TRACKING HURRICANES

BY JAMES B. ELSNER

To better understand and predict regional hurricane probabilities, it is important to consider climate factors that influence where they track.

R egardless of the criteria used in defining North Atlantic hurricane activity, the last six years of the twentieth century are among the most prolific in the modern record (Wilson 1999; Elsner et al. 2000a). Goldenberg et al. (2001) note a 2.5-fold increase in strong hurricanes (maximum sustained near-surface winds exceeding 50 m s⁻¹) and a 5-fold increase in Caribbean hurricanes. This upswing in hurricane activity is related to warmer ocean waters and less vertical wind shear in areas that typically spawn hurricanes. When these conditions coincide hurricane activity increases.

Here we suggest that results from tropical cyclone track research (Harr and Elsberry 1991; Lander 1996; Elsner et al. 2000b; Elsner and Liu 2003) can also inform us about hurricane climate variability. Because they travel over the warmest ocean areas, tropical cyclones that parallel low latitudes are more likely to become hurricanes and strong hurricanes than those that recurve northward. Although this is a generalization, hurricane seasons will tend to be more active when characterized by storms that remain at low latitudes. Since it is difficult to make a physical argument

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In final form 6 September 2002 © 2003 American Meteorological Society that directly links sea surface temperature or wind shear to hurricane steering mechanisms, a connection between climate variability and hurricane abundance (locally and regionally) should include factors related to hurricane tracks.

DATA AND ANALYSIS. Hurricane locations from the "best-track" (HURDAT) data maintained by the National Hurricane Center (NHC) are used. The data are considered reliable beginning with 1944 (Neumann et al. 1999; Jarvinen et al. 1984). This is the year in which aircraft reconnaissance information about the storms is available. Even still, before satellite monitoring beginning in the mid-1960s, a portion of the lifetime of many of the tropical cyclones may have been missed. Since our interest is tropical cyclones of hurricane intensity, this bias will not seriously influence the results. The analysis begins with a broad grouping of hurricane tracks.

Figure 1 is a map showing end locations of all hurricanes over the period 1944–2000 grouped according to their positions at maximum and final hurricane intensities. End location is defined as the last position that the tropical cyclone was classified as a hurricane by the NHC. Grouping is based on a *k*-means cluster analysis using latitude and longitude coordinates at maximum and final hurricane intensities (Elsner et al. 2000b; Elsner and Liu 2003). Cluster analysis is a commonly used automated search for groups of related variables within a dataset. Here we use three clusters, but results are not importantly altered if two or four clusters are used. Tracks plotted represent an average tropical cyclone path for the group based on geo-



FIG. 1. Terminal locations of hurricanes over the period 1944–2000 grouped by track type. Track type is determined using a k-means cluster analysis. Here k = 3. The red circles and path represent straight-moving hurricanes. The black and blue circles and paths represent recurving hurricanes. Track paths are based on the average positions of the hurricanes at initial hurricane intensity, maximum hurricane intensity, and final hurricane intensity. Data are from the U.S. National Hurricane Center.

graphic centroids at initial, maximum, and final hurricane intensities.

As the main development region is the central tropical Atlantic, hurricanes that threaten North America north of about 35°N, or that remain offshore, are termed "recurving" (R) hurricanes, whereas hurricanes that threaten the Caribbean and North America south of this latitude are termed "straight moving" (SM). As anticipated, SM hurricanes have a greater mean maximum intensity (50.6 m s⁻¹) compared to R hurricanes (47.7 m s⁻¹). The one-side *p* value is 0.092 based on Wilcoxon rank-sum test (a nonparametric alternative to the two-sample *t* test) under the null hypothesis of no difference in mean rates, which provides suggestive evidence that despite their shorter average life span (owing to landfall), SM hurricanes tend to reach a greater maximum intensity.

The influence of the El Niño–Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO) on the annual rate of SM hurricanes (λ_{SM}) is modeled with a Poisson regression. Poisson regression is the tool of choice when working with event counts such as the annual numbers of hurricanes (Elsner and Kara 1999; Solow 1989). The model is given as

$$log(\hat{\lambda}_{SM}) = 16.237 - 0.008 \times Year + 0.343$$
(1)
×SOI - 0.219 × NAOI,

where "Year" is the calendar year beginning with 1944, "SOI" is the 3-month (August–October) averaged value that defines ENSO (Ropelewski and Jones 1987), and "NAOI" is a 2-month (May–June) averaged NAO index defined as the normalized sea level pressure difference between Gibraltar and Reykjavik, Iceland (Jones et al. 1997). Both the SOI and NAOI have units of standard deviation (std dev).

The regression indicates that straight-moving hurricanes are more common when the SOI is positive and the NAOI is negative. Positive values of the SOI correspond to colder equatorial sea surface temperatures characteristic of La Niña conditions and negative values of the NAOI indicate a weaker North Atlantic Oscillation featuring higher than average pressures over Iceland and lower than average pressures over the eastern subtropical North Atlantic. Analysis of deviance on the regression indicates that SOI (Year) is the most (least) important predictor in the model. The deviance is a measure of the discrepancy between observed and fitted values, which serves as a generalization of the usual residual sum of squares for non-normal data (see Solow 1989).

Interestingly, NAOI is important after accounting for the SOI with a *p* value on the NAOI coefficient of 0.026 arising from the deviance difference between the full model and the model without this term. Provided the model is adequate, the NAO is important in explaining annual variations in SM hurricane activity after accounting for the influence of ENSO. The regression equation tells us that if Year and SOI are held constant a decrease of one std dev in NAOI is associated with a *K*-fold increase in mean number of straight-moving hurricanes, where $K = \exp(0.219)$ = 1.24 (a 24% increase in mean number of hurricanes per std dev decrease in the value of NAOI). Residual plots (not shown) provide support for the adequacy of the regression model.

To extend this analysis over additional earlier years, hurricane landfalls are used as an indicator of SM hurricanes. As seen in Fig. 1, SM hurricanes that hit the United States tend to do so between Texas and South Carolina. The correlation between annual counts of SM hurricanes and hurricane landfalls along this stretch of coastline is a positive 0.55 during the 1944–2000 period. Although the correlation is not large, it indicates that the probability of a southeast landfall increases with the number of SM hurricanes. A Poisson regression is again used, but annual landfall counts replace counts of SM hurricanes and the model is based on data from the longer 1900–2000 period. As with the shorter SM hurricane record, May–June-averaged NAOI values explain a significant portion (*p* value = 0.011) of U.S. landfalls (Texas–South Carolina) after accounting for trends and ENSO.

The lowest (highest) May-June-averaged NAOI values range between -0.12 and -0.27 (+0.06 and +0.29) standard deviations. The 20 lowest values occurred during 1997, 1928, 1915, 1988, 1916, 1995, 1953, 1927, 1906, 1951, 1985, 1905, 1926, 1949, 1902, 1903, 1924, 1910, 1977, and 1980. The 20 highest values occurred during 1973, 2000, 1911, 1962, 1913, 1979, 1930, 1967, 1918, 1994, 1970, 1972, 1966, 1999, 1908, 1937, 1922, 1919, 1943, and 1956. A majority (73%) of these years are not among extreme ENSO years. Correlation between the NAO and ENSO over the 101-yr period is a mere -0.01. Histograms of the annual Texas-South Carolina hurricane rates during the 20 lowest (highest) NAO index years $\lambda_{\text{TX-SC}}$ (NAO-) [$\lambda_{\text{TX-SC}}$ (NAO+)] are shown in Fig. 2. The histograms are obtained from a Poisson/Gamma specification using Gibbs sampling. Gibbs sampling (Gilks et al. 1996) is a method for Bayesian inference, which in this context amounts to determining the posterior distribution of the hurricane rate given the data. The posterior distribution is obtained by repetitive sampling to produce a stationary set of hurricane rate values. The posterior distributions of landfall rates are centered on 1.7 (0.8) hurricanes per year during weak (strong) NAO years. The posterior rate difference $[\lambda_{TX-SC}(NAO+) \text{ minus } \lambda_{TX-SC}(NAO-)]$ indicates a significant difference in activity between the two NAO extremes with the p value arising as the area under the curve to the right of the zero difference (vertical) line. Thus the NAO is an additional independent factor in explaining annual variations in hurricane landfalls.

Results suggest a strategy to develop seasonal prediction models for the probability of a southeast hurricane. A reliable forecast of the SOI for the three peak hurricane months (August–October) combined with an assessment of the NAO during the two months (May–June) prior to the active part of the season provide values for the two predictors. The Poisson regression equation specifying the logarithm of the annual hurricane rate along the southeast coast (λ_{TX-SC}) using these two predictors is

$$log(\hat{\lambda}_{TX-SC}) = 0.1736 + 0.231$$
×SOI-0.225×NAOI. (2)

Figure 3 shows the results of this model where the annual probabilities of at least one southeast hurricane strike are plotted against values of NAOI and SOI.



FIG. 2. Posterior histograms of the annual hurricane rate along the U.S. coast from Texas to South Carolina during (a) years with low $[\lambda_{TX-SC}(NAO-)]$ and (b) high $[\lambda_{TX-SC}(NAO+)]$ NAOI values. (c) The posterior density of the rate difference indicates that hurricanes affecting the southeast coast are more abundant (higher annual rate) during years characterized by below-average NAOI values. On average, the rate difference is about one hurricane per year. The chance that the difference in landfall rates favors more hurricanes during years of above-average NAOI values is equivalent to the relative small area under the curve to the right of zero.

Probabilities above the climatological value of 73% (upper-left portion of the plot) occur under La Niña conditions (high SOI values) and a weak NAO (low NAOI values). Additional work related to model checks and cross validation (Elsner and Schmertmann 1994) are needed before implementation.

SUMMARY AND CONCLUSIONS. This article examined interannual variation of hurricane tracks across the North Atlantic. An objective clustering was used to characterize hurricane paths broadly into straight moving and recurving. The annual variability of SM hurricanes was reliably modeled using a Poisson regression that included indices for ENSO and NAO as predictors. ENSO appears to control factors conducive to hurricane development while NAO controls where they track (Elsner et al. 2001). This understanding provides the basis for a statistical landfall probability model for the southeastern United States. Texas through South Carolina hurricanes are more likely during La Niña when the NAOI is negative.

Results lead us to emphasize that unravelling the causes of changes in hurricane activity requires not only understanding which factors influence their origin and development, but also understanding which factors influence where they will track. In this regard, the NAO is a leading candidate as below-average



FIG. 3. Probability contours (in %) for the annual chance of at least one hurricane strike somewhere from Texas through South Carolina as a function of the SOI and the NAOI. The Poisson regression provides an annual hurricane landfall rate ($\hat{\lambda}_{TX-SC}$) from NAOI and SOI values. Probabilities are obtained using $1 - \exp(-\hat{\lambda}_{TX-SC})$. Values of the NAOI and SOI are in units of std dev. The red diagonal line (unlabeled) indicates the climatological probability based on hurricane counts during the period 1900–2000, inclusive.

NAOI values during boreal spring are likely associated with a subtropical high pressure cell displaced farther south and west of its mean position (near the Azores) during the following hurricane season (Elsner et al. 2000b, 2001). Tropical cyclones forming and remaining equatorward of the subtropical high tend to intensify at low latitudes, crossing through the Caribbean en route to North America.

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