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Forecasting U.S. hurricanes 6 months in advance

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[1] Katrina is a grim reminder of the serious social and economic threat that hurricanes pose to the United States. Recent advances in hurricane climate science provide skillful forecasts of the U.S. hurricane threat at (or near) the start of the season. Predictions of hurricane landfalls at longer lead times (forecast horizons) for the complete hurricane season would greatly benefit risk managers and others interested in acting on these forecasts. Here we show a model that provides a 6-month forecast horizon for annual hurricane counts along the U.S. coastline during the June through November hurricane season using the North Atlantic Oscillation (NAO) and Atlantic sea-surface temperature (SST) as predictors. Forecast skill exceeds that of climatology. The long-lead skill is linked to the persistence of Atlantic SST and to teleconnections between North Atlantic sea-level pressures and precipitation variability over North America and Europe. The model is developed using Bayesian regression and therefore incorporates the full set of Atlantic hurricane data extending back to 1851. **Citation:** Elsner, J. B., R. J. Murnane, and T. H. Jagger (2006), Forecasting U.S. hurricanes 6 months in advance, *Geophys. Res. Lett.*, *33*, L10704, doi:10.1029/2006GL025693.

1. Introduction

[2] Predictions of basin-wide Atlantic hurricane activity have been around since the middle 1980s [*Gray*, 1984b]. Research focusing on climate factors that influence hurricane frequency regionally [*Lehmiller et al.*, 1997; *Bove et al.*, 1998; *Maloney and Hartmann*, 2000; *Elsner et al.*, 2000; *Murnane et al.*, 2000; *Jagger et al.*, 2001; *Larson et al.*, 2005] is more recent. Insights into regional hurricane activity are used to help predict landfall activity [*Elsner and Jagger*, 2006a; *Saunders and Lea*, 2005; *Lehmiller et al.*, 1997]. However, current landfall forecasts have short lead times (less than 1 month) and rely on data spanning approximately the past half century. In general, statistical models built from longer data records would be expected to perform with greater precision. However, older data tend to be less reliable and more uncertain. Here we maximize the utility of available data by combining the relatively short, high quality time series of observations with older, less precise time series using a Bayesian approach that does not require data to have uniform precision [*Elsner and Bossak*, 2001; *Elsner and Jagger*, 2004]. In doing so we offer for the first time a forecast model that can be used to predict the number of hurricane landfalls along the U.S. coastline (U.S. hurricane activity) by February 1st (4 months prior to the official start of the hurricane season and 6 months prior to the active portion of the season). The work builds on *Elsner and Jagger* [2006b] who demonstrate a skillful prediction model for U.S. hurricanes by July 1st.

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2. Data

[3] A chronological list of all hurricanes that have affected the continental United States in the period 1851–2004 is available from the U.S. National Oceanic and Atmospheric Administration. The approximate length of the U.S. coast line affected by hurricanes from the Atlantic is 6000 km. We do not consider hurricanes affecting Hawaii, Puerto Rico, or the Virgin Islands. Hurricane landfall occurs when all or part of the storm's eye wall passes over the coast or adjacent barrier islands. A hurricane can make more than one landfall as hurricane Andrew did in striking southeast Florida and Louisiana. Here we consider only whether the cyclone made landfall the continental United States at least once at hurricane intensity. Here it is assumed that the annual counts of U.S. hurricanes are certain back to 1899, but less so in the interval 1851–1898. Justification for this cutoff is based partly on U.S. legislation in July 1898 to create a hurricane warning system for the protection of military and merchant ships in the Caribbean that led to the establishment of a Weather Bureau forecast center at Kingston, Jamaica [*Arsenault*, 2005].

[4] We consider as predictors of U.S. hurricanes two variables shown previously to be related to seasonal activity; Atlantic SST and the North Atlantic oscillation (NAO), represented by a sea-level pressure difference between subtropical and polar latitudes [*Hurrell et al.*, 2001]. Atlantic SST values are based on a blend of model values and interpolated observations, which are used to compute anomalies north of the equator. The anomalies are computed by month using the climatological time period 1951–2000 and are available back to 1871. Units are °C. January SST values are obtained online from NOAA-CIRES Climate Diagnostics Center (CDC). The low frequency variation in linearly detrended Atlantic SST is sometimes referred to as the Atlantic Multidecadal oscillation (AMO) [*Enfield et al.*, 2001; *Goldenberg et al.*, 2001]. For shorthand we use the acronym "AMO" for Atlantic SST variation. NAO index values are calculated from sea level pressures at Gibraltar and at a station over southwest Iceland [*Jones et al.*, 1997], and are obtained from the Climatic Research Unit. The values used here are an average over the fall and early winter months of October through January and are available back to 1851. Units are standard deviations.

[5] We also consider the Southern Oscillation Index (SOI) as a predictor, but find no significant relationship

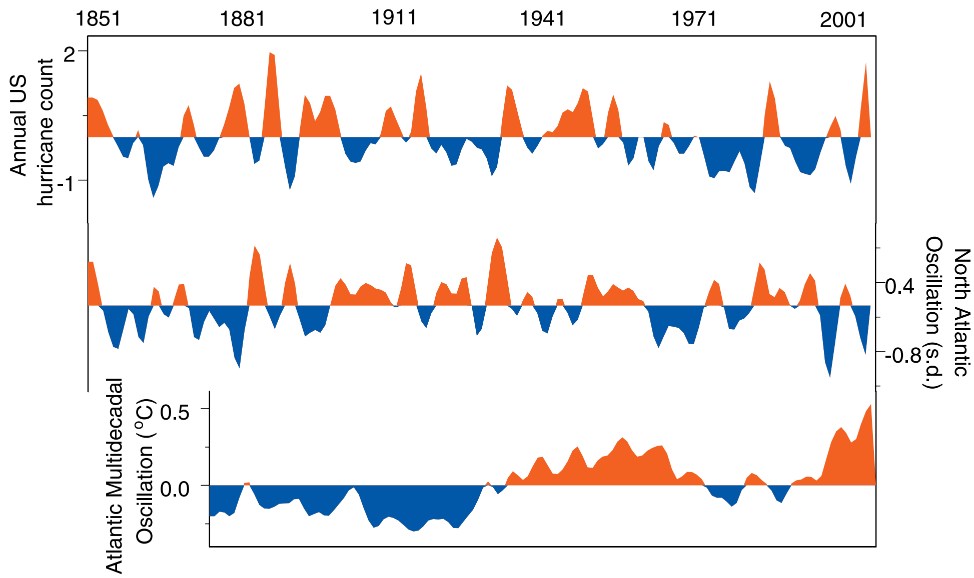

Figure 1. Time series of the predictand and predictors used in the long lead forecast model of U.S. hurricane activity. (top) Annual U.S. hurricane count (predictand). (middle) October–January averaged value of the North Atlantic Oscillation (NAO) (predictor). (bottom) January averaged value of the linearly detrended Atlantic SST (AMO) (predictor). The NAO explains less than 2% of the variation in the AMO. For presentation purposes only, all series have been smoothed using a 3-year kernel (Parzen) filter. Results from correlation analyzes and regression modeling reported in the text are based on unfiltered values.

with U.S. hurricanes at this lead time (6 months). While not used directly in the long-lead forecast model, the SOI helps explain the secular variations in model skill. SOI values are an indicator of ENSO. Although noisier than equatorial Pacific SSTs, values are available back to 1866. The SOI is defined as the normalized sea-level pressure difference between Tahiti and Darwin. The SOI is strongly anti-correlated with equatorial SSTs so that an El Niño warming event is associated with negative SOI values. Units are standard deviations. The relationship between ENSO and hurricane activity is strongest during the hurricane season, so we use an August–October average of the SOI as our predictor. The monthly SOI values [*Ropelewski and Jones*, 1997] are obtained from the Climatic Research Unit.

[6] SST variability is determined by temperatures across the Atlantic basin with a warm ocean resulting in high values for the AMO. NAO variability results from changes in the atmospheric mass and pressure fields that change middle latitude storminess and the strength and geographic position of the subtropical high pressure cell. A strong north-south pressure gradient results in high values for the NAO. A warm tropical ocean provides fuel for tropical cyclones and the subtropical high provides steering. Years coincident with a warm ocean and low NAO values result in a significantly greater threat of U.S. hurricanes.

3. Bayesian Regression Model

[7] Time series of annual U.S. hurricane counts, fall to winter (October–January) averaged values of an NAO index, and January values of Atlantic SST are shown in Figure 1. The NAO shows greater high frequency (year-to-year) variation while the AMO shows pronounced low frequency variability. Only the NAO is available back to 1851. U.S. hurricane landfalls tend to be more abundant when the NAO is low and the Atlantic is warm. The correlation (Pearson) between the annual count and the NAO is −0.19 (P = 0.017) and between the annual count and a linearly-detrended AMO is +0.20 (P = 0.021). We note that the NAO-U.S. hurricane correlation changes to −0.27 (P = 0.006) when the years 1949–1997 are removed from the analysis. Correlation analysis does not provide an equation for prediction nor does it consider missing predictor values or the fact that annual coastal hurricane counts are small non-negative integers and likely uncertain before 1899. We account for these limitations using a Bayesian regression model and forecast the number of hurricanes for each year conditional on values of the NAO, Atlantic SST, and year. Remarkably, these predictors provide useful skill in forecasting the hurricane threat 6 months in advance.

[8] The annual coastal hurricane count is assumed to follow a Poisson distribution. The logarithm of the Poisson rate is logically linked to a summation of the predictors. Although hurricane counts are available back to 1851, older counts are less precise. Therefore we include an indicator variable given a value of 1 for years 1851–1898, and a value of 0 for years 1899–2004. The model coefficient associated with this term is the logarithm of the probability that a hurricane is recorded in the database given that it occurred. In effect, the model allows for the possibility that a hurricane occurred but was not recorded. The model is evaluated using Markov chain Monte Carlo (MCMC) sampling [*Gilks et al.*, 1994; *Spiegelhalter et al.*, 1996]. Diagnostic plots reveal good mixing of the samples. We generate 12K samples and discard the first 2K. The modeling procedure is cross-validated in the spirit of *Elsner and Schmertmann* [1994]. Details of the model and cross

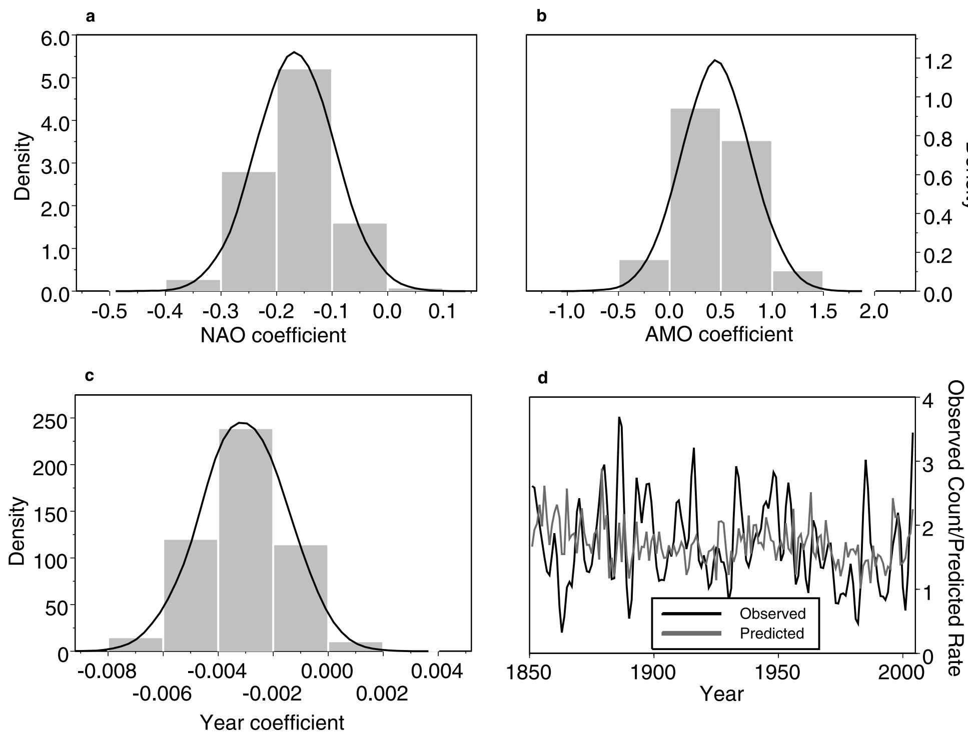

Figure 2. Posterior distributions of regression coefficients from a Bayesian model of U.S. hurricane counts. (a) Regression coefficient of fall/winter NAO. (b) Regression coefficient of January AMO. (c) Regression coefficient of year. (d) Time-series of observed annual number of U.S. hurricanes and model-predicted mean hurricane rate for each year 1851–2004. The observed counts are smoothed as in Figure 1 to better match the smaller variability of the rate.

validation procedure are given by *Elsner and Jagger* [2004, 2006b].

4. Model Results and Discussion

[9] Analysis of the distribution of posterior samples of the regression coefficients (Figure 2) shows the significance of the predictors of hurricane landfall. The posterior mean of the NAO coefficient (Table 1) is −0.166 with a 95% credible interval of (−0.303, −0.027) and a P = 0.0085 (only 85 out of 10K samples had a coefficient value greater than 0). The posterior mean of the Atlantic SST coefficient is +0.455 with a 95% credible interval of (−0.193, +1.106) and a P = 0.085. Correlation between the observed count and the predicted mean number of hurricanes is +0.24, but increases to +0.29 when the years from 1949 through 1997 are removed.

[10] The leading contender model for anticipating U.S. hurricane counts at this long lead time is climatology. The model outperforms climatology in 56% (86/154) of all years and in 61% (42/69) of years in which the number of U.S. hurricanes is zero or more than 2 (below and above average years). These percentages are 55 and 59, respectively when the model is cross-validated. Even for years in which the model under-performs climatology, the forecast probability of what actually occurred is relatively high. Thus, the model anticipates the coastal hurricane season 4–6 months in advance with an out-of-sample skill level that exceeds that of simply predicting an average number each year. Skill levels are modest but useful especially for years of heightened (three or more) and no hurricane landfalls. In comparison, the correlation over the past 13 years (1992–2004) between observed and predicted basin-wide hurricane counts from actual forecasts made by December (W. M. Gray et al., Summary of 1999 Atlantic tropical cyclone activity and verification of author's seasonal activity prediction, Dep. of Atmos. Sci., Colorado State Univ., Fort Collins, 1999, available at http://hurricane.atmos.colostate.edu/Forecasts/1999/nov99/, and W. M. Gray and P. J. Klotzboch, Extended range forecast of Atlantic seasonal hurricane activity and U.S. landfall strike probability for 2005, Dep. of Atmos. Sci., Colorado State Univ., Fort Collins, 2004, Available at http://hurricane.atmos.colostate.edu/Forecasts/2004/dec2004/) is +0.08, which compares with +0.35 from our cross-validated model predicting U.S. hurricane counts by February. Our model also outperforms

Table 1. Bayesian Regression Results[a]

		Model Coefficient		
Term	Averaging Months	Mean	95% CI	P-value
NAO	October–January	−0.166	(−0.303, −0.027)	0.0085
AMO	January	+0.455	(−0.193, +1.106)	0.0850
Year	–	−0.003	(−0.006, −0.001)	0.0220
SOI	August–October	+0.177	(+0.047, +0.304)	0.0046
NAO	May–June	−0.202	(−0.327, −0.077)	0.0003

[a]Posterior mean, 95% credible interval and P-value of the model coefficients. Only the first three terms are used in the long-lead model. The SOI term is added to explain the long-lead model's poor performance over the period 1949–1997. The May–June NAO term improves the model's predictive capability, although it reduces the model's usefulness as the lead time is shortened considerably. The mean October–January NAO coefficient decreases by less than 1% and the mean January AMO coefficient decreases by 14% with the addition of the SOI and May–June NAO terms to the model.

Table 2. Out-of-Sample Skill Comparisons[a]

Forecast Year	Observed Number	Bayesian Regression Predicted Mean	BHRC Method Predicted Mean
2000	0	1.44	2.0
2001	0	1.46	1.8
2002	1	1.68	1.9
2003	2	1.73	1.8
2004	5	2.02	1.9
r	—	0.98	−0.06
MSE	—	2.72	3.54

[a]Observed number of U.S. hurricanes during the most recent five-year period (2000–2004) versus predicted mean rates from our Bayesian regression model and from methods developed at Benfield Hazard Research Centre (BHRC), University College London. Skill is measured by the correlation (r) and mean squared error (MSE) between observed counts and mean rates. To simulate actual forecast situations, predictions made with the Bayesian regression use hurricane data only through the previous year and predictor data only through the forecast year. After each prediction an additional year of data is added. Predictions made by the BHRC were issued in early February for the 2002, 2003, and 2004 seasons, and in late November (previous year) for the 2000 and 2001 seasons.

long-range forecasts of U.S. hurricane activity issued by Benfield Hazard Research Centre (http://tropicalstormrisk.-com), though the comparison is based on a limited number of years (see Table 2).

[11] The model has skill because Atlantic SST predicts how active the basin will be in terms of the number of hurricanes and the NAO predicts the general path the hurricanes will take when they form. Warm Atlantic ocean conditions in January generally persist into the hurricane season. We quantify the relationship between a warm ocean and hurricane number by modeling the total basin-wide hurricane count using the January AMO from 1943–2004 and find a significant lead relationship (P = 0.0047).

[12] The relationship between October–January NAO and hurricane tracks is more complex. A weak fall/winter NAO is associated with weaker middle latitude weather systems (and thus less precipitation) over North America and Europe. The relatively dry fall/winter season continues into spring and the dry conditions subsequently lead to a tendency for greater middle tropospheric ridging during the summer and fall. Ridging over the eastern and western sides of the North Atlantic basin during the hurricane season displaces the middle tropospheric trough of lower pressures to the north. The trough, which induces hurricane movement to the north and east, is therefore unable to recurve hurricanes that are moving westward toward the United States thus increasing the probability of landfalls along the Gulf and southeast coasts. Support for this hypothesis comes from the positive correlation between monthly precipitation totals from January through May at stations in a region extending from Ohio to Massachusetts and fall/winter NAO values. In other words, weak fall/winter NAO conditions lead to less precipitation, more ridging, less recurvature, and a higher probability of landfall.

[13] We consider 11 stations with monthly precipitation totals (from the U.S. Historical Climatology Network dating back at least 100 years from Ohio to Massachusetts and compute the fall/winter-averaged NAO coefficient for an ordinary linear regression model of monthly precipitation on NAO and year for each station and for each month from January through May. Of the 55 coefficients (5 mo × 11 stations), 45 (82%) are positive (for each station at least 3 of the 5 months have a positive coefficient) indicating that fall/winter NAO tends to lead springtime precipitation totals with a weak NAO associated with drier conditions over the Midwest into the Northeast. We repeat the analysis with the January AMO used in place of the NAO and find that only 31 (56%) of the coefficients are negative indicating Atlantic SST explains less of the interannual variation in spring precipitation over this region. These results are similar to *Ogi et al.* [2004] showing a linkage between wintertime NAO and the following summertime high pressure over the Sea of Okhotsk and it's regulation of the Asian summer monsoon.

[14] The El Niño-Southern Oscillation (ENSO) cycle also plays a role in how active the hurricane season will be [*Gray*, 1984a], and it thus modifies the probability of a U.S. strike possibly through changes in tropospheric wind shear [*Goldenberg and Shapiro*, 1996]. This effect is not included in the long-lead model, but it explains why the model performs rather poorly over the period from 1949–1997. We show this by adding the August through October (main hurricane season) averaged value of the SOI to the model. The term is significant (P = 0.0046) after accounting for values of fall/winter NAO and January AMO. In-sample model skill over climatology increases to 58% of all years and to 68% of years in which the number of U.S. hurricanes is zero or more than 2. In particular, the mean value of the hurricane-season SOI over the period 1949–1997 for the 7 years in which the fall/winter NAO is most negative (most favorable for U.S. hurricanes) is −0.92 which compares to an average of −0.12 over the period 1867–2004. Thus in years over the period 1949–1997 that portended favorable conditions for storms to track toward the U.S. (negative NAO), ENSO was an inhibiting factor in hurricane development. This underscores the value of accurate long-lead forecasts of ENSO. Interestingly, since the effect of the NAO is accumulative (more pre-hurricane season months of negative NAO implying more drying) if we also include a May through June averaged value for the NAO to the model (P = 0.0003), model skill over climatology increases to 62% of all years and to 80% of years in which the number of U.S. hurricanes is zero or more than 2.

5. Conclusion

[15] Seasonal prediction of hurricane landfalls is of potentially great value to business, government, and society. Better forecasts provide a sound basis for assessing the likely losses associated with a catastrophic reinsurance contract [*Michaels et al.*, 1997], but forecasts will need to be issued well before January 1, the start date of most reinsurance treaties, to be of greatest value to reinsurers. It is worth noting that although forecasts of the mean hurricane count fluctuate around 2, there can be a sizeable change in the forecast probability of a large number of hurricane landfalls with a small change in the forecast mean, and changes in the tails of these probability distributions are of practical importance to catastrophe reinsurers. Our model of hurricane landfalls, which shows skill at lead times of at least 4 months before the hurricane season, begins to provide risk managers the advance information needed for action.

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