

On the Changes in the Number and Intensity of North Atlantic Tropical Cyclones

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ABSTRACT

Bayesian statistical models were developed for the number of tropical cyclones, the rate at which these cyclones became hurricanes, and the rate at which hurricanes became category 4+ storms in the North Atlantic using data from 1966 to 2006 and from 1975 to 2006. It is found that, controlling for the cold tongue index (CTI), North Atlantic Oscillation index (NAOI), and the Atlantic Multidecadal Oscillation (AMO), it is improbable that the number of tropical cyclones has linearly increased since 1966, but that the number has increased since 1975. The differences between these two results have to do with the numbers of storms at the start of these two periods: it was easier to say a linear increase was present starting from circa 1975 since the storms in that period were at a low point. The *rate* at which storms become hurricanes appears to have decreased, and the rate at which category 4+ storms evolved from hurricanes appears to have increased. Both of these results are also dependent on the starting year. Storm intensity was also investigated by measuring the distribution of *individual* storm lifetimes in days, storm track length, and Emanuel's power dissipation index. Little evidence was found that mean individual storm intensity has changed through time, but it is noted that the variability of intensity has certainly increased. Any increase in cumulative yearly storm intensity and potential destructiveness is therefore due to the increasing number of storms and not due to any increase in the intensity of individual storms. CTI was not always significant, but lower CTIs were associated with more storms, higher rates of conversion, and higher intensities. NAOI was only weakly associated: the effect was negative for the number of storms, the rate of hurricanes evolving from storms, and intensity, but it was positive for the rate of category 4+ storms evolving from hurricanes. AMO was rarely significant except in explaining the number of storms using the 1966–2006 data. Its direction was always positive as expected; however, higher values of the AMO were associated with more storms, higher rates of conversion, and higher intensities.

1. Introduction

It is important to be able to statistically characterize the distribution of the number of storms in the North Atlantic Ocean, especially if this number is increasing or the intensity levels of tropical storms are changing. Several studies have examined this subject (e.g., Landsea et al. 2006; Solow and Moore 2002). One of the most important recent papers on this topic is by Emanuel (2005), in which he argued that hurricanes in the North Atlantic have become more destructive over the past 30 yr. To measure potential “destructiveness,” he developed a measure called the power dissipation index, which is a function of the cubed wind speed of a storm over its lifetime (see section 2 for a precise defi-

nition). In his original paper, this index was not just a measure of a *single* storm's intensity, but a cumulative index over *all* storms during the year. Pielke (2005) and Landsea (2005) criticized the data analysis method used to demonstrate that the index was increasing by pointing out that the smoothing method used on the raw time series data was slightly flawed, that errors in the observations should lead to a less certain statement about increases, and that the wind speed adjustments used by Emanuel were too aggressive.

Our observation is that the lumping together of all storms within a year has led to a different interpretation of what exactly is increasing: storm number or (a function of) wind speed. Other explanations of Emanuel's findings may be that the number of cyclones has remained (distributionally) constant, but that average storm intensity has increased. Or it may also be that the number of cyclones has increased, but that the intensity levels of individual storms have remained constant or

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even decreased. Other combinations are, of course, possible: both storm frequency and individual storm intensity might have increased. We examine these scenarios below.

A first step in such an analysis was taken by Elsner and Bossak (2001), who examined the climatology and seasonal modeling of hurricane rates using a series of Bayesian hierarchical models. Using this modern approach allows modelers to easily make probability statements about important parameters of storm correlation and to specify the uncertainty of future predictions. Here, we use a model that, as a base, is of the identical form as that of Elsner and Jagger (2004) for modeling storm number; we present an innovative technique for modeling the rate at which hurricanes evolved from tropical storms and the rate at which category 4+ storms evolved from hurricanes. Other current examples of the same type of Bayesian statistical models used to model tropical storm behavior are taken from Zhao and Chu (2006), Chu and Zhao (2004), and Elsner et al. (2004).

Elsner and Jagger (2004) continued the Bayesian modeling line by controlling, in their models, for the influence of the cold tongue index (CTI) and the North Atlantic Oscillation index (NAOI). They found that both of these indices were well correlated with the mean hurricane number. We also control for these indices in our models below. Elsner et al. (2001) investigated the relationship between ENSO, of which the CTI is a good indicator, and hurricane numbers. Hoyos et al. (2006) examined these and other factors that may contribute to increases in the mean frequency of hurricanes.

We also control for the Atlantic Multidecadal Oscillation (AMO) sea surface temperature (SST) index (e.g., Knight et al. 2005); the AMO is a detrended (anomaly) measure of sea surface temperatures (the exact definition is provided in section 2b). Landsea et al. (1999) found that multidecadal variability, such as that displayed by the AMO, and not necessarily linear trends, were identified with hurricane activity. The AMO index has been found to be important in explaining some of the variability in rainfall and river flows in the United States (Enfield et al. 2001). It has also been associated with summer climates in Europe and North America (Sutton and Hodson 2005). However, Mann and Emanuel (2006) caution that relying on the AMO assumes that any underlying trend in SSTs is assumed to be linear, which of course may not be the case. They also argue that there is no apparent role of the AMO with tropical cyclone activity, which they measure by a crude linear correlation over yearly summaries of the tropical cyclone data. We argue below that such yearly

sums can result in a misleading picture of what aspects, if any, of tropical cyclones are changing over time.

Elsner et al. (2004) and Jewson and Penzer (2006) examine whether there were shifts or change points in the statistical distribution of hurricane numbers. Both groups of authors did find likely changes, namely around 1900, the mid-1940s, mid-1960s, and the mid-1990s. These shifts may have been due to actual changes in physical mechanisms (such as large-scale shifts in the atmospheric or oceanic circulations) or they may be due to changes in measurements, though all authors agree that the changes are probably a combination of both. In a recent analysis, Landsea (2007) also argues persuasively that before about 1966 many hurricanes (let alone smaller storms) were not counted, and that other aspects of storm quality (such as wind speed, etc.) were observed either with error or simply missed. We take this topic up below, but we do not seek to answer why these changes in the data take place, or even if the dates used to demarcate “good” observations from “bad” ones are certain. It is clear enough, however, that the data have changed in character through time. Thus, we build our models using different ranges of data in an attempt to incorporate this uncertainty.

Kossin et al. (2007) argue that the storm data are rather inconsistent: they proposed, and constructed, a statistical reanalysis of hurricane activity using satellite observations and the Dvorak technique to estimate wind speed (e.g., Velden et al. 2006) to assist in their recreation. We have more to say about this dataset in section 4. But obviously, the models we outline below could certainly be used (in part) with the Kossin et al. database.

Our approach, though similar in that we use Bayesian statistical models, is different from previous analyses in two ways. 1) We hierarchically model the number of tropical storms and then the rate that hurricanes arise from them, then the rate that category 4+ storms evolve from hurricanes, as opposed to directly modeling just the number of hurricanes (or hurricane landfalls, etc.). 2) In line with Webster et al. (2005), we characterize the *distribution* of storm intensity *within* a given year and ask whether this distribution changes through time (in mean and in variance). We investigate storm intensity in a multidimensional way by measuring storm lifetime in days, storm track length, and Emanuel's power dissipation index applied to *individual* storms. We fit linear models and ask whether the data are consistent with linear trends. Nowhere do we try to say why, beyond controlling for certain stated variables, any trends are there (if they are). True causal analyses for such trends are of course more important than these

time series models, but being able to identify possible trends, even though their causes are not known, is still of some importance. SSTs in the North Atlantic have been seen to increase (Santer et al. 2006) over the twentieth century, and obviously SSTs are related to tropical cyclones. But again, we do not seek to answer why (i.e., causally) any increases (or decreases) are seen. This is a flaw that statistical models can never overcome. But where statistical models cannot always answer direct questions about causation, they can answer questions about data quality and confidence, which is of course very important for questions about tropical cyclone changes.

We use the Hurricane Reanalysis Database (HURDAT; Jarvinen et al. 1984; Landsea et al. 2004). This database contains 6-hourly maximum sustained 1-min winds at 10 m, central pressures, and position to the nearest 0.1° latitude and longitude from all known tropical storms from 1851 to 2006. A cyclone was classified using the Saffir–Simpson scale (Landsea et al. 1999) as a “hurricane” if, at any time during its lifetime, the maximum wind speed ever met or exceeded 65 kt ($1 \text{ kt} \equiv 0.514\,444 \text{ m s}^{-1}$). Obviously, this cutoff, though historical, is somewhat arbitrary and other numbers can be used: we discuss this in section 4 below. To investigate the relationship of North Atlantic tropical storms with ENSO, we use the CTI (Deser and Wallace 1990; Cai 2003; Zhang et al. 1997), the NAOI from Jones et al. (1997), and also the AMO index (e.g., Landsea et al. 1999).

Section 2 lays out the statistical models and methods that we use, section 3 contains the main results, and section 4 presents the conclusions and some ideas for future research.

2. Methods

We adopt, as have many before us, Bayesian statistical models. An important advantage to these models is that we can make direct probability statements about the results. We are also able to create more complicated and realistic models and solve them using the same numerical strategy, namely, Gibbs sampling. We do not go into depth about the particular methods involved in forming or solving these models, as readers are likely familiar with these methods nowadays. There are also many excellent references available (e.g., Gelman et al. 2003).

It is important to control for factors that are known to be related, or could cause changes in, the frequency of tropical cyclones and storm intensity. There are many such possible variables, but we choose the cold tongue index and the North Atlantic Oscillation index

as cited, and modeled in a similar way, in the paper by Elsner and Jagger (2004), and the Atlantic Multidecadal Oscillation as cited by Landsea et al. (1999). Readers are encouraged to refer to the original sources and references therein to learn about these indices.

a. Data

Again we use the North Atlantic HURDAT reanalysis. We conduct the analyses using three different starting points and ranges: 1900–2006, 1966–2006, and 1975–2006. Just why these particular dates were selected is explained below; however, the main reason to use the 1900–2006 set is for comparison with other studies, even though it well known that before about 1966 the observations are flawed (there are both missing observations and observations with measurement error). Unlike some other analyses, we use all the storms in this database and not just storms of a certain classification (i.e., hurricanes or stronger storms) or in a certain location (e.g., landfalling). This is for two reasons. The first and most important is that we want to examine the complete range of distributional changes of storm quality in the Atlantic. That is, if we only examined hurricanes, we may miss details of smaller storms. For example, it may be that hurricane quality remains unchanged but there has been an increase in the number or intensity (or changes in other qualities) of smaller storms. Below, we offer evidence that something like this is indeed the case, as we observe that the variance of the intensity has increased through time. The second reason is that the form of our statistical models is different from previous analyses: we model the rate at which hurricanes evolve from smaller storms; we do not directly model the number of hurricanes per se. It is also true that the definition of which storm is a hurricane, or a “category” storm, is arbitrary, and it is not a priori clear that just asking whether the hurricane numbers, etc., have increased would fully capture what the data have to say. As such, we want a complete count of all storms regardless of size.

The CTI is a well-known index of ENSO and comprises an average of the SST anomalies over 6°N – 6°S and 180° – 90° ; here, we average the CTI (within in a year) from August to October following Elsner and Jagger (2004). The NAOI is anomaly of sea level pressure calculated from a station at Gibraltar and a station in southwest Iceland (Jones et al. 1997); here, we average the NAOI from May to June [as was also done in Elsner and Jagger (2004)]. The AMO index is computed by averaging SSTs between 0° and 60°N and 75° and 7.5°W ; here, the monthly AMO was averaged from June through September. These particular start and

stop dates for the averaging points do not seem especially important to the analysis that follows (in the sense that we also tried several other monthly averages, with all giving nearly identical results).

Finally, we do not adjust the observed wind speed in any way (Emanuel 2005; Landsea 2005; Pielke 2005), as the best way to do this, or even the necessity of doing this, is not agreed upon.

b. Number of storms

Most statistical analyses focus on the number of hurricanes or the subset of landfalling hurricanes (e.g., Elsner and Bossak 2001; Elsner and Jagger 2004). The approach here is different. We first model the number of tropical cyclones and then model whether or not, for any given tropical cyclone, a hurricane evolves from it. We then model whether a category 4+ storm evolved from this hurricane. Specifically, we do *not* separately model the frequency of both hurricanes and cyclones, as doing this ignores the relationship of how cyclones develop into hurricanes, and how hurricanes strengthen.

We suppose, in year i of n years, that the number of storms is well approximated by a Poisson distribution as in

$$s_i | \lambda_i \sim \text{Poisson}(\lambda_i), \quad (1)$$

where λ_i describes the mean (and variance) of the number of storms. It is of primary interest to discover whether this parameter is changing (possibly increasing) through time, controlling for known important meteorological and oceanographic variables. Elsner and Jagger (2004) developed this same model for the number of hurricanes (but not cyclones per se). Here, we adapt it to the number of cyclones and add in the possibility that the parameter λ changes in a linear fashion in time (we also adopt some of Elsner and Jagger's notation for ease of reference). Thus, we further model λ_i as a function of the CTI, NAOI, and AMO and allow the possibility that λ_i changes linearly through time. We use the generalized linear model

$$\log(\lambda_i) = \beta_0^s + \beta_1^s t + \beta_2^s \text{CTI}_i + \beta_3^s \text{NAOI}_i + \beta_4^s \text{AMO}_i, \quad (2)$$

where the superscript s indicates we are in the storms portion of the model. The prior for each β_{ki}^s is

$$\beta_{ki}^s | \gamma_k^s, \tau_k^s \sim N(\gamma_k^s, \tau_k^s), \quad k = 0, 1, 2, 3, 4, \quad (3)$$

where τ_k^s is the precision (inverse of variance). We also use the standard noninformative priors:

$$\gamma_k^s \sim N(0, 1 \times 10^{-6}), \quad \tau_k^s \sim \text{Gamma}(0.001, 0.001). \quad (4)$$

If the posterior probability $\Pr(\beta_1^s > 0 | \text{data})$ is large, then we would have confidence that the mean number of storms has increased over the given time period of the data, after controlling for the influence of the other variables. When dealing with time series data, it is not uncommon for "lag" effects to be listed as explanatory variables (Brockwell and Davis 1998); for example, the term $\beta_5 s_{i-1}$ may be added. However, as we show below, no lag effects or other time-series-like model components were found to be necessary in these models (see Fig. 2 below).

Once a tropical storm develops it has a chance to grow into a hurricane. If there are s_i tropical cyclones in year i , the number of hurricanes is constrained to be between 0 and s_i . Thus, a reasonable model for the number of hurricanes h_i in year i given s_i is

$$h_i | s_i, \theta_i \sim \text{binomial}(s_i, \theta_i). \quad (5)$$

It is possible, however, as with λ_i , that θ_i is dependent on CTI, etc., and that it changes through time. To investigate this, we adopt the following logistic regression model:

$$\log\left(\frac{\theta_i}{1 - \theta_i}\right) = \beta_0^h + \beta_1^h t + \beta_2^h \text{CTI}_i + \beta_3^h \text{NAOI}_i + \beta_4^h \text{AMO}_i, \quad (6)$$

where we again let the priors and hyperpriors be of the same form as in the model for s_i , and the h superscript indicates we are in the hurricane portion of the model. And if, for example, $\Pr(\beta_1^h > 0 | \text{data})$ is large, then we would have confidence that the rate at which the number of storms turn into hurricanes has increased over the given time period.

Finally, once a hurricane develops, it has a chance to strengthen into a major hurricane, or a category 4+ storm. If there were h_i hurricanes in year i , the number of category 4+ storms (c_i) is constrained to be between 0 and h_i . We use the same binomial model:

$$c_i | h_i, \xi_i \sim \text{binomial}(h_i, \xi_i) \quad (7)$$

and

$$\log\left(\frac{\xi_i}{1 - \xi_i}\right) = \beta_0^c + \beta_1^c t + \beta_2^c \text{CTI}_i + \beta_3^c \text{NAOI}_i + \beta_4^c \text{AMO}_i, \quad (8)$$

where the priors, etc., are as before and the superscript c indicates we are in the category 4+ portion of the model. The interpretation of β_1^c is analogous to β_1^h , etc.

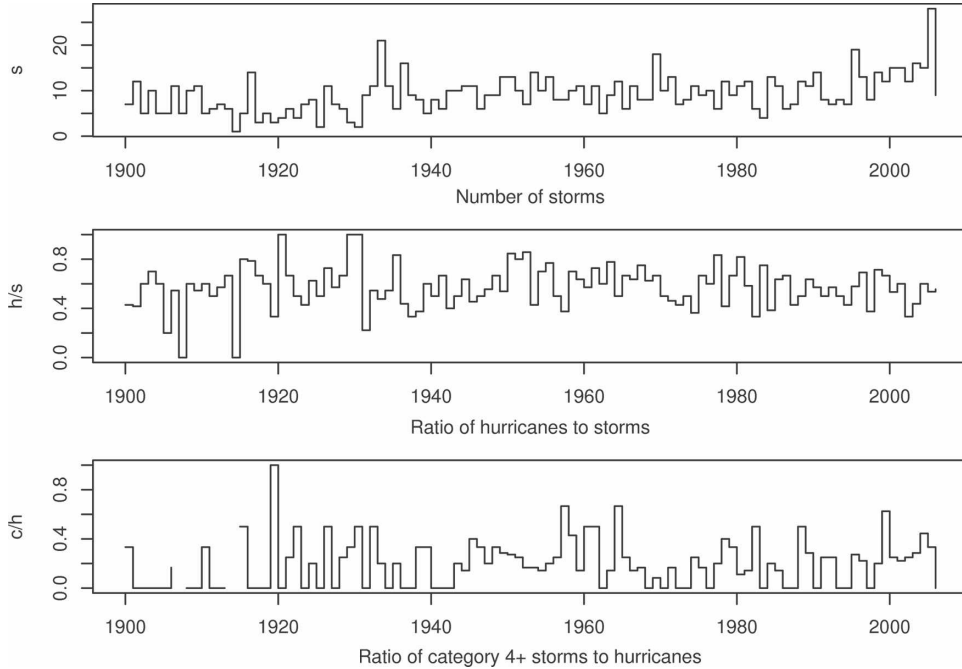


FIG. 1. The number of storms s , the ratio h/s , and the ratio of c/h for the North Atlantic from 1900 to 2006. There are several years prior to 1920 that did not have any reported category 4+ storms or hurricanes.

c. Measures of intensity

It may be that the mean number of storms and hurricanes remains unchanged through time but that other characteristics of these storms have changed. One important characteristic is intensity. We define a three-dimensional measure of intensity, in line with that defined in Webster et al. (2005): 1) the length m (days) that a storm lives, 2) the length of the track (km) of the storm over its lifetime, and 3) the power dissipation index as derived by Emanuel, though here we apply this to each cyclone individually. We stress that we compute these measures for *each storm*; we do not create cumulative summary measures of intensity for a given year. We say nothing directly about storm destructiveness (in terms of money, etc.).

Our value for m was available directly from the HURDAT reanalysis: we approximate the number of days to the nearest 6 h. Track length was estimated by computing the great circle distance between successive 6-h observations of the cyclone, and summing these over the storm's lifetime. The power dissipation index (PDI) is defined by

$$\text{PDI} = \int_0^T V_{\max}^3 dt, \quad (9)$$

where V_{\max}^3 is the maximum sustained wind speed at 10 m and T represents the total time that the storm

lived. Practically, we approximate the PDI—up to a constant—by summing the values $(V_{\max}/100)^3$ at each 6-h observation. The PDI is a crude measure of the strength of the potential destructiveness of a tropical storm or hurricane, as cited by Emanuel (2005). Since many of the storms we consider never reach hurricane strength, it is a stretch to think of the PDI as a destructiveness index; however, it is clear that storm intensity should contain a component that is a function of wind speed, and this one is at least reasonable.

It was found that log transforms of these variables made them much more manageable in terms of statistical analysis. Transforming them led to all of them giving reasonable approximations of normal distributions; thus, standard methods were readily available.

For all three of these measures, we adopt a hierarchical modeling approach because we are interested in whether the distribution within a year of these measures changes through time. It is clear that the three dimensions of intensity are highly correlated with one another. So, to model intensity first let, for year i and storm j (there are $\sum_j s_{ij} = s_i$ storms in year i), $y_{ij} = [\log(m)_{ij}, \log(\text{track length})_{ij}, \log(\text{PDI})_{ij}]'$, that is, a vector quantity. The index k will denote the k th dimension of y [i.e., $y_{ij1} = \log(m)_{ij}$, etc.]. Then, we suppose that

$$y_{ij} \sim \text{MVN}(\mu_{ij}, \Lambda_i), \quad (10)$$

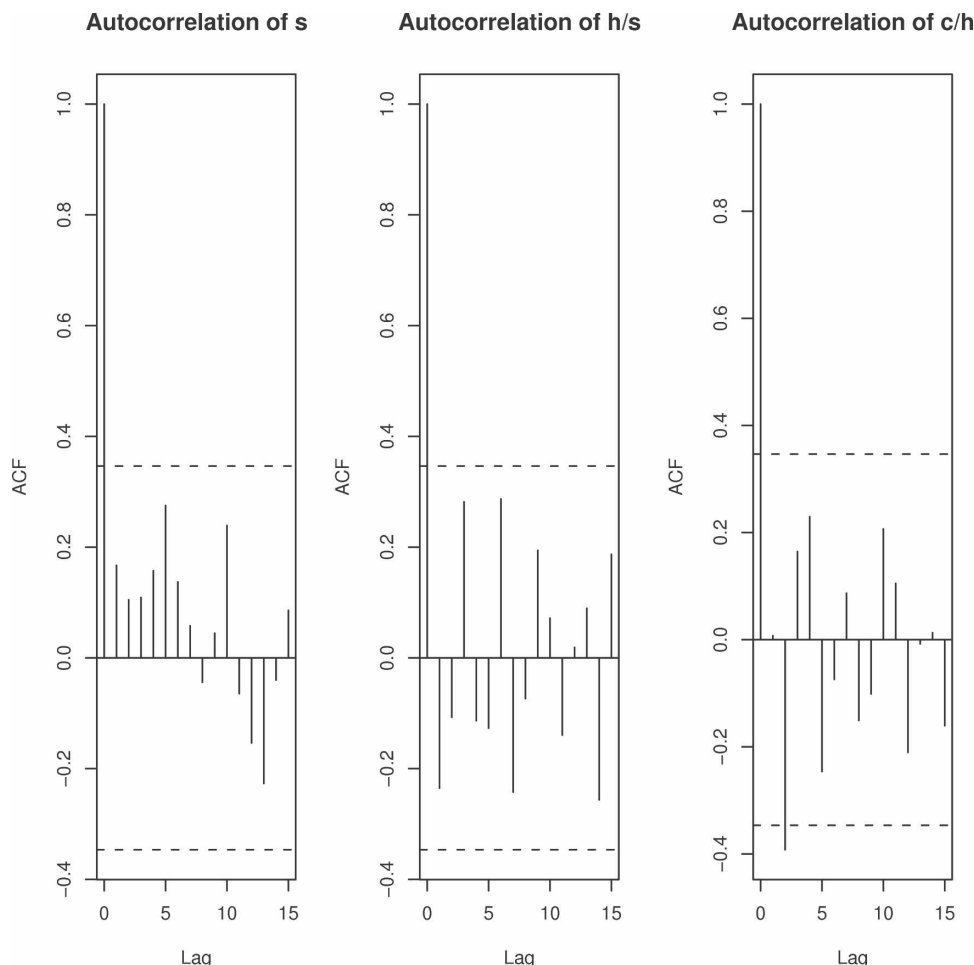


FIG. 2. The empirical autocorrelation for the number of storms s , the ratio h/s , and the ratio of c/h for the North Atlantic from 1966 to 2006. None of the series shows any significant autocorrelation.

that is, a multivariate normal distribution where Λ_i is the 3×3 precision matrix for each year (but not separately for each storm). We model the mean as before:

$$\mu_{ijk} = \beta_{0ik}^z + \beta_{1ik}^z t_i + \beta_{2ik}^z \text{CTI}_i + \beta_{3ik}^z \text{NAOI}_i + \beta_{4ik}^z \text{AMO}_i, \quad k = 1, \dots, 3, \quad (11)$$

where the superscript z denotes that we are in the intensity portion of the model. We further let

$$\beta_{rk}^z \sim N(\pi_{rk}, \phi_{rk}), \quad r = 0, \dots, 4, \quad (12)$$

where these hyperparameters

$$\pi_{rk} \sim N(a_{rk}, b_{rk}), \quad (13)$$

and where we use the standard noninformative priors $a_{rk} \sim N(0, 1 \times 10^{-6})$, $b_{rk} \sim \text{Gamma}(0.001, 0.001)$, and $\phi_{rk} \sim \text{gamma}(0.001, 0.001)$. We explored two priors for the precision Λ_i . The first was the standard flat prior:

$$\Lambda_i \sim \text{Wishart}(\mathbf{I}_i^3, 3), \quad (14)$$

where \mathbf{I}^3 is the 3×3 identity matrix. The second was a prior to account for the noted increase in variance through time (see Fig. 10 below). We additionally built an informative model of this prior where essentially, the variance was allowed to increase linearly in time, and the covariances between the dimensions of intensity remained proportionally fixed. But since there was almost no difference in the results between these two priors, and the space needed to describe the complexity of the second is large and would take us too far afield, we only show results based on the first prior, Eq. (14).

3. Results

All computations were carried out in the R statistical system (R Development Core Team 2006) and the JAGS (just another Gibbs sampler) 0.97 Gibbs sampling software (Plummer 2007) on a Fedora Core 6

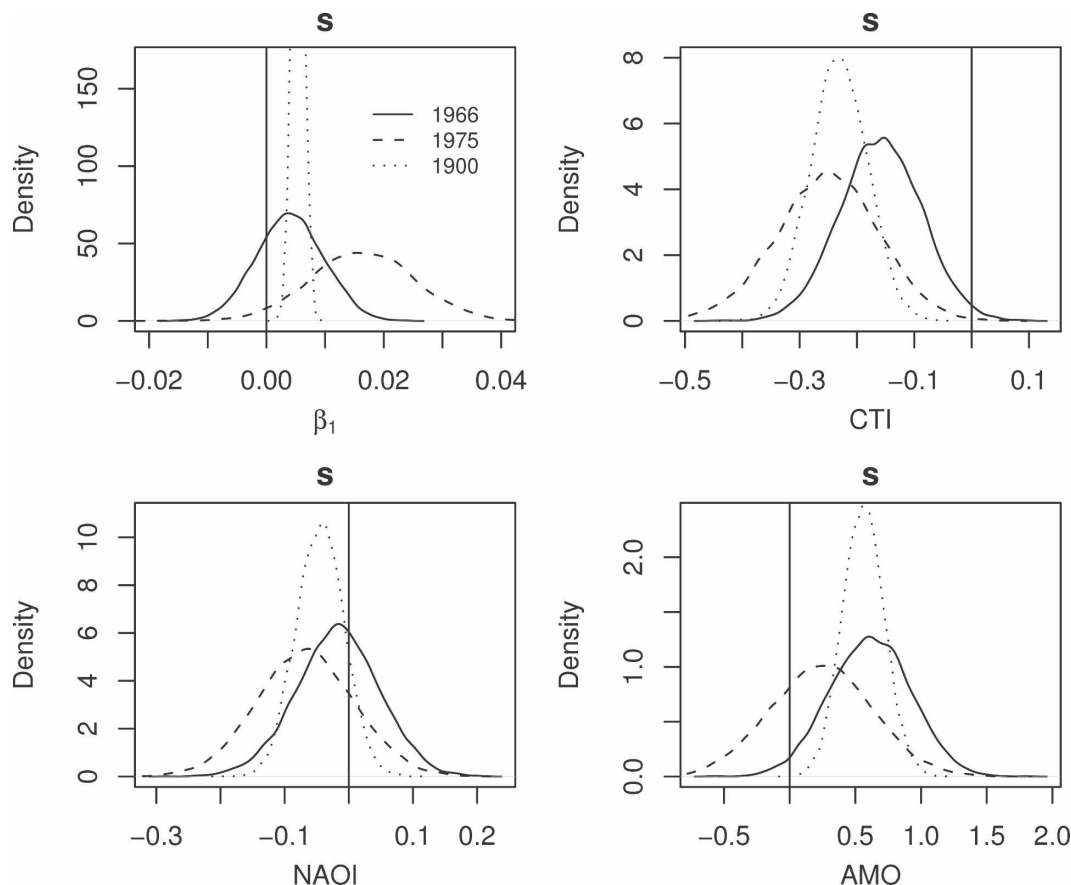


FIG. 3. The posterior distributions for the parameters in Eq. (2), focusing on s . In each case, and in all future figures, the solid line represents the model using all data from 1966 to 2006, the dashed line represents the model using data from 1975 to 2006, and the dotted line represents the model using data from 1900 to 2006. A vertical line at 0 is given to help guide the eye. Posteriors with most of their mass around 0 have little to no effect on the outcome. See the text for a discussion.

platform. Models were fitted using Gibbs sampling. The first 5000 simulations were considered “burn in” and were removed from the analysis; 50 000 additional samples were calculated after this, with every fifth simulation used to approximate the posterior distributions (the other four out of each five were discarded; this thins the posterior simulations and helps remove any small amount of autocorrelation of the simulations). Standard diagnostics (not shown) indicate that all models easily reached convergence.

Data for all of the measures we use were available from 1854, but we use only data from 1900 onward. The data from before this date, as is well known, are suspect enough to cast suspicion on any results based upon them. It is also not clear that a strict linear model over the entire period of 1900–2006 would best fit these data as observation and instruments through that time period have changed (Elsner et al. 2004; Landsea 2007). So we adopt the practice of computing each model over

three different time periods: once for the entire period 1900–2006, the second for dates between 1966 and 2006, and the third between 1975 and 2006. These choices are somewhat arbitrary, but in line with the changepoint results of (Elsner et al. 2004; Jewson and Penzer 2006) and the recent work of (Landsea 2007). Other choices are easily made, however, and we have found that some of our results are robust to changes in these exact start times; however, this is not always true: below, we emphasize where this is not true. This approach also lets us check whether a linear model for the increase–decrease of the parameters through time is reasonable. We do not investigate more complicated models such as linear changepoint regression models here.

a. Number of storms

The top two panels in Fig. 1 show the time series plots of s (number of storms), h/s (ratio of hurricane

TABLE 1. Common quantiles of the model parameters and the posterior probability that these parameters are greater than 0 for 1966–2006 and 1975–2006 data only. Effects that have 95% credible intervals entirely greater or lesser than 0 are highlighted in boldface type.

| Parameter | 1966–2006 | | | | 1975–2006 | | | |
|-------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|-----------------|
| | 2.5% | 50% | 97.5% | Significance | 2.5% | 50% | 97.5% | Significance |
| <i>s</i> | | | | | | | | |
| β_1 | −0.01 | −0.00 | 0.02 | 0.76 | 0.00 | 0.02 | 0.03 | 0.97 |
| CTI | −0.30 | −0.16 | −0.02 | 0.99 | −0.43 | −0.25 | −0.08 | >0.99 |
| NAOI | −0.15 | −0.02 | 0.11 | 0.61 | −0.21 | −0.07 | 0.08 | 0.81 |
| AMO | 0.02 | 0.62 | 1.2 | 0.98 | −0.53 | 0.24 | 1.02 | 0.73 |
| <i>h/s</i> | | | | | | | | |
| β_1 | −0.04 | −0.02 | 0.00 | 0.97 | −0.06 | −0.02 | 0.01 | 0.91 |
| CTI | −0.42 | −0.13 | 0.15 | 0.82 | −0.64 | −0.27 | 0.09 | 0.93 |
| NAOI | −0.34 | −0.06 | 0.21 | 0.67 | −0.47 | −0.13 | 0.20 | 0.78 |
| AMO | −0.04 | 1.09 | 2.25 | 0.97 | −1.11 | 0.58 | 2.32 | 0.75 |
| <i>c/h</i> | | | | | | | | |
| β_1 | 0.00 | 0.04 | 0.08 | 0.96 | −0.05 | 0.01 | 0.07 | 0.60 |
| CTI | −1.31 | −0.67 | −0.07 | 0.99 | −1.39 | −0.67 | 0.05 | 0.96 |
| NAOI | −0.13 | 0.32 | 0.77 | 0.91 | −0.05 | 0.47 | 1.00 | 0.96 |
| AMO | −1.92 | 0.26 | 2.47 | 0.59 | −1.68 | 1.28 | 4.27 | 0.81 |
| <i>log(m)</i> | | | | | | | | |
| β_1 | −0.01 | 0.00 | 0.00 | 0.75 | −0.01 | 0.00 | 0.01 | 0.63 |
| CTI | −0.11 | −0.03 | 0.05 | 0.75 | −0.17 | −0.07 | 0.02 | 0.94 |
| NAOI | −0.14 | −0.07 | 0.01 | 0.96 | −0.13 | −0.05 | 0.04 | 0.87 |
| AMO | −0.14 | 0.20 | 0.54 | 0.88 | −0.30 | 0.14 | 0.60 | 0.73 |
| <i>log(track)</i> | | | | | | | | |
| β_1 | −0.01 | 0.00 | 0.00 | 0.82 | −0.01 | 0.00 | 0.01 | 0.56 |
| CTI | −0.09 | 0.00 | 0.09 | 0.53 | −0.15 | −0.04 | 0.07 | 74 |
| NAOI | −0.18 | −0.01 | −0.02 | 0.99 | −0.16 | −0.06 | 0.05 | 0.86 |
| AMO | −0.16 | 0.24 | 0.64 | 0.89 | −0.25 | 0.28 | 0.86 | 0.85 |
| <i>log(PDI)</i> | | | | | | | | |
| β_1 | −0.02 | −0.01 | 0.01 | 0.88 | −0.02 | 0.00 | 0.02 | 0.53 |
| CTI | −0.29 | −0.13 | 0.03 | 0.94 | −0.45 | −0.26 | −0.07 | >0.99 |
| NAOI | −0.22 | −0.07 | 0.08 | 0.83 | −0.21 | −0.04 | 0.14 | 0.66 |
| AMO | −0.10 | 0.54 | 1.26 | 0.95 | −0.41 | 0.35 | 1.28 | 0.82 |

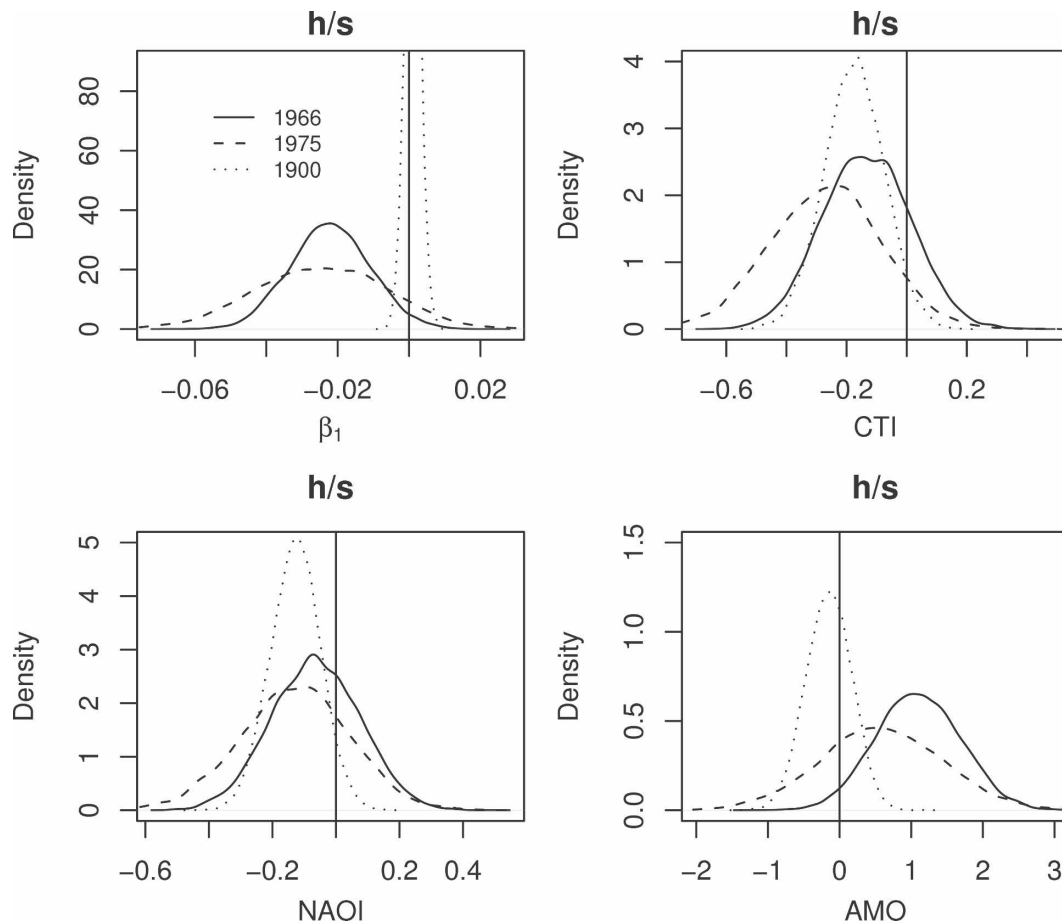
number to storm number), and *c/h* (ratio of category 4+ number to hurricane number) for 1900–2006. There does appear, to the eye, to be an increase in *s* in the past two decades. There do not appear to be any gross trends in *h/s* or *c/h*. Note that for several years prior to 1920, there were no category 4+ storms or hurricanes reported.

The empirical autocorrelation estimates for each of the three time series is shown in Fig. 2. None of the estimates are significant, which suggests that models incorporating lag effects are not needed; the dashed lines have to be exceeded by any individual autocorrelations for the *p* value of the test to be below 0.05; see (Brockwell and Davis 1998).

Fig. 3 shows the posterior distributions from the model in Eq. (2). Table 1 gives the summary statistics for this model. In each case, and in all future figures, the solid line represents the model using all data from 1966

to 2006, the dashed line represents the model using data from 1975 to 2006, and the dotted line represents the model using data from 1900 to 2006. The posterior figures should be used to get a semiquantitative feel for the results, but Table 1 should be referenced to make precise statements.

Whether or not $\Pr(\beta_1^s > 0 | \text{data})$ is large is sensitive to the starting point. It is clear that there has been a linear increase since 1900 (dotted line); of course, the data up to 1966 were certainly measured with error. Landsea (2007) presents strong evidence that the data before 1966 undercount many tropical storm aspects. The same model starting at 1966 shows, via the posterior (solid line), no evidence for an increasing linear trend. However, that year is in something of a high storm period; there were 11 storms in 1966 and up to 18 in 1969, for example. Starting at about 1973, the number of storms dips (to 8 in 1973, 11 in 1974, and 9 in 1975).

FIG. 4. As in Fig. 3 but for Eq. (6) and focusing on the ratio h/s .

Starting the model in 1975 shows (dashed line) good evidence for an increase. The same is true if we restarted the model at, say, 1990 (not shown): an increase is indicated.

There is also strong evidence, as Elsner and Jagger found, and regardless of the time period, that the CTI (β_2^s) is important in estimating λ_i : greater CTIs lead to smaller (log) λ s and therefore to a smaller probability that the mean number of storms will be high, or more plainly, greater CTI means fewer storms. It appears that this relationship has strengthened in later years (1975–2006), as the mode of the distribution has shifted to smaller numbers, though the uncertainty in this effect has also increased in variability (perhaps because the 1975–2006 set has a smaller sample size).

Results for the NAOI (β_3^s) are weaker. The effect, if any, appears uncertain, though it is in the same direction as CTI; that is, high a NAOI indicates fewer storms.

The AMO results are interesting. Regardless of the time period, the relationship, as expected, is positive:

higher AMO indexes are associated with more storms. The AMO index itself starting from 1966 or 1975 shows an upward trend, whereas it has the opportunity to go through at least one cycle from 1900. There was some worry that this known upward trend might have masked any trend (in these models) in the number and conversion rate of storms (see the discussion above about trends and time series models); however, this was not a concern because the association between AMO and storm quality was not especially strong. The AMO effect has also appeared to weaken since 1966.

Table 1 presents the same data as the figures, but only for the 1966–2006 and 1975–2006 periods, in tabular form so that readers can read a best (assuming absolute error loss) estimate of each β at the median (50th percentile). In addition, 95% credible intervals can be read from the table by taking the values from the 2.5% to the 97.5% cells. The last column showing the significance gives the estimated probability that $\Pr(\beta > 0|\text{data})$ or $\Pr(\beta < 0|\text{data})$ (whichever probability is larger). For β_1 , if there is high probability that

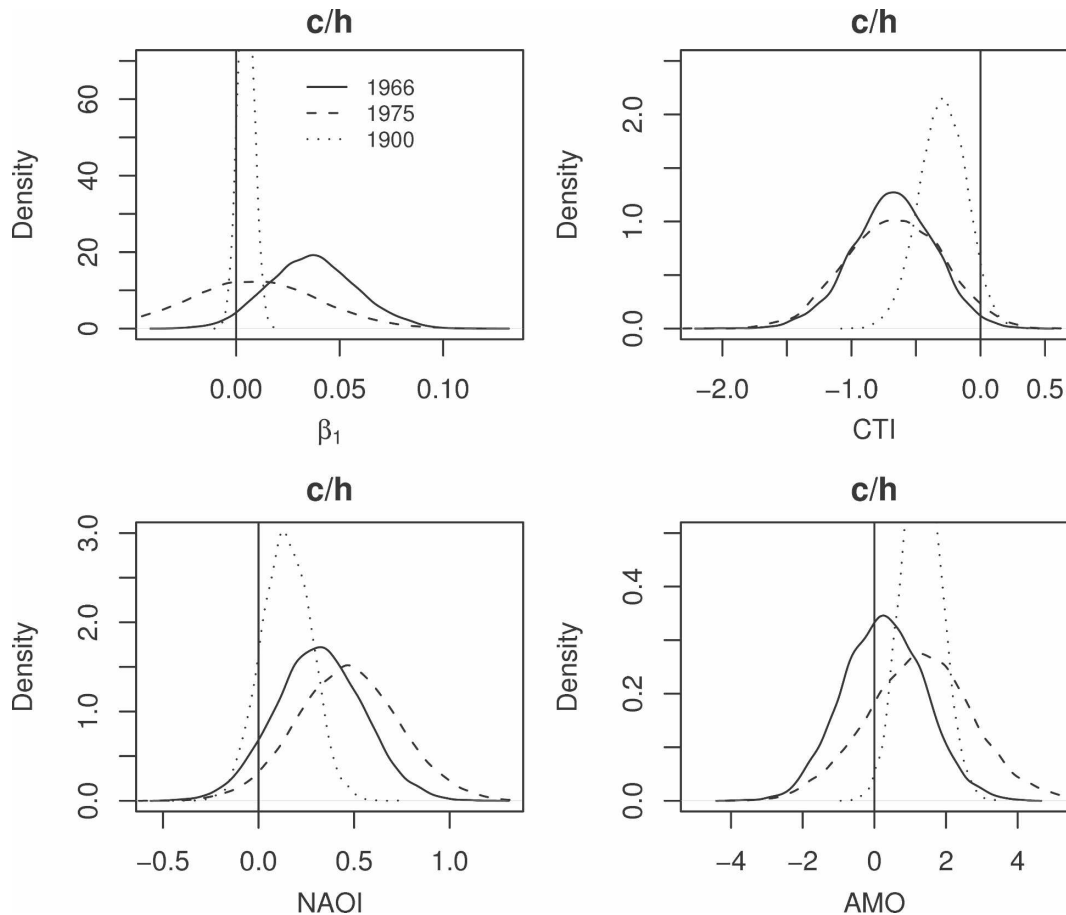


FIG. 5. As in Fig. 3 but for Eq. (8) and focusing on the ratio c/h .

this number is positive, it means we have confidence that a linear increase over the stated time period has taken place (of course, while controlling for CTI, NAOI, AMO, and assuming the model is correct).

The middle panel in Fig. 1 shows the ratio h_i/s_i , which does not give much indication of changing through time. Under this assumption, and using the well-known properties of the posterior (6) for the 1900–2006 data, we estimate that the unconditional (i.e., not controlling for CTI etc.) mean fraction of converting storms is $\hat{\theta} = (\sum h_i - 1)/(\sum s_i - 1) = (564/992) = 0.56$, with a standard deviation of 0.01 (calculation not shown). That is, once a tropical cyclone forms, there is a 56% chance that it will evolve into a hurricane. The results are the same (to three decimal places) for both 1966–2006 and 1975–2006. For the rates of conversion of category 4+ storms to hurricanes, the estimates were 19% for 1900–2006 (however, there is large error here because of missing observations), 18% for 1966–2006, and 21% for 1975–2006.

Applying Eq. (6) gives Fig. 4, which is also summarized in Table 1. The rate at which storms become hur-

ricanes does not appear to change through time, given the data from 1900 to 2006, evidenced by the fact that the probability of $\beta_1^h > 0$ is about 1/2. And there is some evidence, using the data from 1966 to 2006 or from 1975 to 2006, that the mean rate at which hurricanes have evolved has actually *decreased*.

The effect of CTI contributes negatively, though not significantly, in the sense that when CTI increases, the chance of a cyclone becoming a hurricane decreases. The NAOI again does not appear significant, and the direction is the same as it was for the model of s . The AMO is not significant either, and the direction is also the same as for the model of s .

Applying Eq. (8) gives Fig. 5, which is also summarized in Table 1. Given the 1900–2006 data, we can see that there has not been a linear increase in the ratio of category 4+ storms to hurricanes, though of course the reliability of the data from before 1966 is problematic. From 1966 to 2006, the evidence is that there has been an increase in the rate of strong storms evolving. But this increase would not be significant had we only considered the 1975–2006 data.

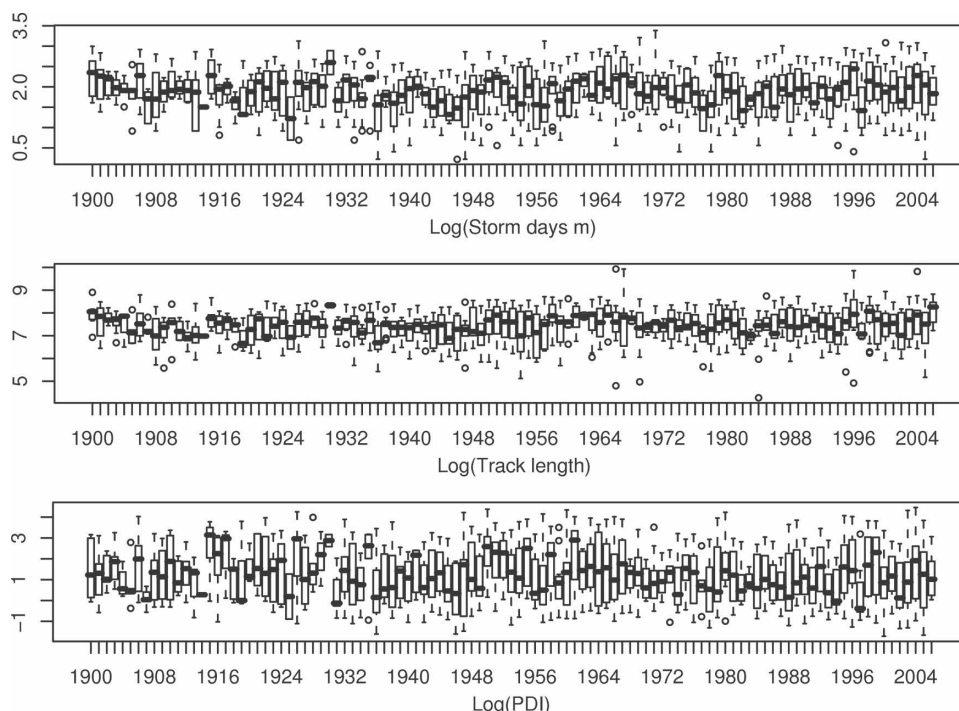


FIG. 6. The time series of box plots, for each year of $\log(m)$, $\log(\text{track length})$, and $\log(\text{PDI})$. There is no apparent trend.

The CTI is again important in the same way: higher CTIs are associated with fewer hurricanes evolving into category 4+ storms. The NAOI finally appears to have some influence: higher values are associated with a greater rate of strong storms evolving. The AMO, except for the flawed 1900–2006 data, does not appear to be a significant association.

The conclusion to be drawn here is that there is good evidence that the number of tropical cyclones has increased, but only if one chooses the right date at which to start one's analysis. Using start dates before around 1975 but after 1966 shows that there has been a definite linear increase. But using any start date from 1966 to about 1974 shows no increase. The rate at which hurricanes evolved from storms does not appear as sensitive to the start date in the data, and there is some evidence that this rate has decreased since at least 1966. The rate at which category 4+ storms evolve from hurricanes does, like s , appear to be sensitive to start date. From 1966, there is evidence that this rate has increased, but from 1975 the increase disappears. We say more about this in section 4.

b. Measures of intensity

Figure 6 shows the time series box plots from 1900 of $\log(m)$, $\log(\text{track length})$, and $\log(\text{PDI})$. Each box plot

gives an indication of the distribution (over storms) of each measure within each year. There is no apparent trend in the sense that the medians show no systematic direction (increase or decrease); the other quantiles appear distributed around a central point. If this graphical view holds under modeling, it means that the cyclonic distribution of intensity has not changed through time.

We now apply Eq. (11) to each of these measures. Figures 7–9 and Table 1 summarize the results.

For none of the measures, using either the 1966–2006 or 1975–2006 datasets, does there appear to be evidence that the mean of the distribution of these measures changed through time: the posteriors for β_1^z in each case have most of their mass around 0. Again, the posteriors for the 1900–2006 dataset are very peaked and concentrated (mostly because of the large sample size), and there is evidence that the mean of $\log(\text{track length})$ has increased and the mean of $\log(\text{PDI})$ has decreased over this time period, but whether these trends represent real physical events or changes in the data, it is impossible to tell.

The association of CTI and intensity has appeared to strengthen over time, judging by the leftward shifting of the posterior modes for each successive dataset, but it is significant only for $\log(\text{PDI})$ in the most recent years. The direction of the effect is again negative: higher CTIs are associated with smaller mean intensities.

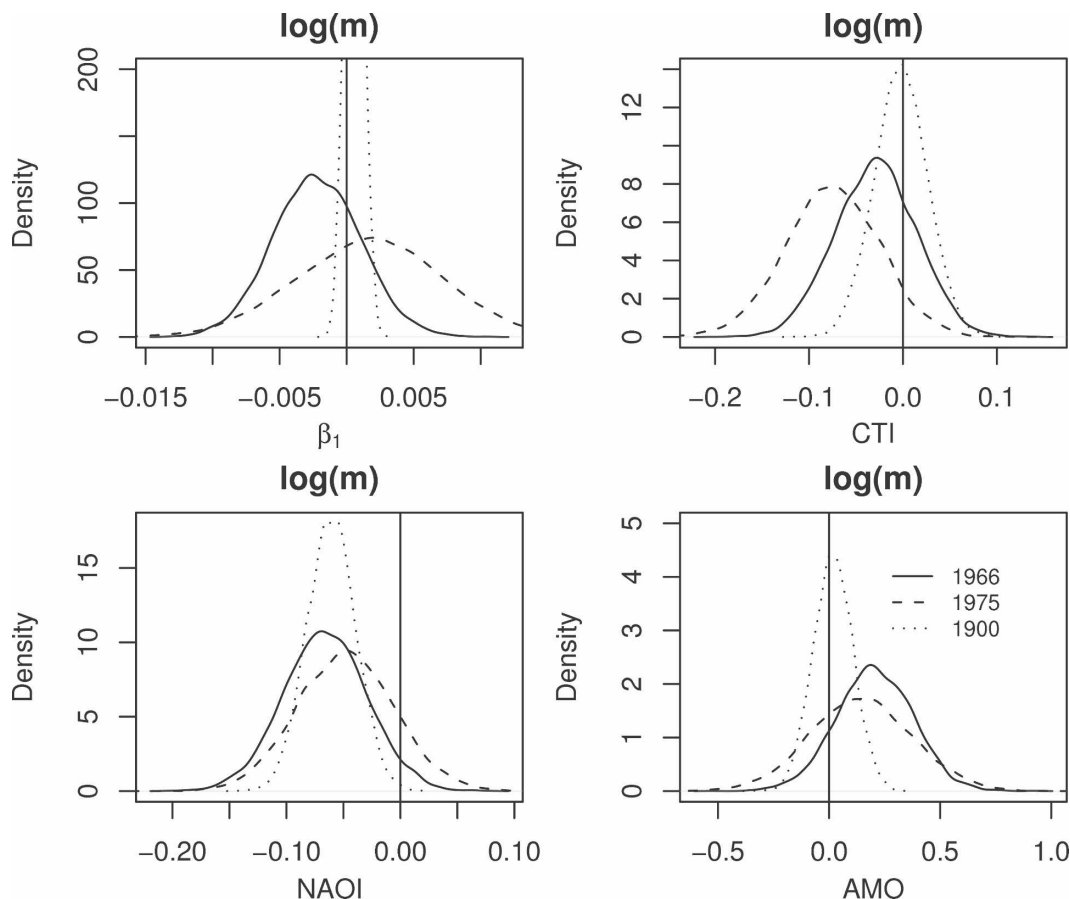


FIG. 7. As in Fig. 3 but for Eq. (11) for the logged number of storm days.

The NAOI is mildly associated with intensity: higher NAOIs imply smaller mean intensities. But the association is only significant for $\log(\text{track length})$ in the 1966–2006 time period. The AMO never became significantly associated with intensity, but the estimated effect was in the positive direction: higher AMOs are somewhat associated with higher mean intensities.

An important finding is that the variance of intensity *has* increased through time: the evidence for this is presented in Fig. 10 which shows the median estimates of the marginal posteriors of the intensity components, $\hat{\Lambda}_{i,j}$, $j = 1, 2, 3$, $i = 1900, \dots, 2006$. The estimates from 1900 to 2006 are the solid time series, and the estimates from 1966 to 2006 are the dashed time series. In fact, the two estimates and those from the 1975–2006 data are nearly identical, suggesting this effect is robust. Overplotted in each panel is a simple linear regression line spanning the relevant time periods. A vertical dashed line indicates 1966. Some of the increase in variance from 1900 is certainly due to changes in the way observations were taken, and this is also probably true for some of the increase since 1966, but perhaps not all

of it. That is, it is likely, though we cannot prove it considering only this data in isolation, that the increase in variance of intensity is due to natural causes.

Note, too, the large demarcation in $(\log)\text{PDI}$, which is of course a function of wind speed, at 1966. Although this is not a formal test of a change point, the existence of this point gives additional weight to the finding that data before 1966 were quantitatively different.

4. Conclusions

We find that to conclude that there has been an increase in the number of tropical cyclones in the North Atlantic basin depends on the starting date used for the analysis. Strong evidence shows that an increase has taken place from 1900; however, early data from that period are certainly tainted by inadequate and missing observations so the confidence we have in this evidence is greatly reduced. Starting from (the years around) 1966 does not give evidence of a linear increase, but starting from (the years around) 1975 does. The statistical explanation for this is that the number of storms

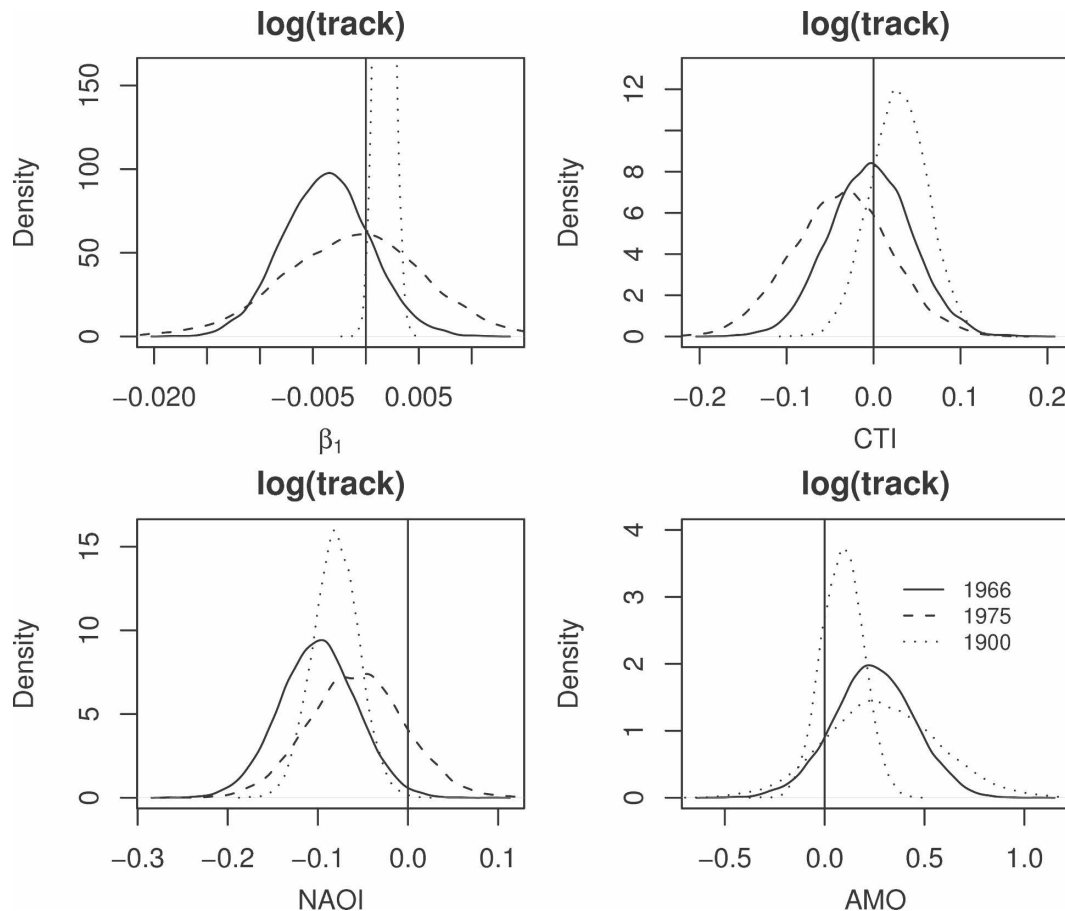


FIG. 8. As in Fig. 3 but for Eq. (11) for the logged track length.

circa 1966 were in a relatively high period, while those circa 1975 were in a relatively low period; and, of course, circa 2005 is a relatively high period. These potential increases are noted after controlling for the effects of CTI, NAOI, and the AMO. These differences due to start date could be real, perhaps because of some underlying cyclicity in the data that coincidentally bottomed out around 1975 (after controlling for AMO, etc.), or it may just be a good lesson that it is possible to pick and choose a starting date to argue either that there has been an increase or there has not been one.

There is some evidence that the rate at which storms evolve into hurricanes has decreased. The evidence is better using the 1966–2006 time frame than when using the 1975–2006 period. Again, the exact starting point makes a difference to the final conclusions, but the results here are less sensitive than are the results for s . The same conclusions are reached for the increased rate at which hurricanes evolved into category 4+ storms: the evidence is strong using the 1966–2006 dataset, but the increase disappears when considering only the 1975–2006 dataset. The plots also show the

results from 1900, and they show no increase in either series, but we do not seriously consider these data because of their inadequacies.

This brings up the question of what start date is the correct start date. Statistically, the answer is the earliest date at which the data become consistent (and consistency here means with respect to observational quality). There is some dispute about this, but clearly a good case can be made for the 1966 start date.

These results are of course conditional on the model we used being adequate or at least being a reasonable approximation to the data. Models of the type used here have long been used successfully by others (see the introduction for sources). The data appear to be consistent with our model, but they are also consistent with other models that we did not try. For example, the trends we have identified may be part of a cycle that has a period longer than that of our data. There is no way to know whether this is so using just these data. We also make no predictions about future increases as it would be foolish to extrapolate the simple linear model we used into the future.

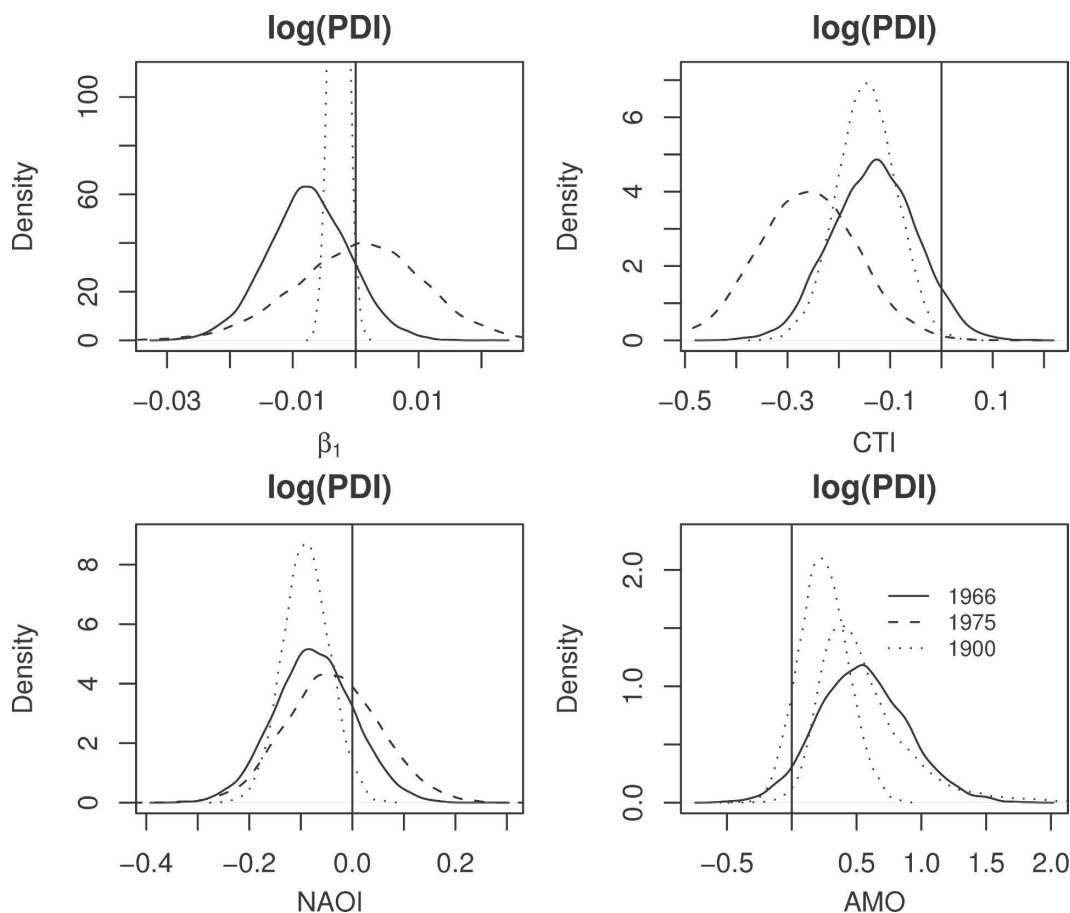


FIG. 9. As in Fig. 3 but for Eq. (11) for the logged PDI.

The effects due to CTI were not always significant, but they were always in a negative direction. That is, lower CTIs were associated with more storms, higher rates of conversion, and higher intensities. The NAOI was more weakly associated than the CTI, and the direction of these effects was not always the same. It was negative for the number of storms, the rate of hurricanes evolving from storms, and intensity, but it was positive for the rate of category 4+ storms evolving from hurricanes. The AMO was rarely significant, except for the number of storms using the 1966–2006 data; it may not have been significant for the 1975–2006 data simply because the fewer data points force less certain conclusions. Its direction was always positive as expected, however: higher values of the AMO were associated with more storms, higher rates of conversion, and higher intensities.

We find no evidence that the distributional mean of individual storm intensity, measured by storm days, track length, or individual storm PDI, has changed (increased or decreased) through time. Any increase in storm intensity at the conglomerated yearly level, as for

example found by Emanuel (2005), is likely due to the increased number of storms and not a result of the increased intensity of individual storms. We also repeated our analysis on the distribution of each storm's (log) maximum wind speed over its lifetime and came to the same conclusion as was reached for the other measures of intensity.

What has increased is the distributional *variance* of individual storm intensity. The increase is seen regardless of the data source used. It is probable, though we cannot prove it using only these data, that at least some of this increase is due to natural causes and not because of changes in observations. These results are consistent with the results that the rate of h/s has possibly decreased, but the rate of c/h has possibly increased. It turns out that the per storm mean of the maximum wind speed is 73 kt (since 1966), which is of course above the cutoff for classifying a hurricane, and below that of classifying a category 4+ storm. Now, PDI is a direct function of maximum wind speed, and the mean of (log)PDI has stayed the same even though its variance has increased. The same is true for the maximum

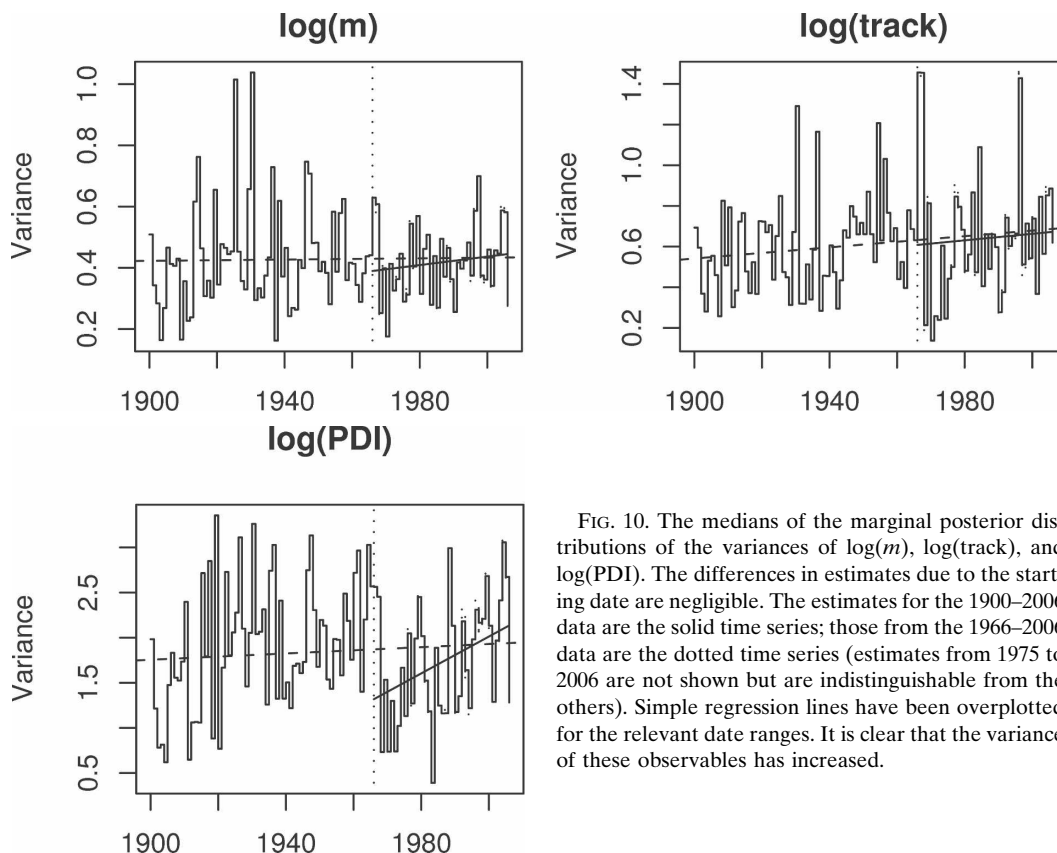


FIG. 10. The medians of the marginal posterior distributions of the variances of $\log(m)$, $\log(\text{track})$, and $\log(\text{PDI})$. The differences in estimates due to the starting date are negligible. The estimates for the 1900–2006 data are the solid time series; those from the 1966–2006 data are the dotted time series (estimates from 1975 to 2006 are not shown but are indistinguishable from the others). Simple regression lines have been overplotted for the relevant date ranges. It is clear that the variance of these observables has increased.

wind speed: its mean has stayed the same, but its variance has increased. So it follows that there should be more storms with higher maximum wind speeds, but there should also be more storms with lower maximum wind speeds, even though the mean remains unchanged. The exact ratio of h/s and c/h depends, of course, on how the rest of the distribution changes.

Much more exact work can be done. A model similar to that used above can certainly be used for storms across all ocean basins for which data are available, as was recently done by Webster et al. (2005). We plan on exploring this in a future paper. In addition, more sophisticated models could be used. For example, spatial Bayesian models such as those developed by Wikle and Anderson (2003) for estimating tornado frequency change could be used for tropical cyclones. This is not an easy task because the tornadoes in that model were treated as point objects, and, of course, hurricanes vary in intensity over vast spatial regions. The statistical characteristics of individual tropical cyclones could be better addressed by asking how the level of intensity (by the three measures given above, and by others such as pressure or other functions of wind, such as shear) changes through a storm's lifetime.

In the introduction we noted the hurricane reanalysis project of Kossin et al. (2007) using the Dvorak technique (e.g., Velden et al. 2006) to construct the new database. The methods used in this paper could certainly be applied to the Kossin et al. database or other datasets like it. The analyses from them might make a valuable comparison to the results presented here, though it is not clear that the states of these databases are such that they are ready for widespread use. Landsea et al. (2006), for example, note that the Dvorak technique has not been a fool-proof correction/estimation scheme. Also, the Kossin et al. database is estimated using a statistical regression model whose predictions, of course, will have some uncertainty in them that can, in part, be estimated. It will be important to be able to incorporate this uncertainty into models like those used in this paper; though how to do so is a matter of future research.

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