A Hierarchical Bayesian Approach to Seasonal Hurricane Modeling

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(Manuscript received 12 June 2003, in final form 12 February 2004)

ABSTRACT

A hierarchical Bayesian strategy for modeling annual U.S. hurricane counts from the period 1851–2000 is illustrated. The approach is based on a separation of the reliable twentieth-century records from the less precise nineteenth-century records and makes use of Poisson regression. The work extends a recent climatological analysis of U.S. hurricanes by including predictors (covariates) in the form of indices for the El Niño–Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO). Model integration is achieved through a Markov chain Monte Carlo algorithm. A Bayesian strategy that uses only hurricane counts from the twentieth century together with noninformative priors compares favorably to a traditional (frequentist) approach and confirms a statistical relationship between climate patterns and coastal hurricane activity. Coinciding La Niña and negative NAO conditions significantly increase the probability of a U.S. hurricane. Hurricane counts from the nineteenth century are bootstrapped to obtain informative priors on the model parameters. The earlier records, though less reliable, allow for a more precise description of U.S. hurricane activity. This translates to a greater certainty in the authors' belief about the effects of ENSO and NAO on coastal hurricane activity. Similar conclusions are drawn when annual U.S. hurricane counts are disaggregated into regional counts. Contingent on the availability of values for the covariates, the models can be used to make predictive inferences about the hurricane season.

1. Introduction

Coastal hurricanes are a serious social and economic concern to the United States. Strong winds, heavy rainfall, and high storm surge kill people and destroy property. Hurricane destruction rivals that from earthquakes. In Florida alone, Hurricane Andrew's strike in 1992 caused more than $30 billion in direct economic losses. Hurricane accounts, even if incomplete, provide clues about future frequency and intensity that go beyond the specificity and lead time of climate prediction models. These data are important for land-use planning, emergency management, hazard mitigation, and (re)insurance contracts.

Empirical and statistical research (Goldenberg et al. 2001; Elsner et al. 1999, 2000a; Gray et al. 1992) identify factors that contribute to conditions favorable for Atlantic hurricanes leading to prediction models for seasonal activity (Gray et al. 1992; Hess et al. 1995). Research shows that climate factors can influence hurricane frequency differentially depending on location. El Niño's effect on the frequency of hurricanes in the deep Tropics is significant, but its effect on the number of hurricanes over the subtropics is small. Additional factors help explain local variations in hurricane activity (Lehmiller et al. 1997). In fact, the North Atlantic Oscillation (NAO) appears to play a significant role in modulating coastal hurricane activity (Elsner 2003; Elsner et al. 2001; Jagger et al. 2001; Murnane et al. 2000).

Insights into regional hurricane activity have yet to be successfully exploited in seasonal landfall models. One reason for this is the limited record length. Reliable annual counts of U.S. hurricanes date back only about 100 years. Because regional hurricane probabilities are quite small, longer records are needed to accurately assess risk. A way around this limitation is to use records that are less reliable. Elsner and Bossak (2001, hereafter EB01) show how to include incomplete records into a climatological analysis of U.S. hurricane activity. Their approach is Bayesian. Here we extend EB01 by taking a Bayesian approach to regression modeling. This allows us to add covariates (predictors) into the analysis of hurricane activity.

The purpose of the present work is to describe a methodological framework for statistical seasonal hurricane modeling that makes use of less precise historical records. Hurricane statistics together with demographic data indicate a greater uncertainty in nineteenth century landfall records. Yet, as demonstrated in EB01, a sharp decision to reject these earlier observations is wasteful. Specifically, the problem is how to statistically model future coastal hurricane activity when it is known that the count data from the early years are incomplete. Here

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we present a way to solve this problem using Bayesian methodology based on Markov chain Monte Carlo (MCMC) simulation. The methodology is general and incorporates the analysis of EB01 as a special case.

There is now abundant statistical literature on hierarchical Bayesian models. A good place to start is Gilks et al. (1996), which brings together contributions from leading authorities and which places emphasis on practice. Congdon (1993) provides an excellent overview of Bayesian modeling through the illustration of a wide range of examples, particularly from the health and social sciences. Only more recently has this approach been applied in climate studies. Wikle (2000) gives a gentle introduction to hierarchical Bayesian modeling for atmospheric and oceanographic processes. Berliner et al. (2000) shows how the hierarchical approach can be used to forecast tropical Pacific sea surface temperatures by combining physical understanding of the El Niño–Southern Oscillation (ENSO) with statistical models. Katz (2002) reviews how hierarchical Bayesian models enable better uncertainty analysis in integrated assessments of climate change issues. Wikle and Anderson (2003) demonstrate how the climatological analysis of tornado reports, complicated by reporting errors and count data, can be performed within a hierarchical Bayesian framework. Elsner et al. (2004) show how Bayesian models can be used to detect change points in hurricane activity.

The present experimental design is a comparison of a Bayesian model with a traditional frequentist model. The goal is to show the usefulness of the Bayesian approach in focusing beliefs we might harbor about the factors that influence coastal hurricane activity from the available information at hand. First the approach is verified by comparing a Bayesian model with its counterpart from a likelihood approach using data from the twentieth century only. The nineteenth century data are then introduced into the Bayesian model. Results confirm the utility of the earlier records through greater precision on the model parameters. The hierarchical Bayesian approach provides a strategy for modeling hurricane activity that makes use of available historical information without assuming the records have identical levels of accuracy.

We begin the paper with a discussion of the hurricane counts and the covariates. In section 3 we explain the general idea behind the MCMC approach to Bayesian inference. In section 4 we discuss the Bayesian approach to statistical modeling in the context of U.S. hurricane activity. In section 5, we apply the Bayesian model to annual counts of U.S. hurricanes and compare the results with those generated using a classical likelihood approach. In section 6 we use the Bayesian model on regional hurricane counts. In section 7 we demonstrate how to make predictive inference within the Bayesian framework. We summarize our results and provide a list of conclusions in section 8.

2. Data

a. *Hurricane counts*

The North Atlantic Hurricane database (HURDAT or best-track) is the most complete and reliable source of North Atlantic hurricanes (Jarvinen et al. 1984). The dataset consists of the six-hourly position and intensity estimates of tropical cyclones back to 1886 (Neumann et al. 1999). A hurricane is a tropical cyclone with maximum sustained (1-min) 10-m winds of 65 kt (33 m s^{-1}) or greater. Hurricane landfall occurs when all or part of the storm's eyewall passes directly over the coast or adjacent barrier islands. Since the eyewall extends outward a radial distance of 50 km or more from the hurricane center, landfall may occur even in the case where the exact center of lowest pressure remains offshore. A hurricane can make more than one landfall as Hurricane Andrew did in striking southeast Florida and Louisiana. For U.S. hurricanes we consider only whether the observations indicate that the cyclone struck the continental United States at least once at hurricane intensity. The approximate length of the U.S. coastline affected by hurricanes from the Atlantic is 6000 km. For regional frequencies we consider multiple landfalls if they occur in different regions. We do not consider hurricanes affecting Hawaii, Puerto Rico, or the Virgin Islands.

Additional contributions to the knowledge of past hurricanes were made by interpreting written accounts of tropical cyclones from ship logs, newspapers, and other nontraditional archives (Ludlum 1963; Fernández-Partagás and Diaz 1996). These studies update and add information about hurricane landfalls during the period 1851 through 1899. For instance, the *New York Times'* reports of damage and casualties often contain enough detail to reconstruct the location and intensity of a hurricane at landfall. Arguably these sources of U.S. hurricane information provide justification to extend the U.S. hurricane record back to the preindustrial era (Elsner and Kara 1999; Elsner et al. 2000b). Recently, the National Oceanic and Atmospheric Administration (NOAA) embarked on a 3-yr hurricane reanalysis project (Landsea et al. 2004). The motivation was, in part, to reduce the level of uncertainty surrounding the historical reports of hurricanes during the last half of the nineteenth century. The hurricane-landfall phase of the project was complete in July 2000. A concatenated dataset of hurricane landfall accounts from historical archives and modern direct measurements is used in the present study. A comparison of the hurricane record in 50-yr intervals is presented in EB01.

In the present study it is assumed that the annual counts of U.S. hurricanes are certain back to 1900, but less so in the interval 1851–99. The justification for this cutoff is based on an increased awareness of the vulnerability of the United States to hurricanes following the Galveston hurricane tragedy of 1900. Using this information, EB01 estimate the hurricane-rate distribution, which is subsequently used in a climatological model (negative binomial distribution) of future activity. Following Epstein (1985) they make use of the fact that the gamma probability density function is the conjugate prior density for the intensity (mean value) of the Poisson process λ. The Poisson distribution is used to characterize North Atlantic hurricane counts (Solow and Moore 2000; Parisi and Lund 2000; Elsner and Kara 1999; Bove et al. 1998; Elsner and Schmertmann 1993) and the log-linear Poisson model (McCullagh and Nelder 1989) is used to describe the influence of climate variables on various aspects of North Atlantic hurricane activity (Elsner and Bossak 2004; Elsner et al. 2001, 2002; Elsner and Schmertmann 1993).

A bootstrap procedure obtains a 90% credible interval on the mean number of hurricanes during the nineteenth century. The ratio of the upper to lower values of the credible interval is equal to the ratio of the corresponding upper to lower quantiles of the χ^2 variable. The "effective" number of years available from the nineteenth century is equal to half the degrees of freedom of this χ^2 distribution. Thus the uncertainty about the exact hurricane counts during the earlier years is expressed as a distribution on the annual rainfall rate. Here we would like to have covariate (predictor) information linked to annual counts through a regression equation. This motivates the present approach.

b. Covariates

A statistical relationship between ENSO and U.S. hurricanes is well established (Bove et al. 1998; Elsner et al. 1999; Elsner and Kara 1999; Jagger et al. 2001). A relationship between the North Atlantic Oscillation and U.S. hurricanes has more recently been identified (Elsner et al. 2000a,b, 2001; Elsner and Bossak 2004). Indices characterizing these two climate variables are described later.

Tropical Pacific sea surface temperatures (SSTs) are characterized by cold values (typically <26°C) in a narrow latitudinal band centered on the equator in the central and eastern longitudes of the basin and warm values (typically >27°C) in the western equatorial Pacific and extending north and eastward to Central America. These features can be seen in the annual mean SST field as well as in individual months. The region of equatorial cold SSTs is commonly referred to as the *cold tongue.* Large year-to-year fluctuations in tropical Pacific SSTs are centered in the cold tongue region and along the South American coast. The basin-scale equatorial fluctuations in SSTs are associated with ENSO. Average SST anomalies over 6°N–6°S, 180°–90°W in the cold tongue region are called the cold tongue index (CTI; Deser and Wallace 1990). Large nonseasonal SST fluctuations along the Peruvian coast are associated with El Niño, which although significantly correlated with the ENSO SST fluctuations, do not exhibit a one-to-one correspondence with cold tongue SST anomalies (Deser and Wallace 1987).

The SST data for 1854–1997 are from the Comprehensive Ocean–Atmosphere Data Set (COADS) and for 1998–2000 are from an empirical orthogonal function (EOF) analysis. The COADS data include an enhanced quality control, which incorporates a large number of newly obtained observations before 1950. A SST climatology is calculated from the COADS data for the years 1950–79, weighted by the number of observations. The climatology is smoothed along latitude circles with successive five- and three-point running means. SST anomalies are calculated by subtracting from each month of data the climatology for that calendar month. The index is then calculated by taking the average of the available observations in the cold tongue region. For the COADS data, the contribution of individual 2° latitude–longitude regions is weighted by the number of observations in that year, month, and region. For each year and month, the global-mean SST anomaly is also calculated, and subtracted from the CTI to remove the change in SST measurement practices in 1942 (Folland and Parker 1995) and the long-term trend in SST (Zhang et al. 1997).

The index values for the years 1854–1997 were computed in the following manner. SST anomalies were calculated for each month and year by subtracting the smoothed climatology from the COADS SST data. CTI and global-mean SST values were calculated as the average anomaly in the two averaging regions, weighted by the number of observations. The global-mean SST was then subtracted from the CTI to remove the spurious step jump in SST in December 1941. Index values for the years beginning in 1998 were calculated in the same manner but with the EOF-based SST. For the period of common record, the CTI derived from the COADS and EOF SST are correlated at 0.95, and the standard deviation of the COADS and EOF CTI values are 0.77 and 0.69, respectively. Values of CTI are obtained from the Joint Institute for the Study of the Atmosphere and the Oceans as monthly anomalies (base period: 1950–79) in hundredths of a degree Celsius. These values are strongly correlated with values from other ENSO SST indices [e.g., Niño-3.4 (5°N–5°S, 170°–120°W) SSTs]. Since the peak of the Atlantic hurricane season runs from August through October, a 3-month averaged (August–October) CTI from the dataset is used in the present study. Sixteen years have at least one of the 3 months missing, so no CTI average is calculated.

Instead proxy tree-ring data representing SSTs in the equatorial Pacific Ocean are used to fill in the missing values. Reconstruction of the ENSO variability for the months of December through February each year based on tree-ring data from northern Mexico and Texas. The reconstruction uses factor scores from a principal component analysis (PCA) of time t and selected $t - 1$ and $t + 1$ lags of 14 tree-ring chronologies from northern Mexico (Durango and Chihuahua) and the southwestern United States (Arizona, Utah, and New Mexico) plus the first two factor scores from a network of nine chro-

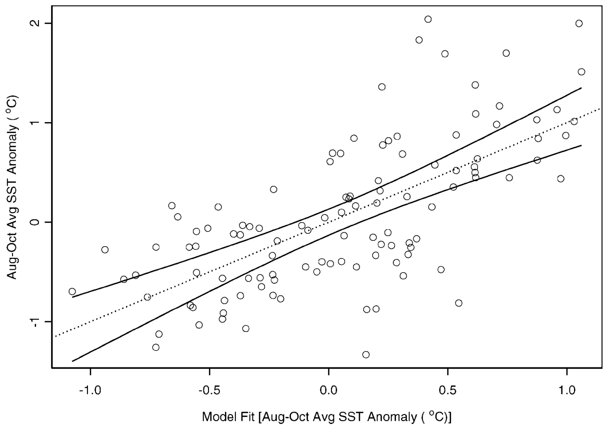

FIG. 1. Regression model (dotted line) with 95% simultaneous confidence bands (solid lines). An ordinary least squares regression is used to model the Aug–Oct averaged SST anomaly over the CTI region using tree-ring proxy as the lone covariate. The model is used to fill in 16 missing CTI values.

TABLE 1. Predicted CTI values. Values are interpolated from a linear regression on tree-ring proxy data. The standard errors (S.E.) of the predicted values are also given.

		Predicted	
Year	Proxy	CTI (°C)	S.E. (°C)
1851	0.621	0.580	0.076
1852	0.538	0.502	0.070
1853	−0.060	−0.056	0.054
1854	0.015	0.014	0.053
1857	0.240	0.224	0.055
1860	0.241	0.225	0.055
1861	−0.296	−0.276	0.063
1862	−0.415	−0.387	0.070
1863	−0.446	−0.416	0.073
1864	0.252	0.235	0.056
1865	0.555	0.518	0.071
1866	0.357	0.333	0.060
1867	0.189	0.177	0.053
1868	0.869	0.811	0.094
1869	−0.199	−0.186	0.059
1873	0.301	0.281	0.057

nologies in Oklahoma and Texas as independent variables. Chronologies are compiled from indices of tree growth (early wood or total ring width) detrended to remove biological effects (Cook et al. 1998). A linear regression of the August–October averaged CTI on the tree-ring index using data over the period 1855–1977 is shown in the Fig. 1. Regression diagnostics indicate a statistically significant model with the tree-ring proxy index explaining 45% of the variation in August–October CTI. The predicted values and their standard errors for August–October averaged CTI are listed in Table 1.

Index values for the NAO (NAOI) 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 are first averaged over the pre- and early hurricane season months of May and June. These months are a compromise between signal strength and timing relative to the hurricane season. The signal-to-noise ratio in the NAO is largest during the boreal winter and spring, whereas the U.S. hurricane season begins in June (see Elsner et al. 2001).

The August–October averaged CTI and the May–June averaged NAOI are the two covariates (predictors) used here to model annual hurricane rates. For reference, Table 2 shows their summary statistics based on 150 yr of data. The upper and lower quartile values of the CTI are 0.54° and −0.41°C, respectively. Years of above (below) normal CTI correspond to El Niño (La Niña) events. The upper and lower quartile values of the NAOI are 0.32 and −1.05 standard deviation (S.D.), respectively. Figure 2 shows their distributions and time series. The correlation between the two indices is a negligible 0.021. The present work makes no attempt to model the level of uncertainty inherent in the predictor values. Next, as a prelude to the modeling strategy, we discuss the general outline of the MCMC approach.

3. A Markov chain Monte Carlo approach

a. Bayesian inference

The MCMC approach is useful for Bayesian inference. Given a sample of data, what conclusions can be made about the entire ‘‘population?’’ Inference about the statistical model can be formalized as follows: Let θ be a population parameter, then statistical inference amounts to a supposition about θ on the basis of observing the data. We contend that a value of θ which gives a high probability to our data y is more likely than one which assigns low probability to y. In essence, the inferences are made by specifying a probability distribution of y for a given value of θ [the likelihood distribution, $f(y\,|\,\theta)$].

For Bayesian inference, θ is treated as a random quantity, and our judgements are based on $p(\theta|y)$; a probability distribution of θ for a given data y. The costs are a need to specifying a prior probability distribution $\pi(\theta)$ representing our beliefs about the distribution of θ before observing the data, and the need to postulate a particular family of parametric distributions. In the Bayesian approach (Carlin and Louis 2000) we combine

TABLE 2. Summary statistics for the covariate (predictor) variables. The units on the CTI index are °C and the units on the NAOI are standard deviation.

Statistic	CTI	NAOI
Min	−1.33	−2.76
1st quartile	−0.41	−1.05
Mean	0.09	−0.34
Median	−0.04	−0.37
3d quartile	0.54	0.33
Max	2.04	2.90
S.D.	0.714	1.005
No. of yr	150	150

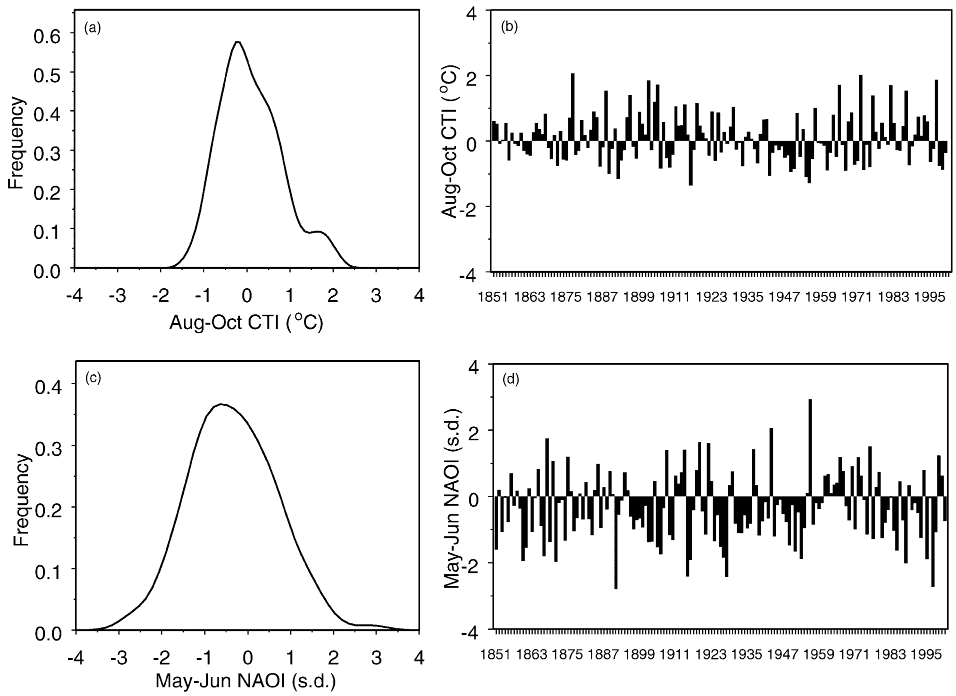

FIG. 2. Density plots and time series graphs of the two covariate (predictor) variables. The density plot uses a normal kernel density smoother with a bandwidth that is 4 times the standard deviation of the values. The correlation between annual values of CTI and NAOI is +0.021.

the likelihood distribution of the data given the parameter with the prior distribution using Bayes' theorem:

$$p(\theta|y) = \frac{f(y\,|\,\theta)\pi(\theta)}{\int f(y\,|\,u)\pi(u)\;du}. \qquad (1)$$

Having observed y, Bayes' theorem is used to determine the distribution of θ conditional on y. This is called the *posterior* distribution of θ, and is the subject of all Bayesian inference. Any feature of the posterior distribution is legitimate for inference including moments, quantiles, and p values. These quantities can be expressed in terms of the posterior expectations of functions of θ. The posterior expectation of a function $g(\theta)$ is

$$E[g(\theta)\,|\,y] = \frac{\int g(\theta)\pi(\theta)f(y\,|\,\theta)\;d\theta}{\int \pi(\theta)f(y\,|\,\theta)\;d\theta}. \qquad (2)$$

Evaluation of the integrals in Eqs. (1) and (2) are a source of practical difficulties, especially for complex problems. Moreover in most cases, analytic evaluation of the expected value of the posterior density is impossible. Numerical approximation methods can be difficult to employ so Monte Carlo integration is a popular alternative.

Monte Carlo integration evaluates $E[g(y)]$ by drawing samples from a probability density. An asymptotic approximation is given by

$$E[g(\theta|y)] \approx \frac{\sum_{i=1}^{N} g(\theta_i)}{N}. \qquad (3)$$

Thus the population mean of $g(y)$ is estimated by a sample mean. The argument for Monte Carlo integration goes as follows:

- Assume that the posterior is the stationary distribution of some Markov chain.
- Regularity conditions of the chain, such as aperiodicity and irreducibility, guarantee that starting from any initial value the marginal distribution of the sampler converges to a stationary distribution. If this distribution is unique, it will be that of the posterior by design.
- Having a process that generates samples from the posterior guarantees that the same law of large numbers that applies to samples from the posterior applies to samples from the chain. However, it does not obey the same central limit theorem since the samples are correlated by design.

b. Gibbs sampler algorithm

A common MCMC integration is the "Gibbs sampler." Let $\boldsymbol{\theta} = (\theta_1, \theta_2, \ldots, \theta_p)'$ be a p-dimensional vector of parameters and let $p(\boldsymbol{\theta}|y)$ be its posterior distribution given the data y. Then the Gibbs sampler is given as

1) Choose an arbitrary starting point $\boldsymbol{\theta}^{(0)} = [\theta_1^{(0)}, \theta_2^{(0)}, \ldots, \theta_p^{(0)}]'$, and set $i = 0$.
2) Generate $\boldsymbol{\theta}^{(i+1)} = [\theta_1^{(i+1)}, \theta_2^{(i+1)}, \ldots, \theta_p^{(i+1)}]'$ as follows:

$$\text{Generate } \theta_1^{(i+1)} \sim p[\theta_1 | \theta_2^{(i)}, \ldots, \theta_p^{(i)}, y];$$

$$\text{Generate } \theta_2^{(i+1)} \sim p[\theta_2 | \theta_1^{(i+1)}, \theta_3^{(i)}, \ldots, \theta_p^{(i)}, y];$$

$$\ldots \quad \ldots \quad \ldots$$

$$\text{Generate } \theta_p^{(i+1)} \sim p[\theta_p | \theta_1^{(i+1)}, \theta_2^{(i+1)}, \ldots, \theta_{p-1}^{(i+1)}, y].$$

3) Set $i = i + 1$, and go to step 2.

In this way each component of $\boldsymbol{\theta}$ is visited in order and a cycle through the scheme results in a sequence of random vectors of length p (Chen et al. 2000). Note that $p[\theta_1 | \theta_2^{(i)}, \ldots, \theta_p^{(i)}, y]$ is the conditional probability distribution of θ_1 given the other parameters and the data. The procedure is a type of stochastic relaxation where the update from previous samples are used on the current conditional. Under general conditions the sequence of $\boldsymbol{\theta}$ values forms a Markov chain, and the stationary distribution of the chain is the posterior distribution. Typically, the chain is run for a large number of iterations until the output is stable (burn-in). A large number of additional iterations are run, the output of which is analyzed as if it were a sample from the posterior distribution (Coles 2001; Carlin et al. 1992).

The Gibbs sampler is performed using the Bayesian Analysis Using Gibbs Sampler (BUGS) software (Gilks et al. 1994). BUGS assumes a Bayesian model in which all parameters are treated as random variables. The model consists of a joint distribution over all unobserved parameters (and missing data) and observed data. The posterior distribution over the parameters is obtained by conditioning on the data. BUGS is freely distributed and available for use on various platforms.

4. A model of annual hurricane counts

a. Model specification

Here we discuss the hierarchical Bayesian approach to statistical modeling in the context of U.S. hurricane activity. We model the annual hurricane count $\{y_i, i = 1, \ldots, N\}$ conditioned on the state of ENSO and the NAO using a generalized linear regression. A practical first step is the construction of a directed graph (Spiegelhalter et al. 1996) that represents model quantities as nodes, with arrows between nodes indicating their directed influence. Nodes are followed in the direction of the arrows. Figure 3 shows a directed graph illustrating the relationships in a model of U.S. hurricane activity. The data y_i are represented as a stochastic node with link (solid arrow) indicating a stochastic dependence on the Poisson parameter λ_i which is a logical function (regression structure) of the stochastic parameter vector $\boldsymbol{\beta} = (\beta_0, \beta_1, \beta_2, \beta_3)$. The logical relationship between λ_i and $\boldsymbol{\beta}$ is represented by a dotted arrow. The parameter vector $\boldsymbol{\beta}$ is specified by a multivariate normal distribution (MVN) having a mean $\boldsymbol{\mu}$ and variance $\boldsymbol{\psi}^{-1}$, where $\boldsymbol{\psi}$ is the precision matrix. The model is hierarchical because the nodes are followed from the top down. The model is expressed in equation form as

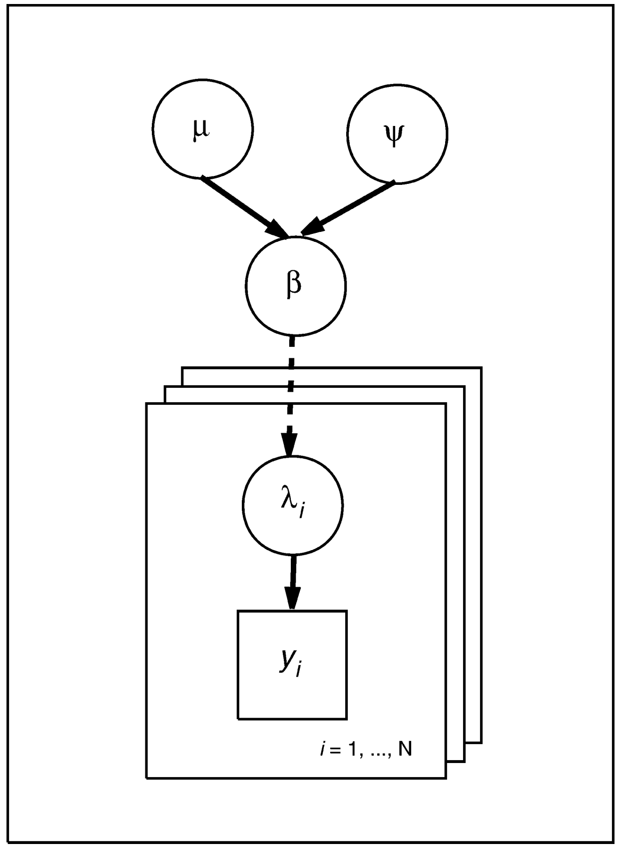

FIG. 3. Direct graph of the hierarchical Bayesian hurricane model. Model quantities are represented as nodes (circles or squares) and arrows between nodes indicate the direction of influence. Solid (dashed) arrows imply a stochastic (logical) dependence. The model starts with prior information for $\boldsymbol{\mu}$ and $\boldsymbol{\psi}$ representing the mean and precision of the parameters β, respectively. Particular values for $\boldsymbol{\beta}$ lead to a particular annual hurricane rate λ_i which is stochastically related to an annual count y_i.

$$\begin{aligned} y_i &\sim \text{Poisson}(\lambda_i) \\ \log(\lambda_i) &= \beta_0 + \beta_1\text{CTI} + \beta_2\text{NAOI} + \beta_3\text{CTI} \times \text{NAOI} \\ \boldsymbol{\beta} &\sim \text{MVN}(\boldsymbol{\mu}, \boldsymbol{\psi}^{-1}). \end{aligned} \tag{4}$$

The regression structure includes terms involving the CTI and NAOI. An interaction term (indicated by a multiplication sign) is also included. The BUGS code for the model is given in the appendix.

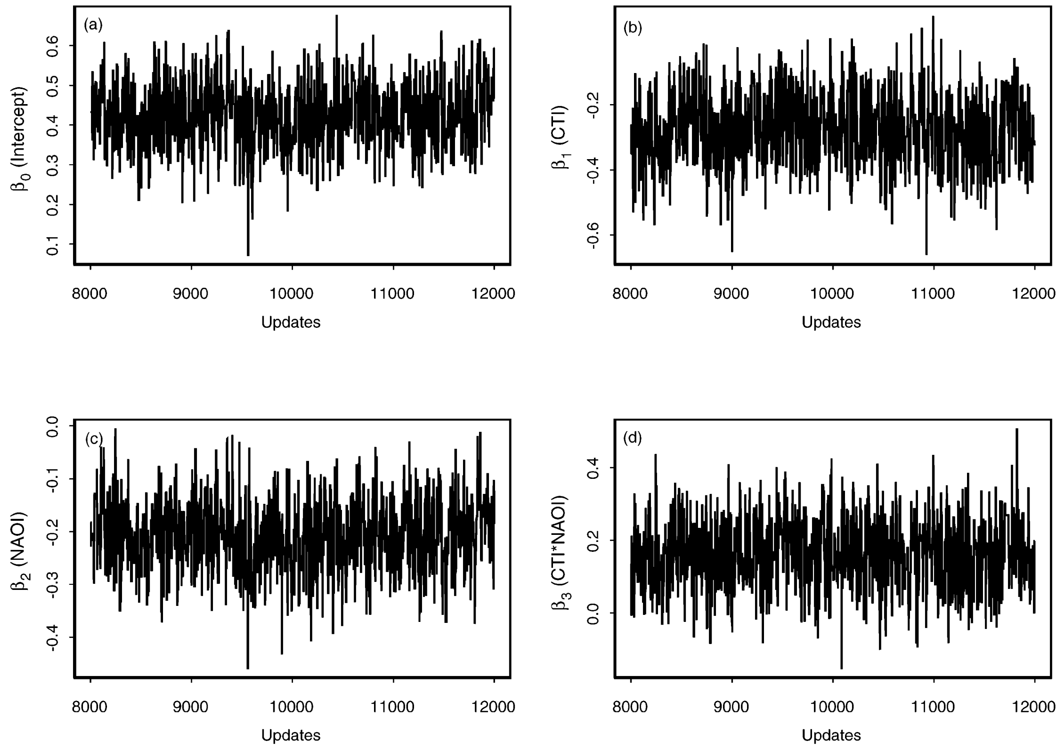

FIG. 4. Values of the regression parameters for iterations 8001 through 12 000 of the Bayesian model. The first 8000 iterations are discarded as burn-in. The values form a Markov chain as explained in the text.

b. Prior specification

As mentioned we make the assumption that annual counts of U.S. hurricanes are certain back to 1900, but less so in the interval 1851–99. A decidedly greater uncertainty surrounds the annual counts of hurricanes during the nineteenth century. Thus we use the data from the twentieth century for the likelihood function and data from the nineteenth century for the prior. To specify prior values for $\boldsymbol{\mu}$ and $\boldsymbol{\psi}$ we fit a Poisson regression to the set of hurricane counts and covariate values from the years 1851–99

$$\log(\lambda_j) = \beta_0^{(k)} + \beta_1^{(k)}\mathrm{CTI} + \beta_2^{(k)}\mathrm{NAOI} + \beta_3^{(k)}\mathrm{CTI} \times \mathrm{NAOI}, \quad (5)$$

where $\boldsymbol{\beta}^{(k)} = [\beta_0^{(k)}, \beta_1^{(k)}, \beta_2^{(k)}, \beta_3^{(k)}]$ for $k = 1, \ldots, M$ represents a bootstrap resampling (Efron and Tibsharini 1993). The resampling is done by choosing 49 yr at random with replacement as a bootstrap sample. The regression is run on the sample and regression coefficients saved. The process is repeated M times. Then

$$\boldsymbol{\mu} = \frac{\sum \tilde{\beta}^{(k)}}{M} \quad \text{and} \quad (6)$$

$$\boldsymbol{\psi}^{-1} = \frac{\sum \boldsymbol{\beta}^{(k)}\boldsymbol{\beta}^{(k)\mathrm{T}} - \boldsymbol{\mu}\boldsymbol{\mu}^{\mathrm{T}}}{M - 1}, \quad (7)$$

where the sum is over all M bootstrap samples. Here we choose $M = 1000$ throughout. In this way we obtain empirical distributions for $\boldsymbol{\mu}$ and $\boldsymbol{\psi}$.

To ensure stability of the results we run the Gibbs sampler for 12 000 updates and discard the first 8000 as burn-in. We use $\boldsymbol{\beta} = (0.5, -0.5, 0.2, -0.2)$ as initial values. Length of burn-in depends on the initial values and the rate of convergence, which is related to how fast the Markov chain mixes. Developing rigorous criteria for deciding chain length and burn-in requires a detailed study of the convergence properties of the chain (Jones and Hobert 2001) that goes beyond the scope of the present work. The chains, represented by successive updates to the model coefficients, are plotted in Fig. 4 after removal of the first 8000 iterations. Visual inspections of the chains indicate stationarity. The set of stationary values is used for posterior inferences.

5. Entire coast

a. Noninformative prior

We begin by using annual counts of U.S. hurricanes as the response variable. The counts are analyzed in EB01. The Bayesian approach is verified by comparing regression coefficients with those from a frequentist model. Here a fair comparison is one in which only the reliable twentieth-century records are used. We expect coefficients generated from the Gibbs sampler to coincide with those from a frequentist model. A noninformative prior is used in the

TABLE 3. Model comparisons.

	Bayesian		Frequentist	
Parameter	Mean	S.D.	Value	S.E.
β_0	0.3527	0.09058	0.3673	0.09094
β_1	−0.3800	0.12480	−0.3777	0.12726
β_2	−0.1912	0.07784	−0.1885	0.08205
β_3	0.1996	0.10240	0.1962	0.10610

Bayesian model to ensure only the twentieth century hurricane counts are included. Inflating the variance matrix of the bootstrap samples by a factor of 100 creates a suitable noninformative (nearly uniform) prior. With a value of 100, the prior probability for 99.95% of the bootstrap samples varies by less than 0.25%.

Table 3 gives statistics of the regression coefficients from the Bayesian and frequentist approaches. Under the Bayesian strategy, model coefficients are random variables with mean and standard deviation computed from the Markov chains. Under the frequentist approach, model coefficients are maximum likelihood estimates (MLE) with a corresponding standard error. Average Bayesian coefficient values compare favorably to the MLE and the standard deviations match the standard errors. Both models indicate the importance of ENSO and the NAO separately and as an interaction term. For the Bayesian model this is clear from density plots of the posterior distributions (Fig. 5). The distributions are plotted using smoothed histograms. Smoothing is done using a normal kernel with bandwidth of 0.17. The choice of bandwidth is a compromise between smoothing enough to remove insignificant bumps but not smoothing too much to hide real peaks (Venables and Ripley 1999). Actual values are plotted as points on the $y = 0$ line and the $x = 0$ line is dotted. Axes scales are fixed to aid visual comparisons.

The influence of ENSO on annual U.S. hurricane activity is indicated by the value of the CTI coefficient β_1. An increase in CTI (warmer equatorial Pacific SSTs) is associated with a K-fold change in the annual mean rate of U.S. hurricanes, where $K = \exp(\beta_1)$. The posterior density of β_1 is centered on the value of −0.38, so an increase of 1°C is associated with a 0.68-fold change in the mean hurricane rate (32% decrease). The posterior distribution of β_1 indicates a model that includes ENSO is more likely than a model that ignores it. Moreover it is quite unlikely that β_1 is greater than zero. Although this is analogous to the frequentist claim that β_1 is significant, the Bayesian approach assumes all models are false but some are more useful.

b. Bootstrap prior

The ability to include additional data that are less precise into the model is the strength of the Bayesian

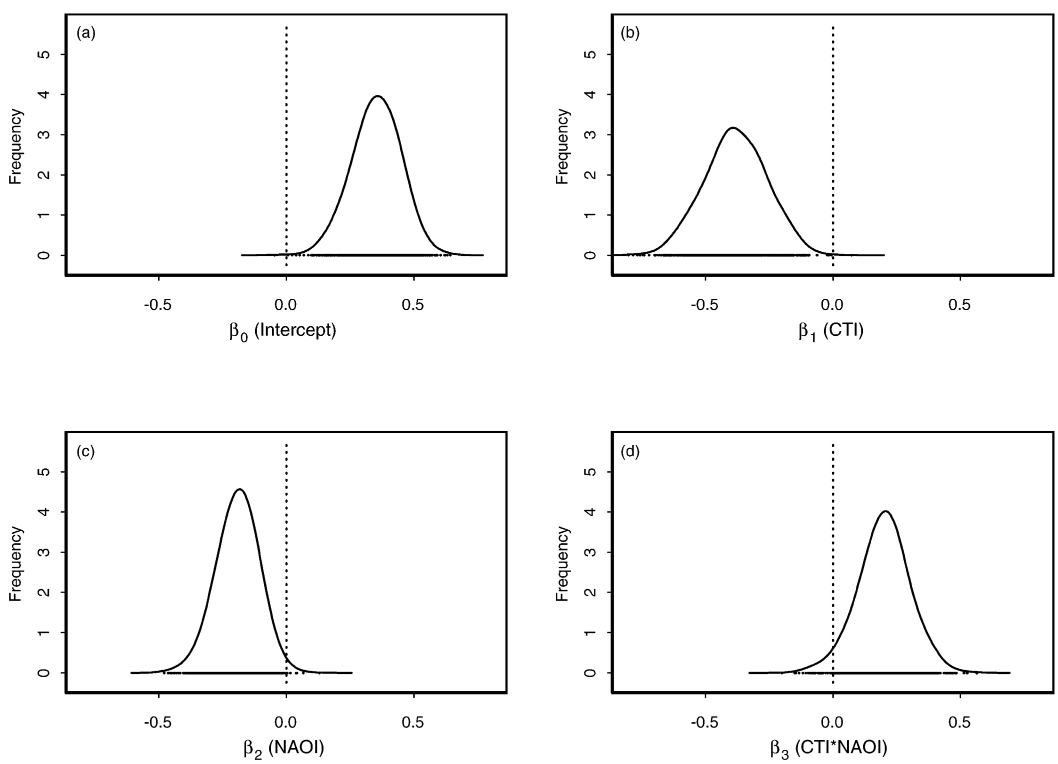

FIG. 5. Posterior distributions of the regression coefficients using a noninformative prior as part of the Bayesian model of U.S. hurricane activity. The distributions are smoothed using a normal kernel density estimator with a bandwidth of 0.17. The actual values are plotted along the $y = 0$ line. The dotted line is the zero reference line. (a) Intercept term, (b) ENSO term, (c) NAO term, and (d) interaction term.

TABLE 4. Model statistics for annual U.S. hurricane activity.

Parameter	Mean	S.D.	2.5%	Median	97.5%
			Noninformative priors		
β_0	0.3527	0.0906	0.1695	0.3525	0.5214
β_1	−0.3800	0.1248	−0.6288	−0.3806	−0.1543
β_2	−0.1912	0.0778	−0.3510	−0.1894	−0.0438
β_3	0.1996	0.1024	−0.0098	0.2009	0.3956
			Bootstrap priors		
β_0	0.4247	0.0739	0.2837	0.4268	0.5694
β_1	−0.2735	0.0989	−0.4716	−0.2754	−0.0812
β_2	−0.2098	0.0652	−0.3390	−0.2122	−0.0738
β_3	0.1647	0.0864	−0.0062	0.1652	0.3375

approach. Here additional data come from the nineteenth-century records and are incorporated using bootstrap sample statistics as outlined above. Table 4 gives statistics on the regression coefficients using noninformative and bootstrap priors. The bootstrap prior is based on data from the period 1851–99. The largest difference occurs on the CTI coefficient (β_1) where a 28% decrease in magnitude is noted. In contrast NAO's influence, as measured by the value of β_2, is a bit stronger, up in magnitude by 10%.

The influence of adding the additional data can be seen by comparing the posterior distributions with and without the earlier years (Fig. 6). Posterior distributions from the Bayesian model using bootstrap (noninformative) priors are shown as a solid (dashed) line. The nineteenth century data has the effect of focusing the model coefficients. For instance, the range on the 95% credible interval for β_1 is 0.20 (0.23) with(out) the nineteenth-century records. The influence of ENSO factors on U.S. hurricane activity decreases (the parameter distribution shifts toward zero) while the effect of the NAO factors is enhanced slightly (the distribution shifts away from zero). A model that includes the interaction term is less likely upon consideration of the earlier records. The additional data increases confidence in the values of the model coefficients. This translates to a greater certainty in our belief about the effect of ENSO and NAO on coastal hurricane activity. Specifying the prior amounts to introducing extra information. The posterior estimate is based on a combination of information (prior and likelihood) and thus has greater precision. We also note a variation in the relative role of the two factors as the effect of ENSO might have a secular component, being weaker during the nineteenth century (see also Elsner et al. 2001).

6. Southeast and northeast coasts

Recent research demonstrates that climatological factors influencing hurricane origin and development are not necessarily the same as those influencing where they

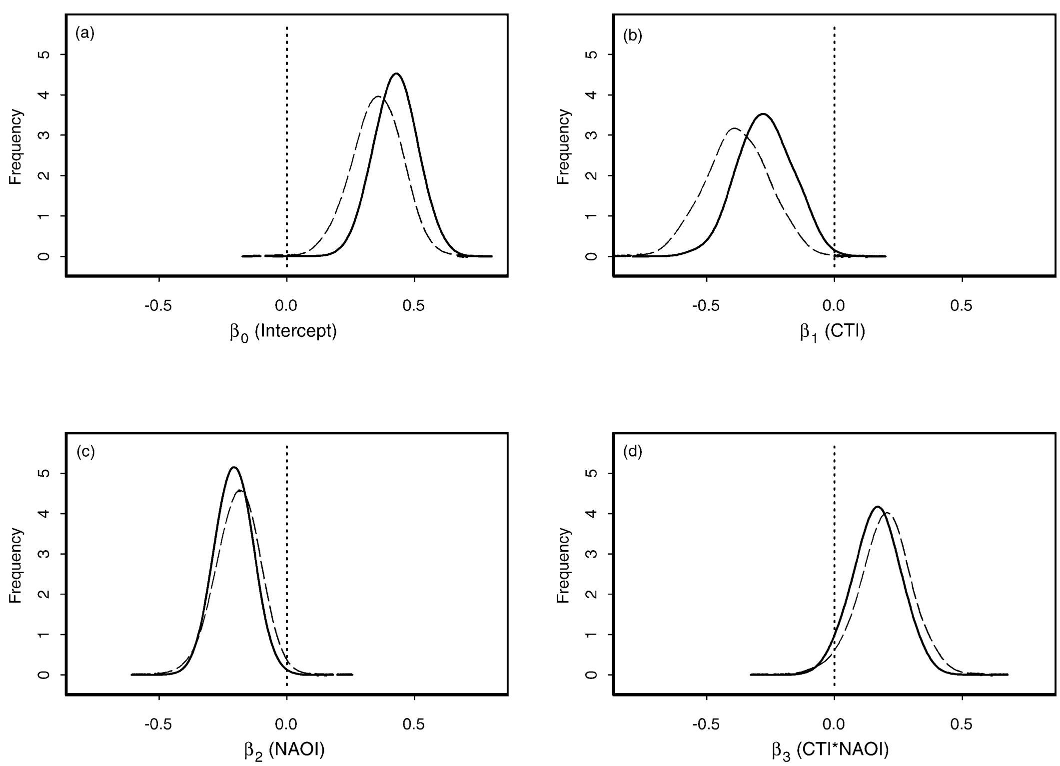

FIG. 6. Posterior distributions of the regression coefficients using the bootstrap (solid) and noninformative (dashed) priors as part of the Bayesian model of U.S. hurricane activity. (a) Intercept term, (b) ENSO term, (c) NAO term, and (d) interaction term.

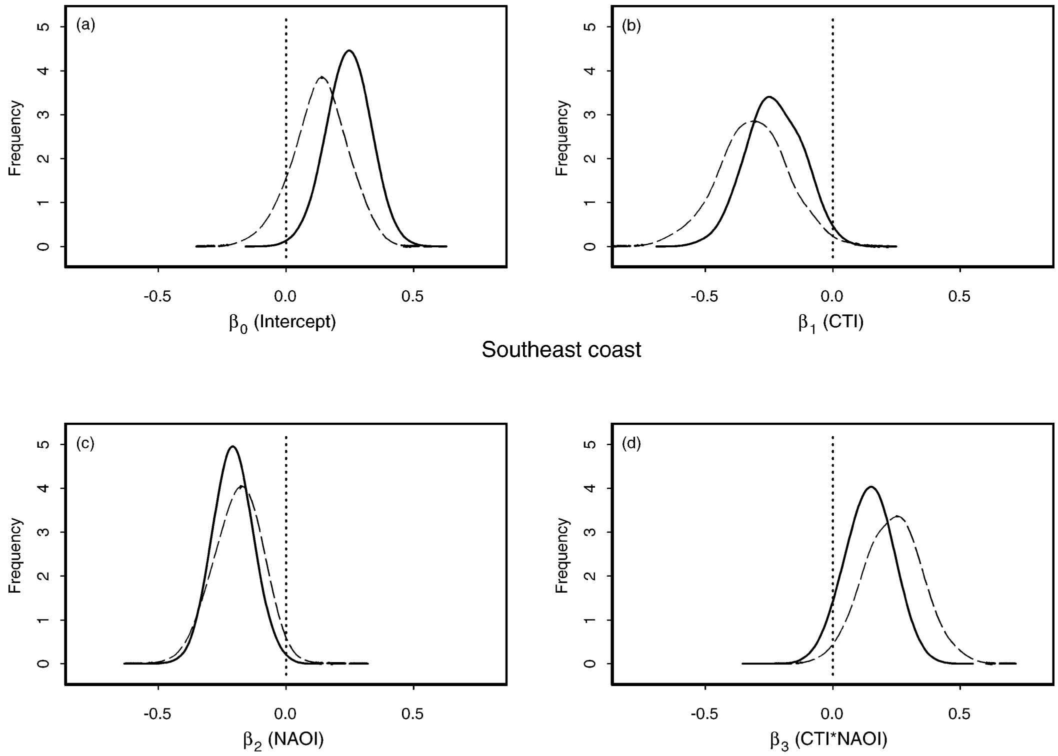

FIG. 7. Same as Fig. 6 except for annual hurricane counts along the southeast U.S. coast. The southeast coast includes the coastal states from Texas through South Carolina.

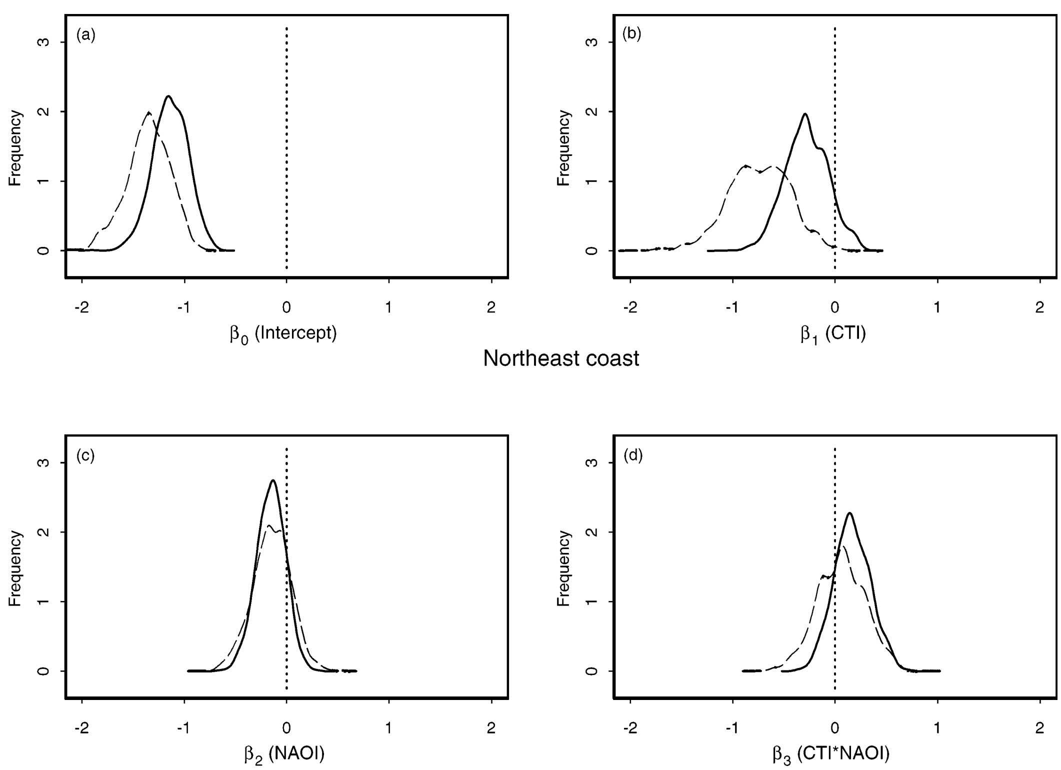

FIG. 8. Same as Fig. 6 except for annual hurricane counts along the northeast U.S. coast. The northeast coast includes the coastal states from North Carolina through Maine.

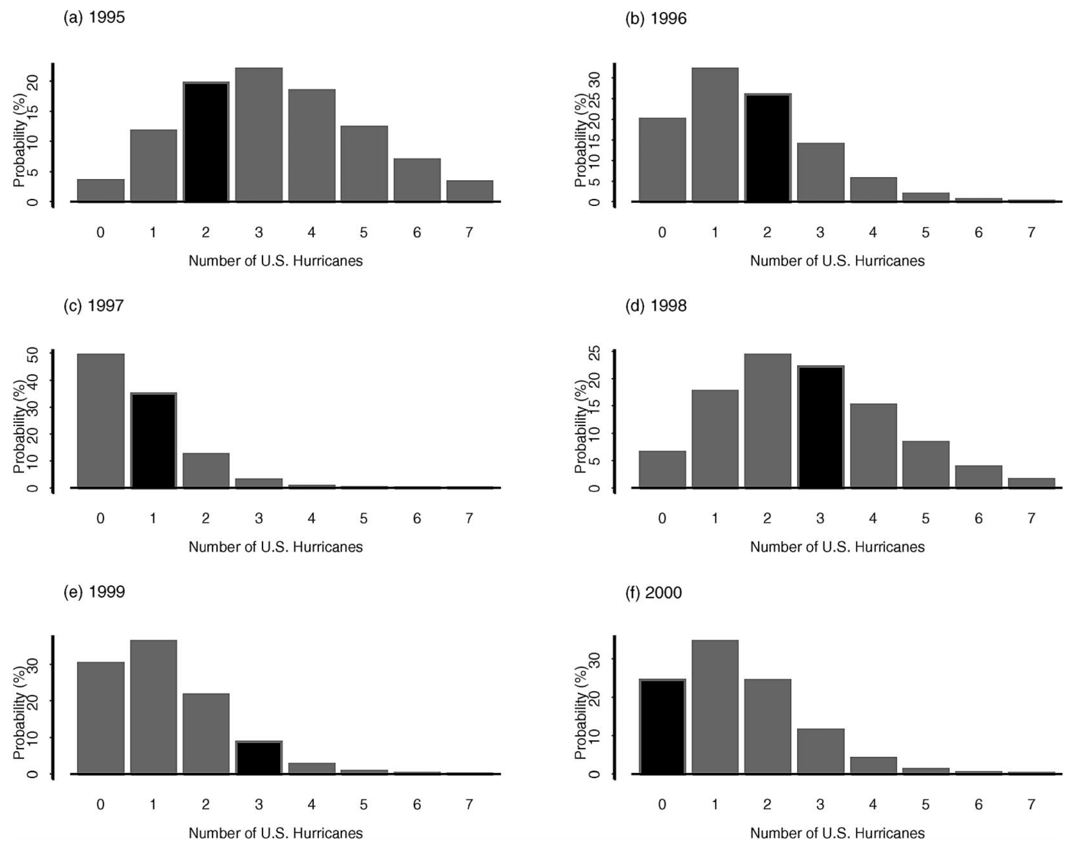

FIG. 9. (a)–(f) Predictive distributions of the number of U.S. hurricanes over the period 1995–2000. The probability of observing H number of hurricanes where $H = 0, 1, \ldots, 7$ is given on ordinate. The black bar indicates the observed number of hurricanes for that year. There were two U.S. hurricanes in 1995 (Erin and Opal).

will track (Elsner et al. 2000b). Certain ENSO-related factors are conducive to hurricane development while NAO-related factors control where they track (Elsner et al. 2001). Thus both covariates are associated with regional hurricane activity. For example, hurricanes affecting the region from Texas through South Carolina are more likely during La Niña when the NAO is suppressed (Elsner 2003). Here we examine Bayesian models of southeast and northeast hurricanes. The southeast (northeast) is defined as coastal states from Texas through South Carolina (North Carolina through Maine). The Gibbs sampler is run from the same initial values and for the same number of updates (12 000). Burn-in is again taken to be the first 8000 updates.

Figure 7 shows the posterior distributions of the regression coefficients when the annual counts of southeast U.S. hurricanes are the response variable. The distributions indicate that a model with ENSO and NAO indices is more useful than a model without them. In contrast, the data are ambiguous in favoring a model that includes the interaction term. This is especially evident when the nineteenth-century counts are included and is consistent with the model of all U.S. hurricanes discussed in the previous section. The nineteenth-century data also appear to give more (less) weight to the NAO (ENSO) factors in statistically explaining annual southeast coastal hurricane activity. Figure 8 shows the posterior distributions when the northeast counts are used as the response. Results are considerably different. Here the most useful model is climatology (constant term only). Alone, the twentieth-century data support a model for northeast hurricanes that includes ENSO. However, when the nineteenth-century records are included, no models more useful than climatology are found.

Results are consistent with other research in showing a significant relationship between coastal hurricane activity and both the ENSO and the NAO. In the Bayesian framework model usefulness is assessed from posterior distributions of the regression parameters. Annual hurricane counts that extend back through the year 1851 are consistent with models that include indices of ENSO and the NAO as covariates. Counts for the entire United States are disaggregated into southeast and northeast coastal regions. A useful covariate model is found for southeast hurricane activity only. We interpret differences between the regional (southeast and northeast) models as indicative of the contingency in hurricane landfalls. Although not entirely random, landfalling hurricanes are influenced by subtle factors unrelated to general steering

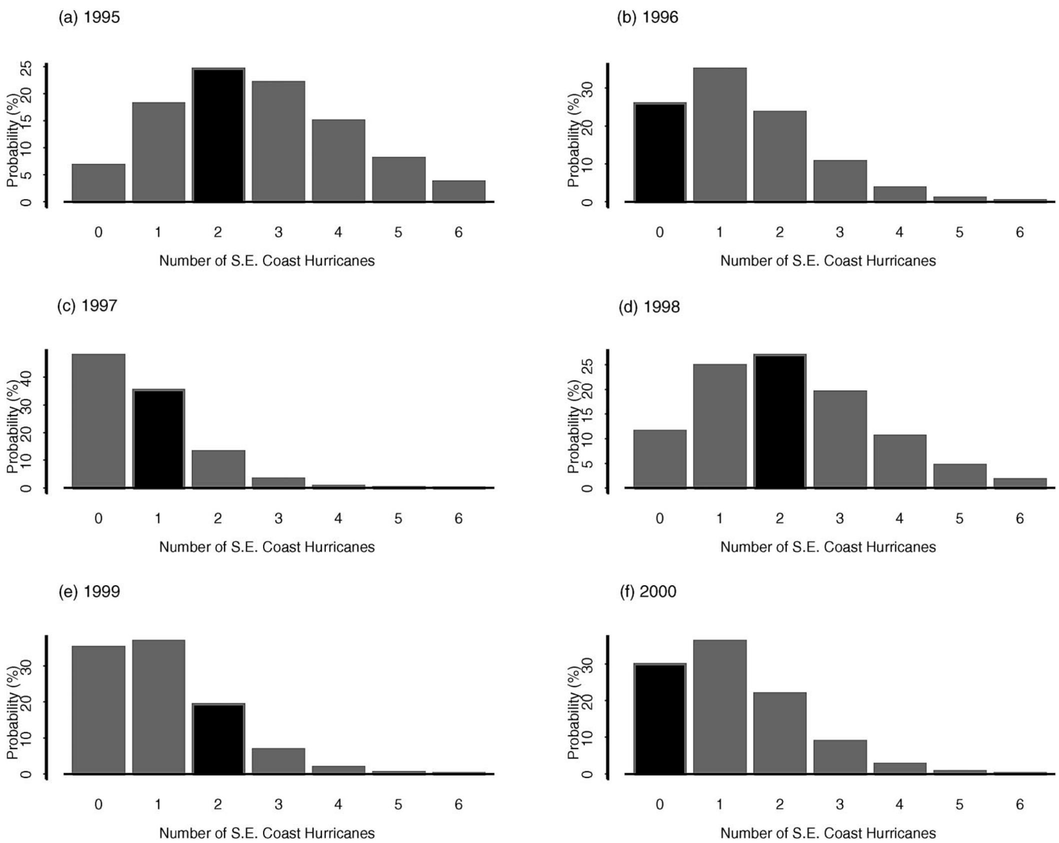

FIG. 10. Same as Fig. 9 except for the number of (a)–(f) southeast coast hurricanes over the period 1995–2000.

mechanisms associated with large-scale climate variability such as the NAO. This is more the case for landfalls in the northeast where storms tend to track parallel to the shoreline. Near misses during years in which the climate is favorable for northeast landfalls results in extra randomness for the annual counts making the climatological average the best estimate of future activity.

7. Predictive inference

A Bayesian approach provides a unified framework for inference and prediction. Uncertainty about model parameters is naturally transferred to predictive inference. Here we generate predictive samples of coastal hurricane activity as a function of year. This is achieved by assigning missing values to the observed annual hurricane count during the last 6 yr (1995–2000) of the record. The Gibbs sampler provides values for these missing observations from which a posterior distribution is generated. This amounts to using data over the period 1851–1994 to build the model and then using the model to predict the probability of coastal hurricane activity during each of the six succeeding years. Since the ENSO covariate describes conditions during the heart of the hurricane season, the predictive model is run in a ‘‘perfect prog’’ hindcast mode, which assumes an exact prediction of each hurricane season’s (August–October average) CTI value. Although from a practical standpoint this is not a wild extrapolation as there is strong persistence of SSTs from July through August–October.

Figure 9 shows the predictive probability of observing H U.S. hurricanes, where $H = 0, 1, \ldots, 7$ for each year starting with 1995. The bars show the probability level. The black-shaded bar indicates the observed number of hurricanes for that year. The predictive distributions change with values of the covariates for each year. The 1995 distribution suggests an active year with more than a 95% chance of at least one U.S. strike. In contrast the 1997 distribution suggests an inactive year with a 50% chance of no hurricanes. With the exception of 1999, the observed number of hurricanes falls within the central region (±1 hurricane from the median) of the predicted distribution. Similar predictive probabilities of observing hurricanes along the southeast coast are shown in Fig. 10.

Hindcast skill is estimated using the maximum a posteriori (MAP) estimate, which is the value that maximizes the posterior. MAP is the Bayesian maximum likelihood estimator. For hindcasts of U.S. hurricanes, the MAP estimates (p_i), assuming the observed data are independent from one year to the next, are 3, 1, 0, 2, 1, 1 for the years 1995, 1996, 1997, 1998, 1999, 2000, respectively. For the hindcasts of southeast U.S. hurricanes, the MAP estimates are 2, 1, 0, 2, 1, 1. The mean absolute error, given by $\mathrm{MAE} = 1/n \sum |p_i - o_i|$, where o_i are the observed number

TABLE 5. Hindcast skill between the observed and predicted annual hurricane counts. The predicted count is the maximum a posteriori (MAP) estimate. Comparisons are made using a mean absolute error (MAE) and the correlation coefficient. The units for MAE are number of hurricanes per year.

Model	MAE	Correlation
U.S. hurricanes	1.4	0.39
Climatology	0.9	0.00
SE hurricanes	0.8	0.50
Climatology	1.0	0.00

of hurricanes, is 1.4 for U.S. hurricanes and 0.8 for southeast U.S. hurricanes. The correlation between o_i and p_i is 0.39 for U.S. hurricanes and 0.50 for southeast hurricanes. These skill estimates are compared to climatology in Table 5. Although the predictive model for all U.S. hurricanes is no better than climatology, the model for southeast hurricanes appears to be marginally better.

8. Summary and conclusions

Hurricanes cause significant social and economic disruption within the United States. Here we examine climate relationships to U.S. hurricanes from data that extend back to early industrial times. Hurricane data come from the reanalysis project made possible by the meritorious works of Ludlum (1963) and Fernández-Partagás and Diaz (1996). The present work expands EB01 to include diagnostic models of U.S. hurricane activity. Better understanding of hurricane occurrences provides a sound basis for assessing the likely losses associated with a catastrophic reinsurance contract (Michaels et al. 1997).

A hierarchical Bayesian approach is used to model U.S. hurricanes using the NAOI and the CTI as covariates. Here the earlier records are used to specify priors and a Poisson generalized linear regression is the likelihood function. A Gibbs sampler is run to update the priors. Computations are done using BUGS software. The central message is the utility of all available records in understanding possible future activity despite the reduced accuracy of the earlier records. This provides an alternative view to the one espoused in Buckley et al. (2003) that, due to technological advances in observing networks, it is necessary to reduce the length of climate records when assessing climate change.

The main conclusions are the following:

- A Bayesian approach is practical for modeling hurricane datasets having varying levels of uncertainty. This is important when relying on historical and proxy data in rare-event analysis.
- Annual coastal hurricane counts from the past century and a half can be successfully modeled using indices of ENSO and NAO as predictors.
- The influence of NAO factors in modulating U.S. hurricane activity is relatively more important during the nineteenth century than during the twentieth century.
- Models with predictors are more useful on the subset of annual counts that exclude the northeast between North Carolina and Maine.

The model can be improved by incorporating additional information. For one thing efforts to extend coastal hurricane counts back to 1800 are currently underway. As a first step, we placed the information from all known historical storms on maps that depict the geographical location of the information source. The maps, which include damage reports, meteorological observations, and ship logs, can be used to estimate the likelihood of coastal hurricane activity during this earlier epoch (1800–50). (Maps are available at http://garnet.acns.fsu.edu/jelsner/www/.) This information as well as information gathered from geological records of overwash deposits associated with storm surge (see Liu and Fearn 1993, 2000; Donnelly et al. 2001) and proxy records of ENSO and NAO can be included in a future version of the model.

Acknowledgments. We appreciate the two thoughtful reviews on our original manuscript. Partial support for this study was provided by the National Science Foundation (ATM-0086958 and BCS-0213980) and The Florida State University's Cornerstone Program. The views expressed within are those of the authors and do not reflect those of the funding agencies.

APPENDIX

Bayesian Model Specification for U.S. Hurricane Activity

```
model{
 beta[1:M] ~ dmnorm(mu[1:M],
  prec[1:M,1:M])
 for(j in 1:M)
 {
  for(k in 1:M)
  {
   var1[j,k]<−1*var[j,k]
   prec[j,k]<−inverse
    (var1[1:M,1:M],j,k)
  }
 }
  for(i in 1:n)
 {
  y[i]~dpois(rate[i])
  log(rate[i])<−inprod
   (beta[1:M],X[i,1:M])
 }
}
```

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