, this is about 2.2 and 1.9, respectively, or approximately a factor of 100. In comparison, the category 2, 3, 4, and 5 ranges are 1.3, 1.5, 1.4, and 1.1, respectively. Thus it makes sense to model tropical storms (category 0) and category 1 hurricanes separately from category 2 and higher storms. However, there is a practical limitation in that we lose 109 of the 212 storms. Thus, for this paper, we restrict our analysis to category 1 and higher tropical cyclones (hurricanes only) as a compromise between removing too much data and keeping too many small loss events.

The total damage from the 221 events (1900–2007) calibrated to 2005 is estimated at US $1.1 trillion. It is often noted that 80% of the total damage from tropical cyclones is caused by 20% of the biggest loss events. Figure 5 shows that the distribution of damage data is more skewed than that. In fact, the top 35 loss events (less than 16% of the total number of loss events) account for more than 81% of the total loss amount.

The relative infrequency of the largest loss events argues for a split that favors more data for modeling the largest losses. Here, we use a threshold of one billion $US and find that 90 of the 160 hurricane events (56.3%) exceed this value. The remaining 70 events

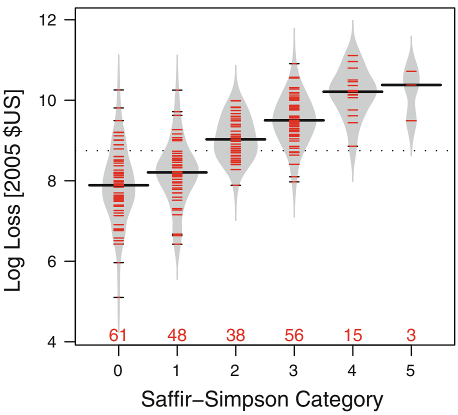

Fig. 4 Damage losses by Saffir-Simpson hurricane category. The actual losses are given as *horizontal red ticks*. The median loss in each category is shown by a *black horizontal line*. The smoothed distribution is shown with a *gray area*. Wider regions correspond to more frequent loss events at that amount of loss. Category 0 refers to tropical cyclones of tropical storm intensity

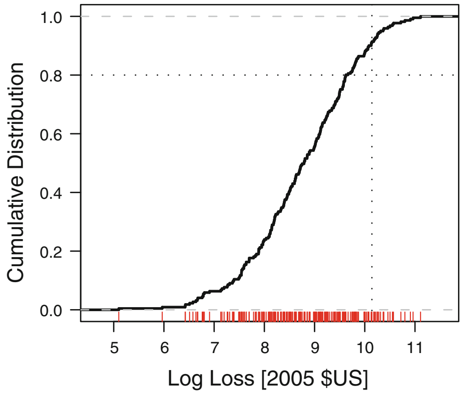

Fig. 5 Cumulative distribution of per storm damage loss. The values on the ordinate are the fraction of damage losses less than or equal to the damage losses on the abscissa. Losses are converted to a logarithmic (base 10) scale. The *horizontal dotted line* is the 80th percentile and the *vertical dotted line* is the loss amount of the 20th largest loss event. The actual values are located as *red tic marks* above the abscissa

(43.7%) account for only 15.4% of the total damages. Thus, it is reasonable to assume that small loss events are below the "noise" level. In summary, our focus here is on the set of large losses from the stronger tropical cyclones. Note also that here we do not examine the geographic variation of losses as was done for the state of Florida in Malmstadt et al. (2009).

5 Annual loss model

Given a loss event, the logarithm of the loss amount is modeled as a truncated normal distribution. The only statistically significant climate signal in the loss amount is the SST. We model this signal by regressing the location parameter of the truncated normal distribution onto SST for large losses. Thus given a loss event, the magnitude of the loss increases with increasing ocean warmth. This is consistent with SST acting as a proxy for upper-ocean heat, a source of energy for hurricanes (Emanuel 1991).

To arrive at an estimate of the annual loss, we need to combine this loss amount estimate given an event with the frequency of loss events. Since we divide loss events into large and small events, we use two models. Thus, given a mean annual rate of large (small) loss events, the annual number of large (small) loss events follows a Poisson distribution with the natural logarithm of the loss event rate given as a linear function of the climate variables. We find that SST, NAO, SOI, and SSN are all statistically significant indicators of the frequency of large losses, but none of the climate variables are important for the frequency of small losses.

Mathematically we write the model for large losses as:

$$\begin{aligned} A &= 10^L \\ L &\sim \text{Normal}(\mu, \sigma^2)\text{T}[9, \infty] \\ \mu &= \alpha_0 + \alpha_1 \text{SST} \\ N &\sim \text{Poisson}(\lambda) \\ \lambda &= \exp(\beta_0 + \beta_1 \text{SST} + \beta_2 \text{NAO} + \beta_3 \text{SOI} + \beta_4 \text{SSN}) \end{aligned} \quad (1)$$

where A is the loss amount for an event, N is the yearly event count and λ is the yearly loss frequency. The symbol $\sim$ refers to a stochastic relationship and indicates that the variable on the left-hand side is a random draw (sample) from a distribution specified on the right-hand side. The equal sign indicates a logical relationship with the variable on the left-hand side algebraically related to variables on the right-hand side. As mentioned, the size of the loss is modeled as a truncated normal distribution with parameters μ and σ^2 indicating the location and scale for the distribution and T[9,∞] indicating the truncation limits. Unlike the normal distribution, the location and scale parameters of the truncated normal distribution are not the same as its mean and variance. In short, the model describes a compound Poisson process with rate λ and logarithm of the loss amount distributed as a truncated normal distribution with parameters μ and σ.

The chi-square goodness-of-fit statistic indicates the rate model is adequate. Furthermore, there is no trend in the deviance residuals implying the rate model for large losses conditioned on the environmental variables chosen is statistically stationary and the addition of a trend term does not improve the model. This suggests to us that there is no significant historical under reporting of the number of loss events from hurricanes in the United States over the period considered here. Note this is not likely the case for losses from weaker tropical storms.

The final model that combines the frequency of loss events with the magnitude of the loss given an event uses a hierarchical Bayesian specification. Bayesian models provide posterior distributions of model parameters, as opposed to a frequentist model using maximum likelihood estimation (MLE) which only provides the parameter estimate and prediction error. For non-normal distributions, these MLEs lead to biased predictions. Here we chose flat (non-informative) priors for the location and precision ($1/\sigma^2$) parameters to minimize their influence on the posterior distributions.

The final model is selected from a set of possible models by comparing the Deviance Information Criterion (DIC) for each model and then choosing the model with the smallest DIC. The DIC is used for selecting among candidate models within a Bayesian framework in the same way that AIC is used for selecting among candidate models within a maximum likelihood framework (Spiegelhalter et al. 2002). DIC is particularly useful when the posterior distributions of the models are obtained by Markov Chain Monte Carlo (MCMC) simulation. The model with the smallest DIC is taken as the one that would best predict a replicate data set having the same statistics as the observed data set.

Given the hierarchical form of the model, samples of the annual losses are generated using WinBUGS (Windows version of Bayesian inference Using Gibbs Sampling) developed at the *Medical Research Council* in the UK (Gilks et al. 1998; Spiegelhalter et al. 1996). WinBUGS chooses an appropriate MCMC sampling algorithm based on the model structure. In this way, annual losses are sampled conditional on the model coefficients and the observed values of the covariates. The cost associated with a Bayesian approach is the requirement to formally specify prior beliefs. As mentioned, here we take the standard route and assume non-informative priors.

MCMC, in particular Gibbs sampling, is used to sample the parameters given the data since no closed form solution exists for the posterior distribution of the model parameters in the truncated normal (or for the generalized Pareto distribution (GPD) used in the next section). Indeed, WinBUGS is useful in that it allows us to sample the parameters from the posteriors created from arbitrary likelihood functions. As far as we are aware, there is no software for finding the maximum likelihood estimates of the regression parameters for a truncated normal distribution.

We check for mixing and convergence by examining successive samples of the parameters. Samples from the posterior distributions of the parameters indicate relatively good mixing and quick settling, as two different sets of initial conditions produce sample values that fluctuate around a fixed mean. Based on these diagnostics, we discard the first

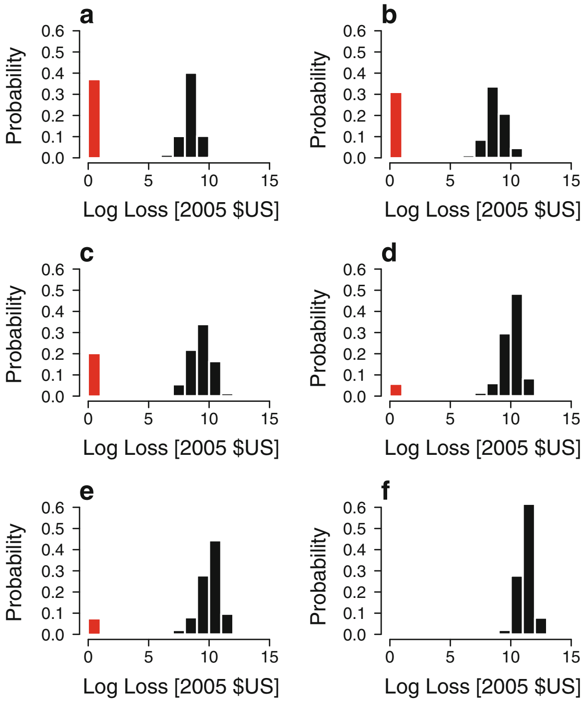

Fig. 6 Modeled annual losses for six different climate scenarios. Each panel is a different scenario with the *red bar* indicating the probability of no loss event for that year and the *black histogram bars* indicating the posterior predictive distribution of the amount of losses. The panels are ordered from *upper left* to *lower right* by conditions increasingly favorable for US hurricanes. **a** SST = −0.52°C, NAO = +2.9 SD, SOI = −2.3 SD, and SSN = 236, **b** SST = −0.24°C, NAO = +0.7 SD, SOI = −1.1 SD, and SSN = 115, **c** SST = +0.01°C, NAO = −0.3 SD, SOI = −0.2 SD, and SSN = 62, **d** SST = +0.27°C, NAO = −1.4 SD, SOI = +0.8 SD, and SSN = 9, **e** SST = +0.43°C, NAO = −1.3 SD, SOI = −0.1 SD, and SSN = 5, and **f** SST = +0.61°C, NAO = −2.7 SD, SOI = +2.6 SD, and SSN = 1

10,000 samples and analyze the output from the next 10,000 samples. The utility of the Bayesian approach for modeling the mean number of coastal hurricanes is described in Elsner and Jagger (2004) and for predicting damage losses is described in Jagger et al. (2008).

Figure 6 shows the posterior predictive distributions of annually aggregated losses for six different climate scenarios. The set of scenarios is ordered by increasingly favorable conditions for hurricanes in the United States from upper left to lower right. Each panel shows the probability of no losses during the year (red bar) and the probability of losses given at least one loss event (black histogram). The upper-left panel shows the posterior probabilities for a year during which the SST is much below normal, the NAO is much above normal, there is a strong El Niño in the Pacific, and the sun is active (many spots). The specific covariate values are listed in the figure caption.

The results show a relatively large probability of no loss events (37%) under this scenario. The estimated annual loss taking into account the non-zero probability of no loss events is centered in the range between $0.1 and $1 bn. As the climate factors change to indicate more favorable conditions for hurricanes, the posterior predictive distribution of annual losses become more ominous. The probability of no losses decreases to less than

1% and the expected annual total loss amount exceeding $100 billion in the most favorable scenario considered (lower-right panel). Keep in mind that all damage loss amounts are converted to 2005 US dollars. Results from the model are remarkable in showing distinct climate signals in property damage losses in the United States from hurricanes. In general, the annual expected loss increases with warmer Atlantic SSTs, La Niña conditions, a negative phase of the NAO, and fewer sunspots.

6 Extreme loss model

While the above model estimates the distribution of annual losses associated with variations in environmental conditions, for financial planning it might be more important to estimate the distribution of extreme losses and the probable maximum loss. In this case, the normal distribution is replaced by the Generalized Pareto Distribution (GPD) for the common logarithm of the loss amount, $L = \log_{10}(A)$. In what follows the term loss refers to the transformed loss amounts on the common logarithmic scale.

Consider observations from a collection of random variables in which only those observations that exceed a fixed value are kept. As the magnitude of this value increases, the GPD family represents the limiting behavior of each new collection of random variables if the limit exists. This property makes the family of GPD a good choice for modeling extreme events including large losses from hurricanes. The choice of threshold, above which we treat the values as extreme, is a compromise between retaining enough observations to properly estimate the distributional parameters (scale and shape), but few enough that the observations follow a GPD.

The GPD describes the distribution of losses that exceed a threshold l but not the frequency of losses exceeding that threshold. As we did with the annual loss model, we specify that, given a rate of loss events above the threshold, the number of loss events follows a Poisson distribution. Here there is no need to separate out small loss events as we are only interested in the large ones. Combining the GPD for large losses with the Poisson distribution for the frequency of loss events above the threshold allows us to obtain return periods for given levels (amounts) of loss.

We model the exceedances, $L - l$, as samples from a family of GPDs so that for any threshold l, and any event with the loss L, the probability that L exceeds some arbitrary level x above l is

$$\Pr(L > x + l | L > l) = \begin{cases} \exp(-\frac{x}{\sigma}) & \xi = 0 \\ \left(1 + \frac{\xi}{\sigma_l} x\right)^{-\frac{1}{\xi}} & \xi \neq 0 \end{cases} \tag{2}$$

$$= \mathrm{GPD}(\mathrm{x}|\sigma_1, \xi) \tag{3}$$

where $\sigma_l > 0$, $x \geq 0$, and $\sigma_l + \xi x \geq 0$. If the exceedances above l_0 follow a GPD then the exceedances above $l > l_0$ follow a GPD with the same shape, ξ and scale that shifts linearly with the threshold:

$$\sigma_l = \sigma_0 + \xi l$$

The parameters σ_l and ξ are the scale and shape parameters respectively. If $\xi \geq 0$ the maximum loss using the GPD model is unbounded but for $\xi < 0$ the GPD has an upper limit of $L_{\max} = l + \sigma_l / |\xi|$ so the maximum probable loss amount is bounded by \$ $10^{L_{\max}}$. The equation for σ_l specifies that if the values follow a GPD, then for any threshold the distribution of exceedances is GPD with the same value of the shape parameter (ξ) from the original distribution and a scale parameter that changes linearly with the threshold at a rate equal to the shape parameter.

We determine the threshold value for the set of losses at 9 i.e. a loss amount of $1 bn US by examining the mean residual life plot (not shown). This is a plot of the mean value of the exceedances as a function of the threshold. If the data follow a GPD, this plot is linear. The threshold is chosen as the smallest value where the function is linear for all larger thresholds (see Coles 2001, Chap. 4).

The GPD describes the distribution losses for each hurricane whose losses exceed l, but not the number of loss events exceeding l. Instead we assume that the number of loss events in year y that exceed l has a Poisson distribution with mean (or exceedance) rate is λ_l. Thus, by combining the exceedance probability and the exceedance rate with our assumption that they are independent, we get a Poisson distribution for the number of loss events per year with losses exceeding m (N_m) with a rate given by

$$\lambda_m = \lambda_l \Pr(L > m | L > l). \tag{4}$$

This specification is physically realistic, since it allows us to model loss occurrence separately from loss amount. Moreover from a practical perspective, rather than a return rate per loss occurrence, the above specification allows us to obtain an annual return rate on the extreme losses, which is more meaningful for the business of risk and insurance.

Now, the probability that the yearly maximum loss will be less than m is the probability that $N_m = 0$. Since N_m has a Poisson distribution

$$\Pr(L_{\max} \le m) = \Pr(N_m = 0) \tag{5}$$

$$= \exp(-\lambda_m) \tag{6}$$

$$= \exp\{-\lambda_l \mathrm{GPD}(\mathrm{m} - 1 | \sigma_1, \xi)\} \tag{7}$$

If we make the substitution for $\xi \neq 0$:

$$\sigma = \lambda_l^{\xi} \sigma_l \tag{8}$$

$$\mu = l + \frac{\sigma - \sigma_l}{\xi} \tag{9}$$

then

$$\Pr(L_{\max} \le m) = \exp\left\{-\left[1 + \xi\left(\frac{m-\mu}{\sigma}\right)\right]^{-\frac{1}{\xi}}\right\} \tag{10}$$

has a Generalized Extreme Value (GEV) distribution, which is in canonical form. If $\xi = 0$ then we make the substitutions

$$\sigma = \sigma_l$$
$$\mu = l + \sigma \log(\lambda_l)$$

then

$$\Pr(L_{\max} \le m) = \exp\left\{-\exp\left[-\left(\frac{m-\mu}{\sigma}\right)\right]\right\}. \tag{11}$$

We convert the peaks-over-threshold parameters λ_l, σ_l, ξ to the canonical GEV parameters μ, σ, ξ, to compare results obtained with different thresholds and calculate return levels. Using the canonical GEV parameters, the yearly (seasonal) return level, $rl(r)$, corresponding to a given return period, r is calculated by solving for m in $\Pr(L_{\max} \geq m) = \frac{1}{r}$ giving

$$rl(r) = \begin{matrix} \mu + \frac{\sigma}{\xi}\left\{\left[\log\left(\frac{r}{r-1}\right)^{-\xi} - 1\right]\right\} & \xi \neq 0 \\ \mu - \sigma \cdot \log\left\{\log\left(\frac{r}{r-1}\right)\right\} & \xi = 0. \end{matrix} \quad (12)$$

Additional details are given in Coles (2001, Chap. 4).

This model of extreme losses also uses a Bayesian specification, and a MCMC method is used to sample from the posterior predictive distributions. Here, we are interested in the return level as a function of return period. The return level is determined by the magnitude of individual extreme loss events and the frequency of such events above a threshold rate. The number of extreme loss events over a specified period is modeled using a Poisson distribution with the natural logarithm of the rate specified as a linear function of the four covariates. The losses minus the threshold $L - l$ is modeled using a GPD where the logarithm of the scale parameter and the shape parameter are both linear functions of the four covariates.

As before, samples of the return levels are generated using WinBUGS with non-informative prior distributions. Samples from the posterior distribution of the model parameters indicate good mixing and good convergence properties. We discard the first 10,000 samples and analyze the output from the next 10,000 samples. Applications of Bayesian extremal analysis are found in Coles and Tawn (1996), Walshaw (2000), Katz et al. (2002), Coles et al. (2003), Hsieh (2004), and Jagger and Elsner (2006).

For a given sample of the GEV parameters Eq. 12 is used to calculate a posterior sample of the return levels associated with each return period of interest. Figure 7 shows the posterior predictive distributions of return levels of individual loss events for four different climate scenarios using quantile values. For each return period, the 0.025, 0.25, 0.5, 0.75, and 0.975 quantile values of the return levels are plotted. The first scenario is characterized by covariates in favor of fewer hurricanes, the second scenario represents long-term climatological conditions, the third scenario is characterized by covariates favoring more hurricanes, and the fourth scenario is characterized by covariates favoring stronger hurricanes. The loss distribution changes substantially depending on the climate scenario and the directions of change are consistent with our understanding about the relationship between climate variability and hurricane activity.

Under the first scenario, we find the median return level of a 50-year extreme event at approximately \$18 bn; this compares with a median return level of the same 50-year extreme event loss of approximately \$793 bn under the fourth scenario. Thus, the model can be useful for projecting extreme losses over time horizons longer than a year given values of the covariates. Note that the results are interpreted as the posterior distributions of the return level for a return period of 50 years with the covariate values as extreme or more extreme than 1 standard deviation. With 4 independent covariates and an annual probability of about 16% that a particular covariate is more than 1 SD. from its mean, the chance that all covariates will be this extreme or more in a given year is less than 0.1%.

7 Summary and conclusions

Hurricanes are capable of generating large financial losses. Annual loss totals are directly related to the intensity and frequency of hurricanes affecting the coast. Since a detectable amount of skill exists in forecasting coastal hurricane activity months in advance of the

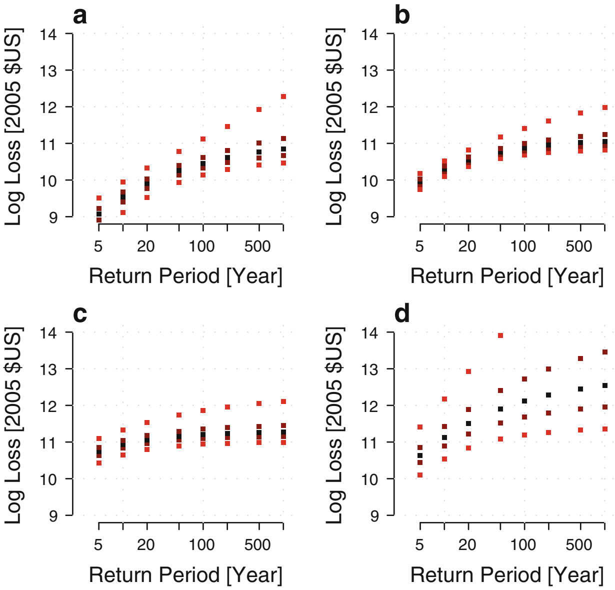

Fig. 7 Modeled return levels for four different climate scenarios. Each panel is a different scenario with the points indicating the 0.025 (*red*), 0.25 (*dark red*), 0.5 (*black*), 0.75 (*dark red*), and 0.975 (*red*) quantiles from the posterior predictive distribution of the return level for each return period. The panels are ordered from *upper left* to *lower right* by conditions increasingly favorable for US hurricanes. **a** SST = −0.243°C, NAO = +0.698 SD, SOI = −1.087 SD, and SSN = 115, **b** SST = +0.012°C, NAO = −0.331 SD, SOI = −0.160 SD, and SSN = 62, **c** SST = +0.268°C, NAO = −1.359 SD, SOI = −0.766 SD, and SSN = 9, **d** SST = +0.268°C, NAO = −1.359 SD, SOI = −1.087 SD, and SSN = 9. Lower quantile return levels in panel (**a**) and upper quantile return levels in panel (**d**) are outside the ranges of the plot

season, it is interesting to investigate the potential of modeling losses directly. This paper demonstrates the existence of climate and solar signals in the set of historical property damage losses.

Two statistical models are developed and posterior predictive samples from the models are generated using MCMC methods. The first model estimates the annual loss. Results show the amount of loss increases with warmer Atlantic SSTs, La Niña conditions in the Pacific, a negative phase of the NAO, and fewer sunspots. The second model estimates the distribution of extreme losses over a multi-year time horizon conditional on the values of the same four covariates.

Results are consistent with current understanding of US hurricane climate variability. While the models are developed from aggregate loss data for the entire United States susceptible to Atlantic hurricanes, it would be possible to model data representing a subset of losses capturing, for example, a particular insurance portfolio. Moreover, since the models make use of MCMC sampling, they can be extended to include error estimates on the losses and censored data (e.g., losses where at least some amount or losses did not exceed more than some amount). Hazard risk affects the profit and loss of the insurance industry. Some of this risk is transferred to the performance of securities traded in financial markets. This implies that early and reliable information concerning potential hazards will be useful to investors. This paper advances those goals.

The study is limited by the historical loss data. As noted above, although the per storm damage losses have been adjusted for increases in coastal population, the number of loss events have not. An early tropical cyclone making landfall in an area void of a built environment did not generate losses, so there is nothing to adjust. This can be rectified using a model (e.g., HAZUS) that can estimate losses from historical hurricanes using constant building exposure data.

Traditional hurricane risk models used by the insurance industry rely on a catalog of storms that represent the historical data in some way or another. While useful for estimating expected annual loss and loss exceedance levels for portfolio losses, these catalogs are not easily suited for anticipating losses based on a variable climate. Specifically, at the core of the catalog is a very large set of synthetic storms (more than 50,000) and a way to assign a probability to each. To condition the synthetic storms on several climate variables would require a catalog size that is at least an order of magnitude larger. The approach demonstrated here provides an alternative way to anticipate losses on the seasonal and multi-year time scales that avoids the problem of excessively large catalogs.

Concerning the future, increases in ocean temperature will raise a hurricane's potential intensity, all else being equal. However, corresponding increases in atmospheric wind shear—in which winds at different altitudes blow in different directions—could tear apart developing hurricanes and could counter this tendency by dispersing the hurricane's heat. However, a recent study based on a set of homogenized satellite-derived wind speeds indicates the strongest hurricanes are getting stronger worldwide (Elsner et al. 2008). This new information could be incorporated in models of the type demonstrated here by placing a discount factor on the older losses relative to the more recent loss events.

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