SEASONAL PREDICTION OF ATLANTIC TROPICAL CYCLONE ACTIVITY

Elinor W. Keith and Lian Xie *
North Carolina State University, Raleigh, NC

1. INTRODUCTION

Many sectors of society could benefit from reliable seasonal hurricane forecasts. Two major potential end-users are insurance and industries with large energy needs. Typically, insured loses are believed to be roughly half of the total financial losses form a hurricane (Knabb et al. 2005.) When hurricanes pass over the Gulf of Mexico, its effect can be felt around the country. Jet fuel is the second largest expense for airlines such as Southwest, behind salaries. By buying oil futures, companies can protect themselves against oil shocks (Sullivan, L., 2000.) When fuel costs soared following Hurricanes Katrina and Rita in 2005 (the cost per gallon increasing by 58% year-over-year), Southwest saved dramatically by having 85% of its oil supply capped at $26 a barrel. While the next-highest earner, Continental, managed a net profit of $61 million, Southwest netted $226 million in the third quarter of 2005 (Bond, D., 2005).

Many climatic factors have been linked with the number of tropical storms, hurricanes and major hurricanes forming on the Atlantic. Several examples are the Atlantic Multidecadal Oscillation (Goldenburg et al 2001,) the Atlantic Meridional Mode (Vimont and Kossin 2007,) Tropical North Atlantic SST (Wang et al 2006,) the Atlantic Dipole Mode (Xie et al. 2005,) and El Niño (Gray 1984.) But using too many independent variables in a regression leads to less-precise estimators and poor prediction (Shumway and Stoffer 2006.) To further complicate model selection, if the data itself is used to select predictors for a final model, any cross-validation statistics could be compromised and the model may be fitting random noise in the data rather than actual signal (Elsner and Schmertmann 1994.)

Here the empirical orthogonal functions of the hurricane track density function are used to retain more of the spatial and temporal information in the tropical storm track data and reduce noise. The EOFs are then used to select predictors for a Poisson regression model of tropical storm, hurricane and major hurricane counts over a total of six regions: the entire Atlantic, the Caribbean, the Gulf of Mexico, and landfalling storms along the US Gulf of Mexico, Southeastern and Northeastern coasts.

* *Corresponding author address:* Lian Xie, Department of Marine, Earth and Atmospheric Sciences, North Carolina State University, Box 8208, Raleigh, NC 27695-8208. Email: xie@ncsu.edu.

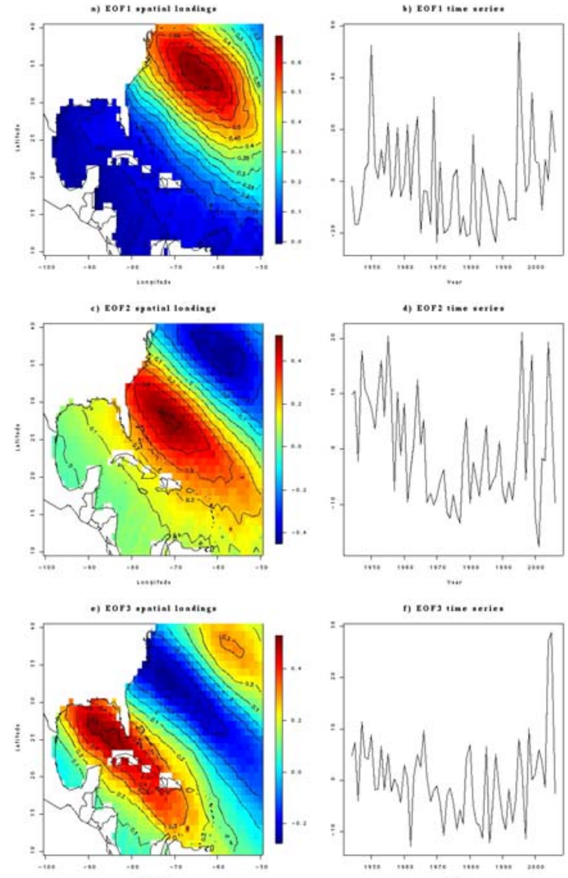

Figure 1: Spatial patterns and time series of the top three EOFs. EOF1 explains 10.2% of the total variance, EOF2 6.2%, and EOF3 5.2%.

2. METHODS

The hurricane track density function (HTDF) used here is the probability of tropical storm-force winds at a point. The prediction equation for tropical storm-force winds is an adaptation of a prediction model given in Kossin et al. (2007) using Extended Best Track Data (Demuth et al. 2006.) The regression predicts for a transformation of the radius of tropical storm-force winds (R34, in km) using the storm's maximum wind speed (Vmax) in knots, the latitude (lat) and age since reaching tropical storm strength in hours. ε is the regression error.

$$\frac{(\sqrt[3]{R34}-1)}{1/3} = 6.56 + 0.0599 \cdot Vmax + 0.0912 \cdot lat + 0.00846\, age + \varepsilon \quad (1)$$

With the expected value and regression variance from this equation, we can use a standard normal probability distribution to generate the probability of tropical storm winds at some distance away. This is done for every day within the hurricane season from

1944-2006 on a 1°x 1° grid between 10°N-40°N and 50°W-100°W, with grid points over land, the Great Lakes, and the Pacific removed.

Next, the HTDF is converted into EOFs, the top three of which are retained. The time series of the EOFs are averaged by month and cross-correlated against common predictors to choose a final set of predictors for each region. The predictors which have 95% significant correlation with a region's EOF with at least 3 months lead time are considered as predictors for the region. It is also important for the correlation to continue over time; after all, even with white noise, one out of every 20 correlations should be significant at a 95% level. At least one of the surrounding correlations is required to be significant at a 90% level.

These predictors are used as the independent variables in Poisson regressions on the counts of tropical storms, hurricanes and major hurricanes by year over the entire Atlantic, Caribbean Sea and Gulf of Mexico. They are also used to predict the number of landfalling storms along the US Gulf of Mexico, Southeast (East Fl-NC) and Northeast (Va-Me) coasts. Lastly, the regressions are validated using hindcasts, where the last several years of data are removed, and leave-one-out cross-validation (LOOCV,) where a single year's data is removed at each step. P-values for these tests are calculated using a Monte Carlo technique to compare against random chance with n = 10,000 repetitions.

Table 1: Model validation. Models where at least two tests resulted in p-values significant at a 95% confidence level are in bold.

Region	Dependent Variable	1990-2007 Hindcast P value	1980-2007 Hindcast P value	LOOCV P value
Whole Atlantic	**TS + Hur**	**0.003**	**0.000**	**<0.001**
	Hur.	**0.036**	**0.007**	**0.003**
	Maj. Hur.	**0.006**	**0.001**	**0.002**
Caribbean Sea	**TS + Hur**	**0.024**	**0.005**	**0.001**
	Hur.	**0.001**	**0.000**	**<0.001**
	Maj. Hur.	**0.027**	**0.010**	**0.002**
Gulf of Mexico (all storms)	**TS + Hur**	**0.034**	**0.029**	**0.008**
	Hur.	0.146	0.147	0.045
	Maj. Hur.	0.470	0.455	0.518
Gulf of Mexico (landfalling)	**TS + Hur**	**0.033**	**0.108**	**0.027**
	Hur.	0.428	0.363	0.341
	Maj. Hur.	0.603	0.687	0.840
Southeast	**TS + Hur**	**0.051**	**0.044**	**0.008**
	Hur.	0.329	0.239	0.128
	Maj. Hur.	0.505	0.496	0.612
Northeast	TS + Hur	0.922	1.000	1.000
	Hur.	0.978	1.000	0.998
	Maj. Hur.	0.158	0.095	0.053

3. RESULTS

The EOF spatial patterns and time series are shown in Fig. 1. The time series of EOF1 reflects tropical cyclone landfalls along the Northeast coast, EOF2 correlates with landfalls along the Southeast coast and EOF3 is connected to activity in the Gulf of Mexico and Caribbean. Predictors which correlate with any of these are also used to predict for the entire Atlantic.

Table 2 contains the model validation for all of the predictions, with regressions where at least two out of three tests were significant at a 95% confidence level shown in bold. All predictions for both the Atlantic as a whole and the Caribbean Sea show highly significant improvement over climatology. The prediction of total tropical storms and hurricanes over the Gulf of Mexico is significant, but the prediction of hurricane and major hurricanes is not.

For landfalling tropical cyclones, the results are poorer. Not only does the model need to predict how many storms will form in a given year, but where they will go. Never the less, prediction of total named storms making landfall was significant along the US Gulf of Mexico and Southeast coasts.

4. CONCLUSIONS

The method described here works well for certain regions (especially storms forming anywhere in the Atlantic or passing over the Caribbean) and types of storms, particularly for all named storms.

Hurricanes and major hurricanes are more difficult to predict – most notably for landfalling numbers. Although hurricanes and major hurricanes do the majority of the damage, weaker storms provide more overall rainfall (Cook-Anderson 2007.)

Storms striking the Northeast were too rare for the regression to forecast accurately. Since 1950, there have only been three years when major hurricanes made landfall along the Northeast.

5. ACKNOWLEDGEMENTS

This study is partially supported by U.S. Department of Energy Grant #DE-FG02-07ER64448 and U.S. National Oceanic and Atmospheric Administration (NOAA) Grant # NA06OAR4810187.

6. REFERENCES

Bond, D., 2005: Southwest and the Rest. *Aviation Week & Space Technology,* **163**, 39.

Cook-Anderson, G., 2007, cited 2008: Smaller Storms Drop Larger Overall Rainfall in Hurricane Season. [Available online at http://www.nasa.gov/mission_pages/hurricanes/archives/2007/smallstorm_largerain.html.]

Demuth, J., M. DeMaria, and J. A. Knaff, 2006: Improvement of advanced microwave sounder unit tropical cyclone intensity and size estimation algorithms. *J. Appl. Meteorol.,* **45**, 1573-1581.

Elsner, J. B., and C. P. Schmertmann, 1994: Assessing Forecast Skill through Cross-Validation. *Weather and Forecasting,* **9**, 619-624.

Goldenberg, S. B., C. W. Landsea, A. M. Mestas-Nunez, and W. M. Gray, 2001: The recent increase in Atlantic hurricane activity: Causes and implications. Science, 293, 474-479.

Gray, W. M., 1984: Atlantic Seasonal Hurricane Frequency .1. El-Niño and 30-Mb Quasi-Biennial Oscillation Influences. Mon. Weather Rev., 112, 1649-1668.

Knabb, R. D., J. R. Rhome, and D. P. Brown, 2006, cited 2008: Tropical Cyclone Report: Hurricane Katrina. [Available online at http://www.nhc.noaa.gov/pdf/TCR-AL122005_Katrina.pdf.]

Kossin, J. P., J. A. Knaff, H. I. Berger, D. C. Herndon, T. A. Cram, C. S. Velden, R. J. Murnane, and J. D. Hawkins, 2007: Estimating hurricane wind structure in the absence of aircraft reconnaissance. *Weather and Forecasting,* **22**, 89-101.

Shumway, R. H., and D. S. Stoffer, 2006: *Time Series Analysis and Its Applications with R Examples.* 2nd ed. 575 pp.

Sullivan, L., 2000: In-Flight Hedges. *Risk Management (00355593),* **47**, 56-56.

Vimont, D. J., and J. P. Kossin, 2007: The Atlantic Meridional Mode and hurricane activity. *Geophys. Res. Lett.,* **34**, L07709.

Wang, C. Z., D. B. Enfield, S. K. Lee, and C. W. Landsea, 2006: Influences of the Atlantic warm pool in western hemisphere summer rainfall and Atlantic hurricanes. *J. Clim.,* **19**, 3011-3028.

Xie, L., T. Z. Yan, and L. Pietrafesa, 2005: The effect of Atlantic sea surface temperature dipole mode on hurricanes: Implications for the 2004 Atlantic hurricane season. Geophys. Res. Lett., 32, L03701.