

Detecting Shifts in Hurricane Rates Using a Markov Chain Monte Carlo Approach

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ABSTRACT

Time series of annual hurricane counts are examined using a changepoint analysis. The approach simulates posterior distributions of the Poisson-rate parameter using Gibbs sampling. A posterior distribution is a distribution of a parameter conditional on the data. The analysis is first performed on the annual series of major North Atlantic hurricane counts from the twentieth century. Results show significant shifts in hurricane rates during the middle 1940s, the middle 1960s, and at 1995, consistent with earlier published results. The analysis is then applied to U.S. hurricane activity. Results show no abrupt changes in overall coastal hurricane rates during the twentieth century. In contrast, the record of Florida hurricanes indicates downward shifts during the early 1950s and the late 1960s. The shifts result from fewer hurricanes passing through the Bahamas and the western Caribbean Sea. No significant rate shifts are noted along either the Gulf or East Coasts. Climate influences on coastal hurricane activity are then examined. Results show a significant reduction in U.S. hurricane activity during strong El Niño events and during the positive phase of the North Atlantic Oscillation (NAO). ENSO effects are prominent over Florida while NAO effects are concentrated along the Gulf Coast.

1. Introduction

Contemporary understanding of global climate processes, including the El Niño–Southern Oscillation and the North Atlantic Oscillation among others, suggest that climate may operate in two or more quasi-stationary states (Lockwood 2001; Tsonis et al. 1998; Tsonis and Elsner 1990; Berger and Labeyrie 1987; Charney and DeVore 1979; Namias 1964; Lorenz 1963). Transition between different climate regimes may occur abruptly rather than slowly varying as a consequence of the dissipative, nonlinear, and nonequilibrium properties of the climate system (Vannitsem and Nicolis 1991). Consequently, successive shifts result in an observed variable that appears to exhibit low-frequency oscillations. Another description is randomly occurring change points. In this case data-analytic tools relying on singular value

decomposition (SVD) are less appropriate as they assume stationarity and regularly varying changes in the underlying system.

Important in the context of climate variability and change problems, changepoint analysis quantitatively identifies temporal shifts in the mean value of the observations (Solow 1987). Moreover there is widespread interest in grouping years into active and inactive periods based on values of some climate index. Changepoint analysis directly addresses the question of when the change is likely to have occurred. Changepoint analysis can serve to pinpoint potential inhomogeneities in records arising from improved observational technologies and changes in station location (Lund and Reeves 2002). A statistical changepoint analysis provides a tool that is consistent with a physical model supporting abrupt rather than slowly varying transitions. In particular, changepoint analysis can be used to study climate variations. Indeed, geological records show large, widespread, abrupt climate changes (Alley et al. 2003) including sudden shifts in tropical cyclone frequency (Liu et al. 2001).

Lack of widespread interest in changepoint analysis might be due to the ad hoc decisions (choice of para-

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metric model, choice of data transformation) necessary for its implementation. For instance, Elsner et al. (2000a) use a log-linear regression to detect change points in the time series of annual counts of North Atlantic major hurricanes during the period 1900–99. A similar approach is employed by Chu (2002) in examining hurricanes over the central North Pacific. The assumption is that the annual counts of hurricanes after a logarithm transformation is approximately normally distributed.

Change point analysis using a Markov chain Monte Carlo (MCMC) approach has received considerable attention from statisticians and engineers. The term *Monte Carlo* refers to drawing random numbers and the term *Markov chain* refers to a series of values (a chain) the next of which depends only on the current value. In hydrology, the approach is applied to the analysis of sudden change at an unknown time in a sequence of energy inflows modeled by normally distributed random variables (Perreault et al. 2000a,b). To our knowledge, it has yet to be applied to climate data.

Our intent here is to shed light on the problem of detecting hurricane climate changes while introducing some of the essential ideas behind the MCMC approach to change point analysis. Our interest is to better understand coastal hurricane variations by applying the methodology to count data that are nonnormally distributed. The message is that change point analysis can provide new insights into climate variability not accessible with other methods. Using this approach, some of the subjective decisions typically associated with change point models can be dispensed with in favor of easier interpretation. In section 2 we outline the underlying philosophy of our MCMC approach to change point analysis. In section 3 we apply the approach to the annual counts of major North Atlantic hurricanes and in section 4 to annual counts of coastal hurricane activity. In section 5 we show how the methodology can be used to examine covariate relationships. In particular we examine the influence of the El Niño–Southern Oscillation and the North Atlantic Oscillation on coastal hurricane activity. Section 6 provides a summary and list of conclusions.

2. Detecting change points

a. Statistical inference

We begin with a short overview of the fundamentals of statistical inference. Given a data sample (either from the climate or a simulation of the climate), what conclusions can be made about the entire “population”? Inference about a statistical model can be formalized as follows: Let θ be a population parameter, then inference amounts to a supposition about θ on the basis of observing the data. We contend that values of θ which result in high probabilities of observing the data that were collected, y , are more likely than those which as-

sign a low probability to these same observations (maximum likelihood principle). In essence, the inferences are made by specifying a probability distribution of y for a given value of θ , $f(y|\theta)$.

In classical statistics, θ is considered a constant, while in Bayesian statistics it is treated as random quantity. Inferences are based on $p(\theta|y)$, a probability distribution of θ given the data y , rather than on $f(y|\theta)$. This seems natural as we are interested in the probability distribution of the parameter given the data, rather than the data given the parameter. The costs of this approach are the need to specify a prior probability distribution, $\pi(\theta)$, which represents our beliefs about the distribution of θ before we have information from the data, and the need to postulate a particular family of parametric distributions (likelihood). The Bayesian approach combines the likelihood distribution of the data given the parameter with the prior distribution to obtain the probability of θ given the data y

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

which is called Bayes’s theorem. Having observed y , Bayes’s theorem is used to determine the distribution of θ conditional on y . This is called the *posterior* distribution of θ .

Any feature of the posterior distribution is legitimate for inference, including moments, quantiles, p values, etc. These quantities are expressed in terms of the posterior expectations of functions of θ . The posterior expectation of a function $g(\theta)$ is

$$E[g(\theta)|y] = \frac{\int g(u)\pi(u)f(y|u) du}{\int \pi(u)f(y|u) du}. \quad (2)$$

Evaluation of the integrals are a source of practical difficulties. Moreover, in most applications, analytic evaluation of the expected value of the posterior density is impossible. The main problem with using numerical methods is that the calculation of the posterior expectation involves a high-dimensional integral if the number of parameters (θ_i) is large. In this case, analytic evaluation of the integral is usually impossible and numerical integration is difficult to apply and time consuming. The MCMC method is employed in statistics to solve this problem. Its use in a wide variety of applications (particularly in the health and social sciences) is illustrated in Congdon (2003).

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

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

Thus the population mean of $g(\theta_i)$ is estimated by a sample mean. A stationary (invariant) posterior distribution is guaranteed because the Monte Carlo sampling produces a Markov chain that does not depend on the starting value. The key here is that N is controlled by the analyst; it is not the size of a fixed data sample (Gilks et al. 1996).

b. Gibbs sampling

A common MCMC algorithm is Gibbs sampling. Gibbs sampling originated with the study of interacting particle systems in statistical physics, where it is known as the heat bath algorithm. In the statistical literature Gelfand and Smith (1990) showed its applicability to Bayesian computations. As an example, let $\theta = (\theta_1, \theta_2, \dots, \theta_p)'$ be a p -dimensional vector of parameters and let $p(\theta|y)$ be its posterior distribution given the data y . Gibbs sampling involves the following:

- 1) Choosing an arbitrary starting point $\theta^{(0)} = (\theta_1^{(0)}, \theta_2^{(0)}, \dots, \theta_p^{(0)})'$, and set $i = 0$.
- 2) Generating $\theta^{(i+1)} = (\theta_1^{(i+1)}, \theta_2^{(i+1)}, \dots, \theta_p^{(i+1)})'$, as follows:
 - generate $\theta_1^{(i+1)} \sim p(\theta_1 | \theta_2^{(i)}, \dots, \theta_p^{(i)}, y)$;
 - generate $\theta_2^{(i+1)} \sim p(\theta_2 | \theta_1^{(i+1)}, \dots, \theta_3^{(i)}, \theta_p^{(i)}, y)$;
 - generate $\theta_3^{(i+1)} \sim p(\theta_3 | \theta_1^{(i+1)}, \theta_2^{(i+1)}, \dots, \theta_p^{(i)}, y)$;
 -
 - generate $\theta_p^{(i+1)} \sim p(\theta_p | \theta_1^{(i+1)}, \theta_2^{(i+1)}, \dots, \theta_{p-1}^{(i+1)}, y)$.
- 3) Setting $i = i + 1$, and going back to Step 2.

In this way each component of θ is visited in order. A cycle through the scheme results in a sequence of random vectors of length p (Chen et al. 2000). Note that $p(\theta_1 | \theta_2^{(i)}, \dots, \theta_p^{(i)}, y)$ 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 the previous samples are used on the current conditional. Under general conditions the sequence of θ 's forms a Markov chain, and the stationary distribution of the chain is the posterior distribution. Typically the chain is run for a number of iterations until the output is stable. 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).

c. MCMC changepoint analysis

Given a series of counts, a change point occurs if at some point t in the series the counts come from a distribution with a common rate up to that time and come from the same distribution but with a different rate afterward. A change point is a location in time that divides

the rate process into independent epochs. Here we define the changepoint time at the first count of the new epoch. Thus in a series of n annual counts, if a change is detected between time k and $k + 1$, we say that $k + 1$ is the changepoint time.

A MCMC algorithm for detecting change points using Gibbs sampling consists of two steps. Step 1 uses the entire record to determine *candidate* change points based on the expected value of the probability of a change as a function of time. A larger mean probability indicates a greater likelihood of a change point. A plot of the mean probabilities as a function of time along with a minimum probability line identifies the candidate change points against the hypothesis of no change points. The candidate change points have mean probabilities at or exceeding the minimum probability line. Step 2 determines the posterior distributions of the hurricane rates before and after the candidate change point, ignoring the other candidates. The fraction of the posterior density of the difference in rates that are greater (or less) than 0 provides evidence of the direction of change given a change has occurred. From a traditional perspective this amounts to a p value. As with all output associated with the Markov chain, the fraction of hurricane-rate differences greater (or less) than 0 is a random variable so additional runs are used to obtain ensemble averaged values. Thus our algorithm is a modification of the single changepoint analysis. A fully Bayesian multiple changepoint analysis (Lavielle and Labarbier 2001; Rotondi 2002) is not attempted here.

For the present problem we are interested in two parameters; the hurricane rates before and after some changepoint year. Let $\lambda = (\lambda_b, \lambda_a)$ be a vector of two parameters, where λ_a is the mean hurricane rate after the change and λ_b is the mean hurricane rate before the change and we wish to simulate from the posterior $f(\lambda|y)$ as described previously. More specifically, the data are counts (Y_i) of the annual number of hurricanes during the period 1900–2001 ($n = 102$). Thus the analysis describes a Poisson distribution with a mean rate λ_b during years $i = 1, \dots, k$ and a Poisson distribution with a different mean rate λ_a during years $i = k + 1, \dots, n$. Since hurricane landfalls occur at different times with little interaction between successive events, and the conditions that generate them do not change significantly, it is reasonable to assume that the number of hurricanes over a given region follows a Poisson process (see e.g., Elsner and Kara 1999; Solow 1989).

Formally, the hierarchical specification for this Poisson/gamma model is given as:

$$Y_i \sim \text{Poisson}(\lambda_b); \quad i = 1, \dots, k; \quad (4)$$

$$Y_i \sim \text{Poisson}(\lambda_a); \quad i = k + 1, \dots, n; \quad (5)$$

where $\lambda_b \sim \text{gamma}(\alpha_1, \beta_1)$, $\lambda_a \sim \text{gamma}(\alpha_2, \beta_2)$, k is discrete uniform over $(1, \dots, 101)$, each independent, and $\beta_1 \sim \text{gamma}(\gamma_1, \varepsilon_1)$ and $\beta_2 \sim \text{gamma}(\gamma_2, \varepsilon_2)$ (Carlin et al. 1992). Note that the two-parameter gamma

distribution is continuous and bounded on the left by 0 with a positive skew. The Poisson–gamma relationship is used because the annual counts follow a Poisson distribution with the rate parameter following a gamma distribution (see Elsner and Bossak 2001).

The specification is hierarchical because in stage one the annual counts are random values following a Poisson distribution with an unknown Poisson rate; in stage two the Poisson rate follows a gamma distribution with two unknown parameters. In stage three the unknown scale parameter follows a gamma distribution; and in the fourth stage the parameters of the gamma distributions follow noninformative priors. The specification leads to the following conditional distributions used in the Gibbs sampling (Carlin et al. 1992):

$$\lambda_b | Y, \lambda_a, \beta_1, \beta_2, k \sim \text{gamma}\left(\alpha_1 + \sum_{i=1}^k Y_i, k + \beta_1\right) \quad (6)$$

$$\lambda_a | Y, \lambda_b, \beta_1, \beta_2, k \sim \text{gamma}\left(\alpha_2 + \sum_{i=k+1}^n Y_i, n - k + \beta_2\right) \quad (7)$$

$$\beta_1 | Y, \lambda_b, \lambda_a, \beta_2, k \sim \text{gamma}(\alpha_1 + \gamma_1, \lambda_b + \epsilon_1) \quad (8)$$

$$\beta_2 | Y, \lambda_b, \lambda_a, \beta_1, k \sim \text{gamma}(\alpha_2 + \gamma_2, \lambda_a + \epsilon_2) \quad (9)$$

and

$$p(k | Y, \lambda_b, \lambda_a, \beta_1, \beta_2) = \frac{L(Y; k, \lambda_b, \lambda_a)}{\sum_{j=1}^n L(Y; j, \lambda_b, \lambda_a)}, \quad (10)$$

where the likelihood function is

$$L(Y; k, \lambda_b, \lambda_a) = \exp\{k(\lambda_a - \lambda_b)\}(\lambda_b/\lambda_a)^{\sum_{i=1}^k Y_i}. \quad (11)$$

Derivation of the likelihood formula is given as an appendix. Starting with some initial (prior) values for α_1 , α_2 , γ_1 , γ_2 , ϵ_1 , and ϵ_2 Gibbs sampling generates sequences of λ_a and λ_b which form Markov chains. The stationary distributions of the chains are the posterior distributions for each of the parameters.

d. Practical considerations

There are several issues that need attention. First is the definition of years relative to the suspected change point. In the previous model specification, year k is the last year of the old epoch with $k + 1$ the first year of the new epoch. To be consistent our earlier analysis (Elsner et al. 2000a) we plot the change point as the first year of the new epoch and refer to this year as the changepoint year.

Second is the choice of starting (or initial) values. In theory if the chain is irreducible, meaning that any set of values results in a positive probability that the chain can reach any other set of values, then the choice of initial values will not influence the final stationary (invariant) posterior distribution. Since the Poisson-rate

parameter is $\text{gamma}(\alpha, \beta)$ with mean α/β and variance α/β^2 , we choose $\alpha_1 = \alpha_2 = 0.3$ and $\gamma_1 = \gamma_2 = 0.1$, and $\epsilon_1 = \epsilon_2 = 1$ as our starting values. Thus the mean values for β_1 and β_2 are $0.1/1 = 0.1$ and the mean values for λ_a and λ_b are $0.3/0.1 = 3$, which is close to the average annual number of major hurricanes per year. It is useful to perform a number of simulations with different starting values to check if the posterior distribution is sensitive to the choice of initial values. Results from these simulations are given in the next section.

Third is the issue of chain length. In general, the chain will converge to a stationary posterior distribution (Roberts 1996). In practice, the chain is run for a large number of iterations until the output is stable with the first 100 or so iterations discarded as “burn-in” and the remaining values considered samples from the stationary distribution. The length of burn-in depends on the initial values and the rate of convergence, which is related to how fast the chain mixes (reaches new values). 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 is beyond the scope of the present work. A discussion of convergence is given in Gelfand et al. (1990). Trial and error, using visual inspection of the chain’s output, is commonly used for determining length of burn-in, and it is the one adopted here. Throughout we choose a burn-in of 50 iterations and estimate the posterior distribution from the subsequent 1000 iterations.

Fourth is the issue of identifying the candidate change points. We take a conservative approach that is unlikely to detect a change point when none exists. If there are no change points in the observed count data, the changepoint probabilities should not be different from those based on counts arising from a Poisson process with a constant rate. We generate 1000 random time series from a Poisson process each of length 102 with a parameter equal to the climatological hurricane rate. Ranking the posterior probabilities, we select the 995th (out of 1000) largest posterior probability as the minimum probability necessary for identifying a candidate changepoint year. Note that the method can detect more than one candidate change point.

This establishes a baseline (empirical confidence line) for identifying multiple candidate changepoint years. With this approach we are comparing a model that describes the overall hurricane rate as constant, against a model that describes at least one change point in the data. If there are no change points in the observed hurricane count data, the changepoint probabilities should not be different from those based on a Poisson process with a constant rate. The approach is conservative in that it is unlikely to detect false positives (change points when none exist). Note that we could sample the assumed homogeneous Poisson rate and then use the rate to generate random Poisson samples. However, the annual probability of a change point is more sensitive to record length than to variation in the rates. In fact, for

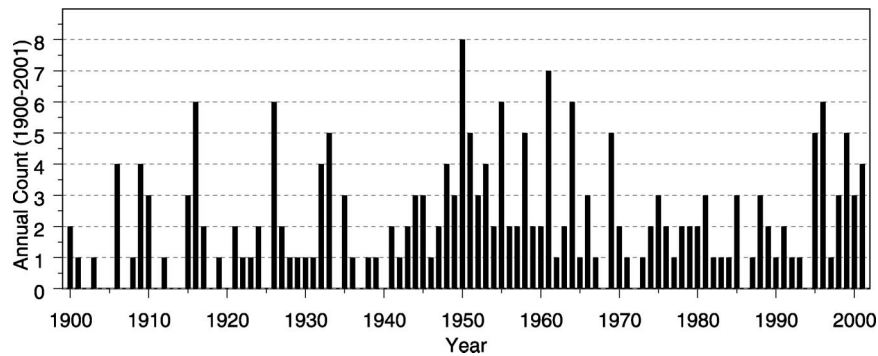


FIG. 1. Annual counts of North Atlantic major hurricanes during the period 1900–2001. Fewer storms are noted during the early half of the twentieth century.

this study we use a single empirical confidence line irrespective of the rates. The line is reestimated when we consider shorter records.

3. North Atlantic major hurricane activity

A hurricane is a tropical cyclone with maximum sustained (1 min) 10-m winds of 33 m s^{-1} (65 kt) or greater. A major hurricane is one in which winds exceed 50 m s^{-1} (category 3 or higher on the Saffir–Simpson hurricane destruction potential scale). The long-term average number of major hurricanes over the North Atlantic is close to 2 yr^{-1} . Landsea et al. (1996) note a downward trend in the occurrence of these powerful hurricanes. Using additional years of data, Wilson (1999) suggests a possible increase in activity beginning with 1995. The regression-based changepoint model employed in Elsner et al. (2000a) shows that indeed 1995 is the start of the most recent epoch of greater major hurricane activity.

We first apply the MCMC changepoint analysis on

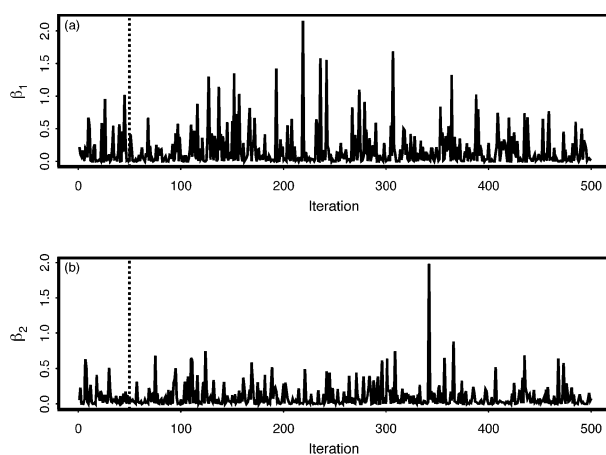


FIG. 2. Values of (a) β_1 and (b) β_2 for the first 500 iterations from the changepoint analysis applied to annual counts of North Atlantic hurricanes over the period 1900–2001. Initial values are $\alpha_1 = \alpha_2 = 0.3$ and $\gamma_1 = \gamma_2 = 0.1$, and $\varepsilon_1 = \varepsilon_2 = 1$. The first 50 iterations (left of the dashed vertical line) are discarded as burn-in.

the time series of annual North Atlantic major hurricanes (Fig. 1). Change points were identified in this time series in Elsner et al. (2000a) using a classical approach. It is understood that the counts are likely biased prior to 1943 before the advent of aircraft reconnaissance, but the intention here is to identify shifts in the time series of annual counts regardless of their origin (natural or artificial). In fact one of the points made by Elsner et al. (2000a) is that, if the model is worthwhile it should detect a shift in activity during the middle 1940s. Landsea (1993) suggests that an overestimation of hurricane intensity might have occurred even after 1943 during the period spanning the 1940s through the 1960s based on an inconsistency in central pressures and wind maxima estimates. Since there is still debate on this issue, and since corrections have yet to be made in the best-track dataset, we do not consider the effect of this potential bias in the present study. In any event, this choice does not influence the work presented here.

To examine convergence of the MCMC, we run the analysis using the initial conditions prescribed in the previous section. Values of β_1 and β_2 are plotted for each iteration (Fig. 2). Convergence is quick as there appears to be no trend in the values or their fluctuations across iterations. Thus the distribution of values for both β_1 and β_2 do not change as the chain is run for a greater number of iterations. This is typical. However, it is still good practice to remove the early iterates to allow the chain to “forget” its starting position.

Figure 3 shows the results from the MCMC changepoint algorithm applied to the annual counts of major North Atlantic hurricanes during the period 1900–2001. The expected value of the transition kernel of the Markov chain [$p(k|Y, \lambda_b, \lambda_a, \beta_1, \beta_2)$], which is the probability that year k is a change point given the data and the parameters, is plotted as a function of year. The expected value represents the average posterior probability of the year being the first year of a new epoch. Large probabilities indicate a likely change occurred with year t . The dashed line shows the minimum probability necessary for detecting a change point based on the null model of no change points. The line is smoothed

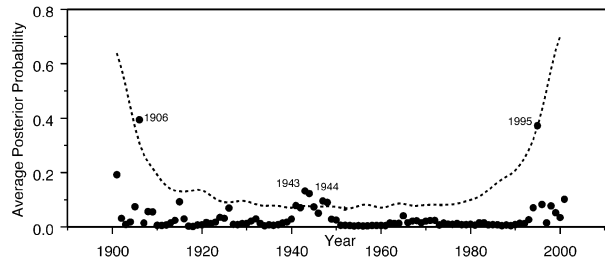


FIG. 3. Average posterior probabilities of each year being the first year of a new epoch in major North Atlantic hurricane activity. Large probabilities on year t indicate a change likely occurred with t as the first year of the new epoch. The dashed line (empirical confidence line) represents the minimum probability necessary for considering a year a candidate change point based on 1000 simulations of a constant rate (homogeneous) Poisson process.

using a 5-yr normal kernel. Years with probabilities above the empirical confidence line include 1906, 1943, and 1995. Note that several years around 1943 are also candidate changepoint years. This indicates that although the algorithm chooses 1943 as the most likely year of the new epoch there is uncertainty surrounding this choice. This is not the case with 1995 or 1906 where no other “nearby” years appear to be in contention. The locally elevated probability at 1965 will be revisited shortly. Also note that years near the beginning and end of the record require substantially larger posterior probabilities to surpass the confidence level. The U-shaped confidence line indicates that there is larger variance on the posterior changepoint probabilities near the ends of the record. Caution is needed when interpreting large probabilities on these years as the chance of a false detection is greater. Ensemble runs of the algorithm can help in this regard.

We examine the influence that the choice of initial values has on the average posterior changepoint probability and thus the selection of candidate years. This is done by running Gibbs sampling 30 times for each value of the α priors equal to 0.1, 0.3, 0.5, and 0.7. Sampling is done for 1050 iterations with the first 50 discarded as burn-in. Figure 4 shows the distribution of probabilities for the candidate years using box and whisker plots. Overall the results demonstrate that the choice of prior values is not a critical factor in identifying candidate years as the chain quickly finds a stationary distribution regardless of where the chain is started. Variability in the average posterior probabilities is largest for candidate years 1906 and 1995. As noted earlier, this results from the fact that these years are near the beginning and end of the time series. Posterior probability distributions based on relatively few data points will have a greater spread.

The procedure continues with a confirmatory analysis of the candidate changepoint years. Once the candidate change point is identified, additional confirmatory analysis is made by comparing the conditional posterior-estimated Poisson rates before and after each change

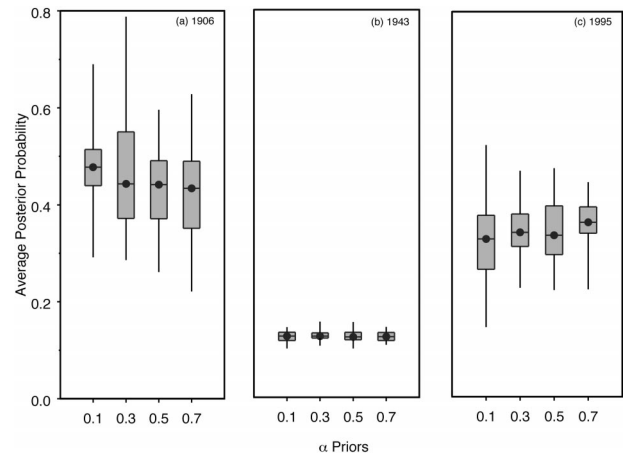


FIG. 4. Distributions of the average posterior probabilities that (a) 1906, (b) 1943, and (c) 1995 are changepoint years in the time series of major North Atlantic hurricanes. Distributions based on 30 simulations are shown with a box and whisker plot where the quartiles are represented by the top and bottom of the box, and the median is shown with a dot and horizontal line inside the box. Whiskers extend from the box to the largest and smallest values in the distribution. The distributions are based on 30 independent simulations.

point. Both statistically and from intuition, the confirmatory analysis will demonstrate the direction of change since it has been established that a change has occurred. We look first at 1943 since the jump in annual major hurricane counts at this time is most likely due to the start of aircraft reconnaissance investigations into the storms (Neumann et al. 1999; Jarvinen et al. 1984). Posterior density estimates of the statistics (β_1 , β_2 , λ_a , λ_b , and $\lambda_a - \lambda_b$) from the Gibbs sampling are shown in Fig. 5. We focus on the probability densities of the annual hurricane-rate parameters before and after (including) 1943. Densities are smoothed versions of the histograms and are based here on a normal kernel with bandwidth equal to 4 times the standard deviation of the values (Venables and Ripley 1999). The choice of bandwidth is a compromise between smoothing enough to remove insignificant bumps but not smoothing too much to hide real peaks.

Gibbs sampling is again run 30 times to get an ensemble average of the mean Poisson rate before $\langle \lambda_b \rangle$ and after $\langle \lambda_a \rangle$ the change point. The ensemble average of the mean rate parameter is 1.51 before 1943 and 2.51 thereafter. The posterior densities of the rate parameters indicate little overlap implying a rate increase beginning with the 1943 season. This is examined directly with the posterior density of the rate differences. Only a negligible fraction of the posterior distribution of $\lambda_a - \lambda_b$ is less than 0 (p value). Thus, conditional on a change occurring with 1943, it is clear that the change is in the direction of more frequent major hurricanes beginning with this year. The methodology does not use the posterior-rate differences to test the hypothesis of a change point. This is a confirmatory analysis, with the actual decision based on the probability for each year assuming

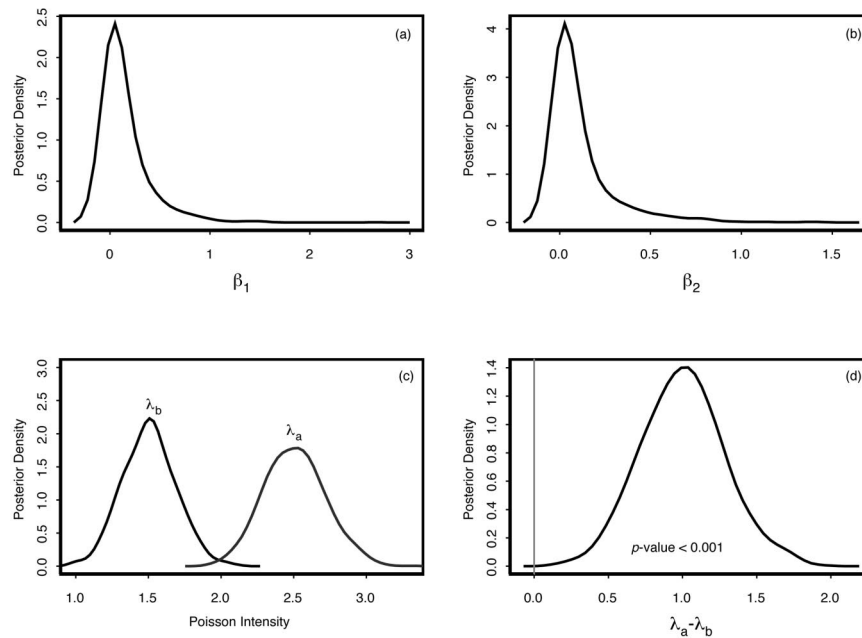


FIG. 5. Posterior density estimates from the changepoint analysis applied to the time series of major hurricane counts. Density of (a) β_1 , (b) β_2 , (c) λ_b (1900–42) and λ_a (1943–2001), and (d) $\lambda_a - \lambda_b$. The ensemble average Poisson rate before 1943 ($\langle \lambda_b \rangle = 1.51$) and the ensemble average rate after (and including) 1943 ($\langle \lambda_a \rangle = 2.51$). This provides an ensemble average p value on the rate difference that is less than 0.001, where the p value is based on the fraction of values from the posterior density of $\lambda_a - \lambda_b$ that are less than 0 and conditional on a change occurring.

each epoch would last at least 10 yr. Ten years is based on the time scale of interest (decades). As stated earlier, the increase in major hurricane activity starting in the middle 1940s is likely due in part to the start of aircraft reconnaissance. Based on this fact we ignore the earlier era and continue examining the record from 1943 onward.

Figure 6 shows the results from the MCMC changepoint algorithm applied to the annual counts of major North Atlantic hurricanes during the period 1943–2001. Both 1965 and 1995 are years with high probabilities. Additional high-probability years clustering around 1965 include 1962, 1966, and 1967. Estimates of the posterior densities conditioned on a change at 1965 are shown in Fig. 7. As before, Gibbs sampling produces an ensemble average of the mean Poisson rate before

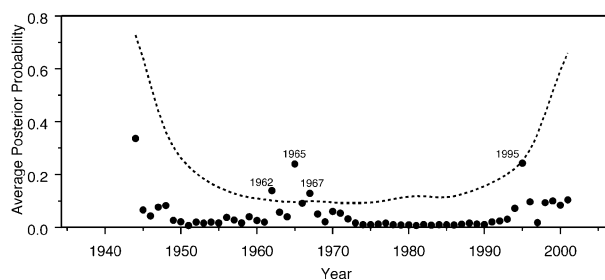


FIG. 6. Same as in Fig. 3 except years prior to 1943 are excluded from the analysis.

($\langle \lambda_b \rangle$) and after ($\langle \lambda_a \rangle$) the change point. The ensemble averaged mean rate is 3.41 before 1965 and 1.97 thereafter. The posterior densities of the rates indicate little overlap implying a decrease in activity beginning with the 1965 season. The ensemble p value is less than 0.001. Similar results are obtained for 1962, 1966, and 1967 indicating that the decline in abundance of major North Atlantic hurricanes might have begun as early as 1962 or as late as 1967 with the most likely year being 1965. Note that although 1965 has a local maximum posterior probability when the longer series is considered, it rises above the noise floor (dashed line) when the earlier, less reliable, portion of the record is removed.

Next we consider 1995. Estimates of the posterior densities are shown in Fig. 8. The ensemble-averaged mean hurricane rate before 1995 is 2.37 (ignoring the earlier change point) and 3.57 thereafter. The density for the hurricane rate since 1995 (λ_a) is considerably flatter owing to the relatively few years of data (7) in the record following this year. The greater uncertainty about the annual rate at the end of the hurricane record creates more overlap on the rate distributions and thus a larger p value on the rate difference. Even still, evidence is convincing that 1995 represents an upward shift in hurricane activity.

Thus a picture emerges of significant quantifiable shifts in the occurrence rates of major North Atlantic hurricanes during the twentieth century. The results for the middle 1940s, 1965, and 1995 are consistent with

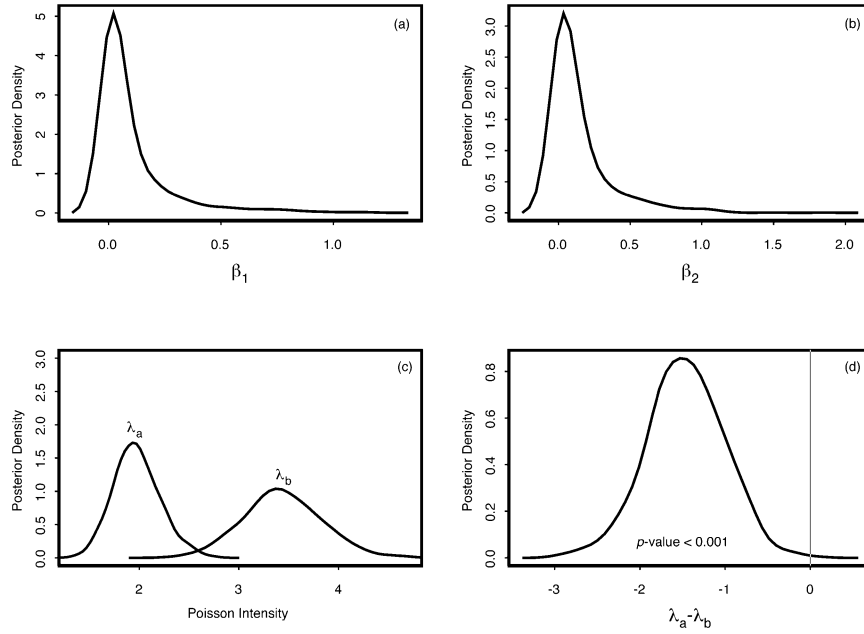


FIG. 7. Posterior density estimates from the changepoint analysis applied to the time series of major hurricane counts. Density of (a) β_1 , (b) β_2 , (c) λ_b (1943–64) and λ_a (1965–2001), and (d) $\lambda_a - \lambda_b$. The ensemble average Poisson rate before 1965 $\langle \lambda_b \rangle = 3.41$ and the ensemble average rate after (and including) 1965 $\langle \lambda_a \rangle = 1.97$. This provides an ensemble average p value on the rate decrease of less than 0.001 conditional on a change occurring.

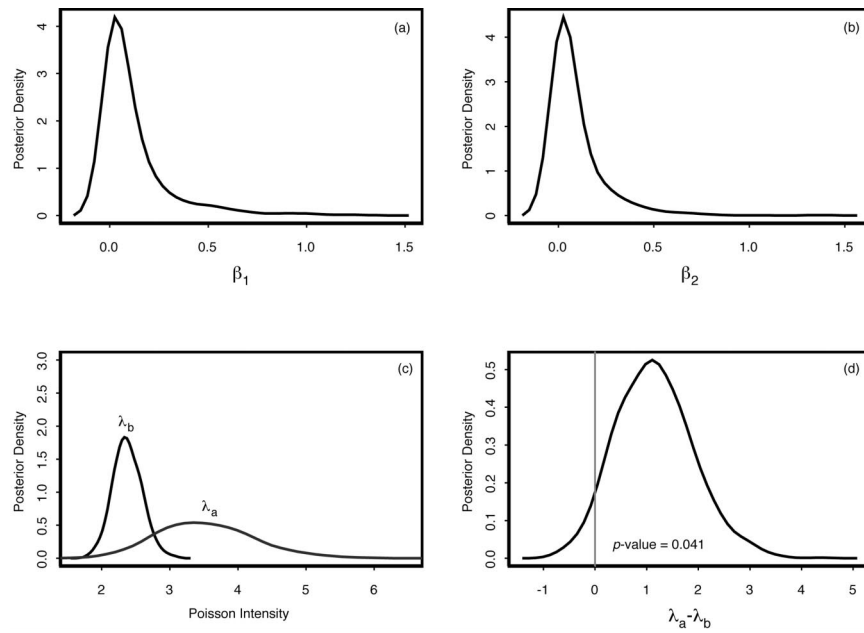


FIG. 8. Estimates of the posterior densities from the changepoint analysis applied to the time series of major hurricane counts. Density of (a) β_1 , (b) β_2 , (c) λ_b (1943–94) and λ_a (1995–2001), and (d) $\lambda_a - \lambda_b$. The ensemble average Poisson rate before 1995 $\langle \lambda_b \rangle = 2.37$ and the ensemble average rate after (and including) 1995 $\langle \lambda_a \rangle = 3.57$. This provides an ensemble average p value on the rate increase equal to 0.041 conditional on a change occurring.

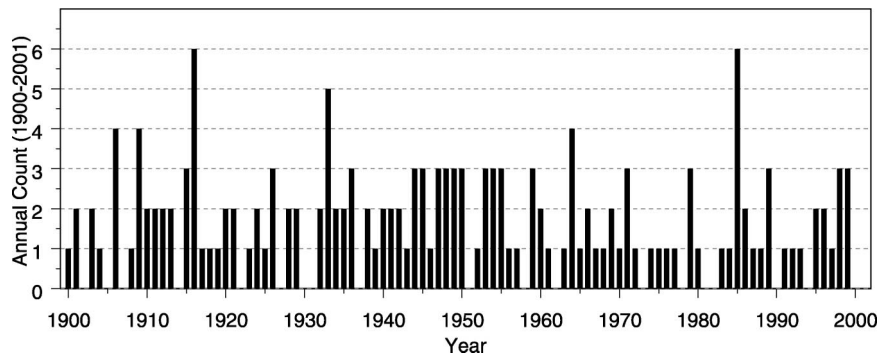


FIG. 9. Annual counts of U.S. hurricanes during the period 1900–2001. The time series appears to be stationary.

results obtained using a nonprobabilistic changepoint model (Elsner et al. 2000a). Beginning with the era of aircraft surveillance, we see that major hurricanes occurred at an average annual rate of nearly 3.5 yr^{-1} . The rate dropped significantly to about two major hurricanes per year beginning sometime during the middle 1960s with the new epoch most likely starting with the 1965 season. The modern era of fewer major hurricanes ends abruptly with the 1995 season. For the next seven seasons through 2001 the mean rate is more than 3.5 major hurricanes per year. An advantage of the probabilistic model is that it provides uncertainty estimates on the rates before and after the change point. It also provides density estimates of rate differences. Next we apply the changepoint analysis to the twentieth century U.S. hurricane record.

4. U.S. hurricane activity

In the previous section the record of major North Atlantic hurricanes was examined using a changepoint analysis. Here we apply the analysis to records of U.S. hurricane activity. We are unaware of changepoint studies on these records. Hurricane landfall occurs when all or part of the eyewall (the central ring of deep atmospheric convection, heavy rainfall, and strong winds) passes directly over the coast or adjacent barrier island. A U.S. hurricane is a hurricane that makes at least one

landfall. A reliable list of the annual counts of U.S. hurricanes back to 1900 is available from the U.S. National Oceanic and Atmospheric Administration (Neumann et al. 1999). These data represent a blend of historical archives and modern direct measurements. An updated climatology of annual coastal hurricane activity is given in Elsner and Kara (1999) and Elsner and Bosak (2001). Here we do not consider hurricanes affecting Hawaii, Puerto Rico, or the Virgin Islands.

a. Overall activity

We consider overall U.S. hurricane activity first. Figure 9 shows that the annual time series of U.S. hurricane counts. The record appears to be stationary over the period (Elsner and Kara 1999). The lag-one autocorrelation is a negligible -0.02 . Figure 10 shows the probability of each year being a change point in the series. In contrast to the posterior probabilities computed earlier from the series of annual major hurricane counts, the probabilities computed based on counts of U.S. hurricanes are considerably lower and all below the empirical confidence line estimated from a homogeneous Poisson process. Notice that no hurricanes reached the U.S. coast during 2000 and 2001, so the algorithm hints at a possible change point following the 1999 season. The evidence, however, is not strong, as historically there are other 2-yr periods without hurricanes (1930–31 and the more recent 1981–82).¹

The temporal uniformity in hurricane landfalls noted here is consistent with the results of Vega and Binkley (1994), although their study was limited to the period 1960–89. Pielke and Landsea (1999) note a decreasing trend in landfalls during the later decades of the twentieth century, but no test of statistical significance is made. Interestingly, the significant shifts in overall major hurricane activity noted in the previous section are not reflected in changes in landfall rates within the United States, suggesting the physical mechanisms respon-

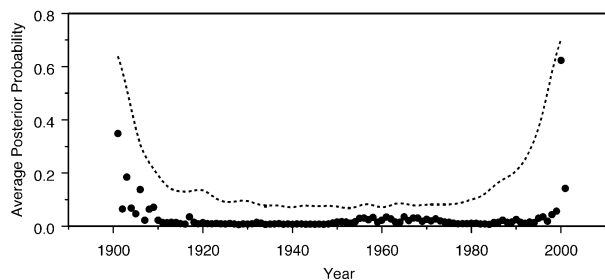


FIG. 10. Same as in Fig. 3 except for U.S. hurricanes. Note in this case there are no years with posterior probabilities that exceed the empirical confidence line.

¹ Indeed, one (two) hurricane(s) hit the United States in 2002 (2003).

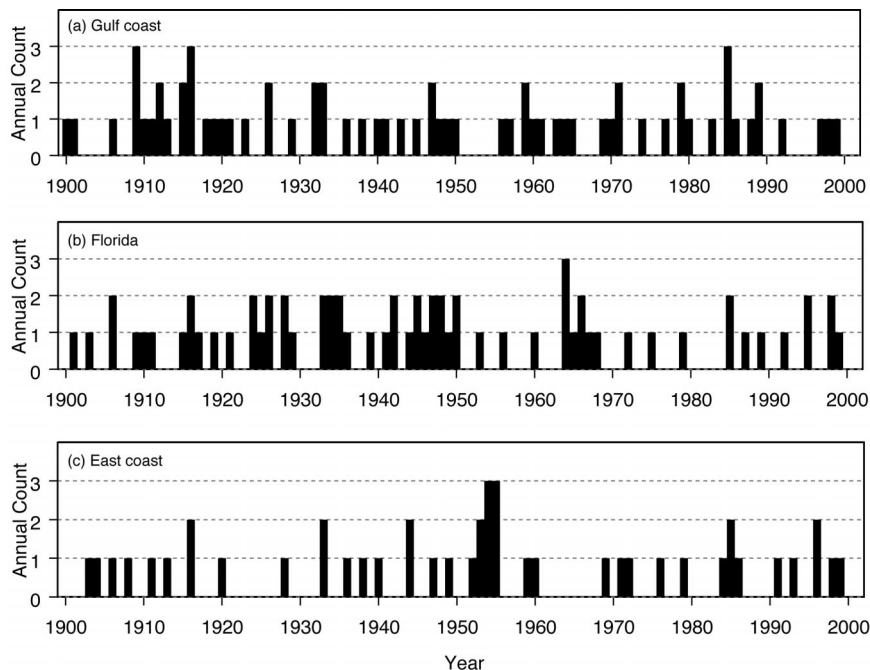


FIG. 11. Annual counts of (a) Gulf Coast, (b) Florida, and (c) East Coast hurricanes during the period 1900–2001. The Gulf Coast and Florida were hit more often than the East Coast.

sible for hurricane formation are different than those responsible for hurricane steering (Namias 1955; Balenzweig 1959; Landsea et al. 1992; Elsner et al. 2000b). Recent studies show interannual to decadal changes to the spatial patterns of U.S. hurricane activity related to large-scale climate factors (Elsner et al. 2000b). For instance, in La Niña years during which the North Atlantic Oscillation is weak, the probability of a hurricane strike to the central Gulf Coast increases significantly (Jagger et al. 2001; Saunders et al. 2000). It is therefore

instructive to consider regional hurricane activity. We divide the coast into three zones; Gulf Coast, Florida, and East Coast and consider the possibility of rate changes over each zone separately. Florida, with its 2171 km of coastline, leads the United States in frequency of hurricanes. The Gulf Coast is defined as the region from Texas to Alabama, while the East Coast is defined as the region from Georgia to Maine. Clearly, other divisions are possible.

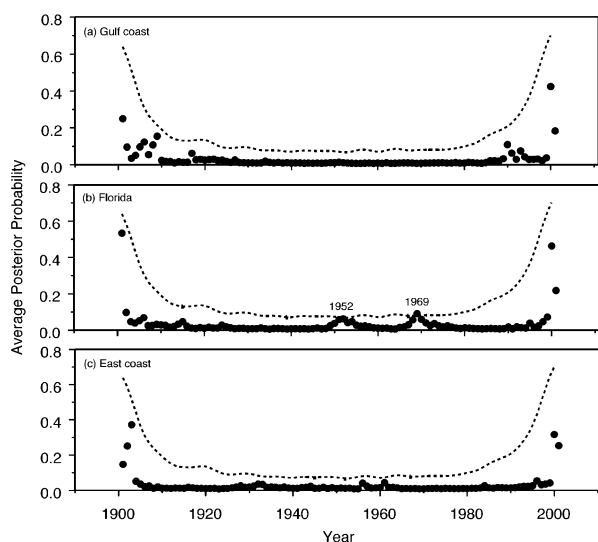


FIG. 12. Same as in Fig. 3 except for annual counts of hurricanes affecting the (a) Gulf Coast, (b) Florida, and (c) East Coast.

b. Regional activity

The time series of regional activity are shown in Fig. 11. The records are reliable back to 1900. Figure 12 shows the average posterior probability of each year being a change point for the Gulf Coast, Florida, and East Coast hurricanes. The hurricane rates along the Gulf and East Coasts appear to be constant over the 102-yr period. No changepoint probabilities extend above the confidence line. Thus, as with overall coastal hurricane activity, we find no significant shifts in the rates of Gulf or East Coast hurricanes. The situation is different in Florida where there is evidence of two rate shifts; one in the early 1950s and another during the late 1960s.

Gibbs sampling produces an ensemble average of the mean Poisson rate of Florida hurricanes before and after 1952. The ensemble average of the mean rate parameter is 0.83 before 1952 and 0.48 thereafter indicating a decrease in Florida hurricanes beginning in the early 1950s. The shift at 1969 is also downward with a mean

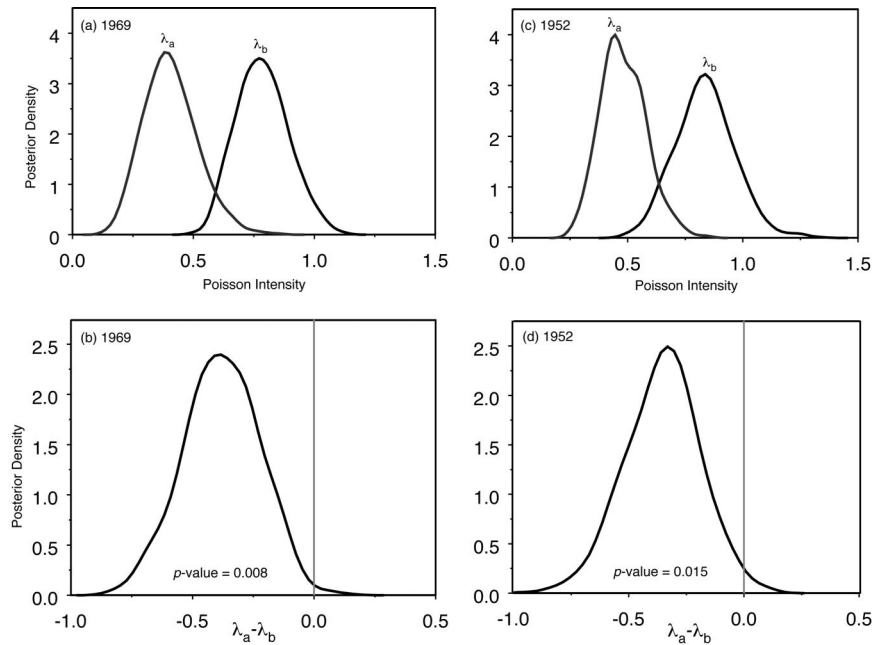


FIG. 13. Estimates of the posterior densities from the changepoint analysis applied to the time series of Florida hurricane counts. Density of (a) λ_b (1900–68) and λ_a (1969–2001), and (b) $\lambda_a - \lambda_b$. The ensemble average Poisson rate before 1969 $\langle \lambda_b \rangle = 0.79$, and the ensemble average rate after (and including) 1969 $\langle \lambda_a \rangle = 0.40$. This provides an ensemble average p value on the rate difference that is equal to 0.008. Density of (c) λ_b (1900–51) and λ_a (1952–2001), and (d) $\lambda_a - \lambda_b$. The ensemble average Poisson rate before 1952 $\langle \lambda_b \rangle = 0.83$, and the ensemble average rate after (and including) 1952 $\langle \lambda_a \rangle = 0.48$. This provides an ensemble average p value on the rate difference equal to 0.015 conditional on a change occurring.

rate of 0.79 before and 0.40 thereafter. Here the difference is offset from 0 with an ensemble p value of 0.008. Posterior density estimates of the rate parameters and their differences are shown for both candidate change points in Fig. 13. The densities indicate a downward shift in Florida hurricane activity during the later half of the twentieth century. The shift appears to occur in two steps dividing the record into three epochs. The rate during the first epoch (prior to 1952) is 0.83 Florida hurricanes per year, but drops to 0.65 hurricanes per year during the second epoch (1952–68) and to 0.39 hurricanes per year during the third epoch (after 1968). The fact that we find no shifts in overall coastal hurricane activity suggests that decreases in Florida hurricanes are compensated by less abrupt increases in Gulf and East Coast activity.

As mentioned earlier, Florida gets hit by more hurricanes than elsewhere in the United States. Two of the three category-5 hurricanes to hit the United States did so in Florida. The warm waters along the Bahamas and Greater Antilles provide an abundant energy source for hurricanes en route to Florida (Maloney and Hartmann 2000). To verify our changepoint results and better understand the decline in Florida hurricanes we compute local estimates of the annual probability of observing a hurricane within 150 nautical miles (278 km) on a 0.5° latitude–longitude grid over the Gulf of Mexico and the

Caribbean Sea. Probabilities are estimated for the early period (1900–51) and the late period (1952–2001) using 1-h interpolated (spline) best-track storm positions (Jarvinen et al. 1984). Local hurricane rates are converted to annual probabilities using the Poisson distribution. Figure 14 displays maps of the annual probabilities for the early and late periods along with a map of the difference in probabilities (early minus late). We find annual probabilities over the southern half of Florida are in the range of 40%–60% during the early period but drop to 15%–25% during the later period. This reduction in Florida was anticipated based on our changepoint results, but additional analysis shows that the reduction is most pronounced over the southern half of the state. The difference map shows a reduction in annual probability of 20%–25% after 1951 in a region extending from central Florida southeastward to the central Bahamas and southward to the western Caribbean Sea. We speculate that this reduction in hurricane activity is related to a change toward a drier middle troposphere (500–300 hPa) over the Caribbean caused by increased subsidence and perhaps related to higher sea level pressures (Knaff 1997) or warmer surface-air temperatures.

5. ENSO and the NAO

The influence of the El Niño–Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO) on

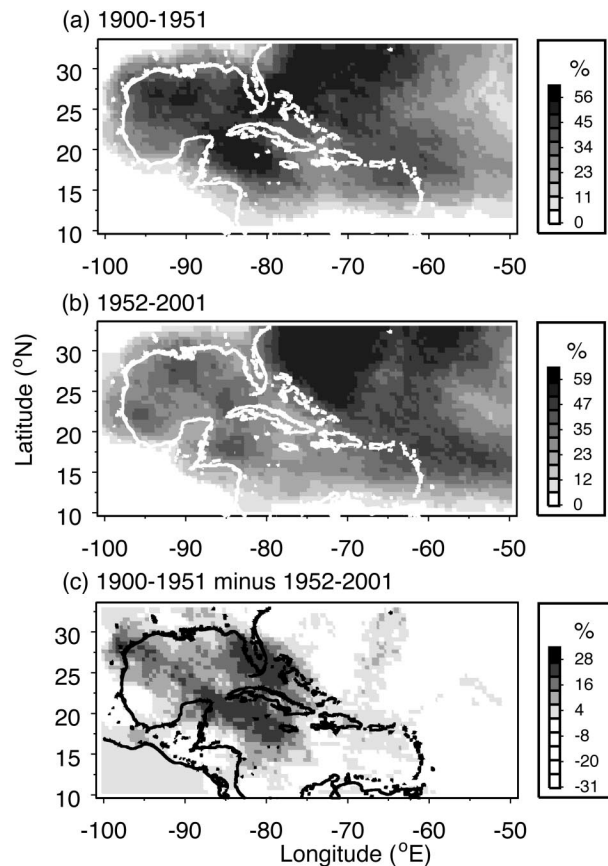


FIG. 14. Estimated annual probability of observing a tropical cyclone at hurricane intensity within a radius of 150 nautical miles (278 km). Probabilities are computed on a 0.5° lat–lon grid. The annual rate (number of hurricanes divided by the number of years) is converted into a probability using the Poisson probability density function. (a) Annual probability of at least one hurricane over the period 1900–51, (b) annual probability over the period 1952–2001, and (c) difference in annual probability (early period minus the later period). For clarity, only positive differences are shaded.

annual coastal hurricane numbers is examined after a small modification to the analysis. Here it is assumed that each year is independent, which is reasonable for annual hurricane counts. The statistical relationship between ENSO and U.S. hurricanes is well known (Bove et al. 1998; Elsner et al. 1999; Elsner and Kara 1999; Jagger et al. 2001), but the relationship between NAO and U.S. hurricanes is less well recognized (Elsner et al. 2000b, 2001).

A reliable time record of the Pacific ENSO is obtained using basin-scale equatorial fluctuations of sea surface temperatures (SST). Average SST anomalies over the region bounded by 6°N – 6°S latitude and 90°W – 180° longitude are called the “cold tongue index” (CTI; Deser and Wallace 1990). 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. Monthly values of the CTI are strongly correlated with values from other

ENSO SST indices. Since the Atlantic hurricane season runs principally from August through October, a 3-month averaged (August–October) CTI from the dataset is used. Values of an index for the NAO 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. This is 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).

We divide the range of ENSO and NAO values occurring over the 102-yr period into equal-interval tercile values (terciles) describing below-normal, normal, and above-normal years. The upper and lower terciles of the August–October average CTI are 0.90° and -0.23°C , respectively. The upper and lower terciles of the May–June average NAO index are 1.05 and -0.85 standard deviations respectively. Years of above- (below-)normal CTI correspond to El Niño (La Niña) events. Years of above- (below-)normal NAO index values correspond to positive (negative) phases of the NAO. With this specification, there are 14 (39) above (below) normal ENSO years and 11 (34) above- (below-)normal NAO years during the twentieth century. We remove the normal years and create a sequence of hurricane counts. The sequence is a set of hurricane counts for years of above-normal climate conditions followed abruptly by the set of counts for years of below-normal conditions. For instance, assuming an equal number of above, below, and normal years, let Y_a be the counts for years in which NAO is above normal where $a = 1, \dots, n/3$ and Y_b be the counts for years in which NAO is below normal, where $b = 1, \dots, n/3$. Then we create a new series by concatenating Y_a and Y_b . In this way we create an artificial time series that contains a potential change point and then compare the hurricane rates for years of above-normal (before the change point) and below-normal (after, and including the change point) climate conditions.

Figure 15 shows the posterior densities of the rate differences (above-normal years minus below-normal years). As anticipated we see that during El Niño years (above normal) the annual rate is significantly less than the rate during La Niña years (below normal). A 30-member ensemble gives an average rate of 0.72 hurricanes yr^{-1} during El Niño years compared with 2.18 hurricanes yr^{-1} during La Niña years. This difference results in a p value that is less than 0.001 conditioned on a change occurring. The influence of El Niño on hurricanes appears along the entire coast, but is strongest over Florida which has a mean rate of 0.37 hurricanes yr^{-1} during El Niño compared with 0.93 hurricanes yr^{-1} during La Niña. This difference corresponds to a p value of 0.011. Figure 15 also shows the effect of NAO on U.S. hurricanes. During its strong phase (above normal),

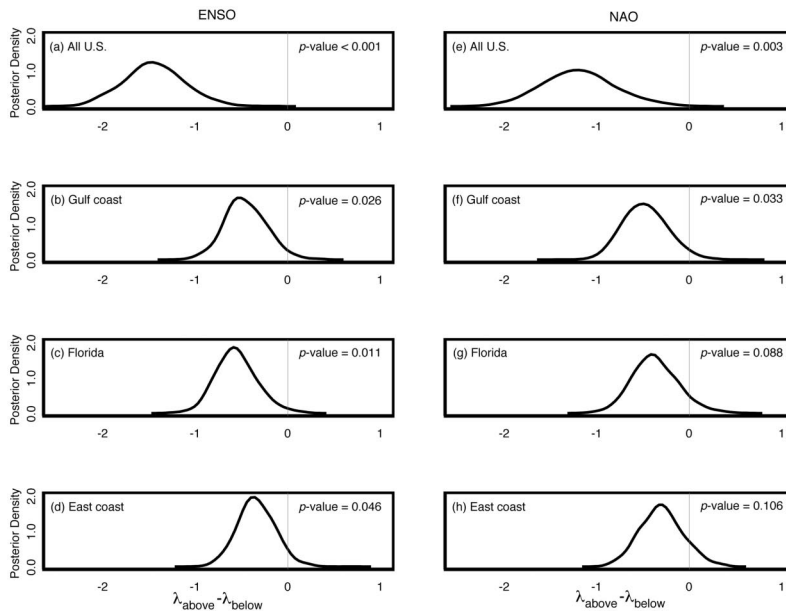


FIG. 15. Posterior densities of the hurricane-rate differences (below-normal years minus above-normal years) for (a) all U.S. hurricanes and ENSO, (b) Gulf Coast hurricanes and ENSO, (c) Florida hurricanes and ENSO, (d) East Coast hurricanes and ENSO, (e) all U.S. hurricanes and NAO, (f) Gulf Coast hurricanes and NAO, (g) Florida hurricanes and NAO, and (h) East Coast hurricanes and NAO.

the ensemble average rate is 1.02 hurricanes yr^{-1} compared with 2.21 hurricanes yr^{-1} during its weak (or negative) phase (below normal). This provides a p value of 0.003. Unlike ENSO the influence of the NAO is only significant along the Gulf Coast. Here the annual rate is 0.38 hurricanes yr^{-1} during the NAO strong phase and 0.86 during the NAO weak phase. This is consistent with the NAO as a factor influencing hurricane tracks as hypothesized in Elsner et al. (2000b, 2001). A weaker NAO during boreal spring is associated with a subtropical high pressure cell displaced farther south and west of its mean position (near the Azores) during the following hurricane season. Tropical cyclones forming and remaining equatorward of the subtropical high tend to intensify at low latitudes, crossing through the Caribbean before reaching the Gulf Coast (see Elsner 2003).

6. Summary and conclusions

This paper demonstrates an application of a probabilistic framework for determining sudden changes at unknown times in records involving counts. The approach is through a hierarchical algorithm involving the Poisson and gamma distributions and Gibbs sampling. Gibbs sampling is a commonly used MCMC procedure to sample from conditional distributions. Our purpose is to use the approach for identifying shifts in the rates of coastal hurricane activity. The technique is also applied to the problem of detecting the influence of covariates (ENSO and NAO) on coastal storm activity.

The changepoint analysis is first run on annual counts

of major North Atlantic hurricanes. Results are consistent with those from a regression-based changepoint model (Elsner et al. 2000a) including an ominous rate increase starting in 1995. When the algorithm is applied to annual counts of overall U.S. hurricane activity there is little evidence for significant rate changes during the twentieth century. A similar result is found when the counts are grouped by regions including the Gulf and East Coasts. The exception is Florida. Results show significant decreases in the number of Florida hurricanes during the early 1950s and likely again during the late 1960s. A closer examination reveals that this decrease results from fewer storms approaching the southern half of the state from the Bahamas and western Caribbean Sea. The decrease occurs during a period of substantial growth in the state's population.

The analysis is then used to study the influence of ENSO and the NAO on coastal hurricane activity. Climate data representing these two modes of variability are divided into terciles representing above-normal, near-normal, and below-normal conditions. As expected from previous studies, we find a statistically significant link to the ENSO. During El Niño years coastal hurricane rates are reduced from Texas to Maine. The most pronounced effect occurs over Florida. The NAO might also play a role. On average during years in which the NAO index is below normal, more than twice as many hurricanes reach the coast. However, unlike the ENSO's influence which is felt along the entire coast, NAO's influence is significant only for the Gulf Coast from Texas to Alabama.

The conclusions are the following:

- A changepoint model utilizing Gibbs sampling is a useful tool for climate analysis.
- Major North Atlantic hurricanes have become more frequent since 1995, at a level reminiscent of the 1940s and 1950s.
- In general, twentieth-century U.S. hurricane activity shows no abrupt shifts in activity.
- The exception is over Florida where activity decreased during the early 1950s and again during the late 1960s.
- Florida’s hurricane decline results from fewer hurricanes passing through the Bahamas and western Caribbean Sea.
- El Niño events tend to suppress hurricane activity along the entire coast with the most pronounced effects over Florida.
- Below-normal NAO conditions are associated with an increase in hurricane activity from Texas to Alabama.

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APPENDIX

Derivation of the Likelihood Function

The conditional distribution of the changepoint location given the data and all the parameters can be estimated from the joint distribution of the data given the rates λ_a, λ_b , and the changepoint location k , using Bayes’s rule. Since the rates are given and the model is hierarchical, the joint distribution does not depend on the hyperparameters (parameters of a parameter) or the parameters of their distributions; that is, $\beta_1, \beta_2, \alpha_1, \alpha_2$, or $\gamma_1, \gamma_2, \varepsilon_1, \varepsilon_2$, respectively. Denote the vector of these eight parameters as θ . Then, the joint distribution of the data Y given the parameters is

$$p(Y|k, \lambda_a, \lambda_b, \theta) = p(Y|k, \lambda_a, \lambda_b) \tag{A1}$$

$$= \prod_{i=1}^k \frac{e^{-\lambda_b} \lambda_b^{Y_i}}{Y_i!} \prod_{i=k+1}^n \frac{e^{-\lambda_a} \lambda_a^{Y_i}}{Y_i!} \tag{A2}$$

$$= \left(\prod_{i=1}^n \frac{e^{-\lambda_a} \lambda_a^{Y_i}}{Y_i!} \right) \left[e^{k(\lambda_a - \lambda_b)} \left(\frac{\lambda_b}{\lambda_a} \right)^{\sum_{i=1}^k Y_i} \right] \tag{A3}$$

$$= f(\lambda_a, Y)L(Y; k, \lambda_b, \lambda_a) \tag{A4}$$

$$L(Y; k, \lambda_b, \lambda_a) = e^{k(\lambda_a - \lambda_b)} \left(\frac{\lambda_b}{\lambda_a} \right)^{\sum_{i=1}^k Y_i}. \tag{A5}$$

Now an application of Bayes’s rule, shows us that

$$p(k|Y, \lambda_a, \lambda_b, \theta) = \frac{p(Y|k, \lambda_a, \lambda_b, \theta)}{\sum_{j=1}^n p(Y|j, \lambda_a, \lambda_b, \theta)} [p(k)] \tag{A6}$$

$$= \frac{p(Y|k, \lambda_a, \lambda_b)}{\sum_{j=1}^n p(Y|j, \lambda_a, \lambda_b)} [p(k)] \tag{A7}$$

$$= \frac{f(\lambda_a, Y)L(Y; k, \lambda_b, \lambda_a)}{\sum_{j=1}^n f(\lambda_a, Y)L(Y; j, \lambda_b, \lambda_a)} [p(k)] \tag{A8}$$

$$= \frac{L(Y; k, \lambda_b, \lambda_a)}{\sum_{j=1}^n L(Y; j, \lambda_b, \lambda_a)} [p(k)]. \tag{A9}$$

If we assume a noninformative prior for the change point, for example, $p(k) = 1/n$, then

$$p(k|Y, \lambda_a, \lambda_b, \theta) = p(k|Y, \lambda_a, \lambda_b) \tag{A10}$$

$$= \frac{L(Y; k, \lambda_b, \lambda_a)}{\sum_{j=1}^n L(Y; j, \lambda_b, \lambda_a)}. \tag{A11}$$

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