Hurricane Landfall Probability and Climate

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This chapter discusses climatological aspects of U.S. hurricane activity during the twentieth century. It focuses on climate factors that are known to be related to the occurrence of hurricanes and major hurricanes along the coast. Statistical models are used to define and describe these relationships. In general it is found that coastal hurricane activity increases during episodes of La Niña, when the North Atlantic Oscillation is weak. Increases are most apparent along the central Gulf Coast, including New Orleans, as well as along portions of the Florida coast. Hurricane activity in the United States diminishes during El Niño episodes. Results of this study can be refined by incorporating additional hurricane information collected from historical proxies and geological records, which are discussed elsewhere in this volume.

Landfalling hurricanes are of important concern to society. In the United States, the potential for damage and loss of life from hurricanes rivals that from earthquakes (Díaz and Pulwarty 1997). In Florida, Hurricane Andrew (1992) caused more than $30 billion in direct economic losses, while Hurricane Floyd (1999) disrupted the lives of 2.5 million of its residents due to evacuation alone. Understanding the past record of hurricane activity provides clues about future frequency and intensity, which is important for land-use planning, emergency management, hazard mitigation, and insurance applications.

Empirical and statistical research has identified climate factors that contribute to conditions favorable for hurricanes over the North Atlantic Basin, which includes the Caribbean Sea and the Gulf of Mexico (Gray et al. 1992; Elsner, Kara, and Owens 1999; Elsner, Jagger, and Niu 2000). These factors influence the occurrence of hurricanes differently depending on the particular region. For instance, the effect of an El Niño on hurricane frequency over the

entire North Atlantic Basin is significant, but El Niño's influence on the frequency of hurricanes forming over the subtropics is small. In fact, additional climate factors are usually needed to explain local variations in hurricane activity (Lehmiller, Kimberlain, and Elsner 1997; Jagger, Elsner, and Niu 2001). During some years there is a tendency for hurricanes to track westward through the Caribbean Sea and threaten Mexico and the United States. At other times, hurricanes tend to move parallel to the East Coast of the United States (Elsner, Bossak, and Niu 2001). To some extent, the degree to which the Gulf Coast is vulnerable to a hurricane in a given year is inversely related to the degree to which the East Coast is vulnerable.

In this chapter, we examine the occurrence of tropical cyclones that make landfall in the continental United States as hurricanes. These are termed "U.S. hurricanes." The focus on U.S. hurricanes allows the use of reliable data extending back to the beginning of the twentieth century, as well as emphasizing the socially relevant component of hurricane activity in this part of the world. Although tropical storms are capable of inflicting damage and loss of life, hurricanes cause significantly more wind destruction and flooding. The goal of this chapter is to describe quantitative changes in hurricane landfall probabilities in response to variations in climate. The assumption is that large-scale climate variations cause changes to hurricane activity.

The chapter is divided into two main sections. First we examine the annual frequency of U.S. hurricanes and show how the frequency is related to climate factors. In particular, we consider the annual occurrence of U.S. hurricanes and U.S. major hurricanes using the technique of generalized linear modeling. The modeling process is used to explore linkages between coastal hurricane activity and climate as well as to identify climate factors for the regional model. Climate factors (or covariates) are variables that have a statistical relationship to U.S. hurricane activity. Next, we make use of a technique for regional modeling of hurricane activity. The model uses covariates in assigning local probabilities of hurricane occurrence. The regions are coastal counties from Texas to North Carolina. Although our analysis is done for the coastal United States, the procedures described here can be applied in other tropical cyclone-prone regions of the world.

Annual Landfall Probabilities

Definitions and Hurricane Data

A hurricane is a tropical cyclone with maximum sustained (1-minute) 10-m winds of 65 kt (33 m s^{-1}) or greater. Major hurricanes of Category 3 or higher

on the Saffir-Simpson damage potential scale have winds of 100 kt (51 m s^{-1}) or greater (Simpson 1974). Hurricane landfall occurs when all or part of the eye wall, the circular region of intense wind and rain surrounding the eye, passes directly over the coastline or over an adjacent barrier island. Because the eye wall can extend outward a distance of 50 km or more from the hurricane center, landfall may occur even when the precise center of lowest pressure remains offshore. A hurricane may make more than one landfall. In 1992, for example, Hurricane Andrew struck Florida and Louisiana. In this section we consider all tropical cyclones that make landfall in the continental United States at least once at hurricane intensity. In the next section we examine landfalls along the coast from Texas to North Carolina.

The HURDAT (best-track) dataset is the most complete and reliable source of North Atlantic hurricanes (Jarvinen, Neumann, and Davis 1984). The data set consists of the six-hourly position and intensity estimates of tropical cyclones back to 1886 (Neumann et al. 1999). These data are used to determine the annual frequency of hurricanes and major hurricanes reaching the United States over the period from 1900 to 1997. Additional U.S. hurricane information extending back to 1851 is now available through the hurricane data reanalysis project (Landsea et al., chapter 7 in this volume). This additional information is not considered in the present analysis.

The historical data indicate a total of 159 U.S. hurricanes and 63 U.S. major hurricanes over the 98-year period in question, for an average of 1.62 hurricanes and 0.64 major hurricanes per year (table 12.1). This amounts to approximately 13 hurricanes and 5 major hurricanes every eight years. But each year is different. In 1985, six hurricanes hit the United States, while in 1994 none did. More than half the years are without a major hurricane landfall. The 95% confidence intervals on the annual means are (1.38, 1.91) for hurricanes and (0.50, 0.80) for major hurricanes. The confidence intervals are based on bias-corrected bootstrapped samples. Whether a hurricane reaches the United States in a given year depends on formation and development

TABLE 12.1 U. S. Hurricane Statistics, 1900–1997

	Mean	Variance	Maximum number	Minimum number	BCMQ[1] 2.5%	BCMQ 97.5%
Hurricanes	1.62	1.660	6	0	1.38	1.91
Major hurricanes	0.64	0.582	3	0	0.50	0.80

[1]Bias-corrected mean bootstrapped (1,000 samples) quantiles.

mechanisms as well as steering currents, which are linked to large-scale climate factors including rainfall in western Africa, the El Niño cycle over the Pacific Ocean, and air pressure differences over the North Atlantic.

On average, the United States can expect one or two hurricanes each year. The distribution of first landfall dates in 10-day intervals is displayed in figure 12.1. The median strike date is September 5 for hurricanes and September 11 for major hurricanes. The interquartile range of U.S. hurricanes is 40 days, meaning that half of all strikes occur between August 17 and September 24. The most active period extends from approximately August 30 through September 28. During the period from 1900 to 1997, the earliest U.S. hurricane occurred on June 9 and the latest on November 30.

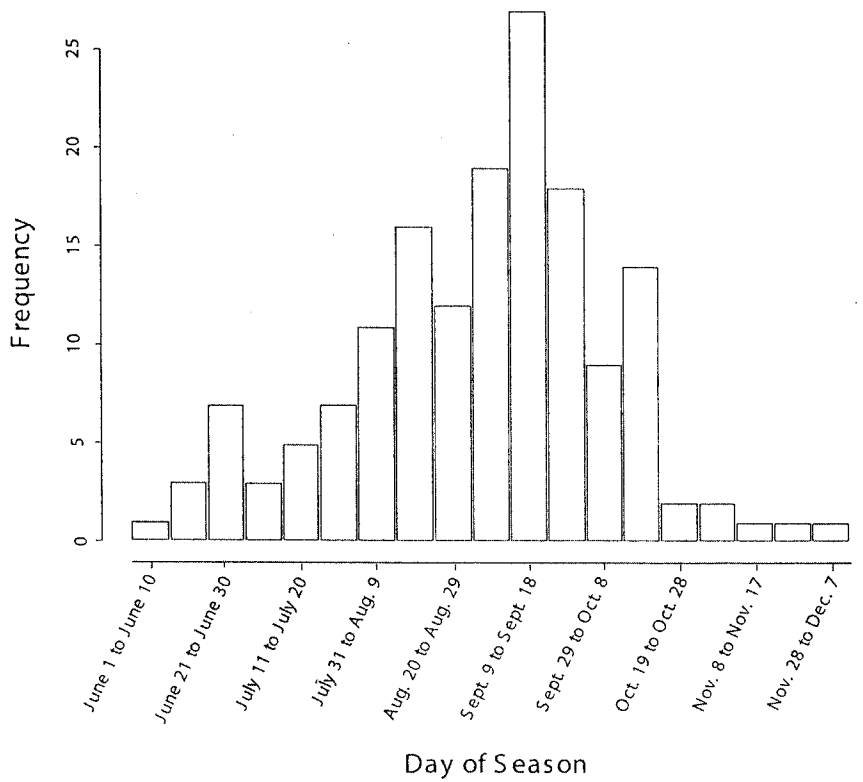

FIGURE 12.1 Histogram of the occurrence of U.S. hurricanes in 10-day intervals based on 159 hurricanes over the period from 1900 to 1997. For hurricanes that make more than one landfall in the United States, only the first landfall date is used. The median strike date is September 5.

Sources of Interannual Variability

It is well known that some of the year-to-year variability in U.S. hurricane activity is linked to the El Niño–Southern Oscillation (ENSO) cycle. In a year dominated by cooler than normal waters off the Peruvian coast (La Niña event), the United States is likely to see a greater number of hurricanes come onshore. In contrast, in a year with warm waters off South America (El Niño event) there tend to be fewer landfalls (Bove et al. 1998; Elsner and Kara 1999). It is speculated that El Niño creates stronger upper-atmospheric westerly winds over the Caribbean that lead to unfavorable wind shear and vorticity over the hurricane genesis and development region (Gray 1984). A greater amount of sinking air (Kimberlain and Elsner 1998) and lower surface air pressures (Knaff 1997) are additional inhibiting factors. During a mature El Niño event, the atmospheric sea level pressure pattern features negative anomalies (departures from average) across the central and eastern equatorial Pacific Ocean and positive anomalies over Australia and Indonesia. The pattern results in negative values of the Southern Oscillation Index (SOI). Formally, the SOI is defined as the normalized pressure difference between Tahiti and Darwin, Australia (Troup 1967). Monthly values of the SOI calculated on the basis of the method proposed by Ropelewski and Jones (1987) are used here to examine the relationship of El Niño to U.S. hurricanes.[1] In particular we focus on the period of August through October and use a cumulative value of the SOI in units of standard deviation (s.d.) over these three months. Cumulative SOI values during 98-year period range between −6.98 s.d. (1982) and +7.83 s.d. (1917).

A portion of the interannual variability of U.S. hurricanes is likely related to climate fluctuations over the Atlantic region. In particular, precipitation amounts over western areas of Africa are associated with the formation of hurricanes over the deep tropics (Gray 1990; Elsner and Schmertmann 1993). Heavy rainfall over the region falls from robust thunderstorm complexes, which are often precursors to easterly waves (African easterly waves) and tropical low pressure systems (lows) that move westward across the Sahel region of Africa toward the Cape Verde Islands. An easterly wave, or low pressure, that develops into a tropical cyclone (most do not) and remains over the warm waters at low latitudes can menace the Caribbean, Mexico, and the United States as a hurricane. A standardized index of Sahel regional rainfall (SRI) during the month of July (Janowiak 1988) is used here. July is the beginning of the rainy season in the Sahel region. The SRI is computed as an area average of standardized rainfall amounts from stations (approximately 14, depending on availability) within

a box bounded by 8°N and 20°N latitudes and by 20°W and 10°E longitudes.[2] July values of the SRI range between −1.82 s.d. (1903) and +5.13 s.d. (1915).

An additional source of year-to-year variability in U.S. hurricane activity is the North Atlantic Oscillation (NAO). The NAO is a meridional difference in atmospheric sea level pressure between Iceland and the subtropics. It has been implicated in modulating tropical cyclone activity over the North Atlantic Basin and elsewhere (Elsner and Kocher 2000; Elsner, Bossak, and Niu 2001). The NAO is strongest when pressures are low over Iceland and high over the eastern and central subtropical North Atlantic Ocean. A normalized index of the NAO (NAOI) is calculated as the difference in monthly sea level pressures between Reykjavik, Iceland, and Gibraltar.[3] We use the May value of the NAOI as a compromise between signal strength and timing relative to the hurricane season. The signal-to-noise ratio of the NAO is largest during the boreal winter and spring, whereas the U.S. hurricane season begins in June. Values of the May NAOI range between −3.21 s.d. (1935) and +4.54 s.d. (1956). A recent study utilizing historical and geological data (Elsner, Liu, and Kocher 2000) finds that climatic conditions associated with strong hurricanes along the Gulf Coast occur with a negative (weak) phase of the NAO. Conversely, major hurricane activity along the northeast occur with a positive (strong) phase of the NAO.

Generalized Linear Modeling

The goal of this chapter is to understand the extent to which climate factors just mentioned are important in modeling U.S. hurricane activity from year to year. To help in this regard, we employed a data modeling approach. Tasks associated with data modeling include choosing the functional form of the model and determining the adjustable parameters. We chose the functional form that is most natural to the type of data being modeled.

Traditional linear regression models assume the response variable is continuous; categorical responses (annual hurricane counts) require a different approach. Here we consider generalized linear models (McCullagh and Nelder 1999). A generalized linear model is a probability model in which the mean of the response variable (μ) is related to the p covariates through a regression equation

$$g(\mu) = \alpha_0 + \alpha_1 x_1 + \ldots + \alpha_p x_p \qquad (1)$$

where $g(\mu)$ is called the *link function* that depends on the type of response variable. In the analysis presented here, the response variable μ is hurricane counts (or count) and the covariates $(x_1, \ldots, x_p)$ are the climate factors such as the SOI and the NAO. Values for the coefficients $(\alpha_0, \alpha_1, \ldots, \alpha_p)$ are estimated using the method of maximum likelihood. The logistic and Poisson regressions are special cases of the generalized linear model. Logistic regression is well suited for categorical responses such as whether or not a major hurricane hits the coast. Poisson regression is suited for describing the annual count of U.S. hurricanes.

Logistic Model for U.S. Major Hurricanes

The historical distribution of annual major U.S. hurricane counts shows that the maximum number in any one year is three. Therefore, we modeled the annual occurrence as a binary response variable. Either a year has at least one major hurricane make landfall or it does not. Logistic regression provides a natural general purpose modeling option in the case where there are only two possible responses. Let μ be the probability of at least one major hurricane, then the link function is called the logit function and is expressed as

$$g(\mu) = \log\left[\frac{\mu}{1-\mu}\right] = \text{logit}(\mu) \qquad (2)$$

The inverse of the logit function is the logistic function. We model $g(\mu)$ as a linear function of the covariates and use the SOI, NAOI, and SRI as the covariates.

Figure 12.2 shows the distribution of the three climate factors divided into years according to whether or not there was a major U.S. hurricane. In years of a major hurricane (Yes) the SOI tends to be positive (indicating a La Niña event) and the NAOI tends to be negative. In years without a major hurricane (No), the SOI tends to be negative (El Niño event) and the rainfall tends to be below normal. The SOI appears to have the strongest relationship to major U.S. hurricanes as the interquartile ranges (boxes) have the least overlap for "No" versus "Yes" years. Bivariate logistic regression models confirm SOI as the best single climate factor of the three, with NAO more important than Sahel rainfall.

The initial logistic model we entertain relates the probability of a U.S. major hurricane to these three covariates as

$$\begin{aligned}\text{logit}(\hat{\mu}) = {} & 0.0843 + 0.2681 \times \text{SOI} - 0.4572 \times \text{NAOI} \\ & + 0.5233 \times \text{SRI}\end{aligned} \qquad (3)$$

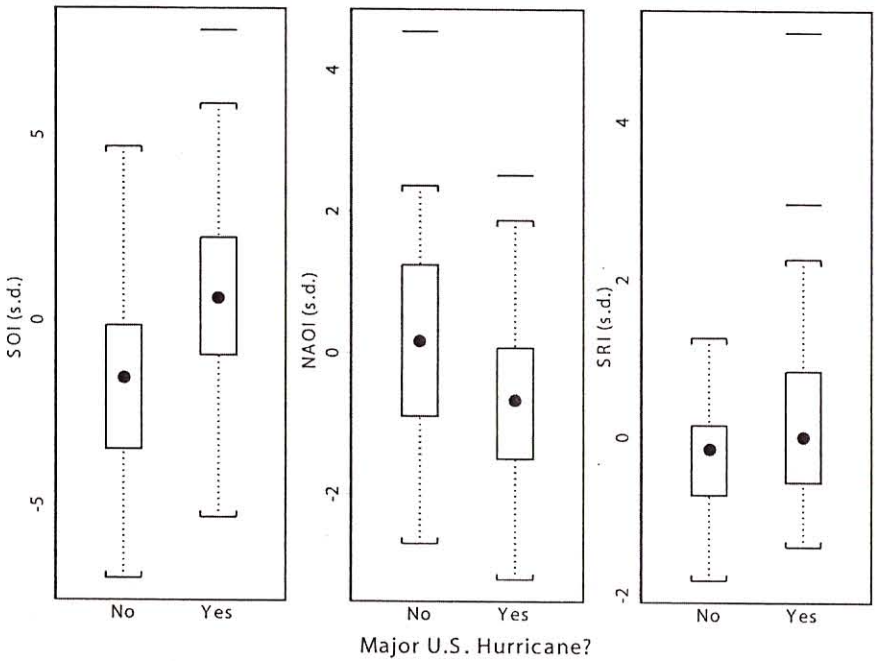

FIGURE 12.2 Box plots of SOI, NAOI, and SRI (covariates) grouped according to whether there was at least one major U.S. hurricane during the year. The circle is located at the median value of the covariate. The box height is equal to the interquartile distance (IQD). The whiskers (dotted lines) extend to the extreme values of the data or a distance of 1.5 IQD, whichever is less. Data points that fall outside the whiskers (outliers) are indicated by horizontal lines.

where a maximum likelihood procedure is used to estimate the coefficients. An analysis of model deviance (table 12.2) shows that the SOI is an important climate factor in the model (low p-value) and that the NAOI is important as a linear predictor after adjusting for the SOI. In contrast, SRI has a p-value that exceeds 0.05, and thus is not considered statistically important after accounting for SOI and NAOI. The deviance is a measure of the discrepancy between observations and fitted values. It serves as a generalization of the usual sum of squares. The magnitude of the deviance difference is proportional to model improvement when that term is added to the model. The deviance difference has a χ^2 distribution from which the p-value is estimated. A quantile plot (figure 12.3) validates the model assumptions by indicating near normal model residuals.

After removing the Sahel rainfall as a climate factor the final model is

$$\text{logit}(\hat{\mu}) = 0.0582 + 0.2903 \times \text{SOI} - 0.4655 \times \text{NAOI} \qquad (4)$$

TABLE 12.2 Analysis of Deviance for the U.S. Major Hurricane Logistic Model

Terms	Deviance difference	d.f.	Residual deviance difference	p-value
Null		97	135.86	
SOI	12.07	96	123.79	0.00051
NAOI	9.20	95	114.59	0.00243
SRI	3.26	94	111.34	0.07109

Note: SOI is the August through October cumulative value of the monthly normalized sea level pressure difference between Tahiti and Darwin, Australia; NAOI is the May value of the monthly normalized sea level pressure difference between Reykjavik, Iceland, and Gibraltar; and SRI is the July area-averaged and standardized index of rainfall over the Sahel region of western Africa. The magnitude of the deviance difference is proportional to model improvement when that term is added and has a χ^2 distribution from which the p-value is estimated.

The correlation between the SOI and NAOI is negligible [r(SOI, NAOI) = −0.06] so the NAO provides additional information about whether or not the United States will be hit by a major hurricane. The correlation between SOI and SRI is +0.25 so Sahel rainfall and U.S. major hurricanes are both, to some extent, related to the ENSO. The model applies to the 98-year data set and it may not generalize to other years.

Interpretation of the model is based on recognizing that the logit function is the logarithm of the odds of a U.S. major hurricane. For fixed values of NAOI the ratio of the odds when the SOI has a value A relative to the odds when the SOI has a value B is $e^{0.2903(A-B)}$. For A = +3 s.d. and B = −3 s.d. (for comparison, the 1997 value of the cumulative SOI during August through October was −5.6 s.d.), the odds ratio is 5.7, indicating that the odds of a U.S. major hurricane under a moderate La Niña event is more than five and a half times the odds of a major hurricane under a moderate El Niño event.

The modeling process verifies a relationship between the El Niño cycle and the fluctuating threat of a major hurricane along the U.S. coast. It also implicates the NAO as an additional independent factor in explaining the annual probability of these catastrophic events. Models of the annual frequency of U.S. hurricanes require a somewhat different statistical approach.

Poisson Model for U.S. Hurricanes

The Poisson distribution is a form of the binomial distribution for a large number of trials with small probabilities of an occurrence on any given trial (e.g., Elsner and Schmertmann 1993). The limiting form of the distribution sets no

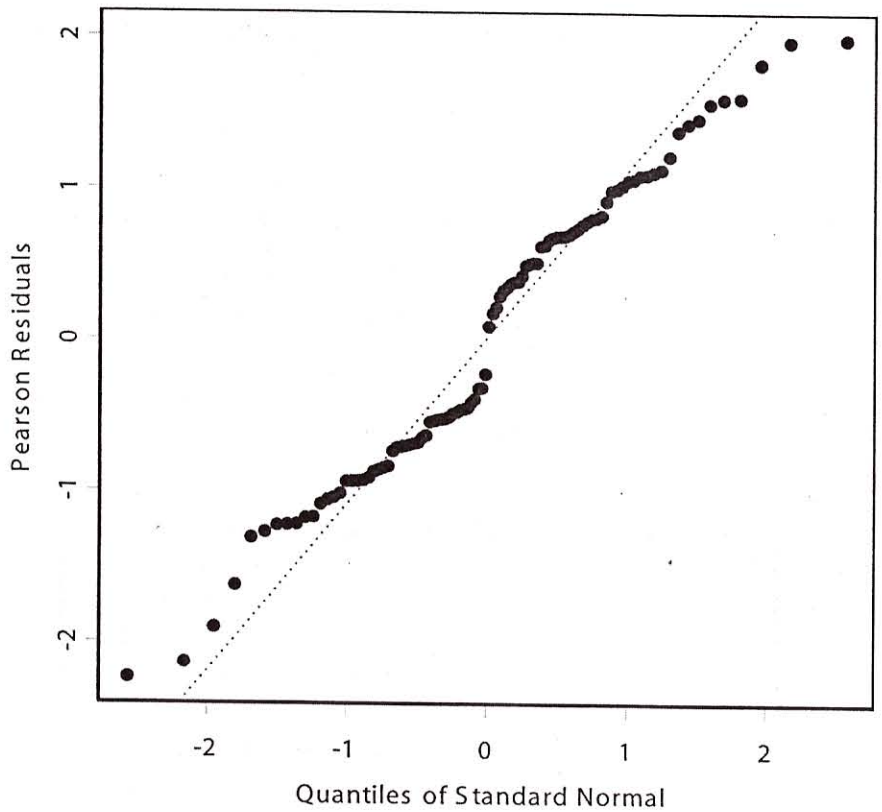

FIGURE 12.3 Normal quantile plot of standardized residuals from the major U.S. hurricane model. The model is a logistic regression with SOI, NAOI, and SRI as the covariates. The dashed diagonal represents a normal distribution. The points lie close to the diagonal indicating no evidence against the assumption of normally distributed residuals.

theoretical limit so it works well for modeling the annual count of U.S. hurricanes. Under this model, the probability of Y U.S. hurricanes is

$$\Pr\{Y\} = \exp(-\lambda)\lambda^{Y}/Y!, \text{ for } Y = 0, 1, 2, \ldots \tag{5}$$

where λ is the annual average. The Poisson distribution is skewed to the right with the skewness most pronounced for small λ. For large λ, the distribution is approximated by the normal distribution.

Figure 12.4 shows the annual distribution of U.S. hurricanes. With a count response (annual number of U.S. hurricanes) and covariates, the Poisson generalized linear model specifies that the distribution of U.S. hurricanes is Poisson (Elsner, Bossak, and Niu 2001) and that the natural logarithm of the mean (link

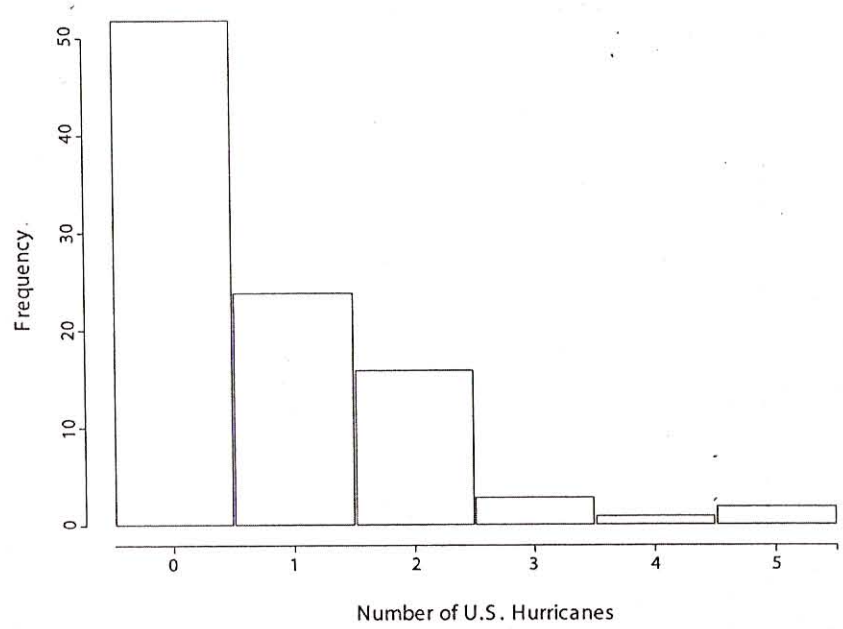

FIGURE 12.4 Histogram of the annual occurrence of U.S. hurricanes. The frequency is the number of years. Note the relative infrequency of years with three or more hurricanes.

function) is linear in the regression coefficients. Using the same covariates as in the major hurricane model, the initial Poisson generalized linear model is

$$\log(\hat{\lambda}) = 0.4597 + 0.0684 \times \text{SOI} - 0.0793 \times \text{NAOI} + 0.1031 \times \text{SRI} \tag{6}$$

where a maximum likelihood procedure is again used to estimate the coefficients. A quantile plot (figure 12.5) indicates a reasonable model. The analysis of deviance (table 12.3) shows that indices of NAO and Sahel rainfall are unimportant after adjusting for the influence of the SOI.

Thus we remove these two climate factors and fit a final model as

$$\log(\hat{\lambda}) = 0.4970 + 0.0828 \times \text{SOI} \tag{7}$$

This model indicates that the mean of the Poisson distribution increases (decreases) with a La Niña (El Niño) event. Accordingly, the probability of one or more U.S. hurricanes is 72% when the SOI is −3 s.d., but increases to 88%

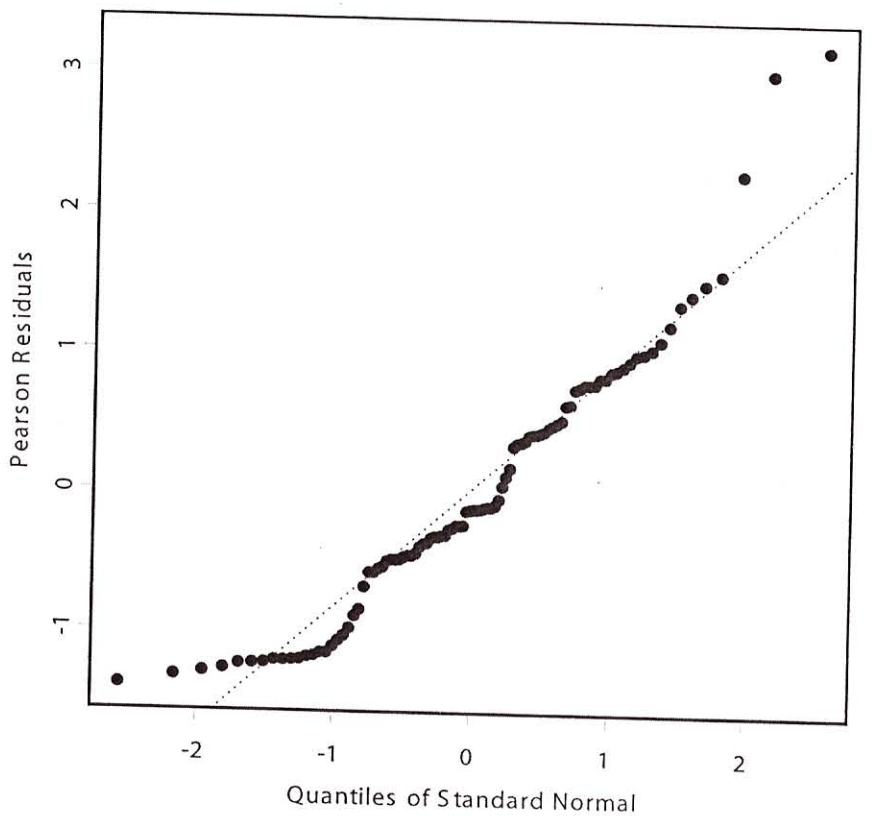

FIGURE 12.5 Normal quantile plot of standardized residuals from the U.S. hurricane model. The model is a Poisson regression with SOI, NAOI, and SRI as the covariates. The dashed diagonal represents a normal distribution. The points lie close to the diagonal indicating no evidence against the assumption of normally distributed residuals.

when the SOI is +3 s.d. These interpretations are strictly applicable only to the 98-year period.

In summary, the generalized linear models establish a statistical basis for the El Niño–Southern Oscillation and the North Atlantic Oscillation as independently important in determining U.S. hurricane activity. The models are based on hurricane landfalls over the entire U.S. coastline from Texas to Maine. The best single predictor of activity is the SOI. The situation is more complicated, however, as the occurrence of a La Niña event increases the probability of a hurricane, but additional factors are important in explaining the probability of a major hurricane. Thus, the annual probability distribution of hurricane winds along the U.S. coast is a function of both tropical cyclone intensity and climate factors. Moreover, the probability of hurricanes regionally

TABLE 12.3 Analysis of Deviance for the U.S. Hurricane Poisson Model

Terms	Deviance difference	d.f.	Residual deviance difference	*p*-value
Null		97	110.48	
SOI	9.00	96	101.48	0.00270
NAOI	2.90	95	98.58	0.08832
SRI	2.09	94	96.48	0.14795

Note: SOI is the August through October cumulative value of the monthly normalized sea level pressure difference between Tahiti and Darwin, Australia; NAOI is the May value of the monthly normalized sea level pressure difference between Reykjavik, Iceland, and Gibraltar; and SRI is the July area-averaged and standardized index of rainfall over the Sahel region of western Africa. The magnitude of the deviance difference is proportional to model improvement when that term is added and has a χ^2 distribution from which the p-value is estimated.

will likely depend upon different combinations of these two factors. In the next section we examine regional landfall probabilities using another data modeling approach.

Regional Landfall Probabilities

Various techniques for estimating annual probabilities of hurricanes locally are proposed in the literature (e.g., Neumann 1987). These approaches are useful in establishing a baseline climatology of extreme wind events, but are predicated on a static distribution of events over time. That is, the methods provide estimates of hurricane probabilities without regard to climate variations. Using these models, the annual probability of a hurricane strike along the Louisiana coast is the same regardless of El Niño. Results from the previous section suggest that regional landfall probabilities will likely change depending upon climate conditions associated with the ENSO and the NAO. In this section we examine results from a model that estimates landfall probabilities conditional upon the SOI and the NAOI (Jagger, Elsner, and Niu 2001).

Weibull Model for Regional Hurricane Winds

Based on a comparison with other distributions, Batts et al. (1980) suggest that the maximal wind speed over an area in a given year be modeled using a Weibull distribution. The survival function (one minus the cumulative distribution function) for the Weibull distribution is an exponential curve. Let V be

the unknown yearly maximum wind speed, and v some known value, then the survival function for the Weibull distribution is

$$\Pr\{V > v\} = e^{-(v/b)^a} \tag{8}$$

where a is the shape parameter and b is the scale parameter.

Here an algorithm that extends the earlier work of Batts et al. (1980) is used. The extensions include (1) hurricane intensity estimates at the county level, and (2) conditioning of the Weibull parameters based on climate factors. The parameters are considered response variables with values changing from year to year, and are modeled with a linear regression. A detailed description of the algorithm including error estimates and model comparisons are given in Jagger, Elsner, and Niu (2001). The algorithm provides a parametric model of the annual probabilities at values of wind speeds corresponding to different hurricane intensity levels.

For each coastal county, a Weibull distribution is fit to the yearly maximum wind speed. The location and scale parameters of the Weibull distribution are estimated using linear regressions on the ENSO and NAO covariates using the maximum likelihood estimator. Using these parameters and the associated covariate information, the distribution of exceedence probabilities for any wind speed is estimated by calculating them directly from the Weibull distribution. Exceedence probabilities are related to the percentage chance of a hurricane strike in any one year. The model gives values that can be plotted on a wind speed versus probability graph.

The dynamic probability model from this algorithm can be used in two ways. First we show results using the model in the raw climatological mode. This means that the model provides annual exceedence probabilities of experiencing winds from a hurricane somewhere in the county at various hurricane intensities without regard to climate variations. The geographic distribution of probabilities for Category 1 and Category 3 hurricanes (categories are based on the Saffir-Simpson hurricane damage potential scale) are provided. We also examine results from the model run in the conditional climatogical mode. This means that the model provides exceedence probabilities conditioned on climate factors. Since the model can be run in a conditional climatological mode, it is referred to as a "dynamic" probability model. In general, the probabilities will be different from their raw climatological values depending on the strength and configuration of the climate anomalies. We show the geographic distribution of conditional probabilities for Category 1 and Category 3 hurricanes along with difference maps indicating the change in probabilities.

Raw Climatology

To examine the geographic distribution of annual exceedence probabilities we ran the model for hurricane winds and major hurricane winds (100 kt or greater) for coastal counties from Texas through North Carolina (plate 7). In counties with an insufficient number of hurricanes during the 98-year period the maximum likelihood estimator failed to converge for the scale and shape parameters and the county was assigned a probability in the lowest quintile.

As expected, the largest annual probabilities in the range of 12 to 25% for hurricane winds occurred over southern Florida and eastern North Carolina. Over eastern Texas, near Galveston Bay, counties also had an historically greater frequency of hurricane force winds. Moderately high probabilities were noted over the central Gulf Coast extending from eastern Louisiana through the Florida panhandle. Lowest probabilities, generally less than 10%, were noted over portions of South Carolina and Georgia and over the northern stretch of peninsular Florida. Florida counties along the northeastern Gulf of Mexico (the Big Bend region) also indicate fewer hurricanes. The geographic distribution of probabilities matches closely the variation of tropical cyclone frequencies given by Neumann et al. (1999), where it is noted that hurricane landfalls tend to be most frequent over eastern North Carolina, southern Florida, central Texas, and southeastern Louisiana.

The probabilities of major hurricane force winds are considerably lower than probabilities of Category 1 winds, although their geographic distribution is quite similar. Highest probabilities occur over Texas, parts of the central Gulf Coast, southern Florida, and eastern North Carolina. Dade and Monroe (which includes the Florida Keys) are the most likely counties to experience major hurricane force winds. In fact, the annual probability of hurricane winds in Pinellas and Hillsborough counties (Tampa–St. Petersburg area) of Florida is close to 10% but the probability of major hurricane force winds is less than 1%. Interestingly, the northern and central counties of peninsular Florida indicate some of the lowest probabilities for Category 3 winds.

Conditional Climatology

A useful addition to raw climatological frequencies of extreme winds are conditional frequencies (e.g., Murnane et al. 2000). Here we allow the model to generate exceedence probabilities conditioned on ENSO and the NAO. The effect of these two climate factors on annual hurricane probabilities in coastal

counties are analyzed for parameter values that correspond to extremes of the covariates (±5.2 s.d. for SOI and ±3.1 s.d. for the NAOI). Plate 8 shows the differences in probabilities for each county (conditional probability minus raw probability) when the climate is favorable (positive values of the SOI and negative values of the NAOI) for U.S. hurricanes. The differences are smoothed using the values from two neighboring counties. Counties shaded in red indicate probabilities that exceed their climatological value.

As anticipated based on results from the previous section, most of the coastal counties show an increase in the probability of Category 1 winds when conditions of La Niña (positive SOI) and a weak NAO prevail. In particular, substantial increases in probability are noted for much of the Florida coast, especially the Big Bend region. Other regions of increased probability extend from Louisiana to the Florida panhandle as well as portions of the Carolinas. Using a different methodology, Saunders et al. (2000) noted that landfall probabilities along the central Gulf Coast and southern Texas are significantly enhanced during La Niña conditions.

Differences in exceedence probabilities for major hurricane force winds indicate a similar geographic pattern, although over Texas there are more counties with a decrease in probability compared with Category 1 probability differences. The largest increases are noted for portions of Florida and South Carolina. Over northeastern Florida, the probability of Category 1 winds is slightly decreased, but the probability of Category 3 winds is slightly increased under this climate scenario. Variations in probability suggest that the influence of large-scale climate anomalies on hurricane activity is regional. Caution is warranted, however, as much of the variation is likely due to a limited data set and random variability.

Plate 9 shows the differences in probabilities when the climate is unfavorable for U.S. hurricanes. Probabilities are generally lower than average. Many of the coastal counties indicate a drop in probability for both Category 1 and Category 3 hurricane winds, although there is considerable spatial variability. In particular, southeastern Florida and portions of the northern Gulf Coast show the largest decreases (between 10 and 15%) in probability for Category 1 winds. But increases in probabilities are noted over the Big Bend region of Florida and the eastern counties of Texas extending into Louisiana. When conditions are favorable for U.S. hurricanes, the largest probability increases are noted along the western counties of the Florida peninsula through the Big Bend region. When conditions are not favorable, decreases in probability occur in many of these same counties with the exception of the Big Bend region.

In summary, the dynamic probability model describes quantitative changes in hurricane landfall probabilities conditioned on climate variations. We find

that positive SOI values combined with negative NAOI values are associated with an increase in the chance of a hurricane or major hurricane strike along the southeastern coastal regions of the United States. In contrast, negative SOI values combined with positive NAOI values are associated with a reduction in the probability of coastal hurricane activity, especially over southeastern Florida, although there is large spatial variability in these changes. This work is one of the first attempts to quantitatively understand the role of climate in modulating regional hurricane activity at the county level.

Future Improvements

The model can be improved in several ways. For instance it is possible to model the maximum intensity of each tropical cyclone as a Weibull distribution and use a Poisson distribution to model the occurrence of hurricanes. In this two-stage model, we can regress three parameters λ, a, b onto the predictors. We also could consider a four-parameter model by using a cutoff wind speed value, v_0, and replace v with $v - v_0$ in the Weibull distribution. In this case, λ is not the rate for the number of tropical cyclones of any velocity affecting the county, but only the rate for cyclones whose wind speeds are v_0 or higher. Another improvement is to incorporate information from adjacent counties into the model for a particular county. A Bayesian approach will work for adjusting the Weibull parameters in this case. Also, the choice of covariates in the model is based on a generalized linear model of activity for the entire coast. The dynamic probability model itself can be used to test the influence of additional climate factors on landfall probabilities if issues of statistical significance are addressed. Another potential improvement is to use the generalized Pareto distribution to model hurricane intensity (e.g., Holmes and Moriarty 1999). The advantage is that this distribution has an upper bound, which could be set using theoretical considerations of a hurricane's maximum potential intensity (e.g., Emanuel 1995; Holland 1997).

A major drawback to work of this kind is the length and quality of the data record. Limitations on sample size are connected to issues of statistical confidence and noise level in the data. Development of a model for prediction will require a cross-validation exercise (Elsner and Schmertmann 1994) with additional data. The hurricane data reanalysis project (Landsea et al., 2002, chapter 7 in this volume) and reconstructions of hurricane records from proxy sources (Liu and Fearn 2000; Donnelly et al. 2001; Liu, Shen, and Louie 2001; Donnelly and Webb, chapter 3, and Liu, chapter 2 in this volume) hold promise of additional data leading to model improvements. For instance, historical data on hurricanes along the coast during the nineteenth century (e.g., Mock,

chapter 5 in this volume) suggest important low frequency changes in activity. Data with greater uncertainty can be combined with the modern record using Bayesian methods as illustrated in Elsner and Bossak (2001).

Differences in hurricane visits between the 1851 to 1900 period and the 1951 to 2000 period are mapped in plate 10. The analysis includes the paths of all tropical cyclones that hit the coast at hurricane intensity for the two 50-year periods. Here a county is considered to be hit if the track of the hurricane's eye wall intersects the county boundary. For inland counties, the winds are generally less than hurricane intensity. Counties with more (fewer) hits during the second half of the nineteenth century compared with the more recent period are shaded in blue (red). The possibility of a data bias exists because portions of southeastern Florida and southern Texas were undeveloped in 1851. In this case, the seemingly greater number of hurricanes during the more recent 50 years might be an artifact of undetected storms during the earlier period; however, many of the Gulf Coast counties show more hurricanes during the earlier, less reliable, period. Differences are most pronounced for the counties of northern Florida and southeastern Georgia. In contrast, eastern North Carolina apparently has become a bigger target for hurricanes in recent years.

The map underscores the need to consider the longest possible record of hurricane activity in assessing annual probabilities or return periods. Future work will incorporate these earlier data into the models to provide a more accurate picture of coastal hurricane vulnerability as it relates to the changing climate. The longer historical record will be used to study the robustness of the climatic relationships outlined in this chapter and how these relationships strengthen or weaken over time.

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Notes

1. SOI values are available from the Climatic Research Unit of the University of East Anglia (www.cru.uea.ac.uk).

2. Monthly values of SRI were obtained from the Joint Institute for the study of the Atmosphere and Ocean of the University of Washington (www.jisao.washington.edu/science2.html).
3. Monthly values of the NAOI are available from the Climatic Research Unit of the University of East Anglia.

References

Batts, M. E., M. R. Cordes, L. R. Russell, J. R. Shaver, and E. Simiu. 1980. *Hurricane wind speeds in the United States.* NBS Building Science Series No. 124. Washington, D.C.: National Bureau of Standards, Department of Commerce.

Bove, M. C., J. B. Elsner, C. W. Landsea, X. Niu, and J. J. O'Brien. 1998. Effect of El Niño on U.S. landfalling hurricanes, revisited. *Bulletin of the American Meteorological Society* 79:2477–82.

Díaz, H. E., and R. S. Pulwarty, eds. 1997. *Hurricanes: Climate and socioeconomic impacts.* Berlin: Springer-Verlag.

Donnelly, J. P., S. S. Bryant, J. Butler, J. Dowling, L. Fan, N. Hausmann, P. Newby, B. Shuman, J. Stern, K. Westover, and T. Webb III. 2001. A 700-year sedimentary record of intense hurricane landfalls in southern New England. *Bulletin of the Geological Society of America* 113:714–27.

Elsner, J. B., and B. H. Bossak. 2001. Bayesian analysis of U.S. hurricane climate. *Journal of Climate* 14:4341–50.

Elsner, J. B., B. H. Bossak, and X. Niu. 2001. Secular changes to the ENSO-U.S. hurricane relationship. *Geophysical Research Letters* 28:4123–26.

Elsner, J. B., T. Jagger, and X. Niu. 2000. Shifts in the rates of major hurricane activity over the North Atlantic during the 20th century. *Geophysical Research Letters* 27:1743–46.

Elsner, J. B., and A. B. Kara. 1999. *Hurricanes of the North Atlantic: Climate and society.* New York: Oxford University Press.

Elsner, J. B., A. B. Kara, and M. A. Owens. 1999. Fluctuations in North Atlantic hurricanes. *Journal of Climate* 12:427–37.

Elsner J. B., and B. Kocher. 2000. Global tropical cyclone activity: A link to the North Atlantic Oscillation. *Geophysical Research Letters* 27:129–32.

Elsner, J. B., K.-b. Liu, and B. Kocher. 2000. Spatial variations in major U.S. hurricane activity: Statistics and a physical mechanism. *Journal of Climate* 13:2293–305.

Elsner J. B., and C. P. Schmertmann. 1993. Improving extended-range seasonal predictions of intense Atlantic hurricane activity. *Weather and Forecasting* 8:345–51.

Elsner J. B., and C. P. Schmertmann. 1994. Assessing forecast skill through cross validation. *Weather and Forecasting* 9:619–24.

Emanuel, K. A. 1995. Sensitivity of tropical cyclones to surface exchange coefficients and a revised steady-state model incorporating eye dynamics. *Journal of the Atmospheric Sciences* 52:3969–76.

Gray, W. M. 1984. Atlantic seasonal hurricane frequency. Part I: El Niño and 30 mb Quasi-Biennial Oscillation influences. *Monthly Weather Review* 112:1649–68.

Gray, W. M. 1990. Strong association between West African rainfall and U.S. landfall of intense hurricanes. *Science* 249:1251–56.

Gray, W. M., C. W. Landsea, P. W. Mielke, Jr., and K. J. Berry. 1992. Predicting Atlantic seasonal hurricane activity 6–11 months in advance. *Weather and Forecasting* 7:440–55.

Holland, G. J. 1997. The maximum potential intensity of tropical cyclones. *Journal of the Atmospheric Sciences* 54:2519–41.

Holmes, J. D., and W. W. Moriarty. 1999. Application of generalized Pareto distribution to wind engineering. *Journal of Wind Engineering and Industrial Aerodynamics* 83:1–10.

Jagger, T., J. B. Elsner, and X. Niu. 2001. A dynamic probability model of hurricane winds in coastal counties of the United States. *Journal of Applied Meteorology* 40:853–63.

Janowiak, J. E. 1988. An investigation of interannual rainfall variability in Africa. *Journal of Climate* 1:240–55.

Jarvinen, B. R., C. J. Neumann, and M. A. S. Davis. 1984. *A tropical cyclone data tape for the North Atlantic Basin, 1886–1983: Contents, limitations, and uses.* NOAA Technical Memorandum, NWS NHC Report No. 22. Coral Gables, Fla.: National Oceanic and Atmospheric Administration.

Kimberlain, T. B., and J. B. Elsner. 1998. The 1995 and 1996 North Atlantic hurricane seasons: A return of the tropical-only hurricane. *Journal of Climate* 11:2062–69.

Knaff, J. A. 1997. Implications of summertime sea level pressure anomalies in the tropical Atlantic region. *Journal of Climate* 10:789–804.

Lehmiller, G. S., T. B. Kimberlain, and J. B. Elsner. 1997. Seasonal prediction models for North Atlantic Basin hurricane location. *Monthly Weather Review* 125:1780–91.

Liu, K.-b., and M. L. Fearn. 2000. Reconstruction of prehistoric landfall frequencies of catastrophic hurricanes in northwestern Florida from lake sediment records. *Quaternary Research* 54:238–45.

Liu, K.-b., Shen, C., and Louie, K.-s. 2001. A 1000-year history of typhoon landfalls in Guangdong, southern China, reconstructed from Chinese historical documentary records. *Annals of the American Association of Geographers* 91:453–64.

McCullagh, P., and J. A. Nelder. 1999. *Generalized linear models.* Second edition. New York: Chapman & Hall/CRC.

Murnane, R. J. and coauthors. 2000. Model estimates hurricane wind speed probabilities. *Eos, Transactions of the American Geophysical Union* 81:433, 438.

Neumann, C. J. 1987. *The National Hurricane Center risk analysis program (HURISK)* [reprinted with corrections, 1991]. NOAA Technical Memorandum, NWS NHC Report No. 38. Coral Gables, Fla.: National Weather Service, National Hurricane Center.

Neumann, C. J., B. R. Jarvinen, C. J. McAdie, and G. R. Hammer. 1999. *Tropical cyclones of the North Atlantic Ocean, 1871–1998.* NOAA Historical Climatology Series 6-2. Asheville, N.C.: National Climatic Data Center.

Ropelewski, C. F., and P. D. Jones. 1987. An extension of the Tahiti-Darwin Southern Oscillation index. *Monthly Weather Review* 115:2161–65.

Saunders, M. A., R. E. Chandler, C. J. Merchant, and F. P. Roberts. 2000. Atlantic hurricanes and northwest Pacific typhoons: ENSO spatial impacts on occurrence and landfall. *Geophysical Research Letters* 27:1147–50.

Simpson, R. H. 1974. The hurricane disaster potential scale. *Weatherwise* 27:169–86.

Troup, A. J. 1967. Opposition of anomalies of upper tropospheric winds at Singapore and Canton Island. *Australian Meteorological Magazine* 15:32–37.

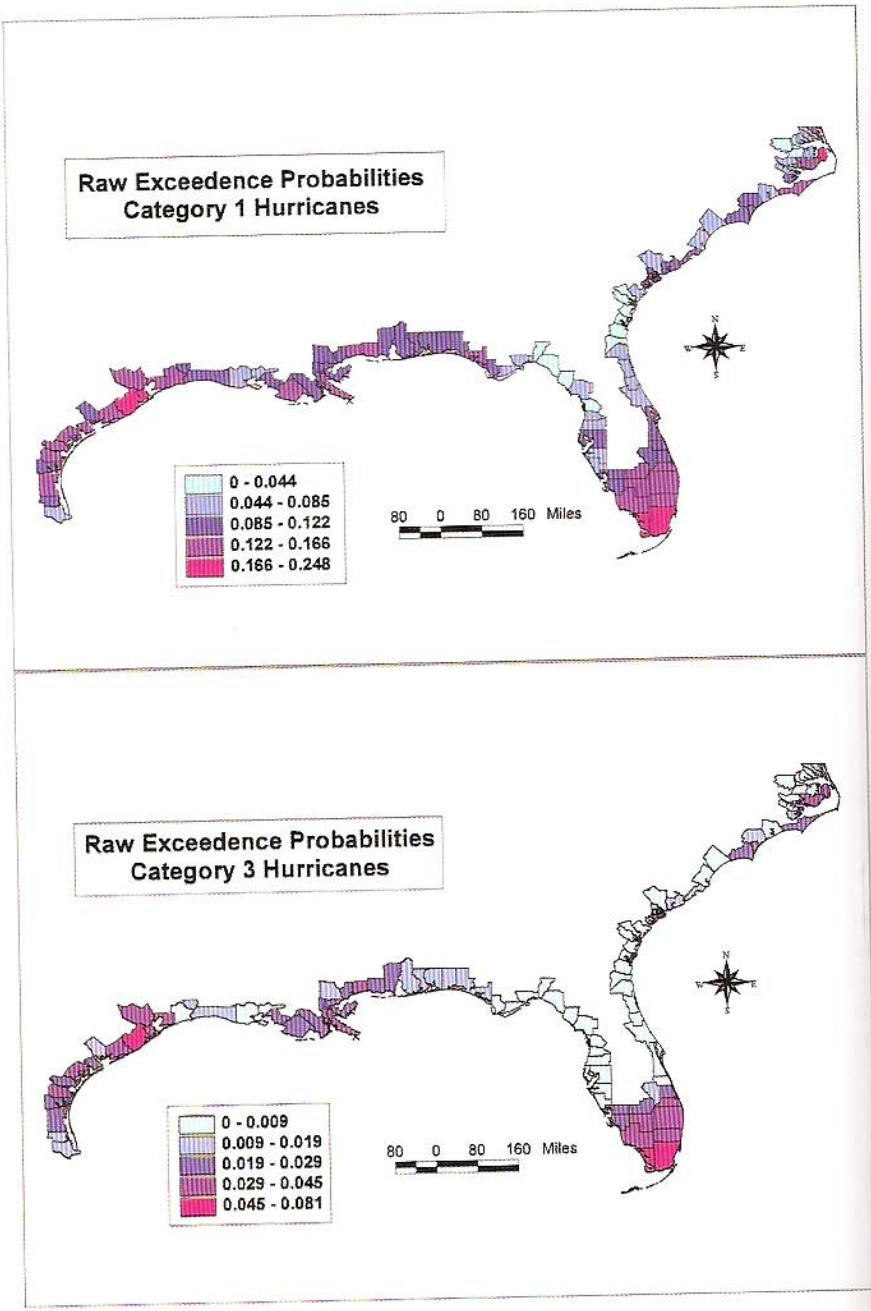

PLATE 7 Annual exceedence probabilities for Category 1 (*top*) and Category 3 (*bottom*) hurricane winds in coastal counties from Texas to North Carolina using the dynamic probability model run in the raw climatological mode. Exceedence refers to wind speeds greater than or equal to the minimum categorical value.

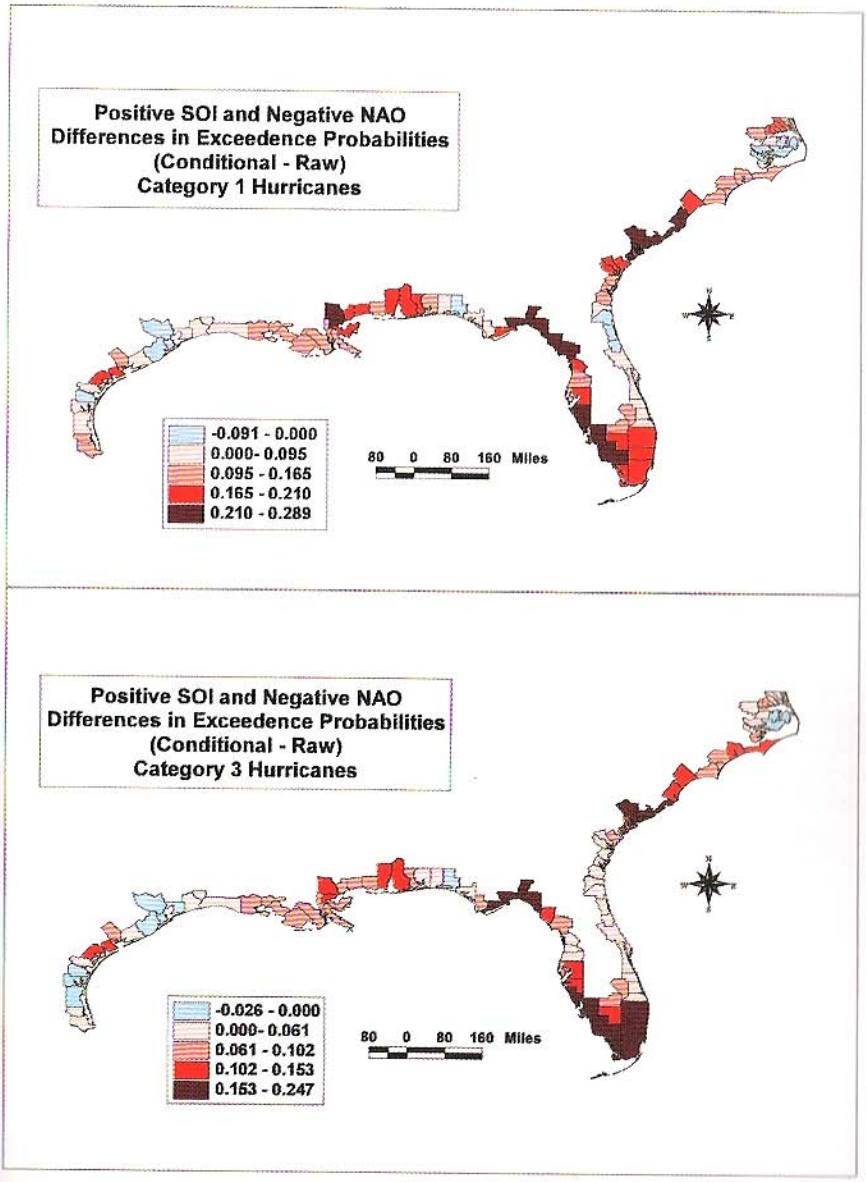

PLATE 8 Differences in annual exceedence probabilities (conditional minus raw) for Category 1 (*top*) and Category 3 (*bottom*) hurricane winds in coastal counties from Texas to North Carolina. The probabilities are based on an SOI value of +5.2 s.d. and an NAO value of −3.1 s.d. The differences in probabilities are spatially smoothed using a triangle kernel-type smoother with a bandwidth of three counties.

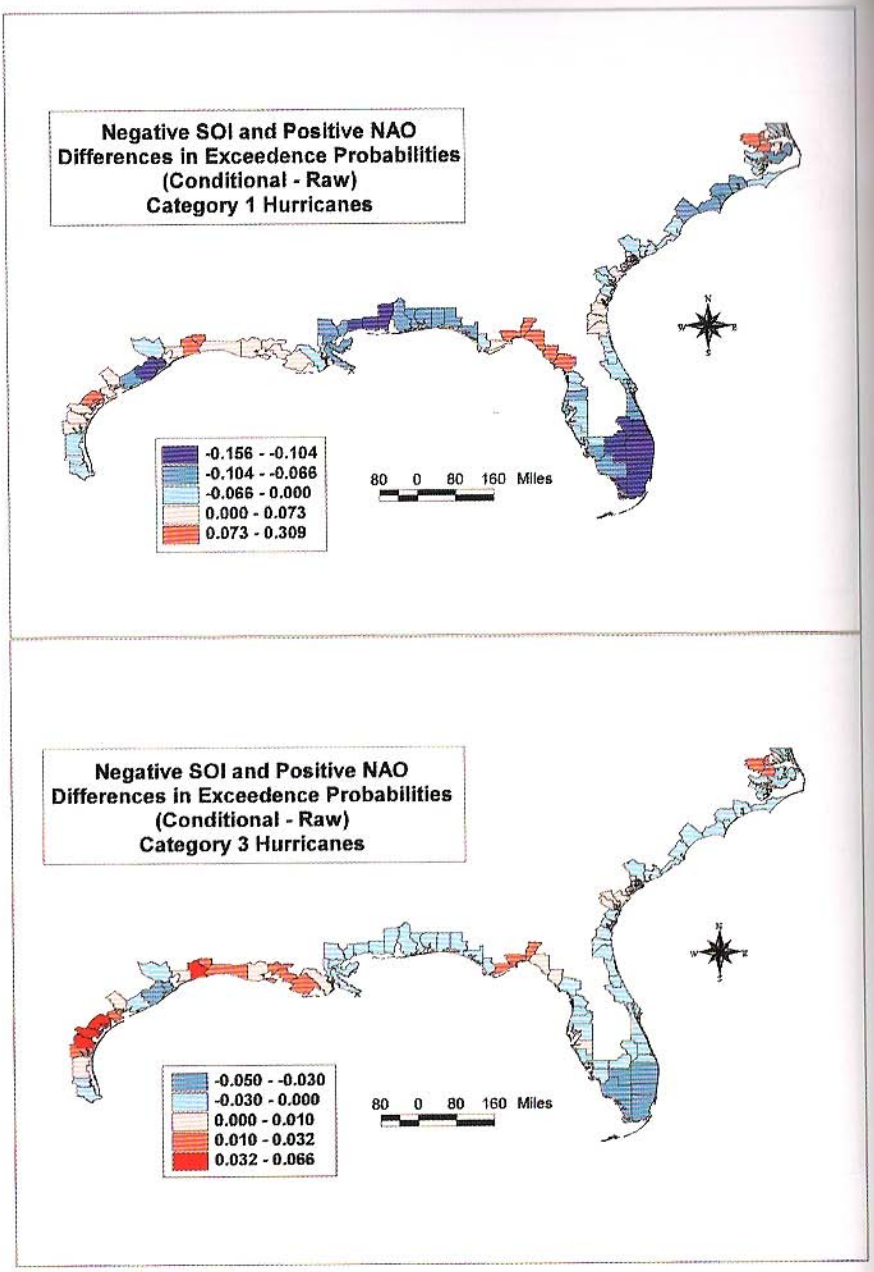

PLATE 9 Differences in annual exceedence probabilities (conditional minus raw) for Category 1 (*top*) and Category 3 (*bottom*) hurricane winds in coastal counties from Texas to North Carolina. The probabilities are based on an SOI value of −5.2 s.d. and an NAO value of +3.1 s.d. The differences in probabilities are spatially smoothed using a triangle kernel-type smoother with a bandwidth of three counties.

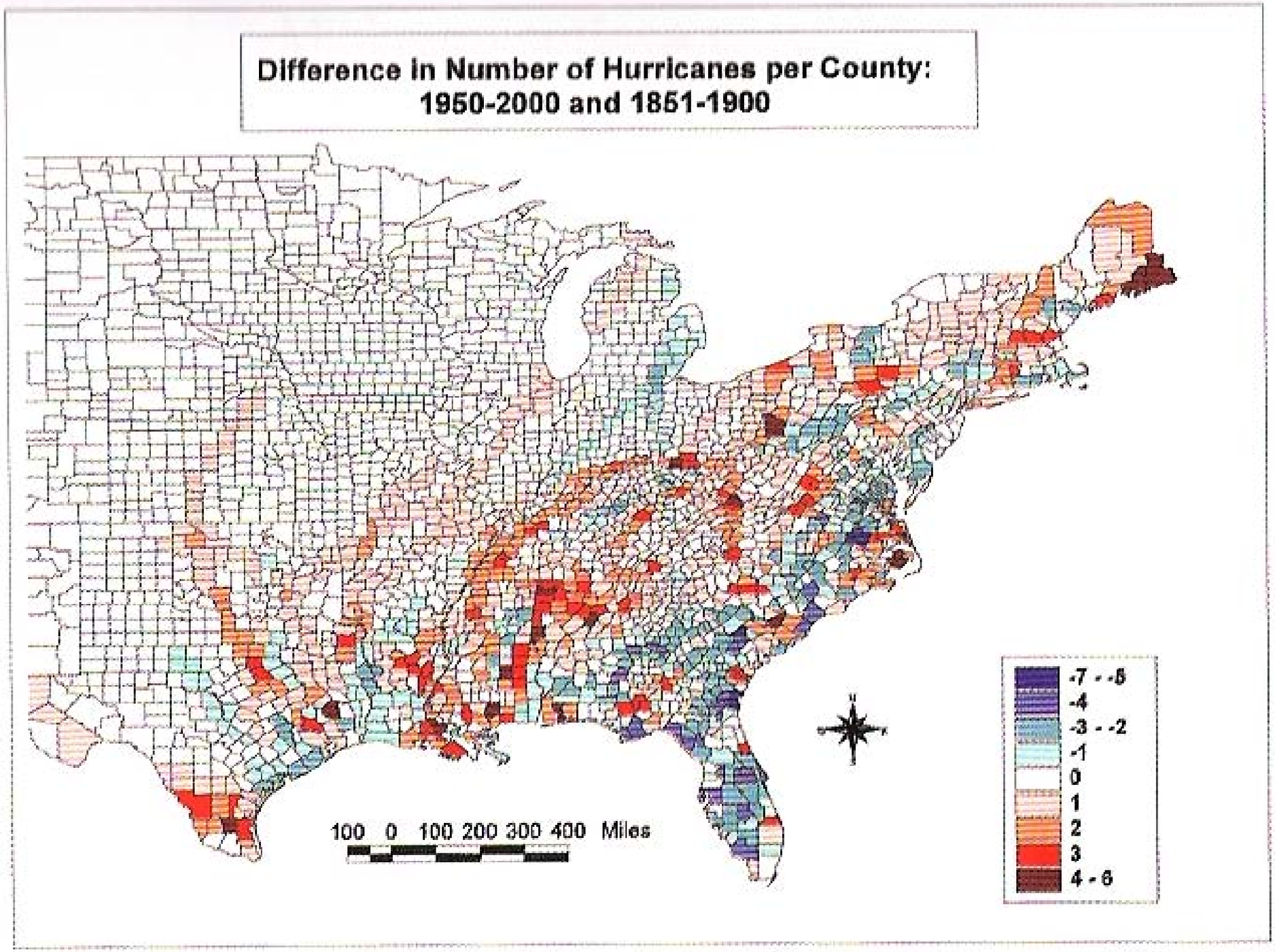

PLATE 10 Differences in the number of hurricanes per county over two 50-year periods. Negative values (blue) indicate that there were more hurricanes in the county during the period 1851 to 1900 than during the period 1950 to 2000. A hurricane is defined as the center of circulation of a tropical cyclone passing through the county borders based on 6-hour positions given in the HURDAT reanalysis dataset. The map considers only tropical cyclones designated as hurricanes at landfall. For inland counties, tropical cyclones have typical wind speeds well below the hurricane threshold.