Changes in number and intensity of tropical cyclones

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ABSTRACT

Bayesian statistical models were developed for the number of tropical cyclones and the rate at which these cyclones became hurricanes and category 4+ hurricanes in the North Atlantic, North and South Indian, and East and West Pacific Oceans. We find that there is small probability that the number of cyclones worldwide has increased since 1975. The North Atlantic has seen an increase, but the North Indian and West Pacific (since 1990) have seen decreases. The *rate* at which these storms become hurricanes appears to be constant since 1975. The rate at which hurricanes evolve into category 4+ storms does appear to have increased and this is due to the increasing variability in individual storm intensity. We investigates storm intensity by measuring the distribution of individual storm lifetime in days, storm track length, and Emanuel's power dissiptation index. We find little evidence that, overall, the mean of the distribution of individual storm intensity has changed since 1975, but the *variability* of the distribution has certainly increased. Intensity has actually *decreased* (in days and track length) since 1990: the power dissipation has likely increased in the North Indian and decreased in the East Pacific. The cold tongue index and the North Atlantic oscillation index were found to be strongly associated with storm quality in the Western, and to a smaller extent, the Eastern Pacific oceans. The North Atlantic oscillation index was strongly associated with the increase in the rate of strong storms evolving.

1. Introduction

This paper carries on work we began in Briggs (2007). In that paper, we statistically characterized the number of tropical cyclones, the chance that these cyclones evolved into hurricanes, and the intensity of individual storms within a year. We asked whether or not the number of storms were increasing, whether the chance that they evolved into hurricanes was increasing, and whether the year-by-year mean of intensity was increasing. We found that it was highly probable that the number of storms had increased, but that the other characteristics reamined constant through the 20th century for the North Atlantic.

Here, we expand this work to include a global statistical model of the North Atlantic, North and South Indian, and West and East Pacific oceans. Work on this topic is not new, e.g. (Kossin et al. 2007; Webster et al. 2005); and e.g. for the Atlantic (Emanuel 2005; Landsea 2005; Pielke 2005). Much interest naturally centers on whether or not observed increases are due to global warming (Goldenberg et al. 2001; Landsea et al. 2006; Trenberth 2005; Trenberth and Shea 2006). We do not seek to answer that question here. We only ask: have the number, and frequency of hurricanes and strong hurricanes that evolve from them, and the distribution of individual storm intensity changed since 1975?

We use the hurricane reanalysis database (HURDAT) (Chu et al. 2002; Jarvinen et al. 1984; Murnane and Liu 2004). The remaining oceans data we got from the "Best Track" data on the UNISYS webs site (http://weather.unisys.com/hurricane/index.html). This database contains six-hourly maximum sustained 1-minute winds at 10 m, central pressures, and position to the nearest 0.1° latitude and longitude from all known tropical storms from 1851-2006 (for the North Atlantic; other oceans data, particularly in the

Indian ocean, is more limited). A cyclone was classified as a "hurricane" if, at any time during its lifetime, the maximum windspeed ever met or exceeded 65 knots. Obviously, this cutoff, though historical, is somewhat aribitrary and other numbers can be used: we also use the "category 4" or "super typhoon" classification of exceeding 114 knots. To investigate the realtionship of tropical storms with ENSO, we also use the cold tongue index (CTI) (Deser and Wallace 1990) and e.g. (Cai 2003). And we use the North Atlantic oscillation index (NAOI) from (Jones et al. 1997).

There are obviously observational problems, even since 1975, with basins other than the Atlantic. Fasullo (2006) investigated observational quality in the North Atlantic in the context of assessing trends and found that the data was reasonably consistent and that trends could be reliably estimated from it. Kossin et al. (2007) argue the opposite point and say that worldwide the data is rather inconsistent: they propose, and construct, a reanalysis of hurricane activity using satellite observations. Below, we will see that, particularly with the Indian oceans, there is some evidence that data is observationally biased through time. We do not seek to correct this bias, and remind our readers that all our results are conditional on the data we use as being correct. Where we suspect it is not, we give our best guess as to how to interpret the results. To give a more proper view, we repeat certain analysis using only the most recent data from 1990, a point at which the observational error is generally agreed to be low. That time point is partially arbitrary, but it is in line dates found using various change-point models (Chu and Zhao 2004; Elsner et al. 2004; Jewson and Penzer 2006; Zhao and Chu 2006). These models sought to discover is and when changes in storm quality (number and intensity) have occurred in various oceans (usually the North Atlantic).

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

2. Methods

We once again adopt Bayesian statistical models. An important advantage to these models is that we can make direct probability statetments 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).

a. Number of storms

We suppose, in ocean i and year j of n, that the number of storms s_{ij} is well approximated by a Poisson distribution as in

$$s_{ij}|\lambda_{ij} \sim \text{Poisson}(\lambda_{ij}). \tag{1}$$

We earlier found that this model well predicted the observed number of storms in the Atlantic (see particularly Figs. 3-4 for a discussion of model fit in Briggs 2007). The number of storms in each ocean is assumed independent—this is backed up by the data where any correlation between the s_{ij} for different i is low. We allow the possibility that λ_{ij}, the mean number of storms, changes linearly through time, and that the CTI and NAOI may influence, or be associated with the mean CIT (Elsner et al. 2001; Elsner and Jagger 2004). We use the generalized linear model

$$\log(\lambda_{ij}) = \beta^s_{0i} + \beta^s_{1i}t_j + \beta^s_{2i}\text{CTI}_j + \beta^s_{3i}\text{NAOI}_j \tag{2}$$

The superscipt s is to show we are in the number of storms portion of the model. The prior for each β^s_{ki} is

$$\beta^s_{ki}|\gamma^s_k, \tau^s_k \sim \mathrm{N}(\gamma^s_k, \tau^s_k), \quad k = 0, 1, 2, 3 \tag{3}$$

where τ^s_k is the precision (inverse of variance), and to further abstract the mean and variance and thus allow them greater flexability, we use the noninformative priors

$$\gamma^s_k \sim \mathrm{N}(0, 1e-6), \quad \tau^s_k \sim \mathrm{Gamma}(0.001, 0.001). \tag{4}$$

Now, it might be that the posterior of β^s_{1i} may be mostly or entirely positive for some but not all i; this would indicate that the mean number of storms is increasing in those oceans i. It may also be that the posterior of $\beta^s_{1i'}$ may be mostly or entirely negative for other oceans i'; this would indicate that the mean number of storms is decreasing in those oceans i'. All β^s_{1i}, over all oceans, are drawn from the distribution $\mathrm{N}(\gamma^s_1, \tau^s_1)$, and so if the mean of this distribution is greater than 0, then we can conclude that the mean number of storms is increasing across all oceans. Thus, we can look to the posterior of γ^s_1 to ascertain whether this is so.

Once a tropical storm develops it, of course, has a chance to grow into a hurricane (or typhoon). If there are s_{ij} tropical cyclones in ocean j and year i the number of hurricanes is constrained to be between 0 and s_{ij}. Thus, a reasonable model for the number of hurricanes h_{ij} in year j given s_{ij} is

$$h_{ij}|s_{ij}, \theta_{ij} \sim \mathrm{Binomial}(s_{ij}, \theta_{ij}). \tag{5}$$

The parameter θ_{ij} can be thought of as the proportion of hurricanes that develop from storms. It is possible, however, as with λ_{ij}, that θ_{ij} is dependent on CTI and NAOI and that it changes through time. To investigate this, we adopt the following logistic regression model

$$\log\left(\frac{\theta_{ij}}{1-\theta_{ij}}\right) = \beta^h_{0i} + \beta^h_{1i} t_j + \beta^h_{2i}\mathrm{CTI}_j + \beta^h_{3i}\mathrm{NAOI}_j \tag{6}$$

where the superscript h denotes the hurricane portion of the model and we again let the priors and hyperpriors be the same form as in the model for s_{ij}. Like before, we will exmaine the posterior β^h_{1i} across each ocean to see whether or not the it is likely that, for ocean i, the rate of hurricanes in increasing. And also if the posterior of γ^h_1 has most of its probability above 0, we can conclude that the rate of hurricanes is increasing across all oceans.

We carry the model one step further by asking about the chance that a category 4 or above (denoted by c_{ij}; these are also called "super typhoons") hurricane develops from an ordinary hurricane: the number of category 4+ storms is of course constrained to be between 0 and h_{ij}. In analogy with the model above, we have

$$c_{ij}|h_{ij}, \xi_{ij} \sim \mathrm{Binomial}(h_{ij}, \xi_{ij}). \tag{7}$$

The parameter ξ_{ij} can be thought of as the proportion of category 4 hurricanes that develop from ordinary hurricanes. And again, we allow ξ_{ij} to be dependent on CTI, NAOI, and time. Thus,

$$\log\left(\frac{\xi_{ij}}{1-\xi_{ij}}\right) = \beta^c_{0i} + \beta^c_{1i} t_j + \beta^c_{2i}\mathrm{CTI}_j + \beta^c_{3i}\mathrm{NAOI}_j \tag{8}$$

where the superscript c denotes the category 4+ portion of the model and we again let the priors and hyperpriors be the same form as in the model for s_{ij}. Like before, we will examine the posterior β^c_{1i} across each ocean to see whether or not the it is likely that, for ocean i, the rate of major hurricanes is increasing. And if the posterior of γ^c_1 has most of its probability above 0, we can conclude that the rate of major hurricanes is increasing across all oceans.

The posteriors of each β^h_{1i}, β^c_{1i} etc. are in *logit* or *log odds* space, so care must be taken in direct interpretation of any estimates. We leave them in this space so that a glace at the posterior density estimates tells the story: if most of the probabiltiy is above or below 0, we can be reasonably sure there is some effect of time. A simple way to transform these posteriors is by taking their exponentiation: the answers then are in *odds* and *odds ratio* space. We give some examples of this below.

b. Measures of intensity

It may be that the frequency 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, in 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 Emmanuel, though here we apply this to each cyclone individually and do not derive a yearly summary.

We approximate the number of days m to the nearest six-hours. Track length was estimated by computing the great circle distance between succesive six-hour observations of the cyclone, and summing these over the storm lifetime. The *per-storm* power dissipation index (PDI) is defined by

$$\mathrm{PDI} = \int_0^m V^3_{\max} dt \tag{9}$$

where $V^3_{\max}$ is the maximum sustained wind speed at 10m. Practically, we approximate the PDI—up to a constant—by summing the values $(V_{\max}/100)^3$ at each six-hour 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). Other than this measure, we say nothing directly about storm destructiveness (in terms of money etc.).

It was found that log transforms of these variables made them much more managable in terms of statistical analysis. Transforming them led to all giving reasonable approximations of normal distributions; thus, standard methods are readily available. There is substantial correlation between these three measures, which we take account of in the model below.

First let, for ocean i, year j, and storm k (there are s_{ij} storms in year j in ocean i), $y_{ijk} = (\log(m)_{ijk}, \log(\text{track length})_{ijk}, \log(\text{PDI})_{ijk})'$, i.e. a vector quantity. The index l will denote the lth dimension of y (i.e. $y_{ijk1} = \log(m)_{ijk}$ etc.). Then we suppose that

$$\log y_{ijk} \sim \text{MVN}(\mu_{ijk}, \Lambda_{ij}) \tag{10}$$

i.e. a multivariate normal distribution where Λ_{ij} is the 3×3 precision matrix for each ocean and year. We model the mean as before

$$\mu_{ijkl} = \beta^z_{0il} + \beta^z_{1il} t_j + \beta^z_{2il}\text{CTI}_j + \beta^z_{3il}\text{NAOI}_j, \quad l = 1 \ldots 3 \tag{11}$$

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

$$\beta^z_{ril} \sim \text{N}(\pi_{rl}, \phi_{rl}), \quad r = 0, 1, 2, 3 \tag{12}$$

and where these hyperparameters

$$\pi_{rl} \sim \text{N}(a_{rl}, b_{rl}) \tag{13}$$

where we use the noninformative priors $a_{rl} \sim \text{N}(0, 1e-6), b_{rl} \sim \text{Gamma}(0.001, 0.001)$ and

$$\phi_{rl} \sim \text{Gamma}(0.001, 0.001). \tag{14}$$

As in the models for number etc., we will exmaine the marginal posterior β^z_{1il} across each ocean and dimension $l = 1, 2, 3$ to see whether or not it is likely that, for ocean i, and dimension l, the mean intensity is increasing. Also analogous to the above models, since each β^z_{1il} has mean π_{rl}, we can examine its posterior: if it has most of its probability above 0, we can conclude that the intensity is increasing across all oceans.

Two classes of priors were considered for the precision (inverse covariance) Λ_{ij}: a simple noninformative and a realistic, but more complicated one. The simple (and standard) prior assumes

$$\Lambda_{ij} \sim \text{Wishart}(I^3_i, 3). \tag{15}$$

i.e. a Wishart distribution with three degress of freedom and I^3_i is the 3×3 identity matrix for ocean i (Gelman et al. 2003).

Below, we give evidence that there is an unambiguous, probably linear, increase in the variance of intensity through time, where the increase is proportionally equal in each of its members. There is also substantial correlation between the parameters, which appears constant over time. The ratio of variances between members of intensity also appears constant in time. So we built an informative prior to take these observations into account. Let σ^2_l indicate the variance of the lth member of intensity, and let $\rho_{lm} = \rho$ indicate the correlation, assumed constant across $l, m = 1, 2, 3$. Let $d_m = \sigma^2_m/\sigma^2_1$. The variance σ^2_1 was modelled as

$$\sigma^2_{ij1} = c_0 + c_1(t_j - 1990). \tag{16}$$

where c_0 and c_1 represent the intercept and slope of the observed increase in variance (subtracting 1990 centers the time and helps eliminate computer roundoff error). Then $\sigma^2_{ij2} = d_2\sigma^2_{ij1}$ and $\sigma^2_{ij3} = d_3\sigma^2_{ij1}$. The covariance between elements 1 and 2 was modeled as $\rho\sqrt{d_2}\sigma^2_{ij1}$: the remainder of the covariances were handled in a similar manner. After the variance matrix V_{ij} was formed, we let

$$\Lambda_{ij} \sim \text{Wishart}(V_{ij}, 3). \tag{17}$$

In practice, with some notable exceptions mainly due to data integrity, both priors for the precision gave about equal results, except that, as expected, the second model gave results (slightly) less certain than the first. The results were also not sensitive to exact values of ρ, c_0 etc. used. They are so insensitive, in fact, that a third prior, defined as $V_{ij} = I^3_{ij}$, gave nearly identical results with (17): the only difference between (17) and (15) is that the former is allowed to change year by year (and over each ocean), and the later can only change over each ocean and is fixed in time.

3. Results

All computations were carried out in the JAGS 0.97 Gibbs sampling software (Plummer 2007) on a Fedora Core 6 platform. The first 2000 simulations were considered "burn in" and were removed from the analysis: 100,000 additional samples were calculated after this, with every 10th simulation used to approximate the posterior distributions (the other 9 out of each 10 were discarded; this thinned the posterior simulations and helped to remove the small amount of autocorrelation of the simulations).

a. *Number of storms*

Figure 1 shows the number of storms s from 1975-2006 for each of the five ocean basins. There is no evident overall trend, though the number of storms seems to increase in some oceans, and decrease in others. Other plots and other formal statistics (not

$\boxed{\text{Fig. 1.}}$

shown) also indicate that the number of storms, in any given year, are independent from ocean to ocean.

The next picture shows h/s for each of the oceans. There is evidentally observational problems with the North and South Indian oceans: note the increase in the late 1970s of the ratio of hurricanes to storms. This is almost certainly due to improvements in observations of wind speed (upon which, of course, a strom being classified as a hurricanes are dependent) and is not entirely due to natural causes. The data settles down after 1990, when observations were uniformly more accurate. FIG. 2.

The third picture shows c/s for each of the oceans. Again, there is no evident overall trend, and the data quality of the Indian oceans is again suspect before about 1990. FIG. 3.

The joint model for number of storms, and the ratio of evolved hurricanes and category 4+ storms was then run. Figs. 4-7 and Tables 1-3 summarize the results. In each case, the solid line are the results of the model run using all the data from 1975-2006; the dotted lines use only the data from 1990-2006. The posteriors for the 1990-2006 data are generally wider than those using the 1975-2006 data, as would be expected because fewer data points give us less certainty. FIG. 4.

Fig. 4 shows, regardless of the data set used, there is high probability that s has increased in the North Atlantic (NA), but decreased in the North Indian (NI), South Indian (SI). The EP has remained constant. The WP is different: using the 1975-2006 data shows evidence of an upward trend, but data from 1990-2006 shows a downward trend. This can be seen in the data too, where the data is seen to increase to the mid 1990s, and then decrease after that. Clearly, then, a straight line fit does not do justice to the WP; but it still a reasonible approximation. Overall, as registered by the posterior of the parameter γ^s, there has been no overall increase or decrease. This is backed up by the results from Table 1. For the model of s, there is a greater than 97.5% chance that there was an increase in s in the NA, because all the percentiles, and in particular, the 2.5%-tile are greater than 0. The same is true of the WP, and the opposite is true for the NI and the SI. Overall, there is about equal probability on either side of 0, indicating that the best guess is to say “no change” in time.

In (Briggs 2007) we went further and calculated the estimated probability that the posterior of β_1^s was greater than 0 for the NA. It was felt that the data quality of the NA was sufficiently good enough to state the results in such precise terms. We do not repeat these calculations here, because doing so is likely to convey more certainty than is warranted. We repeat that the models we use are only as good as the data that go into them: the most precision we offer is in the form of the standard quantiles. We do, however, present one model diagnostic plot: obviously, if the results we present are to be trusted, the model we used should at least fit the observed data. We first compute, for each ocean i and year j,

$$p(\lambda_{ij}|\text{data}) = \int_{-\infty}^{\infty} p(\lambda_{ij}|\beta, \text{data}) p(\beta|\text{data}) d\beta \tag{18}$$

$$p(s_{ij}|\text{data}) = \int_{0}^{\infty} p(s_{ij}|\lambda_{ij}, \text{data}) \times p(\lambda_{ij}|\text{data}) d\lambda_{ij} \tag{19}$$

These are the posterior of λ_{ij} given the data (from 1975), and the posterior predictive distribution of the number of storms s_{ij} given the past data. The later distribution is the one which would be used to predict s_{ij} (given the model and past data etc.). We plot the later distribution of s_{ij}, sorted, in each ocean, from the smallest to largest number of storms (this plot is *not* a time series; note also that the limits of the x-axis changes from ocean to ocean). A small positive number has been added to each distribution so that all fit on one plot. Further, the actual value realized is plotted as a filled circle on the distribution. Most observations fall near the mode of the predictive distribution, giving evidence that the model is good. There are a few points which fall in the tails of the predictive distribution: namely the 28 storms in the NA (in 2005), but overall there is good agreement. This plot can also be used to show that predictions in the NA and NI are tighter than those in the other oceans: tighter in the sense the predictive distributions are more peaked in the NA and NI, and more spread out in the other oceans, meaning, of course, that we cannot be as certain what the actual value of s will be in those oceans. Fig. 5.

Table 1.

Fig. 6.

Fig. 7.

Fig. 6, and Table 1 shows that, using data from 1975-2006 or 1990-2006, there is some probability that the rate that hurricanes evolved from tropical storms has decreased in the NA, WP, and EP, though the result is far from conculsive, except perhaps for the EP since 1990. But there is good evidence (greater than 97.5% chance) that the rate has increased in the NI and SI since 1975. Whether this is due to natural causes or abberations in the data collecting mechanism, particularly in the SI, it is not possible to say. However, the trend completely disappears since 1990, leading us to suspect that the trend since 1975 is spurious. Overall, however, the evidence is nowhere near conclusive that the rate is increasing or decreasing worldwide.

The results for the model of c/h are more striking. It is still true that the observations for the SI are problematic, but, except for the NI since 1975 or 1990 and the EP since 1990, there is good evidence that the rate of category 4+ storms evolving from ordinary hurricanes has increased through time in the other oceans and overall. The odds of a category 4+ storm evolving increase, as estimated by the median overall column, by $\exp(0.04) = 1.04$ times per year: over 10 years this is an increase in the odds of 1.5 times. Table 2.

Tables 2 and 3 show the influence that the CTI and the NAOI have on the different models using only the data from 1975. The results did not change in any qualitative way using 1990-2006 data, leading us to have confidence that the observed associations are real. The results here are mixed, and ocean dependent, as might be expected. Increases in CTI are associated with a decrease the number of storms in the NA, and to a slight extent in the NI, and it tends to be associated with an increase in the number of storms in the EP. Overall, there is not much effect.

Similar results hold for the ratio of hurricanes to storms: increases in CTI tend to be associated with a decrease the rate at which hurricanes evolve in the NA and NI, and are associated with an increase with the rate in the WP. We will find that the CTI, as might be expected, plays a large role for storm quality in the WP. The SI and EP show no change; neither is there an overall effect. Increases in CTI tend to be associated with a decrease in the rate at which category 4+ storms evolve in the NA and SI, and are strongly associated with an increase in the rate in the WP and EP. Overall, the effect is small. Table 3.

The NAOI has little association on either the number of storms or the rate at which these evolve into hurricanes; again using either data set. But it does have a stronger association on rate at which category 4+ storms evolve: in every ocean, and overall, the effect is positive: an increase in a higher NAOI is associated with an increase in the rate at which strong hurricanes evolve.

b. Measures of intensity

There was one missing track length (out of 1756) in the South Indian ocean. There were 28 (out of 622) missing PDIs in the North Indian and 106 (out of 1756) in the South Indian. The multivariate model we used requires that there be no missing values. So we imputed the small number of missing values by forming linear regression models of log track (or log PDI) as a function of log m and log PDI (or log m and log track), and used these to make predictions at the missing values. We do not expect that this unduly effected any of the results.

Figures 8-10 show the boxplot time series of individual storm (within a year and logged) m, track length, and PDI for each ocean. A simple regression trend line (from 1975) for the medians of these distributions is overlayed to help guide the eye as to the overall trend, if any. There is still the same data quality problem with the Indian oceans, but there are some trends evident in these pictures. FIG. 8.

FIG. 9.

FIG. 10.

Within each year we estimated the covariance between intensity and plotted, in Fig. 11, the estimated variance of log(m) (solid line), log(track) (dashed), and log(PDI) (dotted). Log(PDI) has been scaled by dividing by 2 so that all data fits on one picture. There is a clear increase in variance of each measure in Fig. 11, similar across all oceans. Certainly, there is a lot of noise around this trend, particular (again) in the Indian oceans, but its existence is unambiguous. This represents one of our main findings. FIG. 11.

To illustrate this in a different way, we present Fig. 12, which is four estimates of the year-by-year variance of intensity for the Western Pacific: the classical point estimate (solid line); posterior median based on the increasing variance prior (17) (open circles); the posterior median based on the non-informative year-by-year prior; the posterior median based on the simple ocean prior (17) (dashed line) (how we formed the priors is described next). The posterior medians differ trivially for the priors (17) and the simplified year-by-year version. The prior (15) does not track very well with the other priors in this ocean, but it does better in other oceans, particularly the Indian (not shown). The Bayesian and classical estimates are in very close agreement for $\log(m)$ and log(track), but differ markedly for log(PDI): this is also found in the other oceans: the difference appears largest in this ocean, the ocean which also appeared to have the clearest increase in variance over time. This exhibits the typical Bayesian "shrinkage" that is found in multivariate estimation. Note: the classical (solid line) should certainly *not* be taken as the true value of the variance to which the Bayesian estimate aspires. It is merely another estimate, one that may be too high (just as the Bayesian estimate may be too low). In any case, all methods show a clear increase in variance through time, which is all that we are claiming holds. FIG. 12.

From the data in Fig. 11, we estimated the parameters of the second precision prior (17). We estimate (by averaging the classical estimates over the oceans): $\widehat{\rho} = 0.8$ (.11), $\widehat{d_2} = 2$ (.56), $\widehat{d_3} = 6$ (1.7), and $\widehat{c_0} = 0.3$ (0.03), $\widehat{c_1} = 0.004$ (0.0026). The numbers in parentheses are the estimated standard deviations. The model results presented below are very insensitive to the exact values of these parameters. It turns out to be much more important whether the variance is allowed to change through time by each ocean, or that it is the same through time at each ocean. That is, we repeated all the analyses below, but this time with $V_{ij} = I_{ij}$, i.e. nearly the same as the non-informative 'flat' prior $V_{ij} = I_i$, except we allow the variance to change year-by-year: the results below barely changed when this different, but eminently fair, prior was used. FIG. 13.

Figure 13, and Table 4, shows the posteriors of β^z_{1i1} and π_{r1} for $\log(m)$ for each variance prior. The posterior based on the increasing variance prior (17) is the solid line; the posterior based on the "flat" or constant non-informative prior (15) is the dashed line. Both of these use the 1975-2006 dataset. The dotted line is from the result of using the 1990-2006 dataset with prior (17). We comment first on the results using the 1975-2006 dataset.

There is no difference in the NA using the 1975-2006 dataset: both priors indicate that there may be some evidence that $\log(m)$ has increased, but we cannot be very sure this is so. The same conclusion can be reached for the EP. But for the North and South Indian, a complete opposite picture emerges (also partly seen in the West Pacific), particularly for the South Indian (where the data is most suspect). The posterior based on the flat prior (15) gives good evidence that $\log(m)$ has decreased, but the posterior based on the increasing prior (17) gives good evidence that $\log(m)$ has increased! This is partly because of the strong correlation between $\log(m)$ and log(PDI), and the strong rise over time of the later: this is picked up in prior (17). We emphasize that this is not because of some bias in the informative increasing prior: a nearly identical picture arises if we instead use the year-by-year flat prior. The variance in the Indian oceans *has* increased, but some of this is certainly due to increasingly good and uniform observations.

Now, the raw data picture of $\log(m)$ in the Indian oceans show decreases, but there is a strong rise in the log(PDI) in the South Indian, which has about 3 times as many data points as does the North Indian ocean (and would thus receive more weight in the simulations). These factors go a long way into explaining the difference in interpretation. In any case, any result for the Indian Oceans should be viewed with caution because these results are so sensitive on the prior used. FIG. 14.

The overall trend parameter for $\log(m)$ using the 1975-2006 dataset is near 0, meaning it is likely that $\log(m)$ has neither increased nor decreased across all oceans.

A striking contrast is provided by the 1990-2006 dataset: here, where observations are good, and across all oceans, there is some evidence that $\log(m)$ has *decreased*, especially in the West and East Pacific oceans. This result is independent on the number of storms s in each ocean.

The same interpreation for log(track) in Fig. 13 as for $\log(m)$ can be made. The two variance priors give nearly identical results, except for the Indian Oceans; and there is no overall trend using the 1975-2006 dataset. And there is also an indication of *decreasing* mean of log(track), again especially in the West and East Pacific oceans. This is not suprising because, of course, the shorter number of days a storm lives, the less likely it is to travel far.

Roughly the same interprations can be made for log(PDI) in 14. There is some evidence that the mean of log(PDI) has decreased (from 1990) in the Eastern Pacific (where the plot for the later dataset barely even starts because all the values in the posterior were negative), but it has remained constant in the other oceans and overall.

Thus, we conclude that intensity has *not* been increasing, at least since 1975, and certainly not since 1990. Table 4.

Fig. 15.

Table 5.

Table 5 shows how the CTI is related to intensity using the 1975-2006 dataset. For each dimension of intensity, a higher CTI is associated with greater intensity in the WP, and to a smaller extent in the EP. To be clear: a high CTI means longer lived, longer travelling, and windier storms in the Western Pacific. Longer travelling storms in the NI are also associated with higher CTI. There is almost no difference in these results using the 1990-2006 dataset. Table 6.

The association of intensity with NAOI is presented in Table 6 using the 1975-2006 dataset. There is little association in any ocean or overall, with the, perhaps surprising, exception that higher NAOI is associated with longer lived storms in the Western Pacific. There is almost no difference in these results using the 1990-2006 dataset.

4. Conclusions

We find that there is good evidence that the number of tropical cyclones over all the oceans basins considered here have neither increased nor decreased since 1975: some oceans saw increases, others decreases or no changes. There is some evidence that the number of storms has *decreased* in the South Indian and West Pacific oceans since 1990. These results stands even after controlling for CTI and NAOI. These results are of course conditional on the model we used being adequate or at least it being a reasonable approximation to the data: diagnostics show that model we propose fits well to the observed data. As in our first paper, we make no predictions about future increases as it would be foolish to extrapolate the simple linear models we used into the future.

We also found that the rate at which tropical cyclones become hurricanes does *not* appear to be changing through time (since 1975) across oceans, nor is it much influenced by CTI or NAOI. The rate may be increasing in the Indian oceans, but it seems just as likely that flaws in the data would account for the results we have seen. There is evidence that the rate has *decreased* in the East Pacific ocean since 1990.

There is good evidence that the mean rate at which major (category 4+) storms evolve from ordinary hurricanes has increased through time (since 1975 or since 1990 except for the Eastern Pacific), though the increase is small. Classifying a storm a hurricane of category 4+ hurricane is, of course, a direct function of wind speed, a quality which is also an input to definitions of intensity. We comment more on this in a moment.

We find little evidence that the mean of the distribution of individual storm intensity, measured by storm days, track length, or individual storm PDI, has changed (increased or decreased) since 1975 over all the oceans. Again, there were certain noted increases in the Indian oceans, which may be real or may be due to flaws in the data: this is evidenced by the posteriors from these oceans being very sensitive to the priors used. We did, however, find an unambiguous increase in the variance of the distribution of storm intensity over all oceans. We also found that two components of intensity, storm days and track length, have likely *decreased* since 1990 over most oceans.

Thus, we conclude that mean intensity has *not* been increasing, at least since 1975, and certainly not since 1990.

It might be asked, if the overall number of storms has stayed constant, but the rate of category 4+ storms has increased, which implies that the number of category 4+ storms has increased, why has not, say, the mean of PDI (which is a direct function of wind speed) increased because of these stronger storms? This is most likely because the variance of PDI *has* increased, meaning there has been an increase of both stronger *and* weaker storms, but that this change has balanced (in the sense that the mean has stayed the same). Of course, the variance of m and track length have also increased, leading to both shorter and longer lived, and shorter and longer travelling storms.

We cannot answer whether this increase in variance is due to increasingly better observations, a condition which is certainly true from 1975 but perhaps not after 1990, or due to natural fluctuations. We also did not seek to answer whether the changes in storm number and intensity was related to sea surface tempertures (SSTs). This was intentional. SSTs themselves, as is well known, have changed with time. Suppose there is a direct positive realtion with storm number and intensity and SSTs. It is then possible that the linear time coefficient in a statistical model of storms as a function of SSTs and time would be unimportant because the effect due to change in SSTs and the effect due to change in storms would be confounded.

The CTI was particularly associated with storm quality in the Western Pacific: the rate at which hurricanes and category 4+ storms evolve increased with higher CTI. Higher NAOI also led, worldwide, to an increase in the rate at which category 4+ storms evolve. Higher CTI was also associated with longer and more powerful storms in the Western, and to a smaller extent, the Eastern Pacific oceans. Perhaps surprising, was that higher NAOI was associated with longer lived storms in the Western Pacific and nowhere else.

In the Introduction we noted the hurricane reanalysis project of Kossin et al. (2007) using the Dvorak technique (Velden et al. 2006) to construct the new database. The methods used here could certainly be applied to this, and other datasets like it. These analysis from them would make a valuable comparison to the results presented here. We hope that this avenue is pursued when this dataset becomes publicly available.

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Figure Captions

FIG. 1. The number of storms s five oceans from 1975-2006.

FIG. 2. The rate h/s at which tropical cyclones become hurricanes from 1975-2006.

FIG. 3. The rate c/s at which tropical cyclones become category 4+ hurricanes from 1975-2006.

FIG. 4. The posteriors of β^s_{i1} (the regressor for change in time) and γ^s_1 (the parameter for overall change) for each ocean i for the model of s. The solid line uses all data from 1975-2006; the dotted lines only the data from 1990-2006.

FIG. 5. The posterior predictive distrbution of s_{ij}, sorted, in each ocean, from the smallest to largest number of storms (this plot is *not* a time series). A small positive number has been added to each distribution so that all fit on one plot. Further, the actual value realized is plotted as a filled circle on the distribution. Most observations fall near the mode of the predictive distribution, giving evidence that the model is good.

FIG. 6. The posteriors of β^h_{i1} and γ^h_1 (the regressor for change in time) for each ocean i for the model of h/s.

FIG. 7. The posteriors of β^c_{i1} and γ^c_1 (the regressor for change in time) for each ocean i for the model of c/h.

FIG. 8. The time series of boxplots, for each year and each ocean, of $\log(m)$. A simple dashed trend line of the medians in overlayed.

FIG. 9. The time series of boxplots, for each year and each ocean, of log(track length). A simple dashed trend line of the medians in overlayed.

FIG. 10. The time series of boxplots, for each year and each ocean, of log(PDI). A simple dashed trend line of the medians in overlayed.

FIG. 11. The estimated variance of $\log(m)$ (solid line), log(track) (dashed), and log(PDI) (dotted). Log(PDI) has been scaled by dividing by 2 so that all data fits on one picture. The is a clear increase in variability of each measure.

FIG. 12. For the Western Pacific, four estimates of the year-by-year variance of intensity: the classical point estimate (solid line); posterior median based on the increasing variance prior (17) (open circles); the posterior median based on the non-informative year-by-year prior; the posterior median based on the simple ocean prior (17) (dashed line).

FIG. 13. The marginal posteriors of β_1^z and π_1 for $\log(m)$ across all oceans. The solid line represents the posteriors with the increasing variance prior; the dashed line is for the simple, constant non-informative prior: both using data from 1975. The dotted line uses (17) for the data from 1990. The results for both priors, however, are in rough agreement for the 1975-2006 dataset; but see the text for a discussion of the South Indian ocean.

FIG. 14. The same as Fig. 13 but for log(track). Here, both variance priors give closer agreement.

FIG. 15. The same as Fig. 13 but for log(PDI). Here, both variance priors give closer agreement for the 1975-2006 data except for the South Indian ocean.

Tables

TABLE 1. *Common quantiles of the model parameter β_{i1} and γ_1 (the parameters for change in time) for each ocean i. Recall that the interpretion for the models h/s and c/h are in terms of log odds space: these numbers should be exponentiated for odds ratios. Results (increasing or decreasing) for which there is at least 95% certainty are highlighted in bold in this and all other Tables.*

	1975-2006			1990-2006		
Ocean	2.5%	50%	97.5%	2.5%	50%	97.5%
			s			
NA	**0.01**	**0.02**	**0.03**	**0.00**	**0.03**	**0.06**
NI	**-0.04**	**-0.03**	**-0.01**	-0.07	-0.03	0.01
SI	-0.02	-0.01	0.00	**-0.04**	**-0.02**	**0.00**
WP	**0.00**	**0.01**	**0.02**	-0.03	-0.01	0.01
EP	-0.01	0.00	0.01	-0.03	0.00	0.02
Overall	-0.04	0.00	0.03	-.05	-0.01	0.04
			h/s			
NA	-0.03	-0.01	0.01	-0.06	-0.01	0.03
NI	**0.01**	**0.05**	**0.09**	-0.08	-0.01	0.06
SI	**0.04**	**0.06**	**0.07**	-0.04	0.00	0.03
WP	-0.02	-0.01	0.01	-0.04	-0.01	0.02
EP	-0.03	-0.01	0.01	**-0.11**	**-0.06**	**-0.02**
Overall	-0.04	0.02	0.07	-0.07	-0.02	0.04
			c/h			
NA	**0.00**	**0.03**	**0.06**	-0.02	0.05	0.12
NI	-0.02	0.05	0.12	-0.10	0.02	0.12
SI	**0.04**	**0.07**	**0.10**	-0.02	0.03	0.09
WP	**0.01**	**0.03**	**0.05**	**0.00**	**0.05**	**0.09**
EP	**0.00**	**0.03**	**0.06**	-.08	-0.01	0.04
Overall	**0.00**	**0.04**	**0.09**	-0.05	0.03	0.10

Table 2. *The same as Table 1, but for the regressor due to the CTI. Only the results from using the data from 1975-2006 is shown here.*

Ocean	2.5%	50%	97.5%
		s	
NA	**-0.36**	**-0.19**	**-0.04**
NI	-0.27	-0.08	0.08
SI	-0.10	-0.02	0.07
WP	-0.09	0.00	0.08
EP	-0.05	0.06	0.19
Overall	-0.22	-0.04	0.11
		h/s	
NA	-0.52	-0.18	0.09
NI	-0.64	-0.17	0.15
SI	-0.14	0.04	0.21
WP	**0.04**	**0.24**	**0.44**
EP	-0.23	0.00	0.21
Overall	-0.36	-0.01	0.26
		c/h	
NA	-1.16	-0.50	0.07
NI	-0.15	0.56	1.48
SI	-0.63	-0.28	0.05
WP	**0.09**	**0.34**	**0.59**
EP	**0.09**	**0.42**	**0.77**
Overall	-0.61	0.11	0.84

TABLE 3. *The same as Table 1, but for the regressor due to the NAOI.*

Ocean	2.5%	50%	97.5%
		s	
NA	-0.16	-0.04	0.05
NI	-0.14	-0.01	0.11
SI	-0.13	-0.05	0.03
WP	-0.05	0.02	0.10
EP	-0.06	0.03	0.14
Overall	-0.11	-0.01	0.08
		h/s	
NA	-0.31	-0.08	0.08
NI	-0.46	-0.10	0.07
SI	-0.14	-0.01	0.15
WP	-0.16	-0.02	0.12
EP	-0.24	-0.06	0.09
Overall	-0.24	-0.06	0.08
		c/h	
NA	**0.04**	**0.26**	**0.53**
NI	-0.02	0.25	0.59
SI	**0.06**	**0.26**	**0.47**
WP	**0.00**	**0.21**	**0.40**
EP	**0.03**	**0.25**	**0.48**
Overall	**0.05**	**0.25**	**0.46**

Table 4. *Common quantiles of the model parameter* β_{i1}^{z} *and* γ_{1}^{z} *(the regressor for change in time) for each ocean* i *using the full 1975-2006 dataset. Results are for both the increasing variance and non-informative ('flat') priors. There do not appear to be any overall trends.*

	Increasing V			Flat V			1990-2006		
Ocean	2.5%	50%	97.5%	2.5%	50%	97.5%	2.5%	50%	97.5%
					$\log(m)$				
NA	-0.001	0.005	0.012	-0.002	0.004	0.011	-0.023	-0.008	0.007
NI	**0.000**	**0.009**	**0.018**	-0.014	-0.005	0.005	-0.049	-0.018	0.010
SI	**0.004**	**0.008**	**0.013**	**-0.016**	**-0.011**	**-0.006**	**-0.032**	**-0.020**	**-0.008**
WP	-0.002	0.003	0.008	**-0.009**	**-0.005**	**-0.001**	**-0.056**	**-0.045**	**-0.033**
EP	-0.004	0.001	0.006	-0.007	-0.002	0.003	**-0.042**	**-0.029**	**-0.017**
Overall	-0.020	0.005	0.031	-0.030	-0.003	0.023	-0.054	-0.023	0.010
					log(track)				
NA	-0.004	0.004	0.012	-0.003	0.006	0.014	-0.020	-0.002	0.017
NI	**0.000**	**0.010**	**0.024**	-0.006	0.003	0.012	-0.062	-0.029	0.002
SI	**0.001**	**0.006**	**0.020**	-0.009	-0.004	0.001	-0.025	-0.010	0.006
WP	-0.003	0.003	0.009	-0.001	0.004	0.008	**-0.045**	**-0.031**	**-0.015**
EP	-0.006	0.001	0.007	-0.004	0.003	0.009	**-0.033**	**-0.016**	**0.000**
Overall	-0.021	0.005	0.031	-0.024	0.002	0.028	-0.050	-0.017	0.015
					log(PDI)				
NA	-0.004	0.007	0.019	-0.006	0.005	0.016	-0.028	-0.001	0.026
NI	-0.002	0.010	0.022	-0.008	0.002	0.012	-0.020	0.027	0.081
SI	**0.019**	**0.027**	**0.034**	**0.007**	**0.014**	**0.021**	-0.031	-0.005	0.020
WP	-0.006	0.004	0.014	-0.007	0.001	0.009	-0.027	0.000	0.028
EP	-0.011	-0.001	0.009	-0.013	-0.003	0.006	**-0.077**	**-0.052**	**-0.027**
Overall	-0.019	0.009	0.037	-0.023	0.004	0.031	-0.051	-0.008	0.036

Table 5. *Common quantiles of the model parameter* β^z_{i2} *and* γ^z_2 *(the regressor for influence of CTI) for each ocean* i *using the 1975-2006 dataset. Results are for both the increasing variance and non-informative ('flat') priors.*

	Increasing V			Flat V		
Ocean	2.5%	50%	97.5%	2.5%	50%	97.5%
			$\log(m)$			
NA	-0.11	-0.02	0.06	-0.10	-0.01	0.07
NI	-0.01	0.08	0.16	-0.03	0.06	0.16
SI	-0.05	0.00	0.05	-0.03	0.03	0.08
WP	**0.14**	**0.19**	**0.25**	**0.09**	**0.14**	**0.19**
EP	-0.02	0.04	0.10	-0.03	0.03	0.08
Overall	-0.04	0.06	0.15	-0.03	0.05	0.13
			log(track)			
NA	-0.10	0.00	0.10	-0.08	0.03	0.13
NI	**0.05**	**0.14**	**0.23**	**0.07**	**0.16**	**0.27**
SI	-0.08	-0.02	0.04	-0.05	0.01	0.07
WP	**0.15**	**0.22**	**0.29**	**0.12**	**0.19**	**0.25**
EP	**0.00**	**0.08**	**0.15**	**0.00**	**0.07**	**0.14**
Overall	-0.04	0.07	0.18	-0.02	0.08	0.17
			log(PDI)			
NA	-0.28	-0.12	0.03	-0.27	-0.11	0.03
NI	-0.21	-0.09	0.04	-0.19	-0.06	0.05
SI	-0.09	-0.01	0.07	-0.05	0.03	0.11
WP	**0.14**	**0.26**	**0.38**	**0.11**	**0.22**	**0.33**
EP	-0.05	0.06	0.18	-0.02	0.09	0.20
Overall	-0.10	0.04	0.18	-0.07	0.05	0.17

TABLE 6. *Common quantiles of the model parameter β^z_{i3} and γ^z_3 (the regressor for influence of NAOI) for each ocean i using the 1975-2006 dataset. Results are for both the increasing variance and non-informative ('flat') priors.*

	Increasing V			Flat V		
Ocean	2.5%	50%	97.5%	2.5%	50%	97.5%
			log(m)			
NA	-0.07	-0.02	0.03	-0.05	0.00	0.05
NI	-0.03	0.03	0.09	-0.04	0.02	0.09
SI	-0.06	-0.02	0.02	-0.03	0.01	0.05
WP	**0.01**	**0.05**	**0.09**	**0.00**	**0.04**	**0.08**
EP	-0.06	-0.01	0.03	-0.04	0.00	0.04
Overall	-0.05	0.00	0.06	-0.03	0.01	0.06
			log(track)			
NA	-0.10	-0.02	0.04	-0.08	-0.01	0.05
NI	-0.05	0.02	0.09	-0.06	0.00	0.06
SP	-0.04	0.01	0.05	-0.03	0.01	0.06
WP	-0.02	0.03	0.09	-0.02	0.02	0.06
EP	-0.03	0.02	0.07	-0.03	0.02	0.07
Overall	-0.05	0.01	0.06	-0.04	0.01	0.06
			log(PDI)			
NA	-0.07	0.01	0.11	-0.08	0.00	0.09
NI	-0.15	-0.04	0.04	-0.11	-0.02	0.05
SI	-0.04	0.03	0.10	-0.03	0.03	0.10
WP	-0.10	-0.01	0.06	-0.07	0.00	0.07
EP	-0.09	0.00	0.08	-0.07	0.00	0.07
Overall	-0.07	0.00	0.06	-0.06	0.00	0.07

Figures

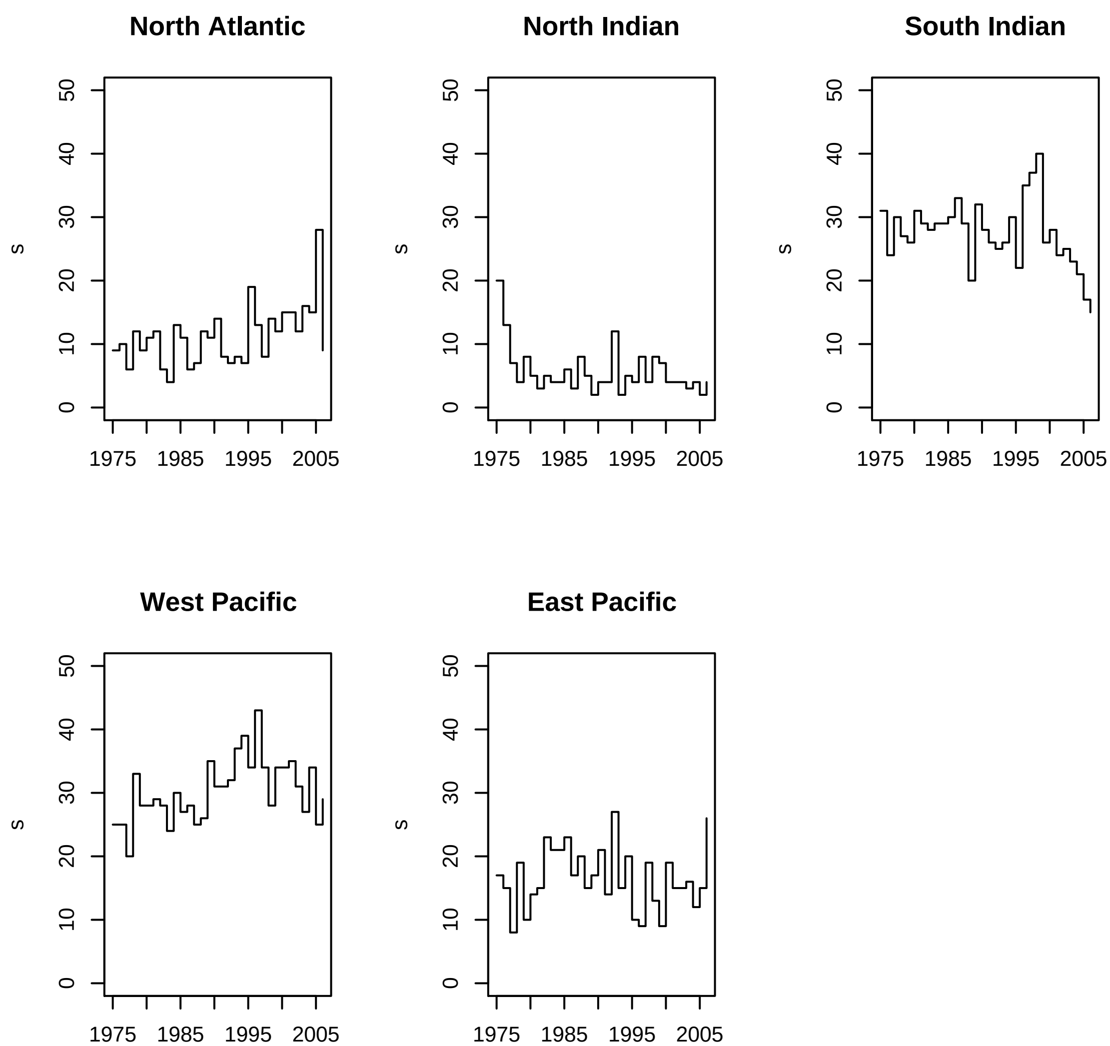

FIG. 1. The number of storms s five oceans from 1975-2006.

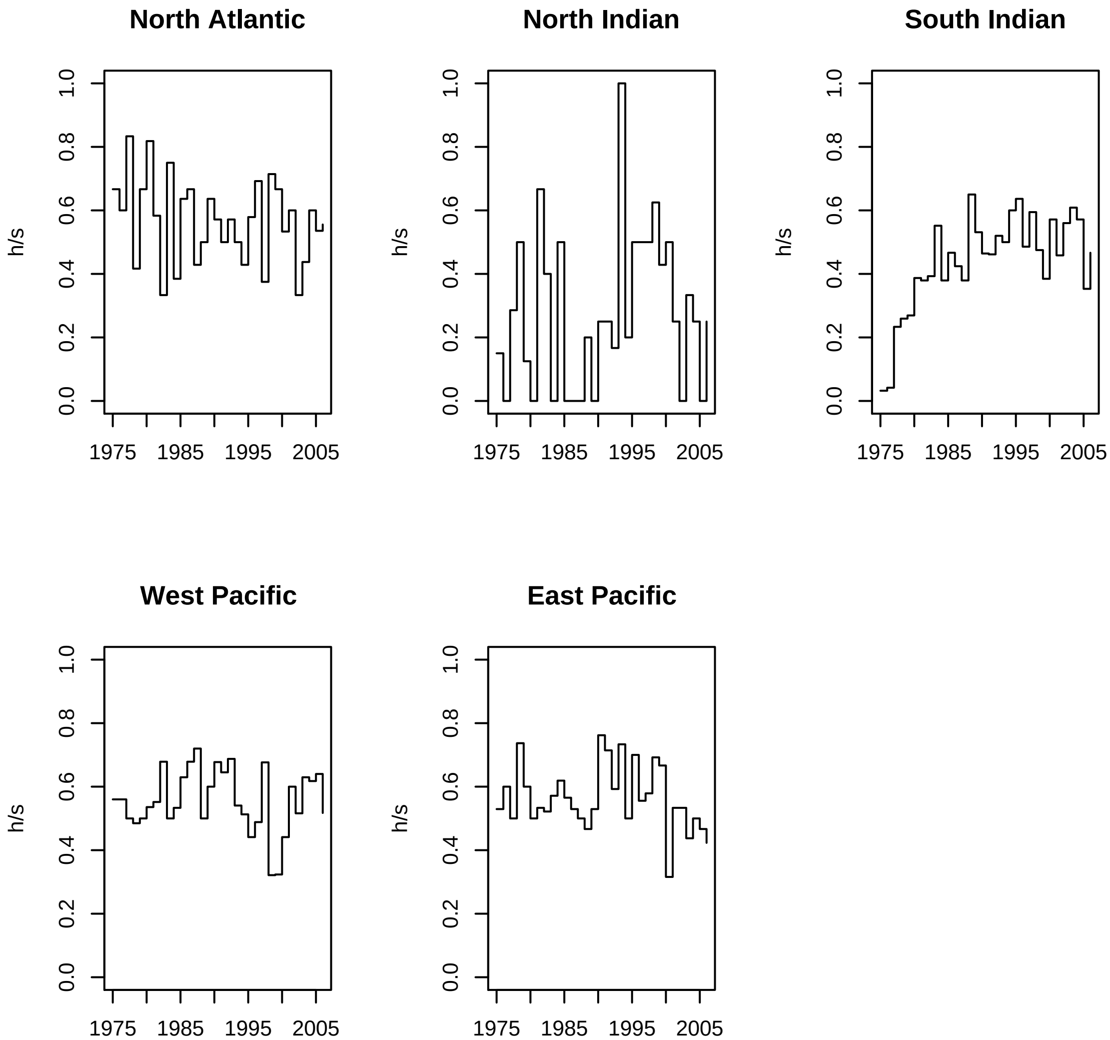

FIG. 2. The rate h/s at which tropical cyclones become hurricanes from 1975-2006.

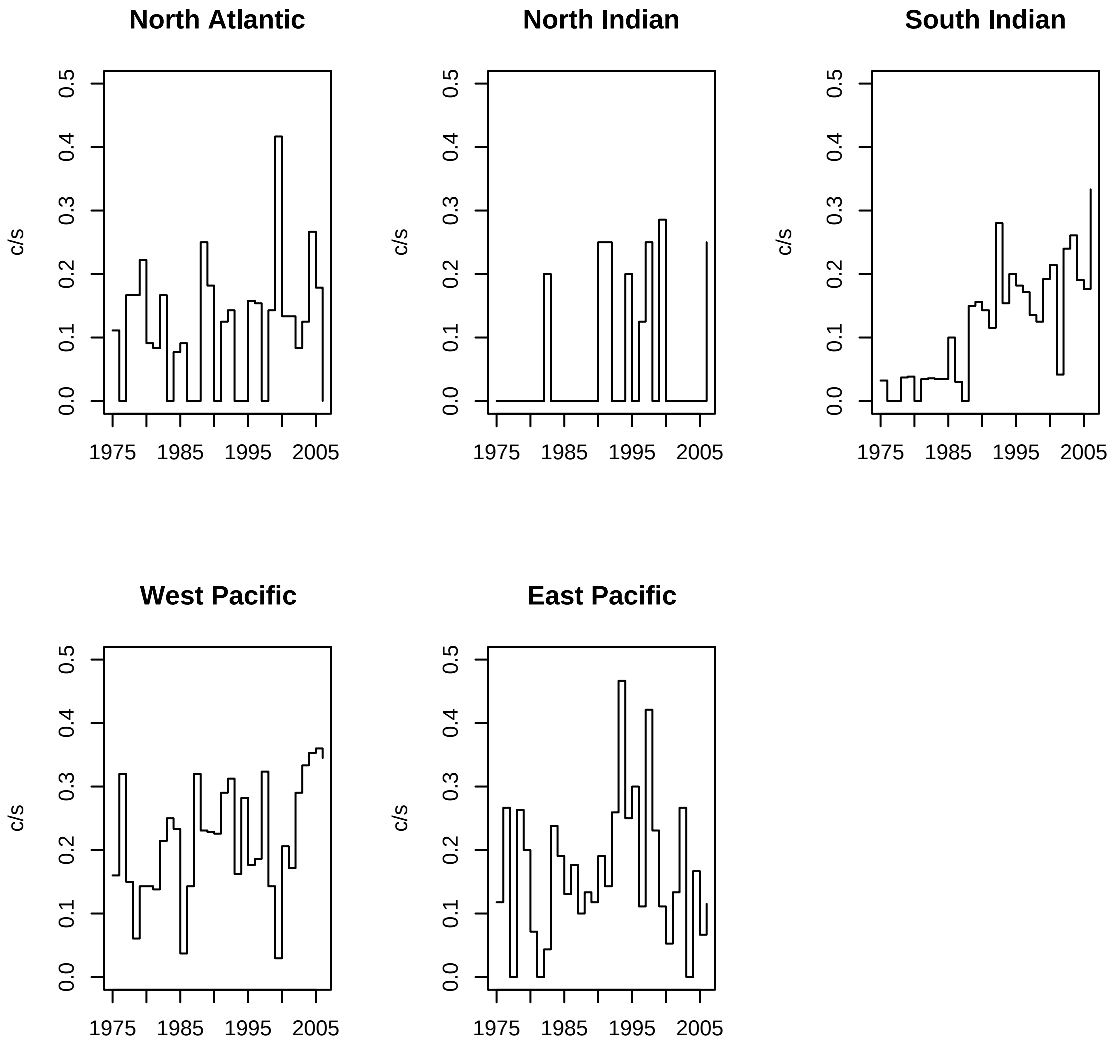

FIG. 3. The rate c/s at which tropical cyclones become category 4+ hurricanes from 1975-2006.

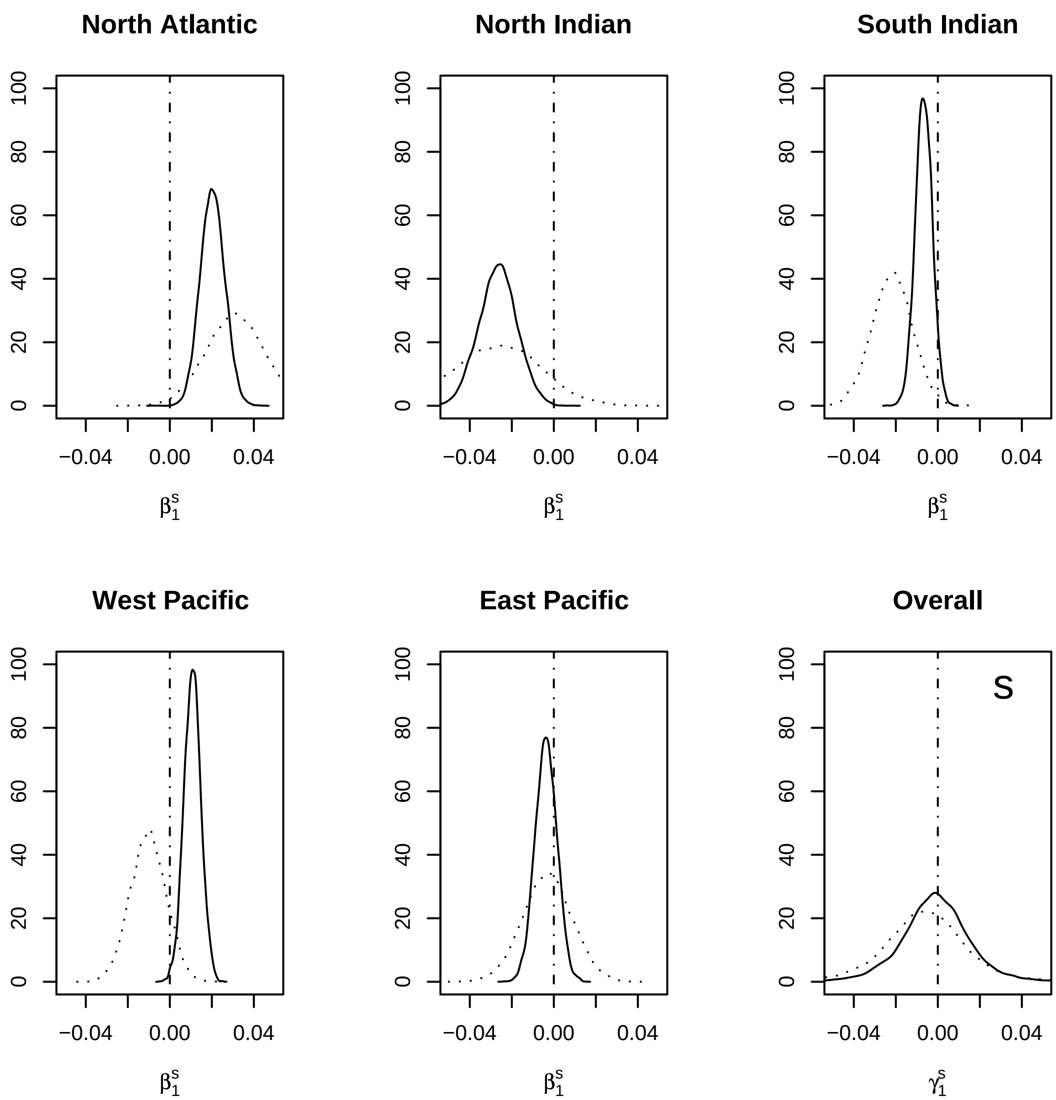

FIG. 4. The posteriors of β_{i1}^s (the regressor for change in time) and γ_1^s (the parameter for overall change) for each ocean i for the model of s. The solid line uses all data from 1975-2006; the dotted lines only the data from 1990-2006.

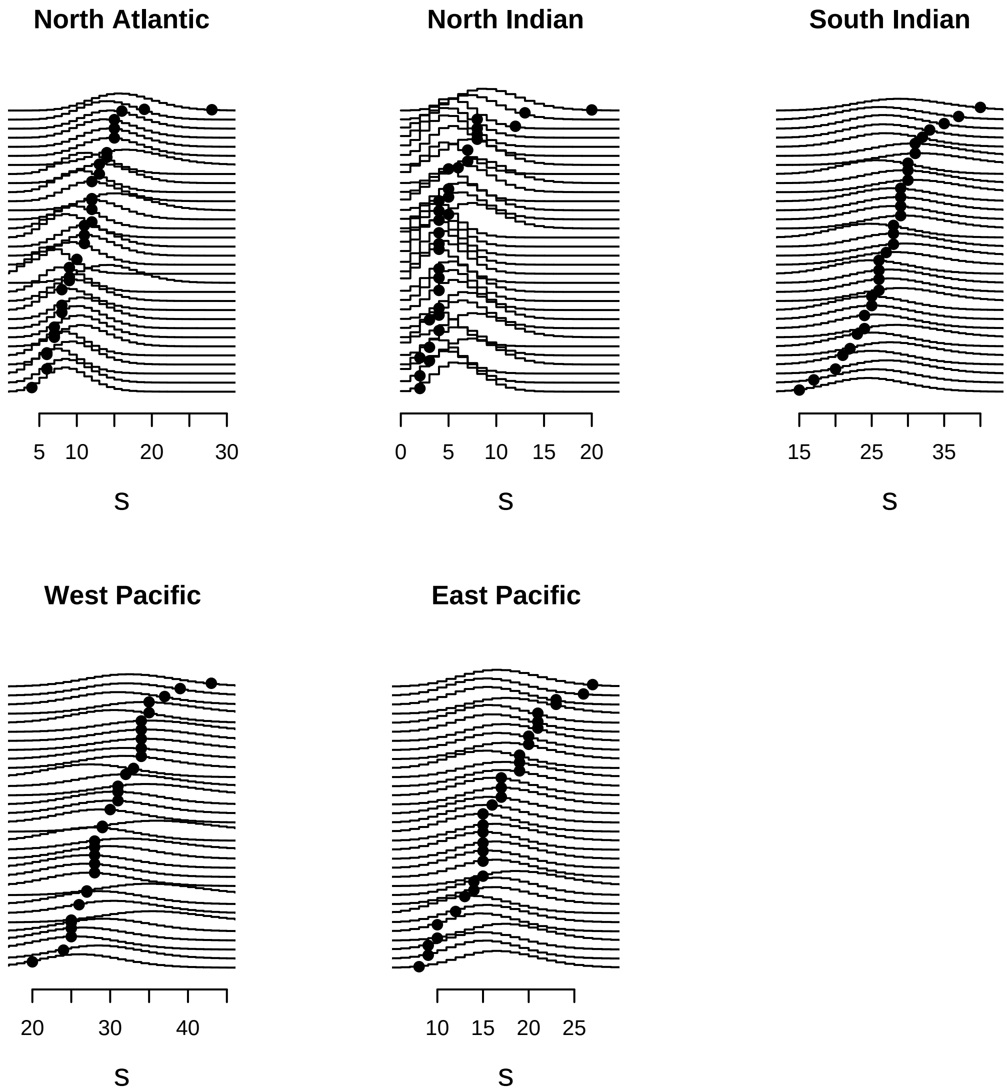

FIG. 5. The posterior predictive distrbution of s_{ij}, sorted, in each ocean, from the smallest to largest number of storms (this plot is *not* a time series). A small positive number has been added to each distribution so that all fit on one plot. Further, the actual value realized is plotted as a filled circle on the distribution. Most observations fall near the mode of the predictive distribution, giving evidence that the model is good.

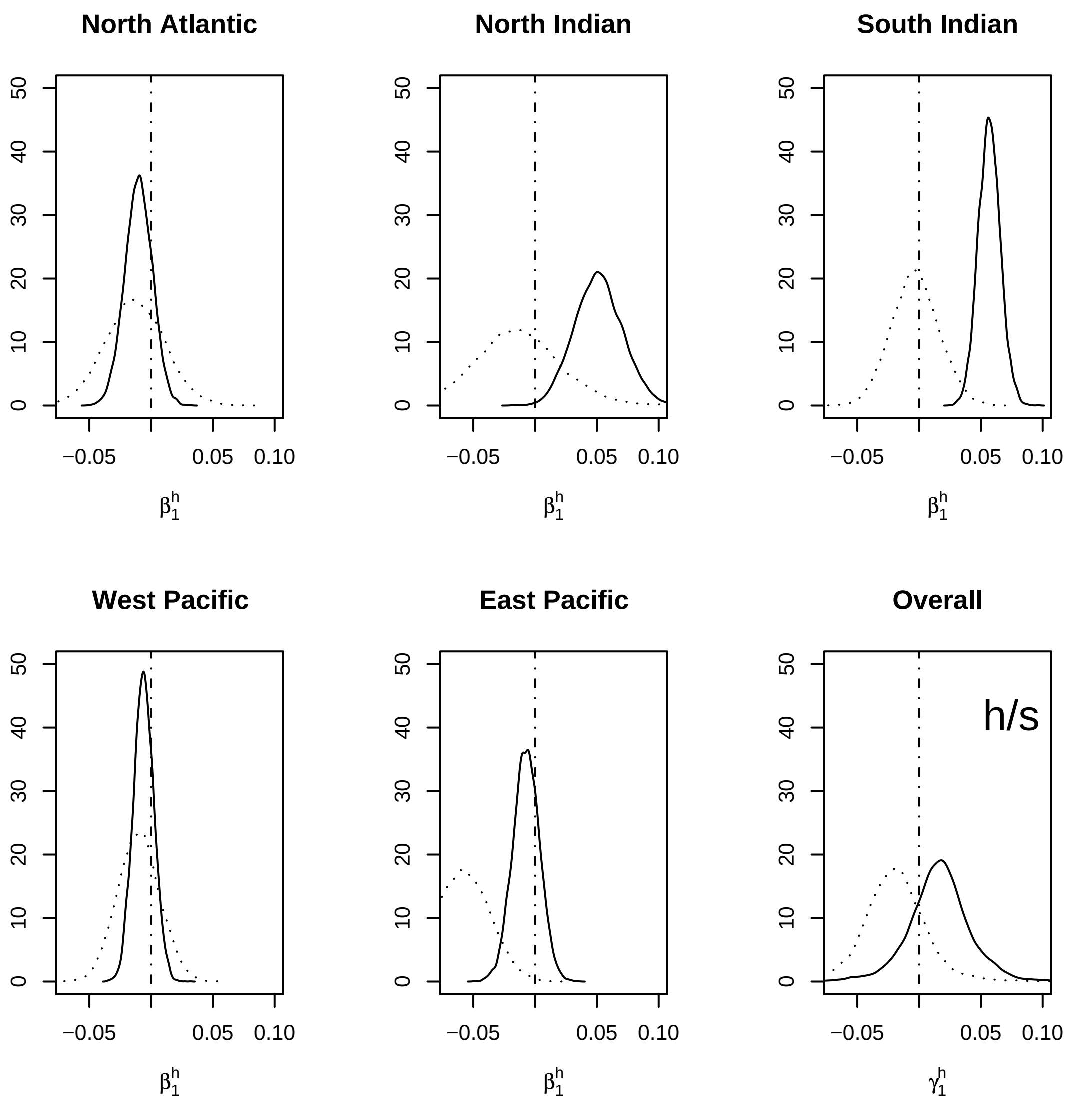

FIG. 6. The posteriors of β_{i1}^h and γ_1^h (the regressor for change in time) for each ocean i for the model of h/s.

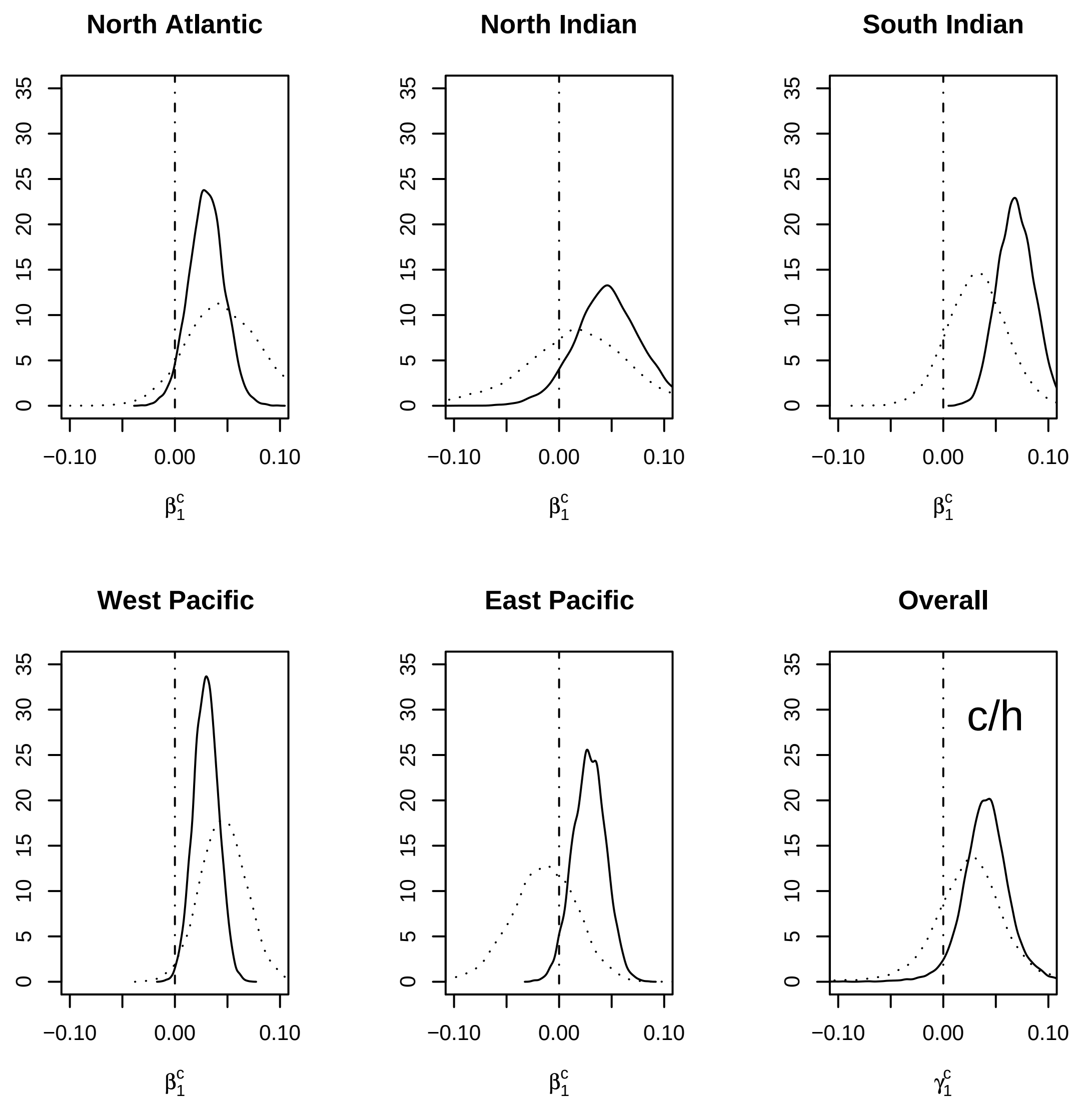

FIG. 7. The posteriors of β_{i1}^c and γ_1^c (the regressor for change in time) for each ocean i for the model of c/h.

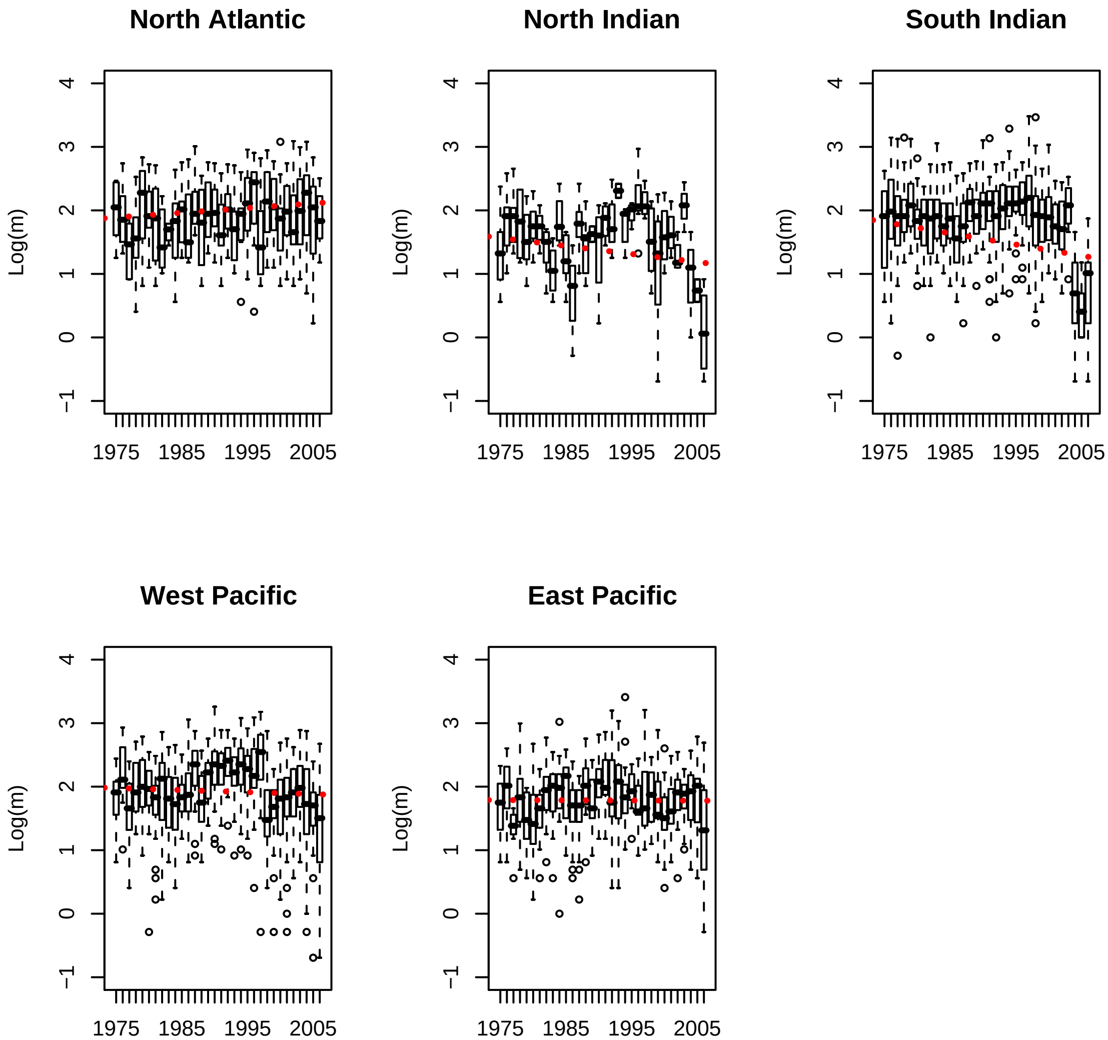

FIG. 8. The time series of boxplots, for each year and each ocean, of $\log(m)$. A simple dashed trend line of the medians in overlayed.

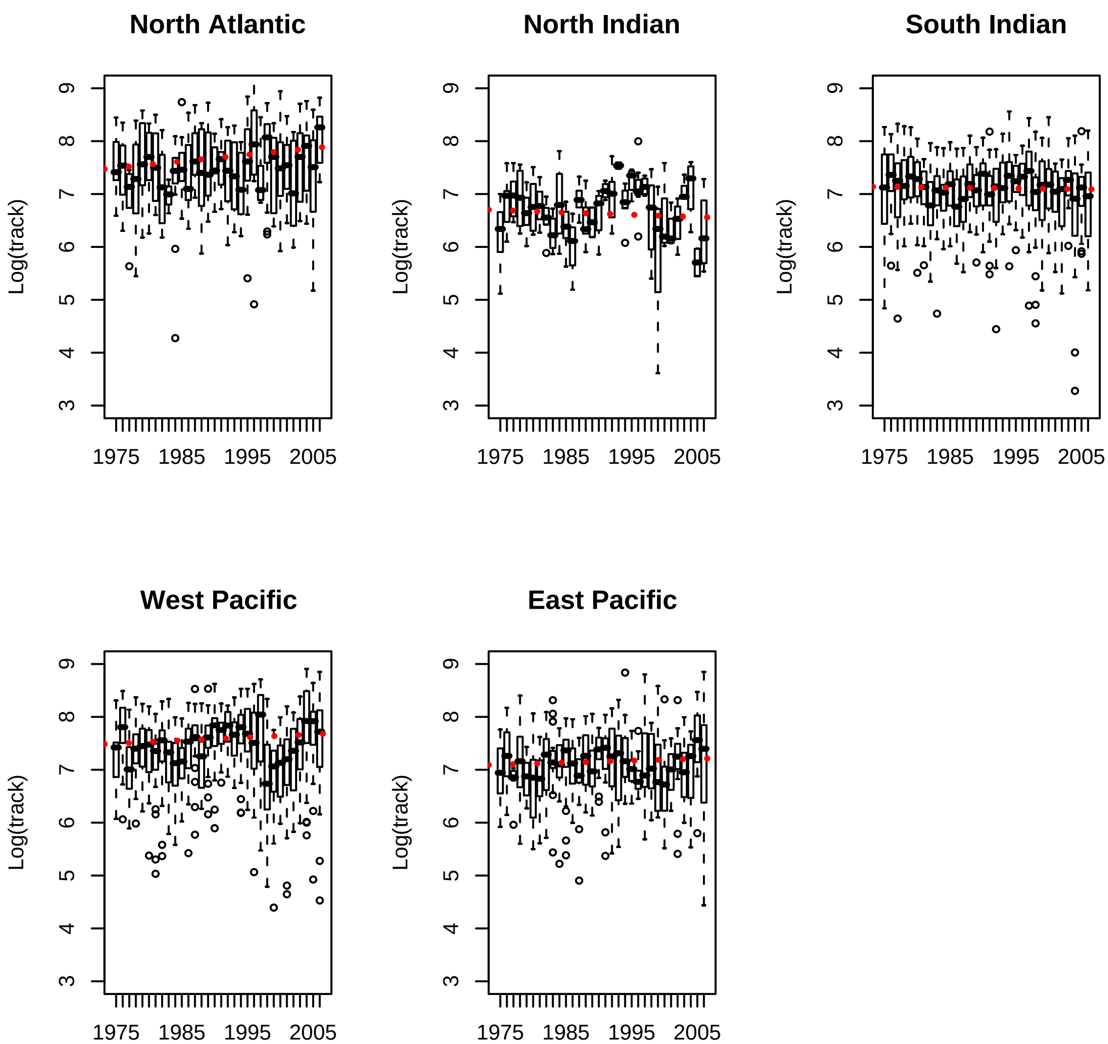

Fig. 9. The time series of boxplots, for each year and each ocean, of log(track length). A simple dashed trend line of the medians in overlayed.

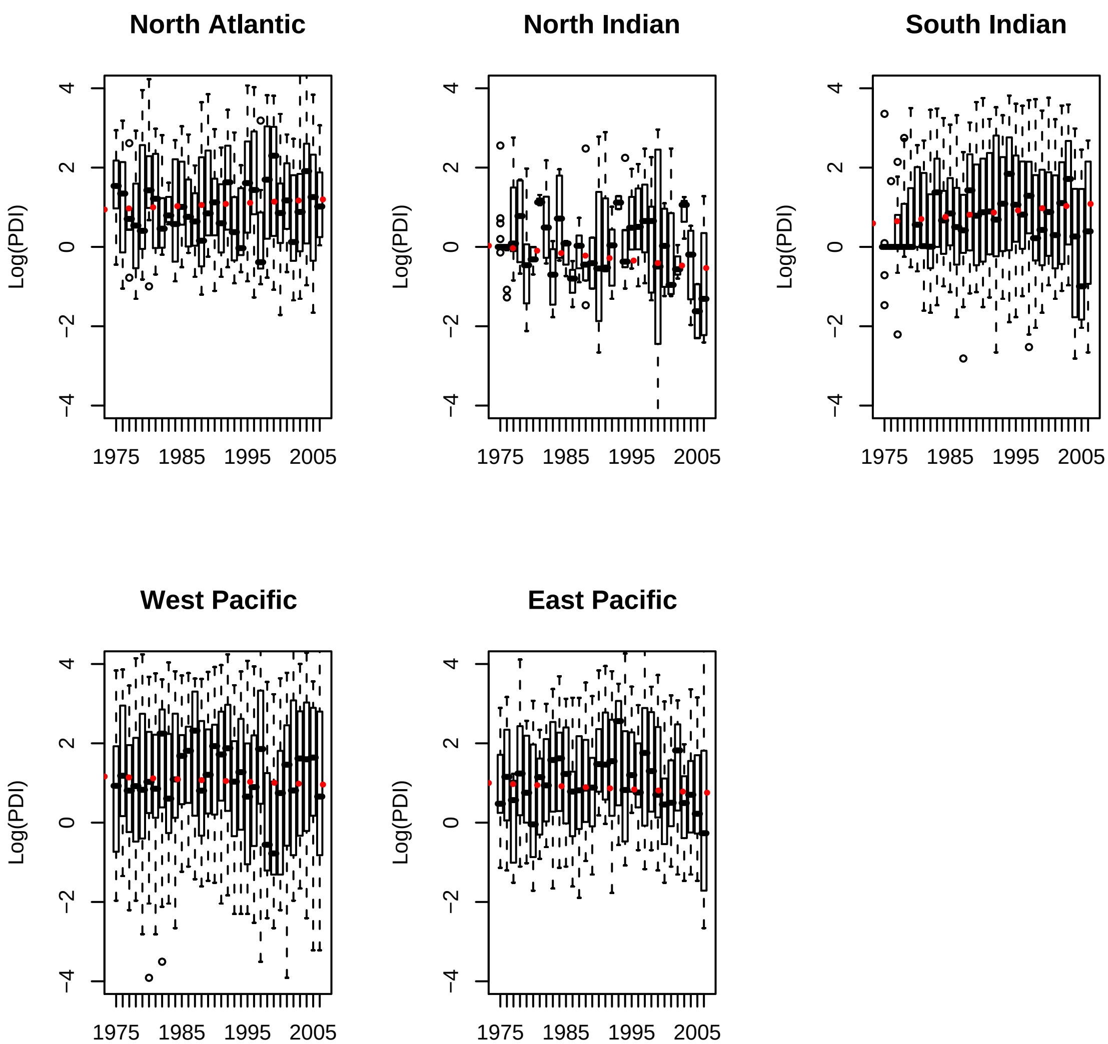

FIG. 10. The time series of boxplots, for each year and each ocean, of log(PDI). A simple dashed trend line of the medians in overlayed.

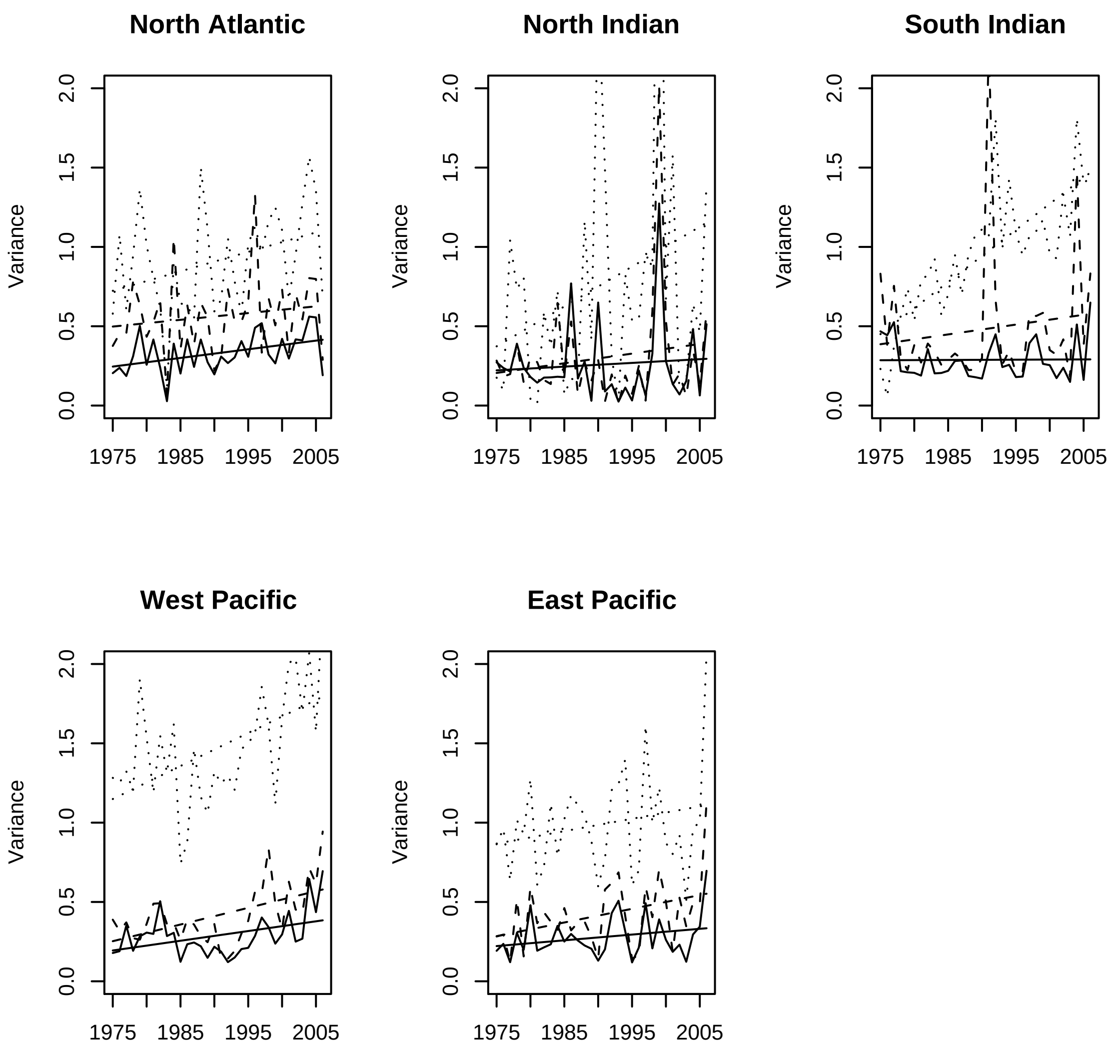

FIG. 11. The estimated variance of log(m) (solid line), log(track) (dashed), and log(PDI) (dotted). Log(PDI) has been scaled by dividing by 2 so that all data fits on one picture. The is a clear increase in variability of each measure.

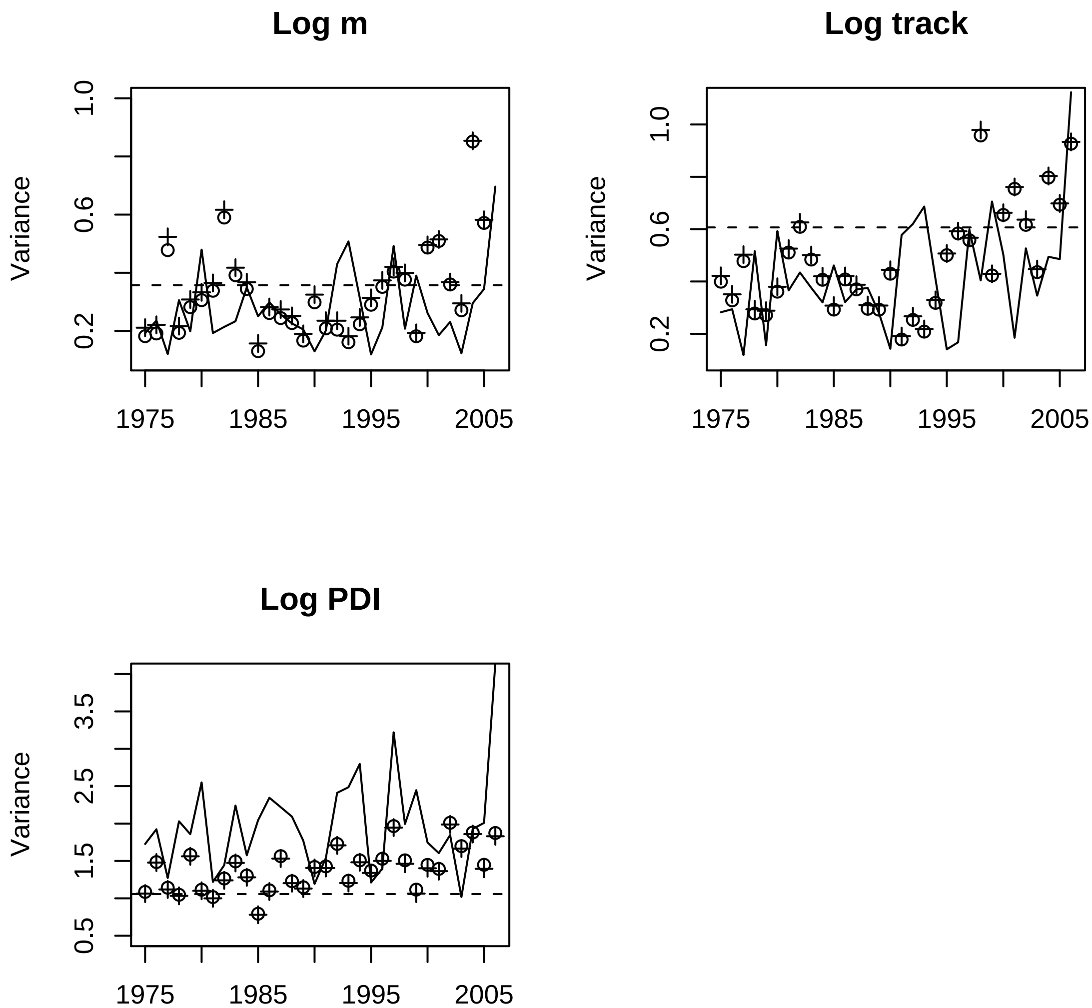

FIG. 12. For the Western Pacific, four estimates of the year-by-year variance of intensity: the classical point estimate (solid line); posterior median based on the increasing variance prior (17) (open circles); the posterior median based on the non-informative year-by-year prior; the posterior median based on the simple ocean prior (17) (dashed line).

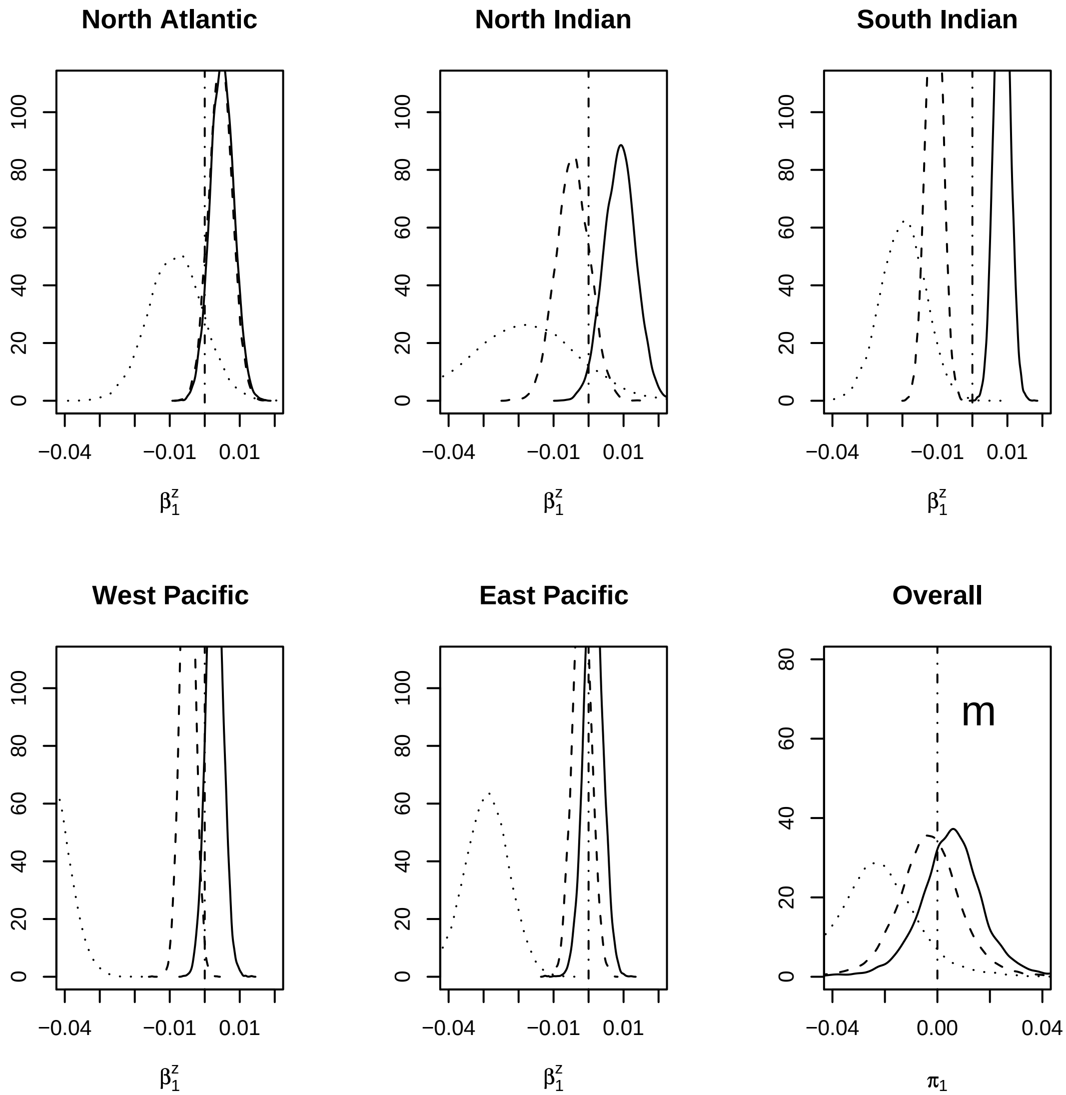

FIG. 13. The marginal posteriors of β_1^z and π_1 for $\log(m)$ across all oceans. The solid line represents the posteriors with the increasing variance prior; the dashed line is for the simple, constant non-informative prior: both using data from 1975. The dotted line uses (17) for the data from 1990. The results for both priors, however, are in rough agreement for the 1975-2006 dataset; but see the text for a discussion of the South Indian ocean.

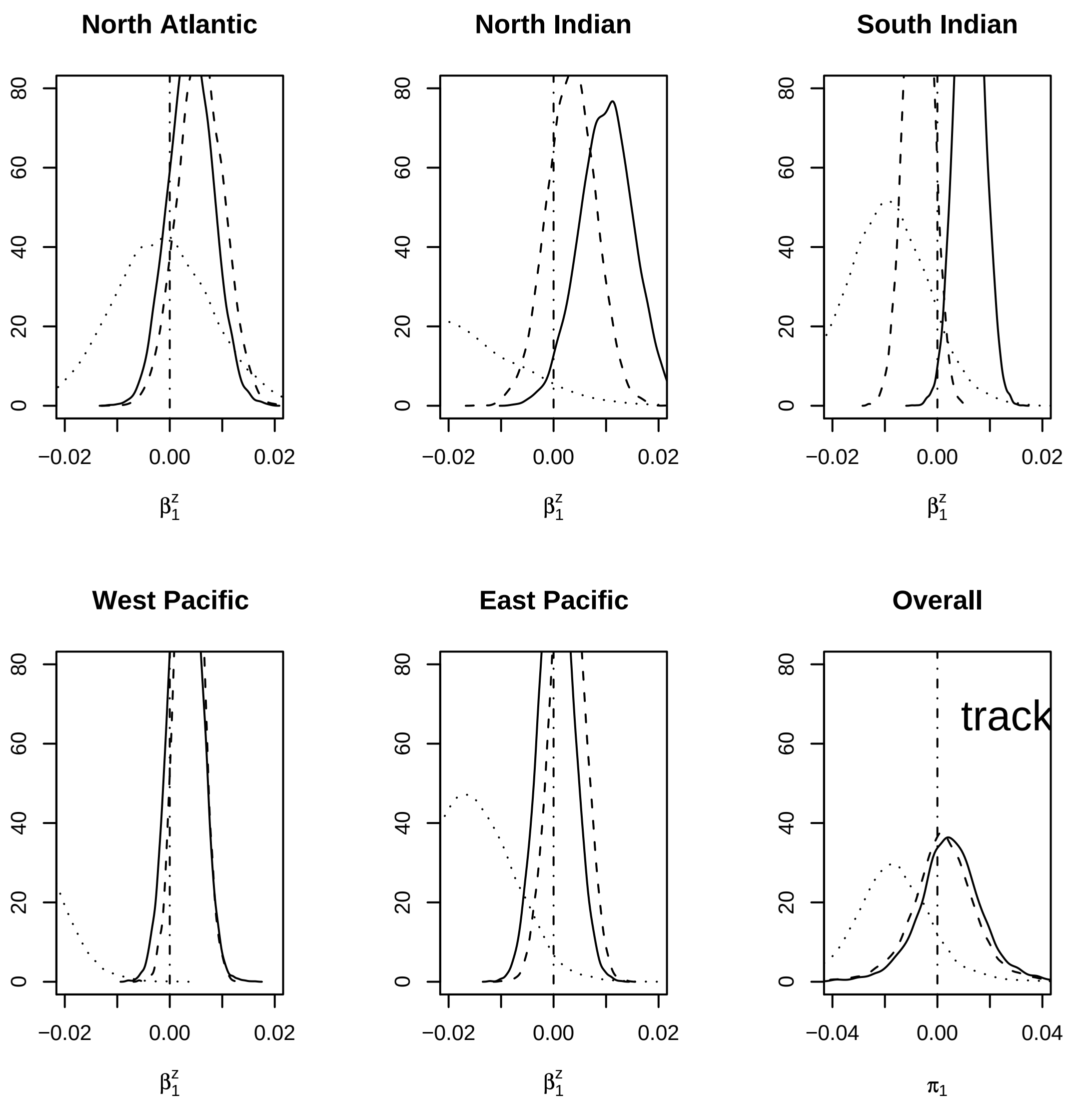

FIG. 14. The same as Fig. 13 but for log(track). Here, both variance priors give closer agreement.

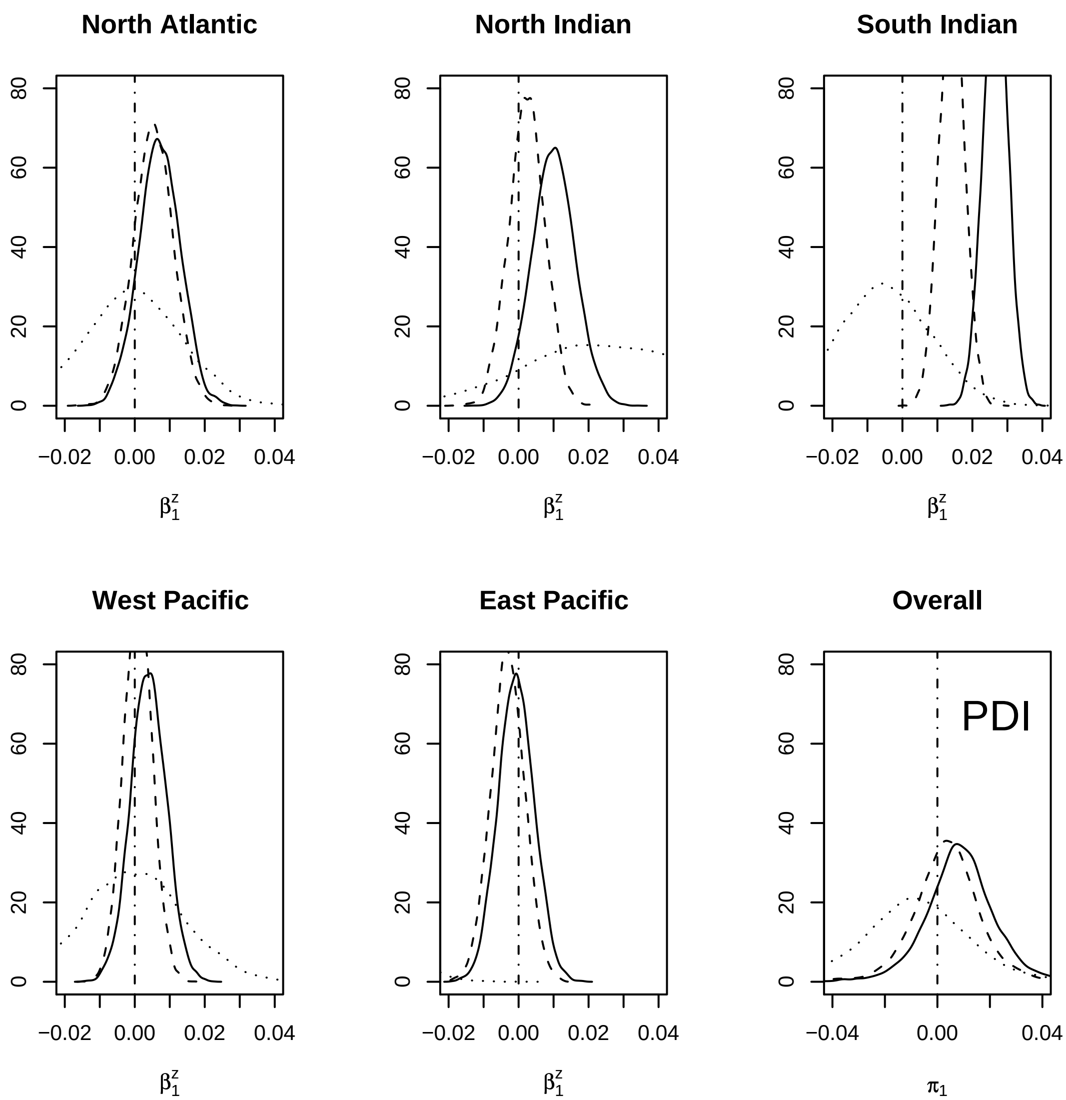

FIG. 15. The same as Fig. 13 but for log(PDI). Here, both variance priors give closer agreement for the 1975-2006 data except for the South Indian ocean.