Modeling the Dependence of Tropical Storm Counts in the North Atlantic Basin on Climate Indices

GABRIELE VILLARINI

Department of Civil and Environmental Engineering, Princeton University, Princeton, New Jersey

GABRIEL A. VECCHI

NOAA/Geophysical Fluid Dynamics Laboratory, Princeton, New Jersey

JAMES A. SMITH

Department of Civil and Environmental Engineering, Princeton University, Princeton, New Jersey

(Manuscript received 11 December 2009, in final form 1 February 2010)

ABSTRACT

The authors analyze and model time series of annual counts of tropical storms lasting more than 2 days in the North Atlantic basin and U.S. landfalling tropical storms over the period 1878–2008 in relation to different climate indices. The climate indices considered are the tropical Atlantic sea surface temperature (SST), tropical mean SST, the North Atlantic Oscillation (NAO), and the Southern Oscillation index (SOI). Given the uncertainties associated with a possible tropical storm undercount in the presatellite era, two different time series of counts for the North Atlantic basin are employed: one is the original (uncorrected) tropical storm record maintained by the National Hurricane Center and the other one is with a correction for the estimated undercount associated with a changing observation network. Two different SST time series are considered: the Met Office's HadISSTv1 and NOAA's Extended Reconstructed SST.

Given the nature of the data (counts), a Poisson regression model is adopted. The selection of statistically significant covariates is performed by penalizing models for adding extra parameters and two penalty functions are used. Depending on the penalty function, slightly different models, both in terms of covariates and dependence of the model's parameter, are obtained, showing that there is not a "single best" model. Moreover, results are sensitive to the undercount correction and the SST time series.

Suggestions concerning the model to use are provided, driven by both the outcomes of the statistical analyses and the current understanding of the underlying physical processes responsible for the genesis, development, and tracks of tropical storms in the North Atlantic basin. Although no single model is unequivocally superior to the others, the authors suggest a very parsimonious family of models using as covariates tropical Atlantic and tropical mean SSTs.

1. Introduction

Understanding, explaining, and predicting variations and changes in tropical storm (TS; defined as tropical cyclones with maximum sustained winds exceeding 17 m s^{-1}) frequency is a topic of profound societal significance (e.g., Pielke and Landsea 1998, 1999; Rappaport 2000; Arguez and Elsner 2001; Negri et al. 2005; Ashley and Ashley 2008a; Pielke et al. 2008; Derrig et al. 2008; Saunders and Lea 2005; Ashley and Ashley 2008b) and intense scientific interest. The occurrence and intensity of TSs has varied on many time scales, from intraseasonal to multidecadal (e.g., Goldenberg et al. 2001; Bell and Chelliah 2006; Holland and Webster 2007; Chylek and Lesins 2008). Furthermore, it has been argued that TS frequency and intensity may be sensitive to changes in atmospheric composition in response to anthropogenic increases of greenhouse gases (e.g., Henderson-Sellers et al. 1998), anthropogenic aerosols (e.g., Mann and Emanuel 2006), and natural aerosols (Evan et al. 2006). However, even the sign of the sensitivity of North Atlantic TS

Corresponding author address: Gabriele Villarini, Department of Civil and Environmental Engineering, Princeton University, Engineering Quadrangle, Princeton, NJ 08540.
E-mail: gvillari@princeton.edu

DOI: 10.1175/2010MWR3315.1

© 2010 American Meteorological Society

frequency to increased greenhouse gases remains elusive (e.g., Trenberth 2005; Shepherd and Knutson 2007; Vecchi et al. 2008b), with studies suggesting an increase (e.g., Emanuel 2005; Mann and Emanuel 2006; Oouchi et al. 2006; Holland and Webster 2007), decrease (e.g., Bengtsson et al. 2007; Knutson et al. 2008; Gualdi et al. 2008), or a possibility for either (Emanuel et al. 2008; Sugi et al. 2009; Zhao et al. 2009).

Whether we are already experiencing a change in TS frequency from increases in greenhouse gas concentrations remains a topic of vigorous discussion; whether the number of tropical storms in the North Atlantic basin has increased since the late nineteenth century and whether the unambiguous increase over the last 20 years is part of a long-term secular change remain unsettled.

Developing a robust empirical understanding of the connections between frequency and large-scale climate conditions is an essential step in order to improve our predictive and explanatory understanding of TS variations. Multiple studies have associated tropical storm activity with different climate indices, such as Atlantic (e.g., Shapiro and Goldenberg 1998; Landsea et al. 1999; Vitart and Anderson 2001; Emanuel 2005; Jagger and Elsner 2006; Bell and Chelliah 2006; Hoyos et al. 2006; Saunders and Lea 2008) and tropical (e.g., Latif et al. 2007; Vecchi and Soden 2007; Swanson 2008; Knutson et al. 2008; Vecchi et al. 2008b) sea surface temperature (SST), West African monsoon (e.g., Gray 1990; Landsea and Gray 1992; Goldenberg and Shapiro 1996; Bell and Chelliah 2006; Donnelly and Woodruff 2007), El Niño–Southern Oscillation (e.g., Gray 1984; Wu and Lau 1992; Bove et al. 1998; Elsner et al. 2001; Jagger et al. 2001; Tartaglione et al. 2003; Elsner et al. 2004; Bell and Chelliah 2006; Camargo et al. 2007; Donnelly and Woodruff 2007), North Atlantic Oscillation (NAO; Elsner et al. 2000b; Elsner and Kocher 2000; Elsner et al. 2000a; Jagger et al. 2001; Elsner et al. 2004; Elsner and Jagger 2004; Pinto et al. 2009), Atlantic multidecadal oscillation (e.g., Zhang and Delworth 2006; Goldenberg et al. 2001), Atlantic Meridional Mode (Vimont and Kossin 2007; Kossin and Vimont 2007), quasi-biennal oscillation (e.g., Shapiro 1982; Gray 1984), and Madden–Julian oscillation (Maloney and Hartmann 2000; Barrett and Leslie 2009; Camargo et al. 2009). However, questions concerning which of these climate indices (or what combination) are most significant and should be included in modeling the tropical storm counts are still debated.

Records of past TS activity provide a basis for empirical models, guiding our assessment of future possibilities for the North Atlantic basin. The Hurricane Database (HURDAT; Jarvinen et al. 1984; Neumann et al. 1993) represents the foundation of many studies. It is maintained by the National Hurricane Center (NHC) and provides location (latitude and longitude), and information about maximum wind speed and minimum pressure of the center of circulation (every 6 h) for recorded tropical storms from 1851 to the present. Yet observing capabilities over this long period have changed considerably, resulting in a possibly inhomogeneous dataset. This inhomogeneity has resulted in criticisms of the reliability of the first part of the record, possibly explaining some of the contradictory results concerning the presence (or absence) of significant trends during the twentieth century. To deal with this shortcoming, several different corrections have been proposed (e.g., Landsea et al. 2004; Landsea 2007; Mann et al. 2007; Chang and Guo 2007; Vecchi and Knutson 2008; Landsea et al. 2010). Accurate count data for the earliest part of the record would allow extending the record back in time with confidence, without having to only rely on the data from the satellite era (from 1966), yet it is clear that we will never know the exact count of tropical storms in the North Atlantic basin. However, comparing the results obtained from the original and corrected HURDAT datasets would provide information about the sensitivity of the results to plausible estimates of data undercount.

Uncertainties in the reference datasets combined with incomplete understanding of physical processes could significantly affect our capability to make meaningful statements about the future. To answer questions about the presence of increasing trends in the data as well as to improve our understanding of the physical mechanisms, two main venues are possible: dynamical models (e.g., Knutson and Tuleya 1999; Sugi et al. 2002; Knutson and Tuleya 2004; Chauvin et al. 2006; Emanuel 2006; Bengtsson et al. 2007; Knutson et al. 2007; LaRow et al. 2008; Emanuel et al. 2008) or statistical–empirical models (e.g., McDonnell and Holbrook 2004a,b; Elsner et al. 2004; Elsner and Jagger 2004; Sabbatelli and Mann 2007; Elsner et al. 2008; Mestre and Hallegatte 2009). The former reflect our understanding of the physical processes, while the latter are used to draw information on physical processes from the existing data. These two approaches represent distinct ways of tackling this problem, which should complement each other.

In this study we use a statistical approach to shed light on the relation between tropical storm count and climate indices. Statistical modeling of the count data has been the object of studies in the past (e.g., Sabbatelli and Mann 2007; Mestre and Hallegatte 2009). Here we build on and expand these previous works. We model not only the count data for the entire North Atlantic basin but also the U.S. landfall events. Moreover, we restrict our analysis on basin-wide frequency of TSs lasting longer than 2 days since it has been argued that an inhomogeneity is likely to exist in the count of storms of shorter

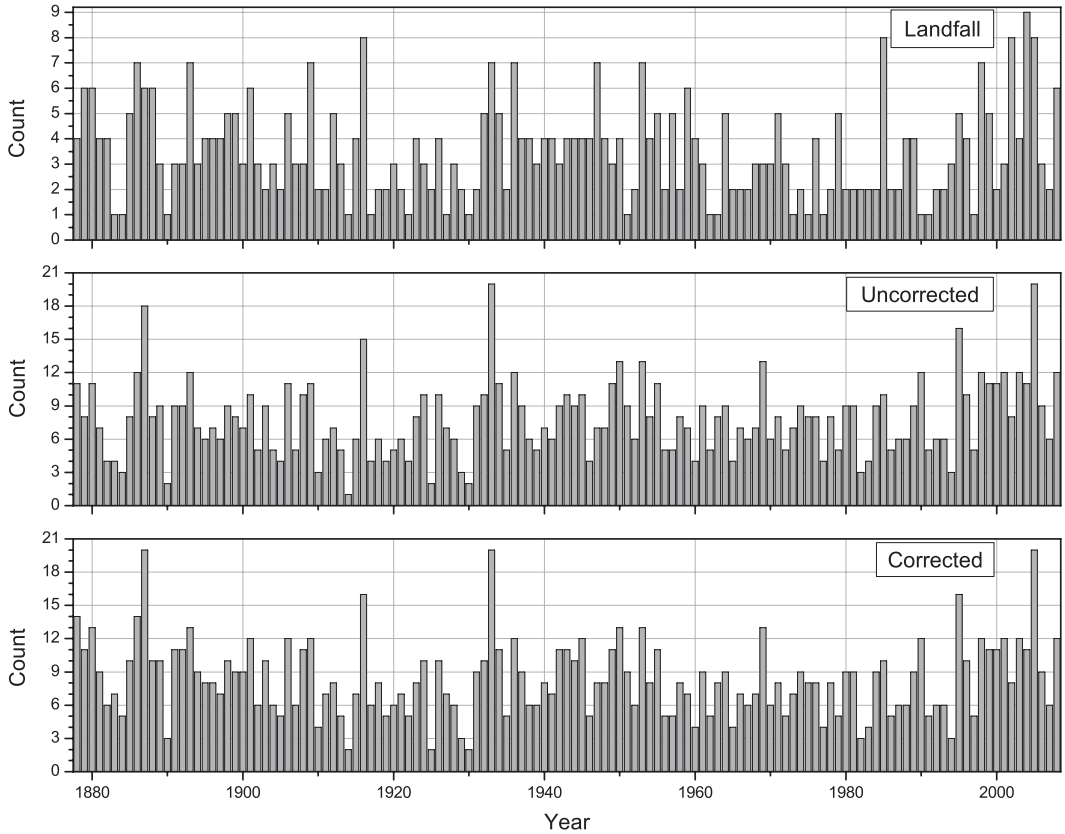

FIG. 1. Time series of the count of (top) U.S. landfalling tropical storms and of (bottom two) North Atlantic basin storms lasting more than two days. (middle) The time series refers to the original HURDAT dataset, while (bottom) accounts for the correction by Landsea et al. (2010).

duration (Landsea et al. 2010). Furthermore, since we cannot neglect the likelihood that the HURDAT data is affected by storm undercount, we consider two datasets: one in which we use the 2-day duration HURDAT data at its "face value" and one in which we apply the recent correction by Landsea et al. (2010) based on Vecchi and Knutson (2008). It will be interesting to see how different the models are for these two datasets. In contrast with other statistical models, we also include tropical SST as a possible covariate, reflecting the idea that warming of the North Atlantic relative to the tropical oceans is more important than the absolute Atlantic warming (e.g., Latif et al. 2007; Vecchi and Soden 2007; Swanson 2008; Knutson et al. 2008; Vecchi et al. 2008b). Finally, the selection of significant covariates will be driven by both statistical and physical reasoning.

Poisson regression represents the natural statistical framework to model tropical storm counts. The key assumption is that the counts are conditionally Poisson, given appropriate covariate random variables. The model simplifies to a standard Poisson distribution if the covariate is a constant rate parameter. This formulation provides a useful approach to examining the dependence of counts on climate indices, assessing overdispersion or underdispersion of counts (relative to the Poisson model), and characterizing temporal dependence of counts on covariate processes. We also examine counts through estimation of parameters of a negative binomial distribution. This distribution has an extra parameter compared to the Poisson distribution that allows modeling overdispersion of count data.

In this study we address the following questions:

1) Can the count data for the North Atlantic basin and U.S. landfall be modeled by a Poisson distribution with constant parameters? Are the counts overdispersed or underdispersed?
2) Which covariates are significant in modeling the tropical storm count data?
3) What is the sensitivity of these models to estimates of tropical storm undercount?

The paper is organized as follows. In section 2 we describe the data and the different climate indices used in this study. In section 3 we provide a brief description of the different statistical models used to describe the data. Section 4 describes the results of our analysis,

while in sections 5 and 6 we discuss some of the issues related to this study and conclude the paper.

2. Data

a. HURDAT dataset

Count data for tropical storms in the North Atlantic basin have been available since 1851 and represent the backbone of studies examining trends in the frequency of tropical storms over the past 150 years. Unfortunately this record is not homogeneous: until 1943 it is based on accounts from ships traveling over the North Atlantic basin and reports of their landfall (even in the ship observing period, observations are not homogeneous and reflect changes over time in the ship tracks; Vecchi and Knutson 2008). Starting in 1944, the ship record is complemented by organized aircraft reconnaissance flights. Finally, starting in 1966, the record is based on satellite observations. The earliest part of this record (in particular before 1944) has been the object of criticism because of the likely storm undercount, and different corrections have been proposed. One of the most recent ones is by Landsea et al. (2010). This correction takes the lead from the approach proposed in Vecchi and Knutson (2008) and focuses on storms lasting more than two days. This correction is not constant over time but tends to be larger the further back in time we go, representing the degree of uncertainty in the current record.

In this study we focus on modeling both the overall count of tropical storms lasting more than two days for the North Atlantic basin and the count of storms making landfall in the United States (it is also possible that in the nineteenth century a small number of these storms may have not been recorded; e.g., Landsea et al. 2004, 2008) during the period 1878–2008. As far as the former is concerned, we analyze storms lasting more than two days and consider both the original HURDAT dataset and the one corrected according to Landsea et al. (2010). We will refer to the former as "uncorrected" and to the latter as "corrected."

In Fig. 1 we show the time series of count data. In the top panel we have the count data for the U.S. landfalling tropical storms. The data exhibit a certain degree of interdecadal variability, with periods of higher activity alternating with periods of lower activity. This variability is also present in the overall count for the North Atlantic basin (Fig. 1). The undercount correction is more evident in the earlier part of the record, and it becomes smaller the closer we get to the satellite era.

b. Climate indices

The relation between tropical storms and climate indices has been the object of several studies. In this study,

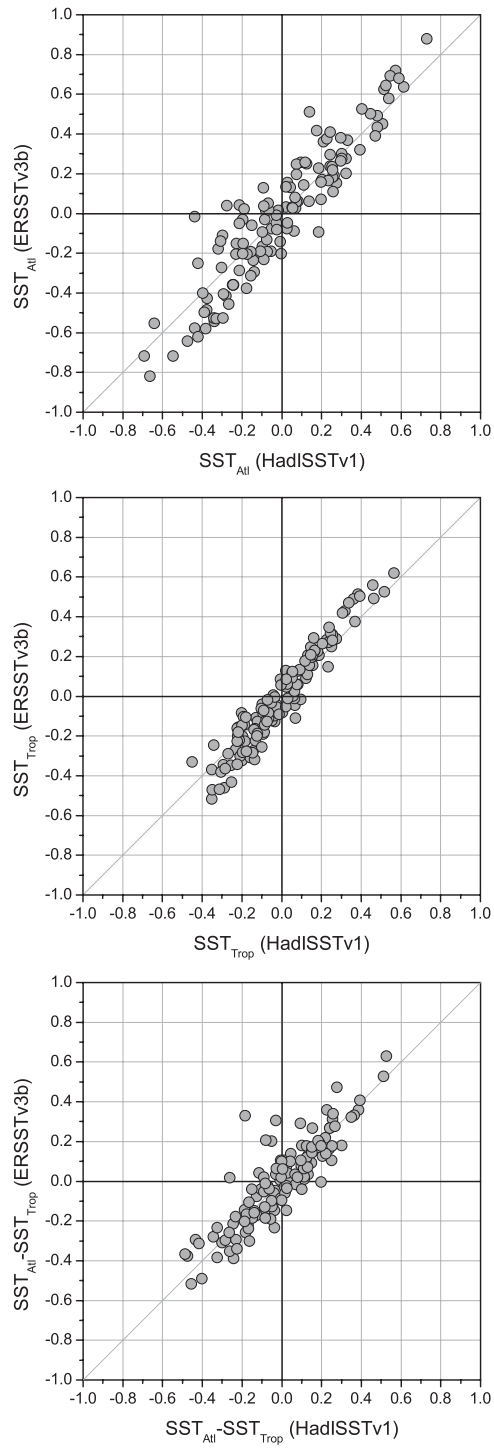

FIG. 2. Scatterplots of the (top) tropical Atlantic SST, (middle) tropical mean SST, and (bottom) tropical Atlantic minus tropical mean SST averaged over the period June–November based on the Met Office's HadISSTv1 and NOAA's ERSSTv3b. The light gray line corresponds to the $x = y$ line.

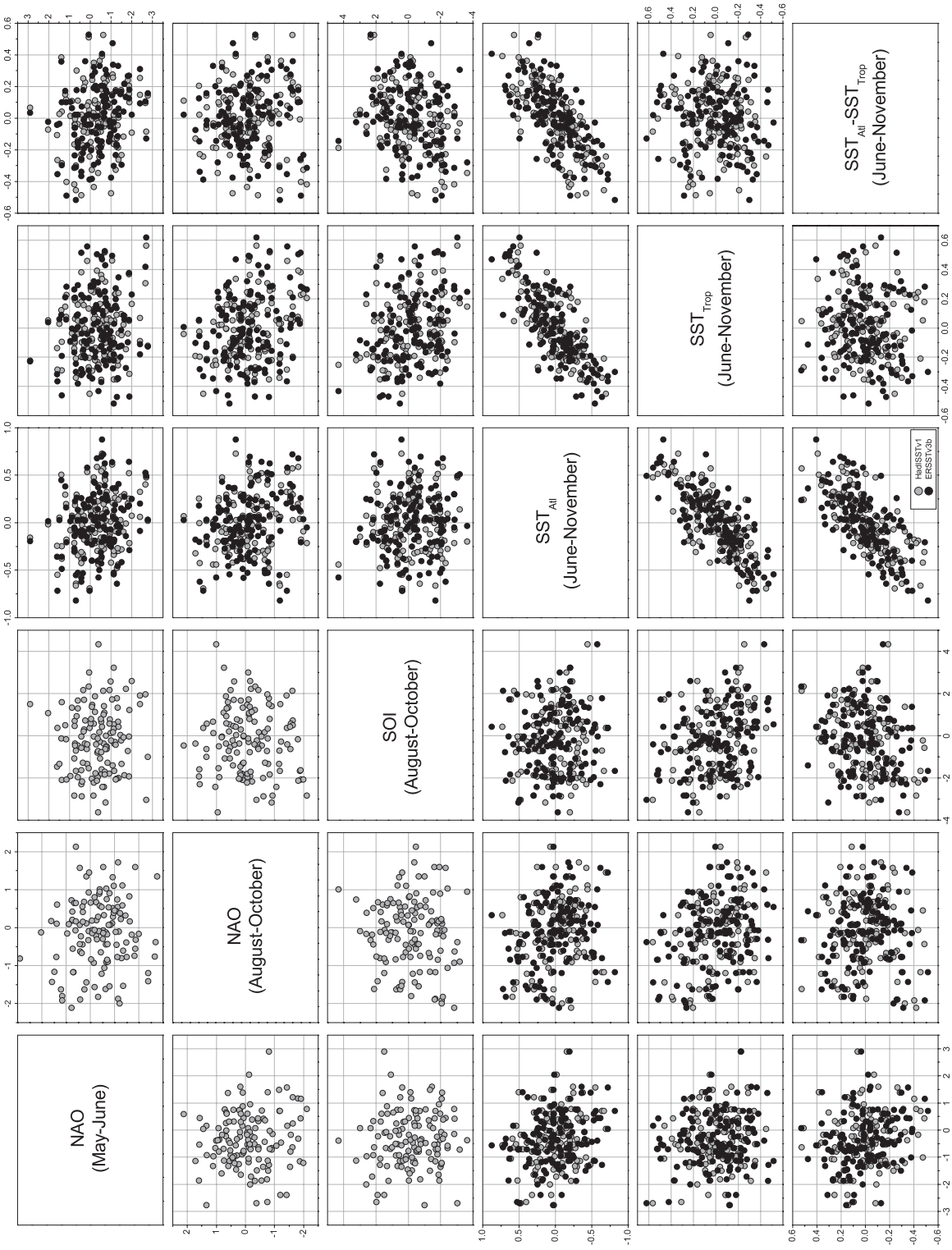

FIG. 3. Scatterplots of the different climate indices used in this study.

we focus our attention on four of these indexes [tropical Atlantic SST (SST_{Atl}), tropical mean SST (SST_{Trop}), Southern Oscillation index (SOI), and NAO] since relatively high-quality data are available for the time period of interest in this study. Various studies have investigated the physical relation between these climate indexes and tropical storms. For example, increasing vertical shear of the upper-level horizontal winds associated with El Niño events tends to suppress tropical storm genesis and development (e.g., DeMaria 1996). In general, a warmer Atlantic would result in increasing tropical storm activity. However, recent studies have suggested that the warming of the Atlantic relative to the state of the tropical ocean may be a better predictor for increasing North Atlantic tropical storm activity than Atlantic SST alone. The possible relation between tropical storms and NAO resides in the relation between the strength of the trade winds and the position of the Bermuda high, which could also affect the steering of the tropical storm tracks.

In this study, the Atlantic SST anomalies are computed for a box 10°–25°N, 80°–20°W while the tropical SST is computed over a box 30°S–30°N (ocean only), averaged over the period June–November. We consider SST time series from two datasets: version 1 of the Met Office's Hadley Centre Sea Ice and SST (HadISSTv1 (Rayner et al. 2003) and the National Oceanic and Atmospheric Administration (NOAA) Extended Reconstructed SST (ERSSTv3b; Smith et al. 2008). As shown in Fig. 2, there are some differences between the two datasets, likely related to the different approaches used to fill in missing sea surface temperature values, different corrections to changing instrumental methods (e.g., the "bucket to intake" adjustment), and different use of the satellite record. These discrepancies tend to be larger for the Atlantic SST compared to the tropical SST, which exhibits a better agreement. In this study we investigate the sensitivity of our models to the two SST datasets. The SOI time series is as in Trenberth (1984) and averaged over the period August–October. Finally, the NAO time series is as in Jones et al. (1997). We consider two averaging periods since the pressure differences used to compute NAO are stronger during the boreal winter and spring (e.g., Hurrell and Van Loon 1997): one that includes May and June (e.g., Elsner et al. 2001; Elsner 2003; Elsner et al. 2004) and one that includes August–October (Elsner et al. 2000b; Mestre and Hallegatte 2009), which represents the core of the tropical storm season. Therefore, we consider five possible predictors to model tropical storm count data: SST_{Atl}, SST_{Trop}, SOI, NAO averaged over May–June, and NAO averaged over August–October. In Fig. 3 we have plotted the scatterplots of the different climate indices. The strongest linear relation is between SST_{Atl} and SST_{Trop}. We also notice that NAO (averaged over May–June and August–October) tends to anticorrelated with SST_{Atl}, while SST_{Trop} seems to be anticorrelated with SOI, representing the tendency of El Niño to be associated with warmer tropics.

3. Statistical models

Denoting the counts in year i by N_i, we say that N_i has a conditional Poisson distribution with rate Λ_i provided that

$$P(N_i = k|\Lambda_i) = \frac{e^{-\Lambda_i}\Lambda_i^k}{k!} \quad (k = 0, 1, 2, \ldots), \tag{1}$$

where Λ_i is a nonnegative random variable.

Poisson regression is a form of regression in which the response variable is in the form of count data. More specifically, it is a form of generalized additive model (GAM) in which the response variable is Poisson distributed (e.g., Hastie and Tibshirani 1990). We will examine the rate of occurrence Λ_i of the following form:

$$\Lambda_i = \exp[\beta_0 + \beta_1 h_1(x_{1,i}) + \beta_2 h_2(x_{2,i}) + \cdots + \beta_n h_n(x_{n,i})], \tag{2}$$

where $(x_{1,i}, \ldots, x_{n,i})$ is a vector of observable covariate random variables for year i [see Smith and Karr (1986) and Karr (1991) for a more general formulation]. These will include Atlantic and tropical SSTs, NAO, and SOI.

In the special case that

$$\beta_1 = \beta_2 = \cdots = \beta_n = 0, \tag{3}$$

the model simplifies to a standard Poisson random variable with parameter $\Lambda_i = \exp(\beta_0)$.

In the case in which $h_1(\cdot), h_2(\cdot), \ldots, h_n(\cdot)$ are linear functions, we have a generalized linear model (GLM; McCullagh and Nelder 1989; Dobson 2001) of the following form:

$$\Lambda_i = \exp(\beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \cdots + \beta_n x_{n,i}). \tag{4}$$

We first consider a case in which the only covariate is time t and two different models:

$$E[N_i] = \Lambda_i = \exp(\text{constant}), \tag{5}$$

$$E[N_i] = \Lambda_i = \exp[\text{cs}(i)], \tag{6}$$

where cs(·) represents a cubic spline. The degrees of freedom of the cubic spline are optimized using the Akaike information criterion (AIC; Akaike 1974) and the Schwarz Bayesian criterion [SBC; Schwarz 1978; for

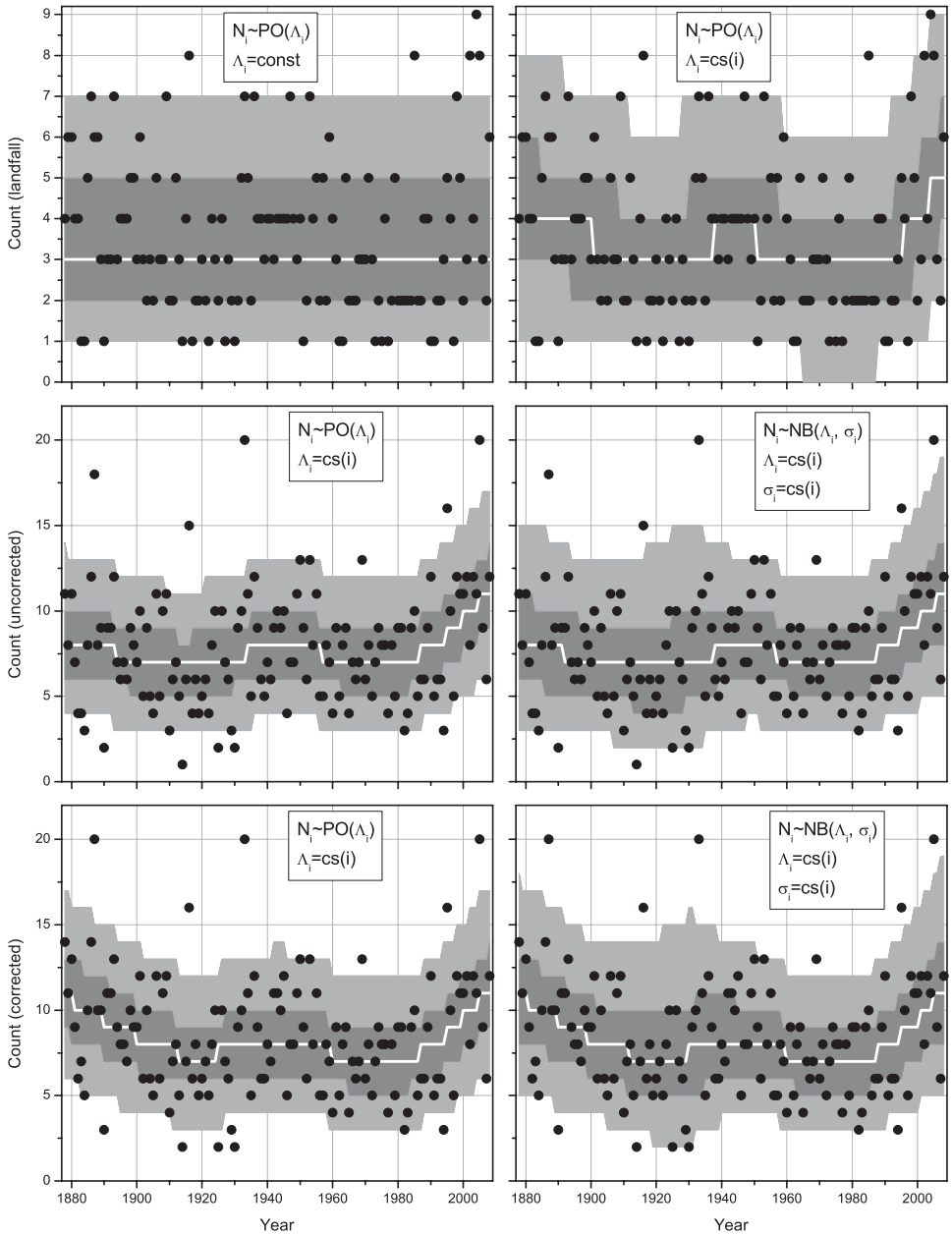

FIG. 4. Modeling the count data for (top) landfalling tropical storms, (middle) "uncorrected" HURDAT dataset, and (bottom) the HURDAT dataset with the Landsea et al. (2010) correction. The only covariate is time. The white line represents the median (50th percentile), the dark gray region the area between the 25th and 75th percentiles, and the light gray region the area between the 5th and 95th percentiles.

a discussion, consult Rigby and Stasinopoulos (2005) and Stasinopoulos and Rigby (2007)]. Notice that as the degrees of freedom tend to zero, the cubic spline tends to a straight line.

For a Poisson-distributed random variable the mean and variance are equal to Λ_i. However, it is possible that the variance is larger (smaller) than the mean, which is commonly referred to as overdispersion (underdispersion), with overdispersion being more common. To examine this behavior, we also estimate the parameters for a negative binomial model (Hilbe 2007). In this case, instead of following a Poisson distribution, the random variable N_i follows a negative binomial type I distribution (Stasinopoulos et al. 2009):

TABLE 1. Summary statistics for the modeling of tropical storm counts using time as covariate. For the parameters Λ_i and σ_i, the first value is the point estimate, while the one in parentheses is the standard error; when more than one estimate is present in a cell, the first estimate refers to the intercept, while the second one is the coefficient of the cubic spline. Four different models are summarized: "PO1" is the Poisson model with constant Λ_i; "PO2" is the Poisson model where Λ_i depends on time via an optimized cubic spline; "NB1" is the negative binomial model with constant Λ_i and σ_i; "NB2" is the negative binomial model where Λ_i and σ_i depend on time via an optimized cubic spline.

Landfall	PO1	PO2	NB1	NB2
Λ_i	1.26 (0.02)	2.58 (2.29) −0.001 (0.001)	1.26 (0.05)	−1.63 (2.29) 0.002 (0.001)
σ_i	—	—	−5.32 (7.19)	1479.7 (2.07) −0.77 (0.001)
Degrees of freedom for the fit	1	6.14	2	9.12
Mean (residuals)	−0.01	0.01	0.00	0.01
Variance (residuals)	0.94	0.91	1.00	0.80
Skewness (residuals)	0.33	0.23	0.32	0.35
Kurtosis (residuals)	2.41	2.60	2.33	2.74
Filliben (residuals)	0.991	0.996	0.988	0.993
AIC	527.3	520.3	529.3	526.1
SBC	530.2	538.0	535.0	552.3
Uncorrected				
Λ_i	2.06 (0.02)	−0.71 (1.56) 0.001 (0.001)	2.06 (0.04)	−0.46 (1.84) 0.001 (0.001)
σ_i	—	—	−2.86 (0.4)	27.03 (26.03) −0.015 (0.01)
Degrees of freedom for the fit	1	5.61	2	10.6
Mean (residuals)	−0.01	−0.02	−0.00	0.01
Variance (residuals)	1.44	1.25	1.00	0.92
Skewness (residuals)	0.40	0.27	0.19	0.13
Kurtosis (residuals)	3.59	3.35	3.54	2.84
Filliben (residuals)	0.991	0.994	0.993	0.996
AIC	692.6	681.3	683.9	678.8
SBC	695.5	697.5	689.7	709.3
Corrected	PO1	PO2	NB1	NB2
Λ_i	2.13 (0.02)	3.23 (1.48) −0.001 (0.001)	2.13 (0.04)	3.43 (1.66) −0.001 (0.001)
σ_i	—	—	−3.07 (0.44)	12.21 (30.71) −0.008 (0.02)
Degrees of freedom for the fit	1	5.82	2	10.6
Mean (residuals)	−0.03	−0.00	0.00	−0.00
Variance (residuals)	1.39	1.15	1.01	0.90
Skewness (residuals)	0.96	0.22	0.20	0.14
Kurtosis (residuals)	3.42	3.42	3.31	2.88
Filliben (residuals)	0.992	0.993	0.994	0.996
AIC	695.8	680.1	689.4	681.3
SBC	698.7	696.9	695.2	711.9

$$P(N_i|\Lambda_i,\sigma_i) = \frac{\Gamma(k+1/\sigma_i)}{\Gamma(k+1)\Gamma(1/\sigma_i)}\left[\frac{(\Lambda_i\sigma_i)^k}{\Lambda_i\sigma_i+1}\right]^{k+(1/\sigma_i)}, \qquad (7)$$

where $\Gamma(\cdot)$ is the gamma function, $\Lambda_i > 0$ is the mean, $(\Lambda_i + \sigma_i\Lambda_i^2)$ is the variance of the negative binomial distribution, and $\sigma_i > 0$ is the dispersion parameter. This distribution has one additional parameter compared to the Poisson distribution, allowing for overdispersion in the data. In this case, we consider two different models: (i) both Λ_i and σ_i are modeled as constants and (ii) both Λ_i and σ_i are modeled as optimized cubic splines.

Apart from modeling the count data as function of time, we also consider the five covariates discussed in the previous section. We include two-way interaction terms (e.g., Elsner and Jagger 2004; Mestre and Hallegatte 2009) and we do not restrict the dependence of Λ_i to a linear function (e.g., Elsner and Schmertmann 1993; Elsner et al. 2000a; Elsner and Jagger 2004, 2006; Sabbatelli and Mann 2007), but we also include smooth dependence of this parameter on these covariates via a logarithmic link function (see also Mestre and Hallegatte 2009). Moreover, to avoid model overfitting and in agreement with the parsimony principle, stepwise methods were used with respect to both AIC and SBC. The use of these criteria represents a trade-off between model complexity and precision. AIC and SBC have the following formulation:

$$\mathrm{AIC} = -2\ln(L) + 2k, \qquad (8)$$

$$\mathrm{SBC} = -2\ln(L) + k\ln(n), \qquad (9)$$

where L is the maximum likelihood value for the model, k is the number of free parameters to estimate, while n is the number of observations (in this case, $n = 131$). Since

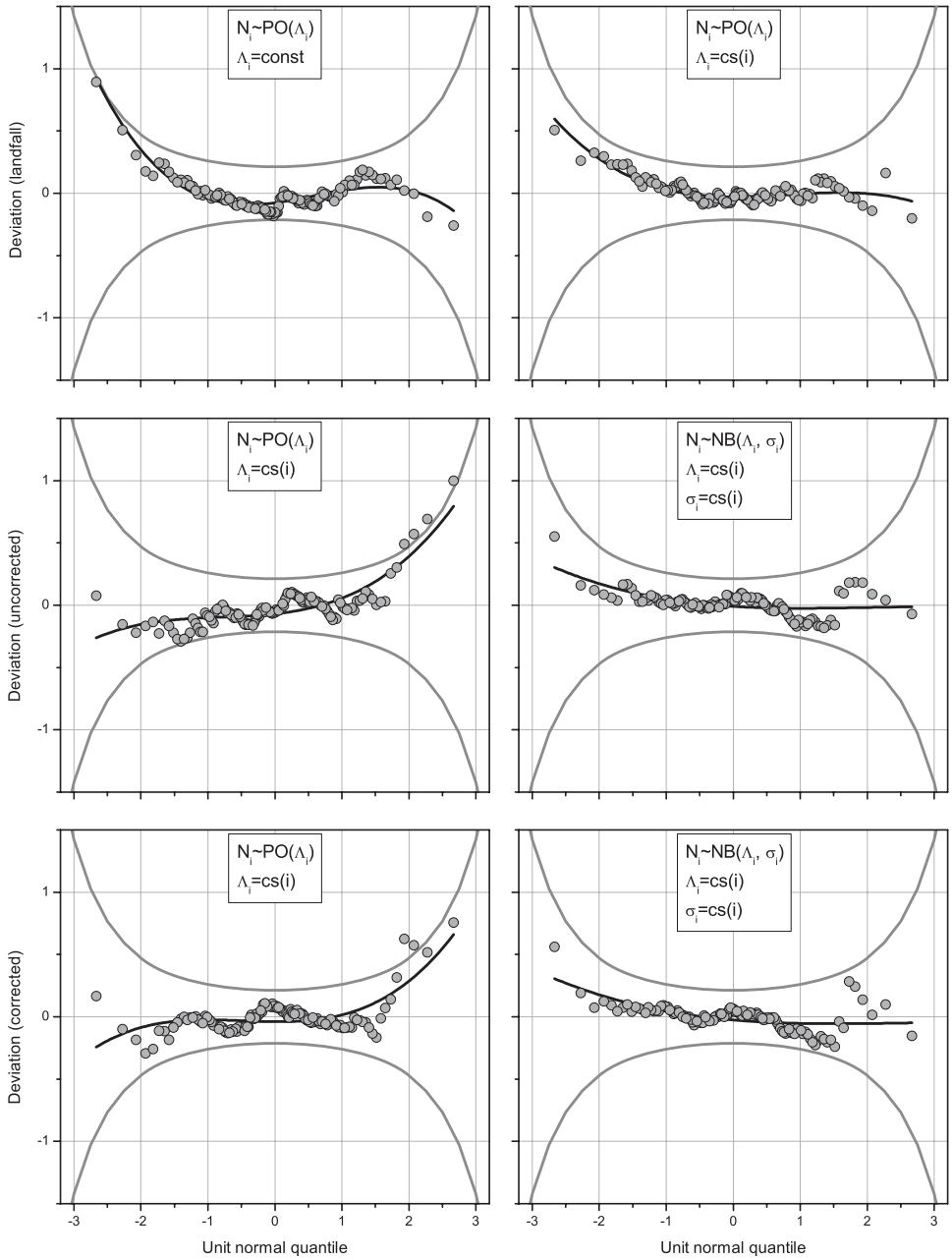

FIG. 5. Worm plots for the six models in Fig. 4. For a good fit, the points should be on the black line and between the two gray lines.

$\ln(n) \simeq 4.9$, SBC will apply a larger penalty for adding extra parameters, resulting in a more parsimonious model compared to AIC. It is clear that a local adapting function like a cubic spline provides a better representation of the data. However, it is important to evaluate whether this increase in complexity is associated with significant additional information extracted from the data. We will show how the "optimal" model depends on the selected penalty criterion. Moreover, we will also complement the statistically driven model selection with additional model configurations driven by physical reasoning.

Since AIC and SBC do not provide indications about the quality of the fit (e.g., Hipel 1981), the performance of the selected model is assessed by analysis of the residuals. If the selected model describes all the systematic information, the residuals should be independent and identically distributed Gaussian noise (e.g., Rigby and Stasinopoulos 2005). We analyze the (normalized

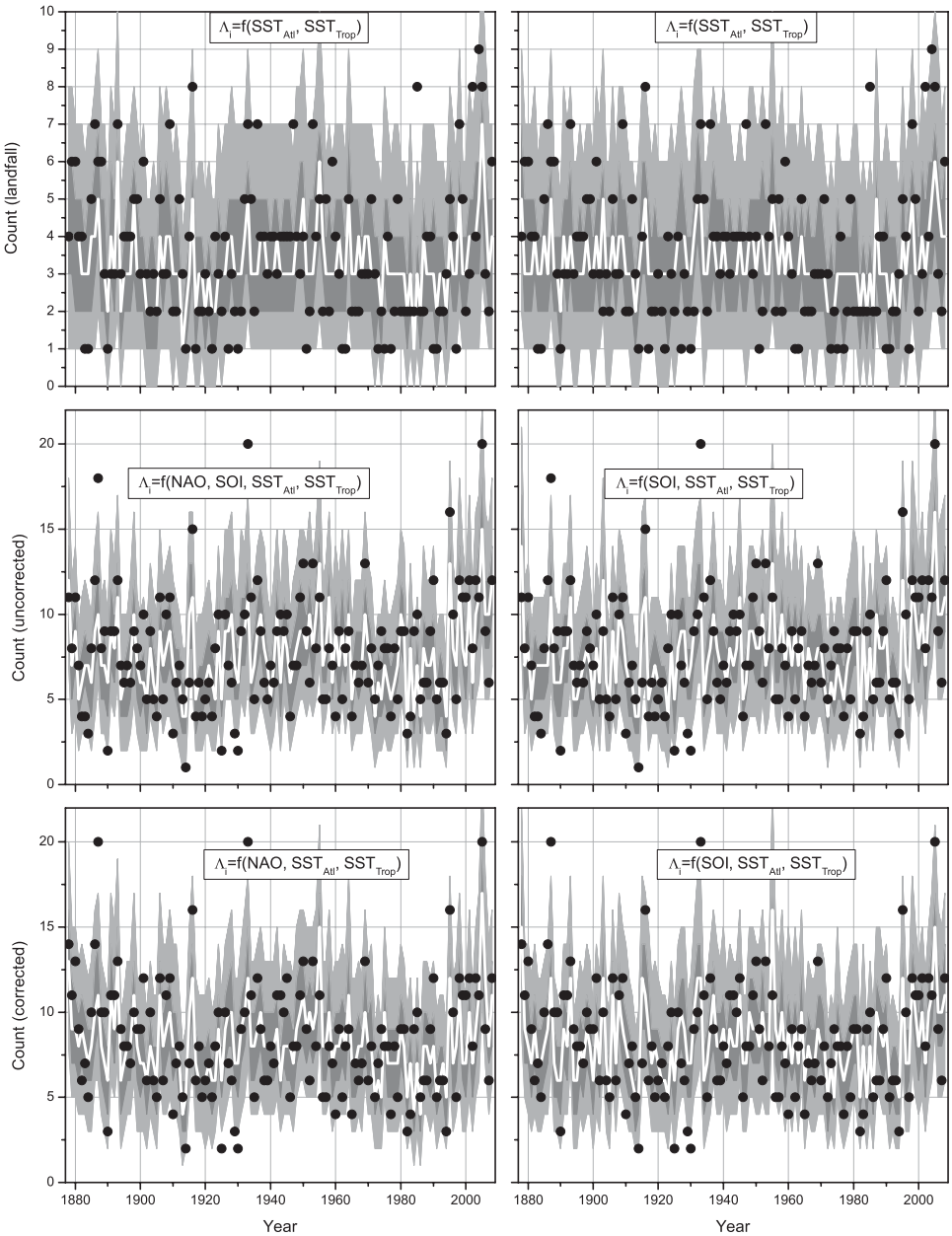

FIG. 6. As in Fig. 4, but using the climate indices as covariates. Model selection is based on AIC. The results by using SST (left) from the HadISSTv1 dataset and (right) from the ERSSTv3b dataset. See Table 2 for more information.

randomized quantile) residuals (Dunn and Smyth 1996) in terms of their mean, variance, coefficient of skewness, coefficient of kurtosis, and Filliben correlation coefficient (Filliben 1975; it represents the correlation coefficient between the order statistics of the residuals and the order statistics of a standard normal distribution), as well as by visual inspection of residual plots, such as quantile–quantile (qq) plots and worm plots (see Fig. 5). Worm plots represent detrended forms of qq plots, where the shape of the ''worm'' provides indications about the agreement between the data and the selected underlying distribution. A flat worm indicates that the data follows the selected distribution. Given the sampling uncertainties, in particular for the high and low quantiles, the points should be within the 95% confidence intervals. For more details, the reader is pointed to van Buuren and Fredriks (2001).

All the calculations are performed in R (R Development Core Team 2008) using the freely available gamlss package (Stasinopoulos et al. 2007).

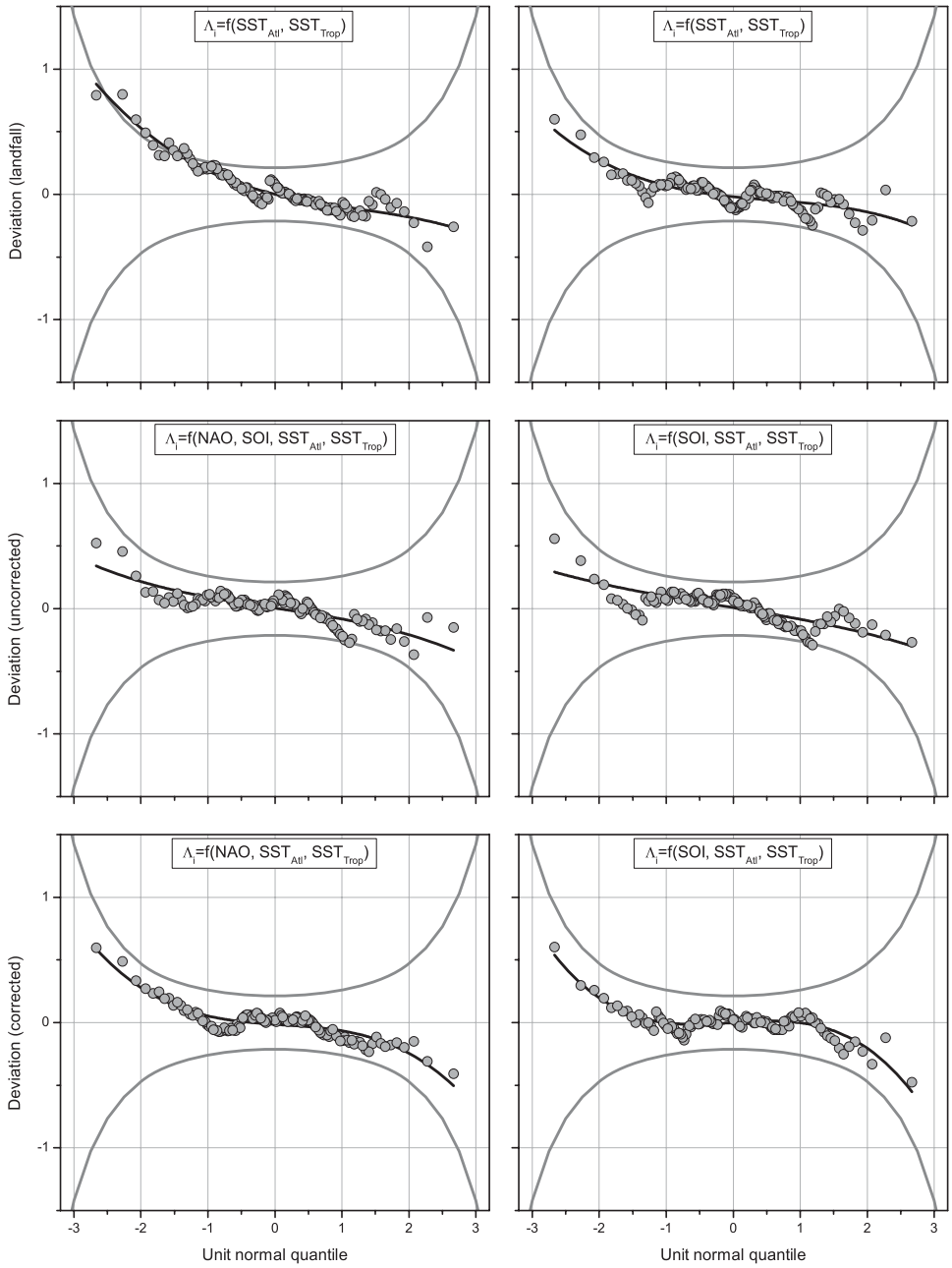

FIG. 7. Worm plots for the six models in Fig. 6.

4. Results

In this section we present the results concerning the modeling of tropical storm counts, and their relation to climate indices.

a. Modeling of tropical storm counts

Here we explore models of tropical storm counts that do not take into account any of the climate indices. Using time as covariate, we have fitted four different models to the tropical storm count data: (i) a Poisson model with constant Λ_i; (ii) a Poisson model in which Λ_i depends on time via an optimized cubic spline; (iii) a negative binomial model with constant Λ_i and σ_i; and (iv) a negative binomial model in which Λ_i and σ_i depend on time via an optimized cubic spline. We have summarized the modeling results in Fig. 4, and the quality of the fit in Fig. 5 and Table 1.

We have started with the U.S. landfalling count by fitting a model in which Λ_i (via a logarithmic link function)

TABLE 2. Summary statistics for the Poisson modeling of tropical storm counts using climate indices as covariate. Model selection is performed with respect to AIC. The first value is the point estimate, while the one in parentheses is the standard error. In each cell, the values in the first (second) row refer to the model using the HadISSTv1 (ERSSTv3b). When "cs" is present, it means that the dependence of Λ_i on that covariate is by means of a cubic spline (otherwise, linear dependence is implied).

	Landfall	Uncorrected	Corrected
Intercept	1.25 (0.05)	2.02 (0.03)	2.09 (0.03)
	1.24 (0.05)	2.04 (0.03)	2.11 (0.03)
NAO	—	−0.06 (0.03)	−0.06 (0.03)
	—	—	—
SOI	—	0.04 (0.02; cs)	—
	—	0.06 (0.02; cs)	0.05 (0.02)
SST_{Atl}	0.91 (0.24; cs)	0.99 (0.17)	1.05 (0.16; cs)
	0.86 (0.22)	0.97 (0.15)	0.97 (0.14)
SST_{Trop}	−0.88 (0.34; cs)	−0.78 (0.25; cs)	−1.15 (0.22; cs)
	−0.87 (0.30; cs)	−0.74 (0.21; cs)	−0.91 (0.20; cs)
Degrees of freedom for the fit	9	11	10
	6	10	7
Mean (residuals)	0.04	0.00	−0.01
	0.00	0.01	−0.00
Variance (residuals)	0.70	0.82	0.81
	0.83	0.82	0.89
Skewness (residuals)	0.27	−0.00	0.03
	0.12	−0.02	−0.01
Kurtosis (residuals)	2.70	2.75	2.44
	2.67	2.81	2.34
Filliben (residuals)	0.995	0.997	0.996
	0.996	0.996	0.996
AIC	511.3	630.0	640.0
	515.1	631.6	641.8
SBC	537.2	661.6	668.8
	532.4	660.4	661.9

is constant. The count record shows a slight tendency toward higher count values in the earlier and later part of the record, as well as in the 1930s and 1940s. In Fig. 4 (top panels) we show the results of the modeling using the Poisson model with parameter Λ_i constant and smooth function of time (see Table 1 for a summary of the four models). These two models were the ones with the lowest SBC and AIC, respectively. In particular, the model with Λ_i modeled as a cubic spline (via a logarithmic link function) highlights the alternation of more and less active periods. In both cases, these models describe the observations reasonably well. This is also supported by the quality of the fit. We have examined the residuals (Fig. 5; Table 1) and the two selected models provide the best agreement with the data, avoiding overfitting. Based on these results, it is difficult to make statements concerning the presence of time trends in the Poisson model for U.S. landfalling tropical storms (see also Elsner and Bossak 2001; Parisi and Lund 2008). This is likely due to the small number of landfalling tropical storms (see also Coughlin et al. 2009; Nzerem et al. 2006) or to the lack of a statistically significant trend.

Visual investigation of the record for the overall number of tropical storms in the North Atlantic basin shows an undulating behavior similar to the observed data for the U.S. landfalling tropical storms, with more active periods alternating with less active ones. In Fig. 4 (middle panels), we show the results of the modeling of the uncorrected dataset, using both a Poisson and negative binomial models with parameters changing over time by means of an optimized cubic spline. These two models were the ones that best described the data. We have summarized the quality of the fit in Fig. 5 and Table 1. Both these models are able to well describe the observed pattern, with the Poisson model that shows a tighter region between the 0.05 and 0.95 quantiles. The behavior of the Λ_i parameters is very similar for the two models. In the negative binomial model, the dispersion parameter tends to be larger than zero in the 1930s and toward the end of the record, expanding the 0.05–0.95 quantile region and improving the model fit. Nonetheless, the negative binomial model uses twice as many degrees of freedom for the fitting, which makes it the least parsimonious model (Table 1).

In the bottom panels of Fig. 4 we show the results of the modeling of the corrected dataset for the Poisson and negative binomial models with parameters changing as a smooth function of time. These two models were the

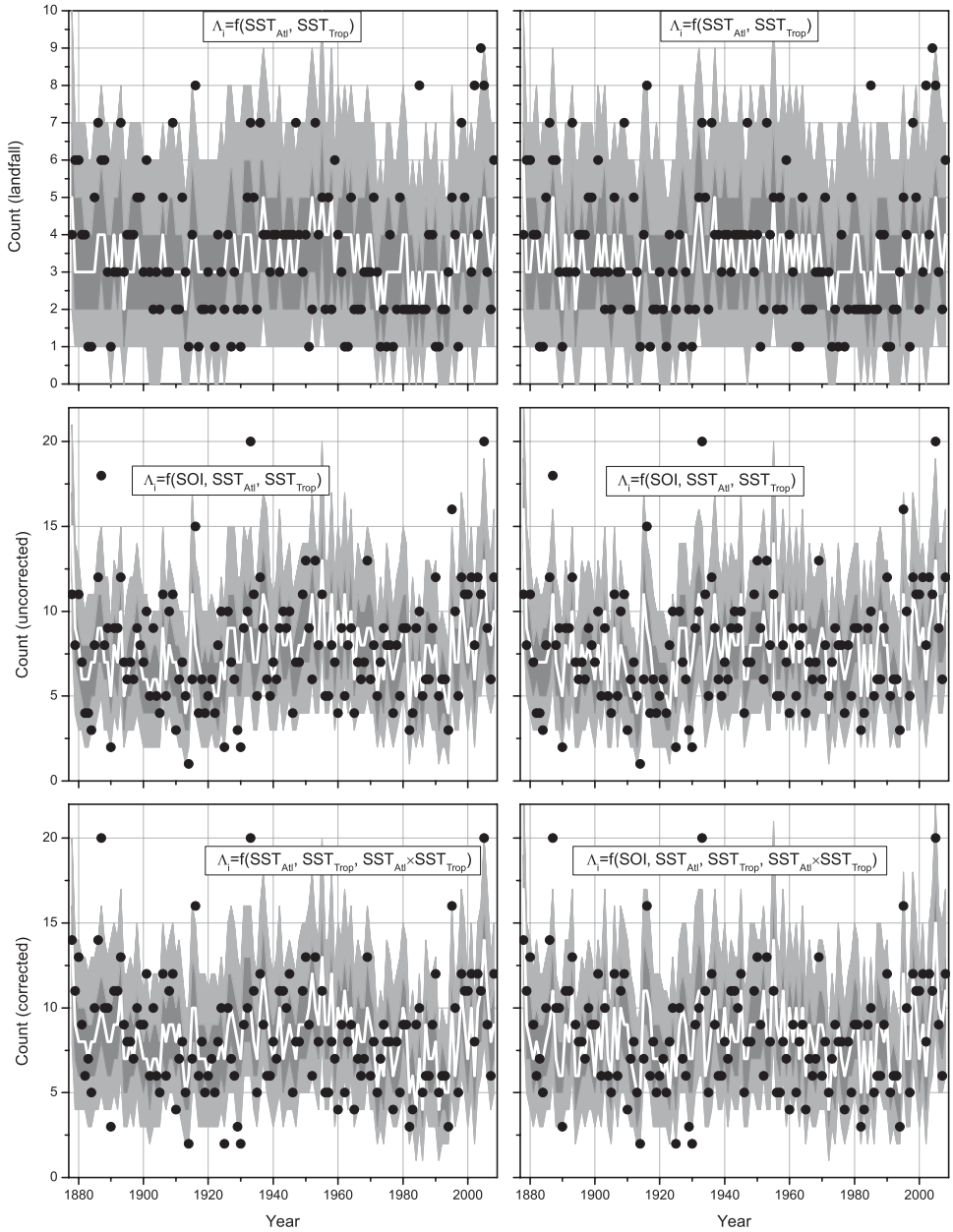

FIG. 8. As in Fig. 6, but using SBC as the penalizing criterion. See Table 3 for more information.

ones that were able to capture the decadal variability in the data. Given the nature of the adjustment, we have the largest discrepancies with respect to the modeling of the uncorrected dataset in the earlier part of the record. Both of the models are capable of describing the data (see Fig. 5 and Table 1), with a slightly better performance for the negative binomial model. This improvement comes at the expenses of many more degrees of freedom used for fitting (Table 1). Similar to the previous case, the dispersion parameter σ_i tends to be close to zero for most of the record, with the exception of the 1930s and toward the end of the record.

Based on these results, it is clear that a Poisson model with a constant parameter cannot be used to describe the count data for the North Atlantic basin (both corrected and uncorrected), pointing toward overdispersion of annual tropical storm counts (representing the multidecadal clustering of tropical storms). In section 4b we will explore which of the aforementioned climate indices is a significant covariate in the modeling of tropical storm count.

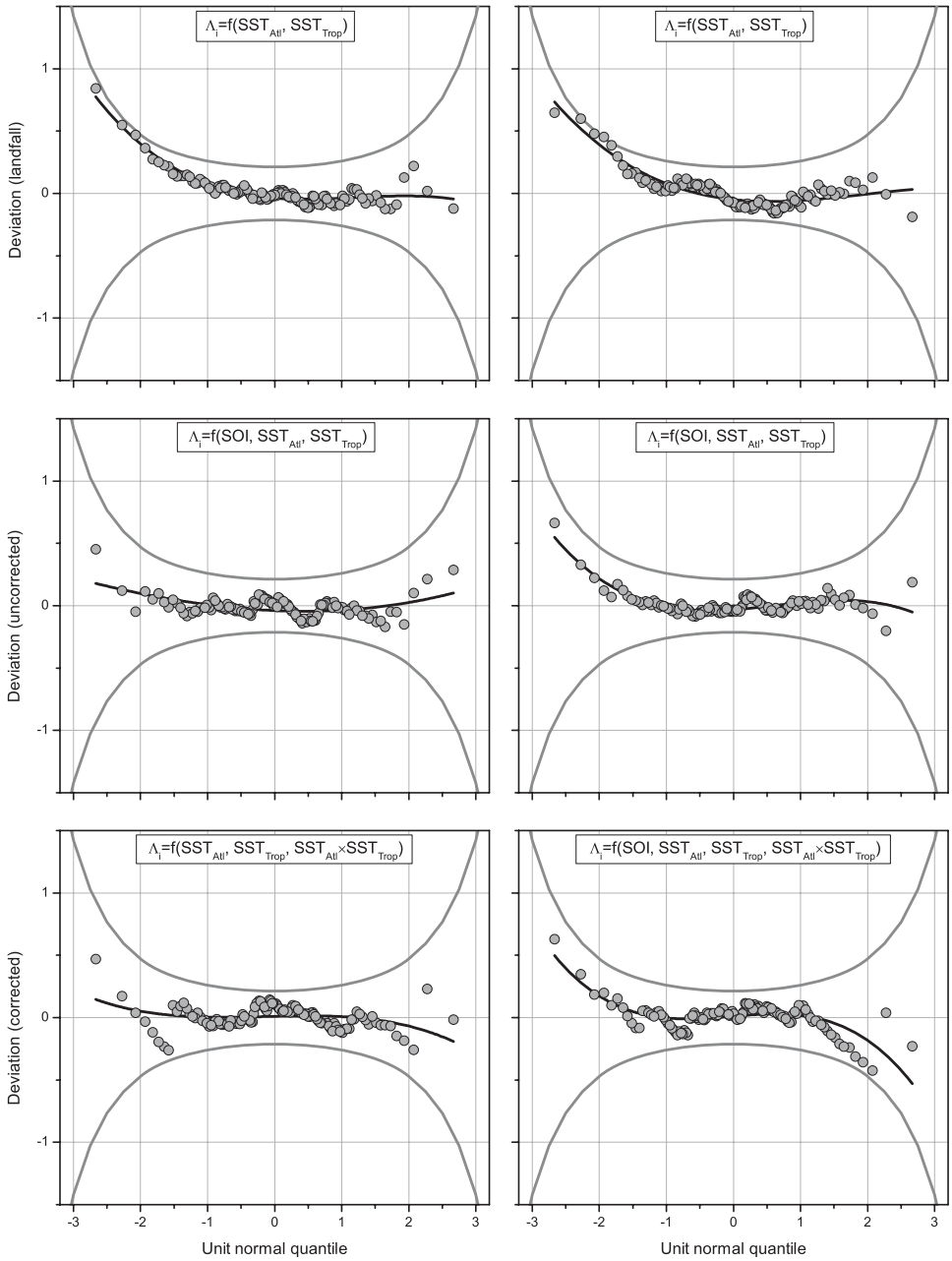

FIG. 9. Worm plots for the six models in Fig. 8.

b. *Tropical storm counts and climate indexes*

In this section, we examine the link between tropical storm counts and four climate indices (NAO, SOI, SST_{Atl}, and SST_{Trop}), for a total of five covariates (NAO is averaged over both May–June and August–October periods).

1) CHARACTERISTICS OF THE CLIMATE INDICES

We have looked at the scatterplots (figure not shown) between these covariates and U.S. landfalling tropical storm counts and overall counts (both uncorrected and corrected datasets). We notice that higher values of NAO (May–June) tend to be associated with smaller count values. While the effects of NAO are generally associated (through statistical associations) with the location of the Bermuda high, possibly affecting the steering of the tropical storm tracks, its link to the genesis of tropical storms in the North Atlantic basin is less clear (Elsner et al. 2000a; Landsea 2001). Moreover, the relation between count data and NAO averaged over the

TABLE 3. As in Table 2, but using SBC as penalizing criterion. SST_{Atl}:SST_{Trop} indicates the interaction term.

	Landfall	Uncorrected	Corrected
Intercept	1.24 (0.05)	2.04 (0.03)	2.07 (0.04)
	1.24 (0.05)	2.04 (0.03)	2.07 (0.04)
NAO	—	—	—
	—	—	—
SOI	—	0.05 (0.02)	—
	—	0.06 (0.02)	0.05 (0.02)
SST_{Atl}	0.89 (0.24)	1.00 (0.17)	1.06 (0.15)
	0.86 (0.22)	0.96 (0.15)	0.97 (0.15)
SST_{Trop}	−0.89 (0.34)	−0.71 (0.25)	−1.22 (0.23)
	−0.86 (0.30)	−0.70 (0.21)	−0.98 (0.21)
SST_{Atl}:SST_{Trop}	—	—	0.82 (0.42)
	—	—	0.58 (0.30)
Degrees of freedom for the fit	3	4	4
	3	4	5
Mean (residuals)	0.02	−0.01	0.01
	0.01	0.01	0.01
Variance (residuals)	0.84	0.97	0.97
	0.84	0.96	0.91
Skewness (residuals)	0.32	0.14	−0.04
	0.35	0.20	−0.03
Kurtosis (residuals)	2.73	2.95	2.73
	2.79	2.60	2.37
Filliben (residuals)	0.995	0.997	0.996
	0.994	0.996	0.994
AIC	516.9	639.7	650.7
	515.7	635.3	641.4
SBC	525.5	651.2	662.2
	524.3	646.8	655.8

August–October period is weaker than the one observed for NAO in the springtime. The behavior of SOI is opposite to the one observed for NAO, with larger values now associated with higher count values, consistent with the tendency of El Niño to increase wind shear and thermodynamic stability in the Atlantic, inhibiting TS genesis. Finally, we investigate the dependence of the count data to SST_{Atl}, SST_{Trop}, and their differences, using both the estimates from the HadISSTv1 and ERSSTv3b datasets. As expected, increasing Atlantic SST is associated with an increasing number of tropical storms (this dependence is weaker as far as the landfalling tropical storms are concerned). The count data does not show a significant dependence on the tropical SST alone (it is related to the differences between the two SSTs). The two SST datasets tend to give similar results for smaller count values, while they tend to be different for the largest ones. These differences are larger for the Atlantic SST while they are much smaller for the tropical SST (see also Fig. 2).

2) MODELING TROPICAL STORM COUNTS WITH CLIMATE INDICES

We now focus our attention on the modeling of the count data using these climate indexes as covariates. In this case, we focus on a Poisson model, in which $\ln(\Lambda_i)$ is modeled as both a linear and smooth function of NAO, SOI, SST_{Atl}, and SST_{Trop}, including two-way interaction terms as well. To avoid model overfitting, we select the statistically significant covariates using a stepwise approach with respect to AIC and SBC. Even though we included NAO averaged over the August–October period, we found that it was not a significant covariate in any of the models described below (likely because of the low signal-to-noise ratio; Elsner et al. 2001). For this reason, in the remainder of the paper, NAO will refer to the index averaged over the period May–June.

Let us start with the results obtained using AIC as penalty criterion. In Fig. 6 we show the modeling results, using both HadISSTv1 (left panels) and ERSSTv3b (right panels) datasets for SSTs. In Fig. 7 and Table 2 we summarize the fitting performance and the values of the parameters. The modeling of the landfalling tropical storms as a function of covariates shows that the selected model is able to describe the complex behavior exhibited by the data reasonably well. According to the model selection procedure, when using the HadISSTv1 dataset SST_{Atl} and SST_{Trop} are included as significant covariates (no two-way interaction terms are added). The dependence of Λ_i on the SSTs is by means of a cubic spline. Similar covariates are found when using the ERSSTv3b dataset

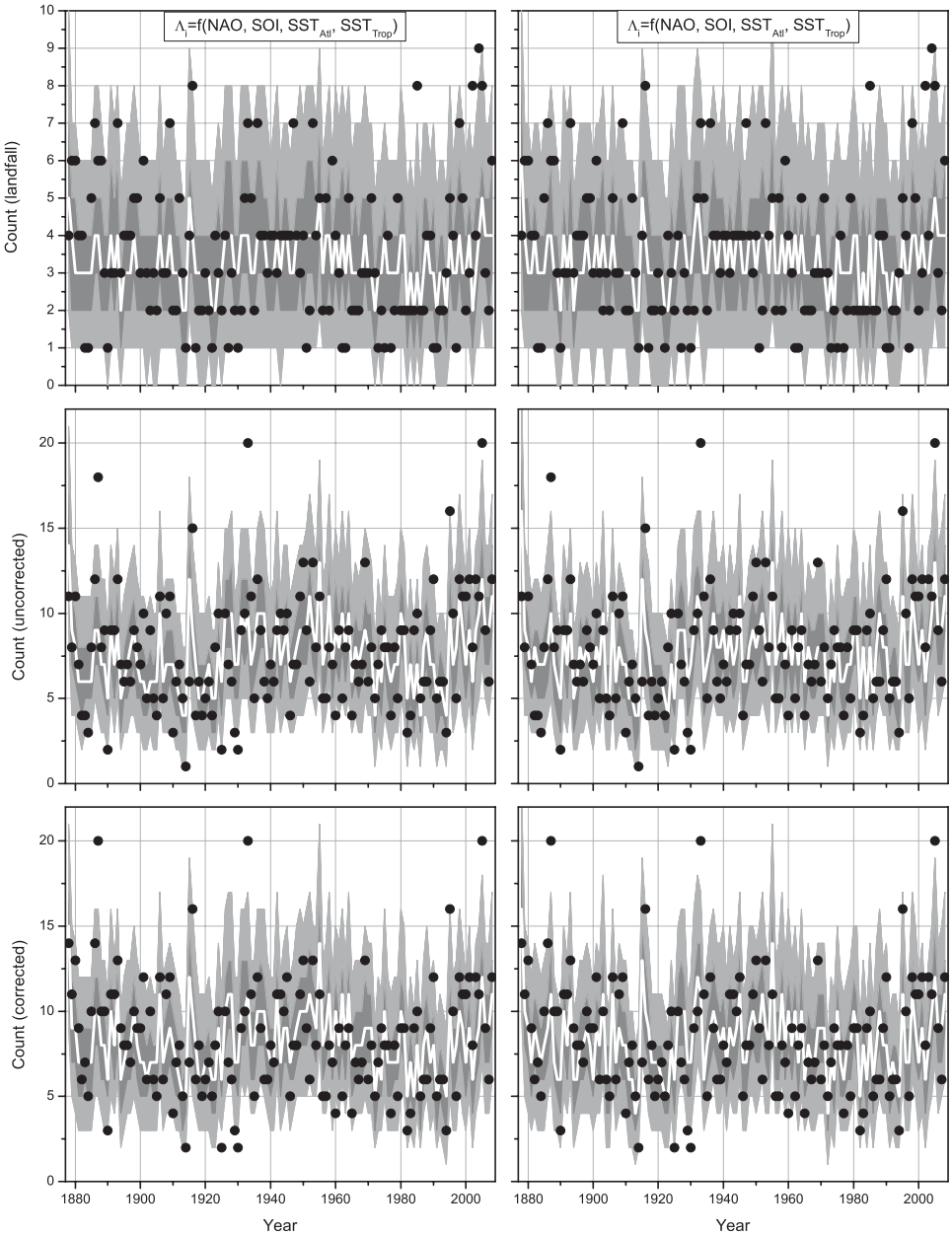

FIG. 10. As in Fig. 6, but the natural logarithm of the parameter Λ_i is modeled as a linear function of NAO, SOI, SST_{Atl}, and SST_{Trop}. See Table 4 for more information.

with the only difference being that the dependence on Atlantic SST is now linear. The coefficients for the Atlantic and tropical SST have opposite sign, suggesting that the latter has a dampening effect, supporting the idea that increases of Atlantic SST relative to the tropical SST are more significant than the absolute increase in Atlantic SST. Model fitting (Fig. 7 and Table 2) suggests a slightly better fit when using the ERSSTv3b dataset.

In the middle and bottom panels of Fig. 6 we show the modeling of the count of the tropical storms in the North Atlantic basin for both corrected and uncorrected datasets and using both HadISSTv1 (left panels) and ERSSTv3b (right panels) datasets. Visual investigation of the modeling results shows that these models are able to describe the undulating behavior exhibited by the data, with periods of higher activity alternating with periods of lower activity. For the uncorrected HURDAT dataset, SOI and both Atlantic and tropical SSTs are significant covariates (Λ_i depends on SOI and SST_{Trop} by means of a cubic spline, and on SST_{Atl} via linear dependence). On

TABLE 4. As in Table 2, but for a model in which $\ln(\Lambda_i)$ is a linear function of NAO, SOI, SST_{Atl}, and SST_{Trop}.

	Landfall	Uncorrected	Corrected
Intercept	1.23 (0.05)	2.02 (0.03)	2.09 (0.03)
	1.23 (0.05)	2.02 (0.03)	2.10 (0.03)
NAO	−0.05 (0.05)	−0.05 (0.03)	−0.06 (0.03)
	−0.04 (0.05)	−0.04 (0.03)	−0.04 (0.03)
SOI	0.02 (0.03)	0.05 (0.02)	0.04 (0.02)
	0.03 (0.03)	0.06 (0.02)	0.05 (0.02)
SST_{Atl}	0.80 (0.25)	0.97 (0.17)	0.91 (0.16)
	0.77 (0.23)	0.92 (0.15)	0.90 (0.15)
SST_{Trop}	−0.78 (0.38)	−0.72 (0.25)	−0.91 (0.25)
	−0.72 (0.32)	−0.67 (0.21)	−0.83 (0.20)
Degrees of freedom for the fit	5	5	5
	5	5	5
Mean (residuals)	−0.00	0.01	0.01
	0.04	−0.00	0.00
Variance (residuals)	0.83	0.96	0.99
	0.82	0.97	0.93
Skewness (residuals)	0.23	0.11	0.04
	0.27	0.02	−0.04
Kurtosis (residuals)	2.62	2.74	2.67
	2.94	2.52	2.47
Filliben (residuals)	0.996	0.997	0.997
	0.997	0.997	0.997
AIC	519.2	638.9	649.3
	518.1	635.8	643.6
SBC	533.6	653.3	663.6
	532.5	650.2	657.9

the other hand, NAO is an additional significant covariate only when the HadISSTv1 is used. Based on examination of the residuals (Fig. 7 and Table 2), the model fitting does not highlight any significant problem with these models.

When looking at the corrected dataset, the model is able to account for the larger count values at the beginning of the study period. However, we notice some discrepancies in terms of covariates depending on the SST dataset. Both of the SSTs are significant covariates when using HadISSTv1 and ERSSTv3b datasets. However, there are differences in the dependence of Λ_i on Atlantic SST, as well as in the significance of NAO and SOI: the former (the latter) is included in the model using HadISSTv1 (ERSSTv3b) SST. Since both of the models are able to capture well the observed behavior, it is difficult to say whether SOI and/or NAO should be included in the model based only on the statistical results. Apart from data correction, these results show the sensitivity of the model to different input forcing.

These results are related to the use of AIC as penalizing criterion. We also investigate the modeling results using SBC as penalizing criterion. Based on Eqs. (8) and (9), we would expect more parsimonious models in terms of covariates and/or functional dependence of Λ_i on them. We have summarized the modeling results in Fig. 8 and the goodness of fit in Fig. 9 and Table 3. As expected, the models are more parsimonious than when using AIC, with almost half of the degrees of freedom used compared to AIC (3–5 versus 6–11; Table 3). Moreover, Λ_i (via a logarithmic link function) is always a linear function of the covariates and the cubic spline is never selected. In the top panels of Fig. 8 we have the results for the landfalling tropical storm count. As in the previous case, the SSTs are the only significant covariates and their coefficients have opposite sign. The model is able to capture the observed behavior reasonably well, with the alternation of more and less active periods. Overall, based on residual plots and statistics (Fig. 9 and Table 3), the quality of the fit is reasonably good.

Modeling of the count data for the entire North Atlantic basin (Fig. 8, middle and bottom panels) shows that the selected models are able to capture the observed pattern in the data. The models are rather parsimonious, with the Atlantic and tropical SSTs significant covariates in all of them. For the uncorrected dataset and independent of the SST dataset (Fig. 8, middle panels), the final model according to SBC has SOI in addition to SSTs. These models are able to well describe the results and, based on the model's residuals, there is no evidence of poor model fitting. Moreover, independent of the SST dataset, these models have the same covariates and functional dependence on Λ_i, allowing a comparison between the two SST time series. Based on the AIC and SBC values,

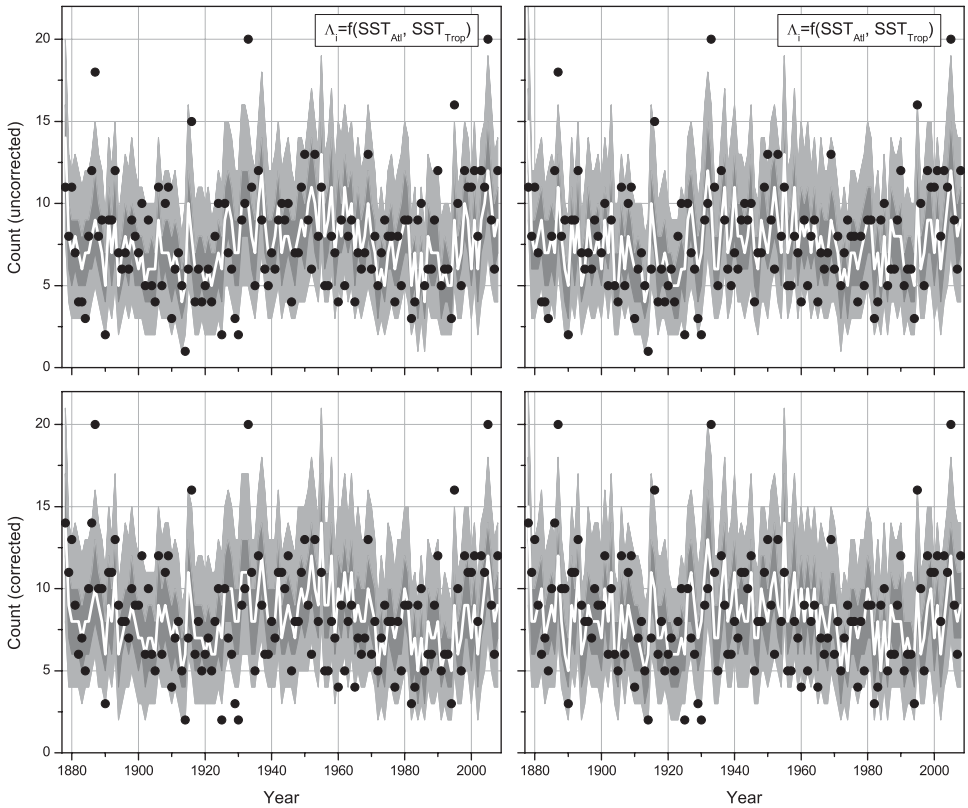

FIG. 11. As in Fig. 10, but the natural logarithm of the parameter Λ_i is modeled as a linear function of SST_{Atl} and SST_{Trop}. See Table 5 for more information.

given everything else the same, a model with ERSSTv3b describes the data better than the HadISSTv1.

As far as the uncorrected dataset is concerned, in addition to the SSTs, we know that the interaction term between Atlantic and tropical SSTs are significant. When using the ERSSTv3b dataset, the SOI is significant as well. Both of these models are able to capture the observed variability and fit the data well. Again, notice how the Atlantic and tropical SSTs have different signs, reinforcing the idea that the relative, rather than absolute increases in Atlantic SST with respect to tropical SST are important factors that should be taken into account.

These results show how model selection is sensitive to the selected penalty criterion and SST datasets. In the rest of the section we consider two additional models in which we consider $\ln(\Lambda_i)$ depending linearly on the four covariates (NAO, SOI, SST_{Atl}, and SST_{Trop}) and only on Atlantic and tropical SSTs. In Fig. 10 we show the modeling of the count data for the case in which the four covariates are considered. As in the previous figures, the panels on the left (right) refer to the cases in which we used the HadISSTv1 (ERSSTv3b) dataset. For the count of U.S. landfalling tropical storms this model is able to capture the behavior observed in the data. When considering the count for the North Atlantic basin (Fig. 10, middle and bottom panels), we observe that the model is able to describe well the pattern in the count data, in agreement with the results using AIC and SBC, in which these four covariates were found to be significant predictors. We have summarized the point estimates for the models' parameters in Table 4. Examination of the residual plots (figure not shown) and of their statistics (Table 4) does not suggest any particular issue with these models.

Since these models use the same covariates and their relation with Λ_i, we can compare the results from the two different SST datasets using AIC and SBC. As shown in Table 4, the models using the ERSSTv3b dataset show smaller values of AIC and SBC, suggesting that, given that everything else stays the same, this dataset provides a better fit to the data compared to the HadISSTv1 dataset.

Given the previous results, Atlantic and tropical SSTs are significant covariates in all the previous models. For this reason, we investigate how a parsimonious model with only these two covariates and with $\ln(\Lambda_i)$ linearly depending on them would perform. In Fig. 11 we have summarized our modeling results for the overall count

TABLE 5. Summary statistics for the Poisson modeling of tropical storm counts using SST_{Atl} and SST_{Trop} as covariates. The first value is the point estimate, while the one in parentheses is the standard error. In each cell, the values in the first (second) row refer to the model using the HadISSTv1 (ERSSTv3b). The natural logarithm of Λ_i depends linearly on the two covariates.

	Uncorrected	Corrected
Intercept	2.03 (0.03)	2.11 (0.03)
	2.03 (0.03)	2.10 (0.03)
SST_{Atl}	1.13 (0.16)	1.05 (0.15)
	1.05 (0.15)	1.02 (0.14)
SST_{Trop}	−0.98 (0.23)	−1.12 (0.22)
	−0.91 (0.20)	−1.05 (0.19)
Degrees of freedom for the fit	3	3
	3	3
Mean (residuals)	−0.01	−0.01
	0.02	0.00
Variance (residuals)	1.00	1.02
	1.00	0.97
Skewness (residuals)	0.24	0.05
	0.15	0.10
Kurtosis (residuals)	2.74	2.71
	2.59	2.35
Filliben (residuals)	0.995	0.998
	0.997	0.996
AIC	643.2	652.4
	641.9	647.6
SBC	651.8	661.0
	650.6	656.2

(see Fig. 8 and Table 3 for the modeling of the U.S. landfalling tropical storms). When looking at the modeling of the count for the entire North Atlantic basin we observe that this model is able to capture the observed behavior for both corrected and uncorrected datasets. Looking at the residual plots (figure not shown) and at the residuals' statistics (Table 5), these models fit the data well. Once again, the AIC and SBC values using the ERSSTv3b dataset are smaller than those obtained using the HadISSTv1 dataset. Additionally, in agreement with the previous results the coefficients of these two covariates have opposite signs (Table 5).

For the sake of completeness, we have also considered a model for the corrected dataset in which we use SOI, SST_{Atl}, and SST_{Trop} as covariates [with linear dependence of $\ln(\Lambda_i)$]. We have summarized the results in Fig. 12 for both SST datasets. This model is able to describe well the observed behavior (top panels), as also suggested by the quality of the fitting (bottom panels). As for the previous cases, the ERSSTv3b dataset shows better values of AIC and SBC compared to the HadISSTv1.

Given all these models, a question that still needs to be addressed concerns the selection of the "best" model. As shown in this study, there is not a unique best model. We think that model selection should be driven by both statistical and physical reasoning. Based on the results of this study, we can provide some suggestions. First of all, we would suggest using the ERSSTv3b dataset for estimates of the Atlantic and tropical SSTs. We also suggest modeling $\ln(\Lambda_i)$ as a linear function of the covariates, in order to have a more parsimonious model that could also be used to study future scenarios. As far as covariate selection is concerned, we think that statistical model selection can provide helpful guidelines, even though we should also consider our understanding of the underlying physical processes. For this reason, we suggest modeling the U.S. landfalling tropical storms using a model with only Atlantic and tropical SSTs. It is the one that provides the best fit with the smallest number of degrees of freedom used for the fit.

When dealing with the overall count for the North Atlantic basin, we suggest not including NAO (it should mostly affect the tracks of the tropical storms rather than their genesis and/or development). When dealing with both corrected and uncorrected datasets, we would suggest a model with only Atlantic and tropical SSTs as covariates, since it provides a good fit with a small number of degrees of freedom used for the fit.

One final element that we have investigated concerns an evaluation of the correction for the North Atlantic count proposed by Vecchi and Knutson (2008) and implemented in Landsea et al. (2010). It is clear that it is not possible to make conclusive statements concerning its correctness, since it is not possible to test all the underlying assumptions (this is a general statement, valid with any correction so far proposed for the HURDAT dataset). However, we can evaluate the correction within our modeling framework by splitting the corrected and uncorrected datasets into two subperiods (pre- and postsatellite era; 1878–1965 and 1966–2008). We can then fit a Poisson model with $\ln(\Lambda_i)$ linearly depending on SST_{Atl} and SST_{Trop} (from the ERSSTv3b dataset) to the count data for the presatellite era, and use the computed parameters to "predict" the count over the postsatellite era. We can do this for both corrected and uncorrected datasets. We have summarized our results in Fig. 13. These models are able to describe reasonably well the count data for the 1966–2008 period. This is particularly true for the corrected dataset (bottom panel), in which the observations are better described by the model. Since the model is the same for the two datasets, this is linked to the correction for undercount, which tends to move the 90% region of the model to slightly larger values. The root-mean-square error (RMSE) is 4.1 for the uncorrected dataset and 3.6 for the corrected one. Similar improvement is obtained with respect to the mean absolute error (MAE), with a value of 3.1 and 2.7 for the uncorrected and corrected datasets, respectively. Based on these results, even though we cannot say that the proposed correction

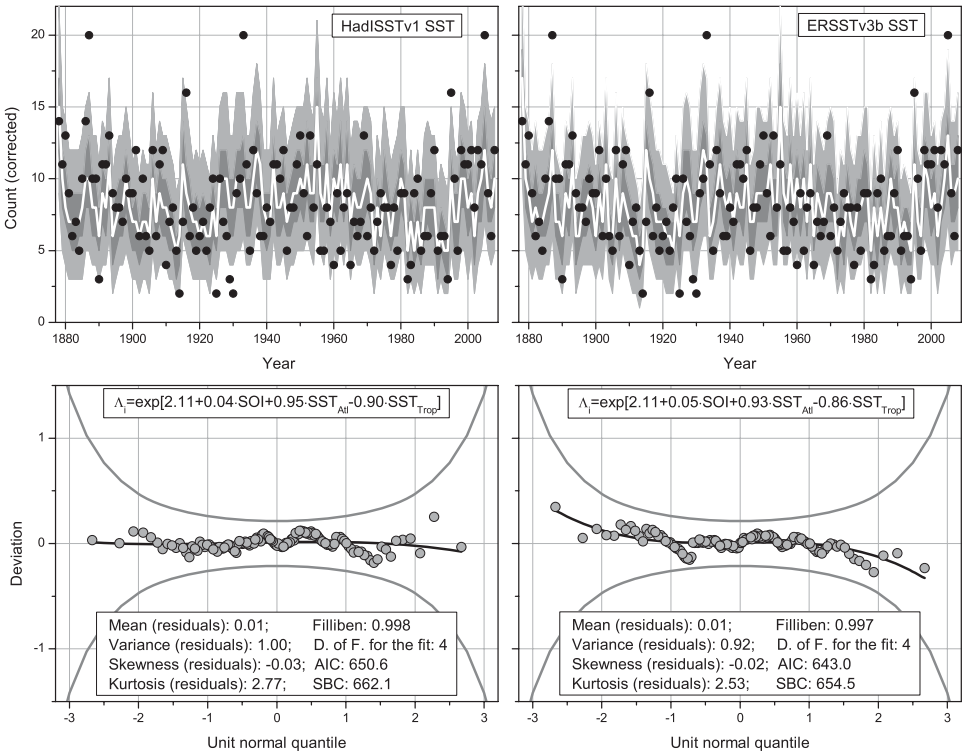

FIG. 12. (top) Modeling of the ''corrected'' count data for the North Atlantic basin using a Poisson model in which the parameter $\ln(\Lambda_i)$ is a linear function of SOI, SST_{Atl}, and SST_{Trop}. (bottom) The worm plots for the above models are shown, together with numerical values of the some of the summary statistics. The results using SST (left) from the HadISSTv1 dataset and (right) from the ERSSTv3b dataset.

was able to identify all the missing storms, our results tend to support its validity over no correction.

5. Discussion

Since the data and the predictors exhibit large interannual variability, it is possible that, while the model is able to describe well this variability, it may not describe the decadal variability as well. When applying these models for periods outside of the one used for training, it would be good to have a model that is able to describe both the interannual and decadal fluctuations, since future climate variations could be different from what we have observed. In this context, a model robust across dominant types of changes should be sought.

To investigate the model sensitivity to decadal varying data, we have smoothed both the input time series and the count data. As far as the former are concerned, we have used a 5-yr smoothing window (with equal weights). On the other hand, we cannot use the same smoothing approach on the count data, since the values might not be integers (for a Poisson model, the variable we want to model has to be a positive integer). Therefore, within each 5-yr window we have computed the sum of the number of tropical storms. To avoid border effects, we have excluded from the analyses the first two and last two years of the record, fitting the new models over the period 1880–2006.

We have followed an approach similar to the one discussed above. We have first selected the best model according to AIC, then SBC, and finally a model with only Atlantic and tropical SSTs. We have performed the analyses only on the corrected counts for the North Atlantic basin, using both the HadISSTv1 and ERSSTv3b time series. We have summarized the results in Tables 6–8, where, for comparison we have also included the results for the annual count.

When modeling the ''smoothed'' corrected data, both of the tropical and Atlantic SSTs are always included as significant covariates, independent of the SST time series and the penalty criterion. When considering AIC as penalty criterion, NAO is a significant covariate as well, while SOI is significant only when using the ERSSTv3b SST time series. On the other hand, with respect to SBC, NAO and SOI are no longer significant covariates, and only Atlantic and tropical SSTs are retained. Notice that the dependence of $\ln(\Lambda_i)$ on these covariates is in general

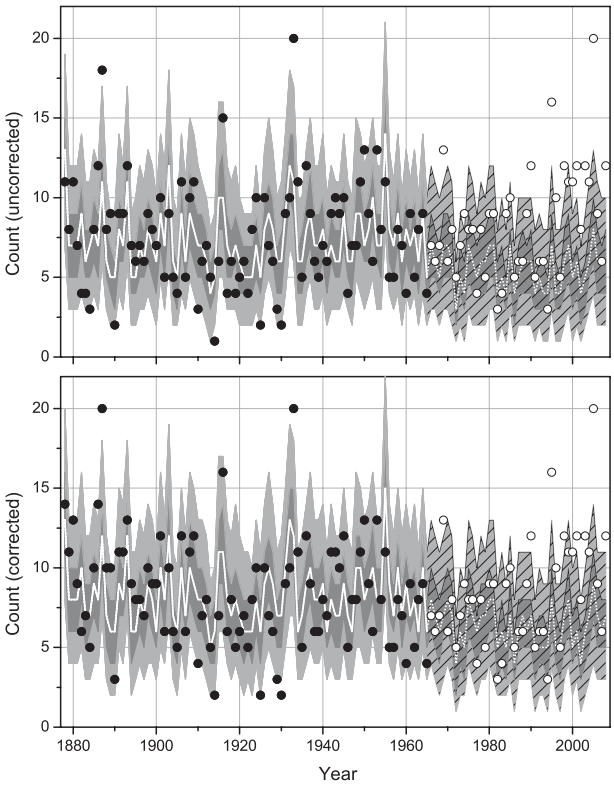

FIG. 13. Modeling of the count data (bottom) with and (top) without undercount correction using SST_{Atl} and SST_{Trop} (from the ERSSTv3b dataset) as covariates. The model is fitted to the period 1878–1965 and the computed parameters are used to "predict" the count for the period 1966–2008.

by means of a cubic spline, likely related to the smoothing of the input time series (see also Table 8).

We have also repeated these analyses using an 11-yr window (from 1883 to 2003). In this case, the quality of the fit was not good independent of the penalty criterion. Nonetheless, Atlantic and tropical SSTs were always retained as significant covariates for both SST dataset and penalizing criterion.

Even though a direct link between these results and those from the count data is not possible since we modeled the sum of tropical storms within a 5-yr window, the modeling of the smoothed data tends to support the suggestions provided at the end of the previous section regarding the selection of the best models.

6. Conclusions

The focus of this study was the statistical modeling of the number of tropical storms lasting more than two days in the North Atlantic basin [with and without the correction for undercount by Landsea et al. (2010)] and of those making landfall in the United States for the period 1878–2008. The findings of the present study can be summarized as follows:

1) Analyses exploring the presence of overdispersion in the count data were performed. We have used both a Poisson and a negative binomial model. For the U.S. landfalling tropical storms, it was difficult to make conclusive statements concerning the validity of the independence assumption or the presence of overdispersion given the nature of the data (see also Coughlin et al. 2009; Nzerem et al. 2006). The count for the North Atlantic basin showed that the data should be described by a Poisson model with parameter Λ_i changing smoothly over time or by a negative binomial model (with variable parameters). This finding implies that the tropical storm count data for the North Atlantic exhibits serial clustering (the events are not independent in time; e.g., Mailier et al. 2006; Vitolo et al. 2009). This statement was valid for both corrected and uncorrected datasets.

TABLE 6. Summary statistics for the Poisson modeling of the "corrected" tropical storm counts using climate indices as covariate over annual and 5-yr time scales. Model selection is performed with respect to AIC. The first value is the point estimate, while the one in parentheses is the standard error. In each cell, the values in the first (second) row refer to the model using the HadISSTv1 (ERSSTv3b). When "cs" is present, it means that the dependence of Λ_i on that covariate is by means of a cubic spline (otherwise, linear dependence is implied).

	Annual	5-Yr
Intercept	2.09 (0.03)	3.72 (0.02)
	2.11 (0.03)	3.73 (0.02)
NAO	−0.06 (0.03)	−0.03 (0.03; cs)
	—	−0.02 (0.03; cs)
SOI	—	—
	0.05 (0.02)	0.04 (0.03)
SST_{Atl}	1.05 (0.16; cs)	0.78 (0.11; cs)
	0.97 (0.14)	0.58 (0.12)
SST_{Trop}	−1.15 (0.22; cs)	−0.65 (0.13; cs)
	−0.91 (0.20; cs)	−0.43 (0.14; cs)
Degrees of freedom for the fit	10	13
	7	11
Mean (residuals)	−0.01	0.01
	−0.00	−0.00
Variance (residuals)	0.81	0.74
	0.89	0.85
Skewness (residuals)	0.03	0.07
	−0.01	−0.05
Kurtosis (residuals)	2.44	3.55
	2.34	4.23
Filliben (residuals)	0.996	0.992
	0.996	0.988
AIC	640.0	825.2
	641.8	833.2
SBC	668.8	862.2
	661.9	864.5

TABLE 7. As in Table 6, but using SBC as penalizing criterion. SST_{Atl}:SST_{Trop} indicates the interaction term.

	Annual	5-Yr
Intercept	2.07 (0.04)	3.73 (0.01)
	2.07 (0.04)	3.73 (0.01)
NAO	—	—
	—	—
SOI	—	—
	0.05 (0.02)	—
SST_{Atl}	1.06 (0.15)	0.80 (0.11; cs)
	0.97 (0.15)	0.63 (0.12)
SST_{Trop}	−1.22 (0.23)	−0.67 (0.13; cs)
	−0.98 (0.21)	−0.51 (0.14; cs)
SST_{Atl}:SST_{Trop}	0.82 (0.42)	—
	0.58 (0.30)	—
Degrees of freedom for the fit	4	9
	5	6
Mean (residuals)	0.01	0.00
	0.01	−0.00
Variance (residuals)	0.97	0.81
	0.91	0.95
Skewness (residuals)	−0.04	0.15
	−0.03	0.01
Kurtosis (residuals)	2.73	3.22
	2.37	3.80
Filliben (residuals)	0.996	0.994
	0.994	0.992
AIC	650.7	826.0
	641.4	837.6
SBC	662.2	851.6
	655.8	854.7

TABLE 8. As in Table 6, but using only SST_{Atl} and SST_{Trop} as covariates.

	Annual	5-Yr
Intercept	2.11 (0.03)	3.73 (0.01)
	2.10 (0.03)	3.73 (0.01)
SST_{Atl}	1.05 (0.15)	0.58 (0.11)
	1.02 (0.14)	0.72 (0.12)
SST_{Trop}	−1.12 (0.22)	−0.43 (0.13)
	−1.05 (0.19)	−0.59 (0.14)
Degrees of freedom for the fit	3	3
	3	3
Mean (residuals)	−0.01	−0.01
	0.00	−0.01
Variance (residuals)	1.02	1.40
	0.97	1.32
Skewness (residuals)	0.05	−0.05
	0.10	0.03
Kurtosis (residuals)	2.71	2.56
	2.35	2.76
Filliben (residuals)	0.998	0.998
	0.996	0.999
AIC	652.4	888.7
	647.6	879.2
SBC	661.0	897.2
	656.2	887.7

2) Different final models both in terms of covariate and functional dependence of Λ_i are obtained depending on the penalty criterion. We tried to find a compromise between model complexity and performance by using the Akaike information criterion (AIC) and the Schwarz Bayesian criterion (SBC) for model comparison. As expected, in this study the use of SBC resulted in a more parsimonious model than AIC (both in terms of number of covariates as well as model dependence on them). These results showed how there is not an "overall best" statistical model.
3) For all the models, Atlantic and tropical SSTs are retained as significant covariates. These results support the idea that the increases (or decreases) in Atlantic SST relative to tropical SST are preferable to the absolute values of Atlantic SST in modeling the tropical storms count in the North Atlantic basin and U.S. landfalling storms. This result can have large implications in looking at tropical storm counts over the twenty-first century and interpreting the extent to which historical increases in tropical storm counts are due to increased greenhouse gases (e.g., Vecchi et al. 2008b).

NAO is seldom found to be a significant covariate. Our results do not seem to add supporting evidence to the idea that this climate index should be included when modeling U.S. landfalling tropical storms. Therefore, more research is needed to clarify the relation between NAO and tropical storm frequencies from both a physical and statistical standpoint. Moreover, SOI tends to be a significant predictor for the overall counts, consistent with the increase of shear (e.g., Goldenberg and Shapiro 1996) and atmospheric stability (Tang and Neelin 2004), both of which would have adverse effects on tropical storm genesis and development.

4) Modeling results suggest that the ERSSTv3b rather than HadISSTv1 dataset provides a better description of the count data over 1878–2008. This result begs the question of whether circumstantial evidence of this type is relevant to resolving disagreements in the trend patterns of SST exhibited by these SST datasets (e.g., Vecchi et al. 2008a; Bunge and Clarke 2009).
5) Given these covariates, it is not possible to identify an overall best model. However, given the current understanding of the processes underlying storm genesis and development, we suggest modeling U.S. landfalling count and the overall count for the North Atlantic (for both corrected and uncorrected datasets) with a conditional Poisson distribution with $\ln(\Lambda_i)$ linear function of only tropical and Atlantic SSTs.

6) Based on our results, the undercount correction by Vecchi and Knutson (2008) for the presatellite era as implemented in Landsea et al. (2010) seems to have a beneficial effect on the tropical storm count modeling.

Acknowledgments. This research was funded by the Willis Research Network and the National Science Foundation (Grant CMMI-0653772). The authors thank Dr. Stasinopoulos, Dr. Rigby, and Dr. Akantziliotou for making the gamlss package (Stasinopoulos et al. 2007) freely available in R (R Development Core Team 2008) and Renato Vitolo (Exeter) for helpful discussions.

REFERENCES

Akaike, H., 1974: A new look at the statistical model identification. *IEEE Trans. Automat. Contrib.,* **19,** 716–723.

Arguez, A., and J. B. Elsner, 2001: Trends in U.S. tropical cyclone mortality during the past century. *Florida Geogr.,* **32,** 28–37.

Ashley, S. T., and W. S. Ashley, 2008a: Flood fatalities in the United States. *J. Appl. Meteor. Climatol.,* **47,** 805–818.

——, and ——, 2008b: The storm morphology of deadly flooding events in the United States. *Int. J. Climatol.,* **28,** 493–503.

Barrett, B. S., and L. M. Leslie, 2009: Links between tropical cyclone activity and Madden–Julian oscillation phase in the North Atlantic and Northeast Pacific basins. *Mon. Wea. Rev.,* **137,** 727–744.

Bell, G. D., and M. Chelliah, 2006: Leading tropical modes associated with interannual and multidecadal fluctuations in North Atlantic hurricane activity. *J. Climate,* **19,** 590–612.

Bengtsson, L., K. I. Hodges, M. Esch, N. Keenlyside, L. Kornblueh, J. J. Luo, and T. Yamagata, 2007: How many tropical cyclones change in a warmer climate. *Tellus,* **59A,** 539–561.

Bove, M. C., J. B. Elsner, C. W. Landsea, X. Niu, and J. J. O'Brien, 1998: Effect of El Niño on U.S. landfalling hurricanes, revisited. *Bull. Amer. Meteor. Soc.,* **79,** 2477–2482.

Bunge, L., and A. J. Clarke, 2009: A verified estimation of the El Niño index Niño-3.4 since 1877. *J. Climate,* **22,** 3979–3992.

Camargo, S. J., K. A. Emanuel, and A. H. Sobel, 2007: Use of a genesis potential index to diagnose ENSO effects on tropical cyclone genesis. *J. Climate,* **20,** 4819–4834.

——, M. C. Wheeler, and A. H. Sobel, 2009: Diagnosis of the MJO modulation of tropical cyclogenesis using an empirical index. *J. Atmos. Sci.,* **66,** 3061–3074.

Chang, E. K. M., and Y. Guo, 2007: Is the number of North Atlantic tropical cyclones significantly underestimated prior to the availability of satellite observations? *Geophys. Res. Lett.,* **34,** L14801, doi:10.1029/2007GL030169.

Chauvin, F., J. F. Royer, and M. Deèquè, 2006: Response of hurricane-type vortices to global warming as simulated by ARPEGE-Climat at high resolution. *Climate Dyn.,* **27,** 377–399.

Chylek, P., and G. Lesins, 2008: Multidecadal variability of Atlantic hurricane activity: 1851–2007. *J. Geophys. Res.,* **113,** D22106, doi:10.1029/2008JD010036.

Coughlin, K., E. Bellone, T. Leapple, S. Jewson, and K. Nzerem, 2009: A relationship between all Atlantic hurricanes and those that make landfall in the USA. *Quart. J. Roy. Meteor. Soc.,* **135,** 371–379.

DeMaria, M., 1996: The effect of vertical shear on tropical cyclone intensity change. *J. Atmos. Sci.,* **53,** 2076–2087.

Derrig, R. A., J. S. Fishman, M. Grace, and J. Schmit, 2008: Catastrophe management in a changing world: The case of hurricanes. *Risk Manage. Insur. Rev.,* **11,** 269–280.

Dobson, A. J., 2001: *An Introduction to Generalized Linear Models*. 2nd ed. Chapman & Hall, 240 pp.

Donnelly, J. P., and J. D. Woodruff, 2007: Intense hurricane activity over the past 5,000 years controlled by El Niño and the West African monsoon. *Nature,* **447,** 465–467.

Dunn, P. K., and G. K. Smyth, 1996: Randomized quantile residuals. *J. Comput. Graph. Stat.,* **5,** 236–244.

Elsner, J. B., 2003: Tracking hurricanes. *Bull. Amer. Meteor. Soc.,* **84,** 353–356.

——, and C. P. Schmertmann, 1993: Improving extended-range seasonal predictions of intense Atlantic hurricane activity. *Wea. Forecasting,* **8,** 345–351.

——, and B. Kocher, 2000: Global tropical cyclone activity: A link to the North Atlantic Oscillation. *Geophys. Res. Lett.,* **27,** 129–132.

——, and B. H. Bossak, 2001: Bayesian analysis of U.S. hurricane climate. *J. Climate,* **14,** 4341–4350.

——, and T. H. Jagger, 2004: A hierarchical Bayesian approach to seasonal hurricane modeling. *J. Climate,* **17,** 2813–2827.

——, and ——, 2006: Prediction models for annual U.S. hurricane counts. *J. Climate,* **19,** 2935–2952.

——, T. Jagger, and X. F. Niu, 2000a: Changes in the rates of North Atlantic major hurricane activity during the 20th century. *Geophys. Res. Lett.,* **27,** 1743–1746.

——, K. B. Liu, and B. Kocker, 2000b: Spatial variations in major U.S. hurricane activity: Statistics and physical mechanisms. *J. Climate,* **13,** 2293–2305.

——, B. H. Bossak, and X. F. Niu, 2001: Secular changes to the ENSO–U.S. hurricane relationship. *Geophys. Res. Lett.,* **28,** 4123–4126.

——, X. Niu, and T. H. Jagger, 2004: Detecting shifts in hurricane rates using a Markov chain Monte Carlo approach. *J. Climate,* **17,** 2652–2666.

——, J. P. Kossin, and T. H. Jagger, 2008: The increasing intensity of the strongest tropical cyclones. *Nature,* **455,** 92–95.

Emanuel, K., 2005: Increasing destructiveness of tropical cyclones over the past 30 years. *Nature,* **436,** 686–688.

——, 2006: Climate and tropical cyclone activity: A new model downscaling approach. *J. Climate,* **19,** 4797–4802.

——, R. Sundararajan, and J. Williams, 2008: Hurricanes and global warming: Results from downscaling IPCC AR4 simulations. *Bull. Amer. Meteor. Soc.,* **89,** 347–367.

Evan, A. T., J. Dunion, J. A. Foley, A. K. Heidinger, and C. S. Velden, 2006: New evidence for a relationship between Atlantic tropical cyclone activity and African dust outbreaks. *Geophys. Res. Lett.,* **33,** L19813, doi:10.1029/2006GL026408.

Filliben, J. J., 1975: The probability plot correlation coefficient test for normality. *Technometrics,* **17,** 111–117.

Goldenberg, S. B., and L. J. Shapiro, 1996: Physical mechanisms for the association of El Niño and West African rainfall with Atlantic major hurricane activity. *J. Climate,* **9,** 1169–1187.

——, C. W. Landsea, A. M. Mestas-Nuñez, and W. M. Gray, 2001: The recent increase in Atlantic hurricane activity: Causes and implications. *Science,* **293,** 474–479, doi:10.1126/science.1060040.

Gray, W. M., 1984: Atlantic seasonal hurricane frequency. Part I: El Niño and 30-mb quasi-biennal oscillation influences. *Mon. Wea. Rev.,* **112,** 1649–1668.

——, 1990: Strong association between West African rainfall and U.S. landfall of intense hurricanes. *Science,* **249,** 1251–1256.

Gualdi, S., E. Scoccimarro, and A. Navarra, 2008: Changes in tropical cyclone activity due to global warming: Results from a high-resolution coupled general circulation model. *J. Climate,* **21,** 5204–5228.

Hastie, T. J., and R. J. Tibshirani, 1990: *Generalized Additive Models*. Chapman and Hall, 352 pp.

Henderson-Sellers, A., and Coauthors, 1998: Tropical cyclones and global climate change: A post-IPCC assessment. *Bull. Amer. Meteor. Soc.,* **79,** 19–38.

Hilbe, J. M., 2007: *Negative Binomial Regression*. Cambridge University Press, 251 pp.

Hipel, K. W., 1981: Geophysical model discrimination using the Akaike Information Criterion. *IEEE Trans. Automat. Contrib.,* **26,** 358–378.

Holland, G. J., and P. J. Webster, 2007: Heightened tropical cyclone activity in the North Atlantic: Natural variability or climate trend. *Philos. Trans. Roy. Soc. London,* **365A,** 2695–2716.

Hoyos, C. D., P. A. Agudelo, P. J. Webster, and J. A. Curry, 2006: Deconvolution of the factors contributing to the increase in global hurricane activity. *Science,* **312,** 94–97.

Hurrell, J. W., and H. Van Loon, 1997: Decadal variations in climate associated with the North Atlantic Oscillation. *Climatic Change,* **36,** 301–326.

Jagger, T. H., and J. B. Elsner, 2006: Climatology models for extreme hurricane winds near the United States. *J. Climate,* **19,** 3220–3236.

——, ——, and X. Niu, 2001: A dynamic probability model of hurricane winds in coastal counties of the United States. *J. Appl. Meteor.,* **40,** 853–863.

Jarvinen, B. R., C. J. Neumann, and M. A. S. Davis, 1984: A tropical cyclone data tape for the North Atlantic Basin, 1886–1983: Contents, limitations, and uses. Tech. Memo. NWS NHC 22, National Oceanic and Atmospheric Administration, 24 pp.

Jones, P. D., T. Jonsson, and D. Wheeler, 1997: Extension to the North Atlantic Oscillation using early instrumental pressure observations from Gibraltar and south–west Iceland. *Int. J. Climatol.,* **17,** 1433–1450.

Karr, A. F., 1991: *Point Processes and Their Statistical Inference*. 2nd ed. CRC/Marcel Dekker, 512 pp.

Knutson, T. R., and R. E. Tuleya, 1999: Increased hurricane intensities with CO_2-induced warming as simulated using the GFDL hurricane prediction system. *Climate Dyn.,* **15,** 503–519.

——, and ——, 2004: Impact of CO_2-induced warming on simulated hurricane intensity and precipitation: Sensitivity to the choice of climate model and convective parameterization. *J. Climate,* **17,** 3477–3495.

——, J. J. Sirutis, S. T. Garner, I. Held, and R. E. Tuleya, 2007: Simulation of recent increase of Atlantic hurricane activity using an 18-km-grid regional model. *Bull. Amer. Meteor. Soc.,* **88,** 1549–1565.

——, ——, ——, G. A. Vecchi, and I. Held, 2008: Simulated reduction in Atlantic hurricane frequency under twenty-first-century warming conditions. *Nat. Geosci.,* **1** (6), 359–364.

Kossin, J. P., and D. J. Vimont, 2007: A more general framework for understanding Atlantic hurricane variability and trends. *Bull. Amer. Meteor. Soc.,* **88,** 1767–1781.

Landsea, C. W., 2001: Comment on ''Changes in the rates of North Atlantic major hurricane activity during the 20th century.'' *Geophys. Res. Lett.,* **28,** 2871–2872.

——, 2007: Counting Atlantic tropical cyclones back to 1900. *Eos, Trans. Amer. Geophys. Union,* **88,** 197–202.

——, and W. M. Gray, 1992: The strong association between Western Sahel monsoon rainfall and intense Atlantic hurricanes. *J. Climate,* **5,** 435–453.

——, R. A. Pielke, Jr., A. M. Mestas-Nunez, and J. A. Knaff, 1999: Atlantic basin hurricanes: Indices of climatic changes. *Climatic Change,* **42,** 89–129.

——, and Coauthors, 2004: The Atlantic hurricane database reanalysis project: Documentation for 1851–1910 alterations and additions to the HURDAT database. *Hurricanes and Typhoons—Past, Present, and Future,* R. J. Murnane and K. B. Liu, Eds., Columbia University Press, 178–221.

——, and Coauthors, 2008: A reanalysis of the 1911–20 Atlantic hurricane database. *J. Climate,* **21,** 2138–2168.

——, G. A. Vecchi, L. Bengtsson, and T. R. Knutson, 2010: Impact of duration thresholds on Atlantic tropical cyclone counts. *J. Climate,* in press.

LaRow, T. E., Y. K. Lim, D. W. Shin, E. P. Chassignet, and S. Cocke, 2008: Altantic basin seasonal hurricane simulations. *J. Climate,* **21,** 3191–3206.

Latif, M., N. Keenlyside, and J. Bader, 2007: Tropical sea surface temperature, vertical wind shear, and hurricane development. *Geophys. Res. Lett.,* **34,** L01710, doi:10.1029/2006GL027969.

Mailier, P. J., D. B. Stephenson, C. A. T. Ferro, and K. I. Hodges, 2006: Serial clustering of extratropical cyclones. *Mon. Wea. Rev.,* **134,** 2224–2240.

Maloney, E. D., and D. L. Hartmann, 2000: Modulation of hurricane activity in the Gulf of Mexico by the Madden–Julian oscillation. *Science,* **287,** 2002–2004.

Mann, M. E., and K. A. Emanuel, 2006: Atlantic hurricane trends linked to climate change. *Eos, Trans. Amer. Geophys. Union,* **87,** 233–244.

——, T. A. Sabbatelli, and U. Neu, 2007: Evidence for a modest undercount bias in early historical Atlantic tropical cyclone counts. *Geophys. Res. Lett.,* **34,** L22707, doi:10.1029/2007GL031781.

McCullagh, P., and J. A. Nelder, 1989: *Generalized Linear Models*. 2nd ed. Chapman and Hall/CRC, 532 pp.

McDonnell, K. A., and N. J. Holbrook, 2004a: A Poisson regression model approach to predicting tropical cyclogenesis in the Australian/southwest Pacific Ocean region using the SOI and saturated equivalent potential temperature gradient as predictors. *Geophys. Res. Lett.,* **31,** L20110, doi:10.1029/2004GL020843.

——, and ——, 2004b: A Poisson regression model of tropical cyclogenesis for the Australian/southwest Pacific Ocean region. *Wea. Forecasting,* **19,** 440–455.

Mestre, O., and S. Hallegatte, 2009: Predictors of tropical cyclone numbers and extreme hurricane intensities over the North Atlantic using generalized additive and linear models. *J. Climate,* **22,** 633–648.

Negri, A. J., and Coauthors, 2005: The hurricane–flood–landslide continuum. *Bull. Amer. Meteor. Soc.,* **86,** 1241–1247.

Neumann, C. J., B. R. Jarvinen, C. J. McAdie, and J. D. Elms, 1993: Tropical cyclones of the North Atlantic Ocean. Tech. Memo., National Climatic Data Center/National Hurricane Center, 193 pp.

Nzerem, K., S. Jewson, and T. Leapple, 2006: Change-point detection in the historical hurricane number time series: Why can't we detect change points at U.S. landfall? 7 pp. [Available online at http://arxiv.org/abs/physics/0611107.]

Oouchi, K., J. Yoshimura, H. Yoshimura, R. Mizuta, S. Kusumoki, and A. Noda, 2006: Tropical cyclone climatology in a global-warming climate as simulated in a 20 km-mesh global atmospheric model: Frequency and wind intensity analysis. *J. Meteor. Soc. Japan,* **84,** 259–276.

Parisi, F., and R. Lund, 2008: Return period of continental U.S. hurricanes. *J. Climate,* **21,** 403–410.

Pielke, R. A., Jr., and C. W. Landsea, 1998: Normalized hurricane damage in the United States: 1925–95. *Wea. Forecasting,* **13,** 621–631.

——, and ——, 1999: La Niña, El Niño, and Atlantic hurricane damages in the United States. *Bull. Amer. Meteor. Soc.,* **80,** 2027–2033.

——, J. Gratz, C. W. Landsea, D. Collins, M. A. Saunders, and R. Musulin, 2008: Normalized hurricane damage in the United States: 1900–2005. *Nat. Hazards Rev.,* **9,** 29–42.

Pinto, J. G., S. Zacharias, A. H. Fink, G. C. Leckebusch, and U. Ulbrich, 2009: Factors contributing to the development of extreme North Atlantic cyclones and their relation with NAO. *Climate Dyn.,* **32,** 711–737.

Rappaport, E. N., 2000: Loss of life in the United States associated with recent Atlantic tropical cyclones. *Bull. Amer. Meteor. Soc.,* **81,** 2065–2073.

Rayner, N. A., D. E. Parker, E. B. Horton, C. K. Folland, L. V. Alexander, D. P. Rowell, E. C. Kent, and A. Kaplan, 2003: Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. *J. Geophys. Res.,* **108,** 4407, doi:10.1029/2002JD002670.

R Development Core Team, cited 2008: R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. [Available online at http://www.R-project.org.]

Rigby, R. A., and D. M. Stasinopoulos, 2005: Generalized additive models for location, scale and shape. *Appl. Stat.,* **54,** 507–554.

Sabbatelli, T. A., and M. E. Mann, 2007: The influence of climate state variables on Atlantic tropical cyclone occurrence rates. *J. Geophys. Res.,* **112,** D17114, doi:10.1029/2007JD008385.

Saunders, M. A., and A. S. Lea, 2005: Seasonal prediction of hurricane activity reaching the coast of the United States. *Nature,* **434,** 1005–1008.

——, and ——, 2008: Large contribution of sea surface warming to recent increase in Atlantic hurricane activity. *Nature,* **451,** 557–560.

Schwarz, G., 1978: Estimating the dimension of a model. *Ann. Stat.,* **6,** 461–464.

Shapiro, L. J., 1982: Hurricane climatic fluctuations. Part II: Relation to large-scale circulation. *Mon. Wea. Rev.,* **110,** 1014–1023.

——, and S. B. Goldenberg, 1998: Atlantic sea surface temperature and tropical cyclone formation. *J. Climate,* **11,** 578–590.

Shepherd, J. M., and T. Knutson, 2007: The current debate on the linkage between global warming and hurricanes. *Geogr. Compass,* **1,** 1–24.

Smith, J. A., and A. F. Karr, 1986: Flood frequency analysis using the Cox regression model. *Water Resour. Res.,* **22,** 890–896.

Smith, T. M., R. W. Reynolds, T. C. Peterson, and J. Lawrimore, 2008: Improvements to NOAA's historical merged land–ocean surface temperature analysis (1880–2006). *J. Climate,* **21,** 2283–2296.

Stasinopoulos, D. M., and R. A. Rigby, 2007: Generalized additive models for location scale and shape (GAMLSS) in R. *J. Stat. Softw.,* **23,** 1–46.

——, ——, and C. Akantziliotou, cited 2007: Gamlss: Generalized Additive Models for Location Scale and Shape. R package. [Available online at http://cran.r-project.org/web/packages/gamlss/index.html.]

——, ——, ——, G. Heller, R. Ospina, and N. Motpan, cited 2009: Gamlss.dist: Distributions to be used for GAMLSS modelling. [Available online at http://cran.r-project.org/web/packages/gamlss.dist/index.html.]

Sugi, M. A., A. Noda, and N. Sato, 2002: Influence of the global warming on tropical cyclone climatology: An experiment with the JMA global model. *J. Meteor. Soc. Japan,* **80,** 249–272.

——, H. Murakami, and J. Yoshimura, 2009: A reduction in global tropical cyclone frequency due to global warming. *SOLA,* **5,** 164–167.

Swanson, K. L., 2008: Nonlocality of Atlantic tropical cyclone intensities. *Geochem. Geophys. Geosyst.,* **9,** Q04V01, doi:10.1029/2007GC001844.

Tang, B. H., and J. D. Neelin, 2004: ENSO influence on Atlantic hurricanes via tropospheric warming. *Geophys. Res. Lett.,* **31,** L24204, doi:10.1029/2004GL021072.

Tartaglione, C. A., S. R. Smith, and J. J. O'Brien, 2003: ENSO impact on hurricane landfall probabilites for the Caribbean. *J. Climate,* **16,** 2925–2931.

Trenberth, K. E., 1984: Signal versus noise in the Southern Oscillation. *Mon. Wea. Rev.,* **112,** 326–332.

——, 2005: Uncertainty in hurricanes and global warming. *Science,* **308,** 1753–1754.

van Buuren, S., and M. Fredriks, 2001: Worm plot: A simple diagnostic device for modeling growth reference curves. *Stat. Med.,* **20,** 1259–1277.

Vecchi, G. A., and B. J. Soden, 2007: Effect of remote sea surface temperature change on tropical cyclone potential intensity. *Nature,* **450,** 1066–1071.

——, and T. R. Knutson, 2008: On estimates of historical North Atlantic tropical cyclone activity. *J. Climate,* **21,** 3580–3600.

——, A. Clement, and B. J. Soden, 2008a: Examining the tropical Pacific's response to global warming. *Eos, Trans. Amer. Geophys. Union,* **89,** 81–83.

——, K. L. Swanson, and B. J. Soden, 2008b: Whither hurricane activity? *Science,* **322,** 687–689.

Vimont, D. J., and J. P. Kossin, 2007: The Atlantic Meridional Mode and hurricane activity. *Geophys. Res. Lett.,* **34,** L07709, doi:10.1029/2007GL029683.

Vitart, F., and J. L. Anderson, 2001: Sensitivity of Atlantic tropical storm frequency to ENSO and interdecadal variability of SSTs in an ensemble of AGCM integrations. *J. Climate,* **14,** 533–545.

Vitolo, R., D. B. Stephenson, I. M. Cook, and K. Mitchell-Wallace, 2009: Serial clustering of intense European storms. *Meteor. Z.,* **18,** 411–424.

Wu, G., and N. C. Lau, 1992: A GCM simulation of the relationship between tropical-storm formation and ENSO. *Mon. Wea. Rev.,* **120,** 958–977.

Zhang, R., and T. L. Delworth, 2006: Impact of Atlantic multidecadal oscillations on India/Sahel rainfall and Atlantic hurricanes. *Geophys. Res. Lett.,* **33,** L17712, doi:10.1029/2006GL026267.

Zhao, M., I. M. Held, S. J. Lin, and G. A. Vecchi, 2009: Simulations of global hurricane climatology, interannual variability, and response to global warming using a 50-km resolution GCM. *J. Climate,* **22,** 6653–6678.