North Atlantic Tropical Storm Frequency Response to Anthropogenic Forcing: Projections and Sources of Uncertainty

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ABSTRACT

The impact of future anthropogenic forcing on the frequency of tropical storms in the North Atlantic basin has been the subject of intensive investigation. However, whether the number of North Atlantic tropical storms will increase or decrease in a warmer climate is still heavily debated and a consensus has yet to be reached. To shed light on this issue, the authors use a recently developed statistical model, in which the frequency of North Atlantic tropical storms is modeled by a conditional Poisson distribution with rate of occurrence parameter that is a function of tropical Atlantic and mean tropical sea surface temperatures (SSTs). It is shown how the disagreement among dynamical modeling projections of late-twenty-first-century tropical storm frequency can be largely explained by differences in large-scale SST patterns from the different climate model projections used in these studies. The results do not support the notion of large (~200%) increases in tropical storm frequency in the North Atlantic basin over the twenty-first century in response to increasing greenhouse gases (GHGs). Because the statistical model is computationally inexpensive, it is used to examine the impact of different climate models and climate change scenarios on the frequency of North Atlantic tropical storms. The authors estimate that the dominant drivers of uncertainty in projections of tropical storm frequency over the twenty-first century are internal climate variations and systematic intermodel differences in the response of SST patterns to increasing GHGs. Relative to them, uncertainties in total GHG emissions or other climate forcings, within the scenarios explored here, represent a minor source of uncertainty in tropical storm frequency projections. These results suggest that reducing uncertainty in future projections of North Atlantic tropical storm frequency may depend as critically on reducing the uncertainty in the sensitivity of tropical Atlantic warming relative to the tropical mean, in response to GHG increase, as on improving dynamical or statistical downscaling techniques. Moreover, the large uncertainties on century-scale trends that are due to internal climate variability are likely to remain irreducible for the foreseeable future.

As a further illustration of the statistical model's utility, the authors model projected changes in U.S. landfalling tropical storm activity under a variety of different climate change scenarios and climate models. These results are similar to those for the overall number of North Atlantic tropical storms, and do not point to a large increase in U.S. landfalling tropical storms over the twenty-first century in response to increasing GHGs.

1. Introduction

The investigation of the effects of greenhouse gas–dominated warming on tropical storm activity in the North Atlantic basin has been the topic of a number of studies with contradicting results and conclusions. Some studies point to an increase in tropical storm frequency (Henderson-Sellers et al. 1998; Emanuel 2005; Mann and Emanuel 2006; Oouchi et al. 2006; Holland and Webster 2007), others to a decrease (Bengtsson et al. 2007; Knutson et al. 2008; Gualdi et al. 2008; Bender et al. 2010), while others suggest a possibility for either an increase or decrease (Emanuel et al. 2008; Sugi et al.

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2009; Zhao et al. 2009). The interested reader is pointed to Knutson et al. (2010) for a recent review. These results are based on both statistical and dynamical models with the dynamical models having structural differences (grid resolutions, parameterizations, etc.), using different control and perturbation periods, and in some cases specifying different forcing scenarios (particularly for nongreenhouse gas forcings, such as aerosols).

As outlined in Vecchi et al. (2008), the main argument in support of projecting a large (~200%) twenty-first-century increase in tropical storm activity is related to the projected substantial increase of Atlantic sea surface temperature (SST) in climate model scenarios, assuming a causal relation from local SST to tropical storm count. The underlying idea is that a warmer Atlantic SST (local effect) is the primary factor influencing the tropical storm genesis and development. Even though in the present climate a warm Atlantic SST is a necessary condition for the genesis and development of tropical storms, recent studies have suggested that the remote influence of tropical SST outside of the Atlantic also plays a key role in providing the atmospheric conditions necessary for the tropical storm formation (e.g., Swanson 2008; Vecchi et al. 2008). In this case, the relative (rather than absolute) increase in Atlantic SST with respect to the tropical mean SST represents a better indicator of North Atlantic tropical storm activity.

The disagreement among the different dynamical modeling studies is both in terms of magnitude and sign of the change in tropical storm frequency under projected human-induced climate warming (e.g., Trenberth 2005; Shepherd and Knutson 2007; Vecchi et al. 2008; Knutson et al. 2010). One natural question is the following: could it be that existing dynamical downscaling model studies actually agree, within a certain context, about the effects of climate change on the tropical storm activity in the North Atlantic basin? In this article, we argue that this is the case, and we further outline dominant sources of the large disagreement in the projections.

Apart from information about changes in tropical storm activity in a warmer climate for the entire North Atlantic basin, changing frequency of U.S. landfalling tropical storms is of greater societal relevance (e.g., Pielke and Landsea 1998; Rappaport 2000; Pielke et al. 2008; Villarini and Smith 2010). Pielke (2005) focused on hurricane destruction and did not find increasing or decreasing trends over the historical period. However, to the best of our knowledge only Knutson et al. (2008) has examined projections of increasing greenhouse gases on the frequency of U.S. landfalling tropical storms over the twenty-first century, finding a 30% reduction in U.S. landfalling hurricanes compared to an 18% reduction in the basinwide hurricanes. Therefore, the effects of different climate models for a given scenario, as well as the impact of different climate change scenarios for a given model on projected activity of U.S. landfalling tropical storms still remains an open question.

Using the recently proposed statistical model by Villarini et al. (2010), the main points addressed in this study revolve around the following:

1) reconciling differing model projections of changes in the frequency of North Atlantic tropical storms in a warmer climate, and
2) examination of the impact of different climate models and climate change scenarios on North Atlantic and U.S. landfalling tropical storm activity.

The paper is organized in the following way. In the next section we briefly describe the statistical model used to assess changes in tropical storm activity, followed by section 3 in which we discuss the results. The main points of the study are summarized in section 4.

2. Statistical model

In a recent study, Villarini et al. (2010) developed a Poisson regression model in which the count of tropical storms N_i has a conditional Poisson distribution of the following form:

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

where Λ_i is a nonnegative random variable and represents the rate of occurrence for the ith year in the record. Different covariates related to the tropical storm genesis, development, and tracking (tropical Atlantic and tropical mean SSTs, North Atlantic Oscillation, and Southern Oscillation index) were considered to describe the variability over time of Λ_i.

Villarini et al. (2010) modeled the rate of occurrence of U.S. landfalling tropical storms, together with the tropical storm frequency for the entire North Atlantic basin. They used different penalty criteria for variable and model selection, two different SST datasets [the National Oceanic and Atmospheric Administration (NOAA) Extended Reconstructed (ERSSTv3b; Smith et al. 2008) and the Met Office Hadley Centre Sea Ice and SST model version 1 (HadISSTv1; Rayner et al. 2003) data], as well as two different time series of counts for the North Atlantic basin lasting longer than two days [the original (uncorrected) tropical storm record maintained by the National Hurricane Center (Jarvinen et al. 1984; Neumann et al. 1993), and one with a correction for the estimated undercount associated with a changing observation network (Landsea et al. (2010)].

One of the main findings was that both tropical Atlantic and tropical mean SSTs are always significant covariates in explaining the variability exhibited by the tropical storm counts over the period 1878–2008. It is interesting to note that the coefficients for the two SST covariates have similar magnitudes but opposite signs (positive for tropical Atlantic SST and negative for the tropical mean SST), suggesting that in terms of tropical storm counts, an increase in tropical Atlantic SST would be offset by an increase in the tropical mean SST of the same magnitude.

In this study we use the parsimonious model recommended in Villarini et al. (2010) for the homogenized tropical storm count with the correction by Landsea et al. (2010). In our approach, the logarithm of the rate of occurrence of tropical storms can be statistically modeled as a linear function of only tropical Atlantic and tropical mean SSTs:

$$\Lambda_i = \exp[b_0 + b_1\mathrm{SST}_{\mathrm{Atl}} + b_2\mathrm{SST}_{\mathrm{Trop}}], \qquad (2)$$

where $\mathrm{SST}_{\mathrm{Atl}}$ represents tropical Atlantic SST, while $\mathrm{SST}_{\mathrm{Trop}}$ represents the tropical mean SST. For the overall tropical storm activity for the North Atlantic basin, based on ERSSTv3b (HadISSTv1) SST dataset b_0 is estimated as 2.11 (2.10), b_1 as 1.05 (1.02), and b_2 as −1.12 (−1.05). For U.S. landfalling tropical storms, b_0 is estimated as 1.24 (independently of the SST dataset), b_1 as 0.89 and 0.86, and b_2 as −0.89 and −0.86 based on ERSSTv3b and HadISSTv1 SST datasets, respectively. The coefficients of these two SST predictors point to the importance of the differences between tropical Atlantic SST and tropical mean SST in describing the frequency of North Atlantic and U.S. landfalling tropical storms. Consult Villarini et al. (2010) for more details.

Even though none of the results in Villarini et al. (2010) point to tropical Atlantic SST as the only predictor necessary to describe variability of tropical storm frequency in the North Atlantic basin, in this study we also include the results for a Poisson regression model, in which the rate of occurrence Λ_i is a linear function (via a logarithmic link function) of only tropical Atlantic SST:

$$\Lambda_i = \exp[\beta_0 + \beta_1\mathrm{SST}_{\mathrm{Atl}}]. \qquad (3)$$

We have summarized the modeling results in Fig. 1 and Table 1. For the North Atlantic tropical storm frequency, β_0 is estimated as 2.12 (for both ERSSTv3b and HadISSTv1), while β_1 is estimated as 0.42 for ERSSTv3b and 0.47 for HadISSTv1. As far as U.S. landfalling tropical storm frequency is concerned, β_0 is estimated as 1.25 (for both ERSSTv3b and HadISSTv1), while β_1 is estimated as 0.37 for ERSSTv3b and 0.43 for HadISSTv1.

3. Results

a. Comparison between statistical and dynamical model projections

We compare the results that we would obtain from the statistical model in Eq. (2) with published results from dynamical and hybrid statistical dynamical models (Oouchi et al. 2006; Bengtsson et al. 2007; Knutson et al. 2008; Gualdi et al. 2008; Emanuel et al. 2008; Sugi et al. 2009; Zhao et al. 2009; Bender et al. 2010). All of these works explored the impact of climate changes as projected by the climate models used for the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4). However, different climate models, different control and perturbation periods, and often different implementations of the ''benchmark'' forcing scenarios were used in each study. As input for the statistical model we use tropical Atlantic and tropical mean SST time series from the corresponding scenario using the same climate models, and control and perturbation periods as each of these 8 studies, for a total of 26 different cases.

We have summarized our results in Fig. 2. For illustration, we have also included the results obtained from a statistical model in which the rate of occurrence of tropical storms depends only on tropical Atlantic SST (Fig. 1). Since all the dynamical and statistical/dynamical studies to which we are comparing the statistical model have an explicit duration threshold in their definition of tropical cyclone (Oouchi et al. 2006; Bengtsson et al. 2007; Knutson et al. 2008; Gualdi et al. 2008; Emanuel et al. 2008; Sugi et al. 2009; Zhao et al. 2009; Bender et al. 2010), it is appropriate that we use the statistical model of Villarini et al. (2010) built on the homogenized data of Landsea et al. (2010), which excludes storms lasting two days or less. When comparing our results (using the median as reference, and both tropical Atlantic and tropical mean SSTs as predictors for the statistical model) against those from the dynamical models, we observe a very good agreement, with the vast majority of the dynamical models' points within the 90% prediction intervals of our statistical model (Fig. 2, top panels). We obtain a correlation coefficient of 0.67 and 0.68 (based on ERSSTv3b and HadISSTv1 SST datasets, respectively), indicating that we explain with a very

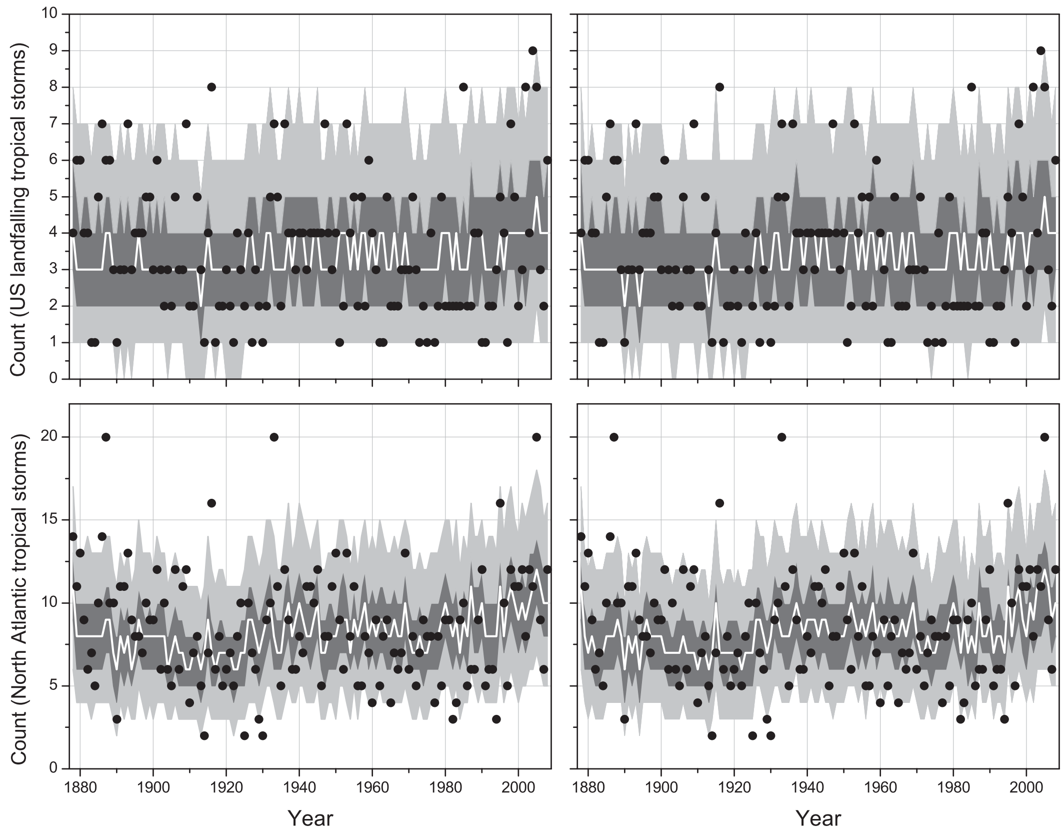

FIG. 1. Modeling of the (top) U.S. landfalling tropical storms and (bottom) tropical storm count data [lasting longer than 2 days and adjusted based on Landsea et al. (2010) for the entire North Atlantic basin] using a Poisson regression model in which the rate of occurrence depends linearly (via a logarithmic link function) only on tropical Atlantic SST. The points represent the observations, the white line represents the median (50th percentile), the dark gray region represents the area between the 25th and 75th percentiles, and the light gray region represents the area between the 5th and 95th percentiles. Results by using SST from the (left) ERSSTv3b and (right) HadISSTv1 dataset. Summary statistics for these models are presented in Table 1.

simple observationally derived model close to half of the variance exhibited across the various modeling studies, with a root-mean-squared error (RMSE) of 27.6% and 24.6%, and a mean absolute error (MAE) of 23.4% and 20.3%. We have also computed the correlation coefficients for the subsets of modeling results from Emanuel et al. (2008), Sugi et al. (2009), and Zhao et al. (2009). Using the statistical model based on ERSSTv3b (HadISSTv1) data, for the subset of Emanuel et al. results, we obtain a correlation coefficient of 0.66 (0.60), explaining 43% (36%) of the variance among these results. For the subset of Sugi et al. results, the correlation coefficient is equal to 0.85 (0.86) and the explained variance among the results is 72% (73%). For the subset of results from Zhao et al., the correlation coefficient is equal to 0.94 (0.95), explaining 88% (90%) of the variance among the results. Despite the high correlation values, the results derived for the individual studies should be interpreted with caution because of the small sample size. Nonetheless, they suggest that the statistical model is able to reproduce the variability in tropical storm projections exhibited both across different studies and within the same study, increasing our confidence in the utility of the statistical model.

The agreement between the statistical and dynamical models is rather remarkable, considering the simplicity of the statistical model, and the variety of dynamical modeling frameworks used (e.g., different grid resolutions, parameterizations, different control and perturbation periods, and specification of different forcing scenarios). Based on these results, it appears that differences among the published results can be largely reduced to differences in the climate model projections of tropical Atlantic SST changes relative to the global tropics used by the studies. Once these differences are accounted for, these studies tend to provide a much more consistent picture. That is, uncertainty in projected patterns of tropical SST changes in the twenty-first

TABLE 1. Summary statistics for the Poisson modeling of North Atlantic tropical storm counts using tropical Atlantic SST as covariate. In the "Intercept" and "SST_{Atl}" cells, the first value is the point estimate, while the one in bracket is the standard error. In each cell, the values in the first (second) row refer to the model using the HadISSTv1 (ERSSTv3b).

	Landfall	Corrected
Intercept	1.25 (0.05)	2.12 (0.03)
	1.25 (0.05)	2.12 (0.03)
SST_{Atl}	0.43 (0.16)	0.47 (0.10)
	0.37 (0.14)	0.42 (0.09)
Degrees of freedom	2	2
for the fit	2	2
Mean (residuals)	−0.00	−0.01
	0.00	−0.04
Variance (residuals)	0.98	1.23
	0.93	1.23
Skewness (residuals)	0.29	0.33
	0.30	0.34
Kurtosis (residuals)	2.61	3.34
	2.52	3.36
Filliben (residuals)	0.992	0.995
	0.991	0.993
AIC	521.75	676.4
	522.09	675.3
SBC	527.50	682.1
	527.84	681.1

century is a leading cause of uncertainty in North Atlantic tropical storm frequency projections. Thus, understanding the mechanisms that produce patterns of SST changes should be a primary effort in the quest to reduce uncertainty in tropical storm projections.

On the other hand, if we hypothesize that Atlantic SST alone is the primary factor affecting tropical storm frequency, we arrive at a statistical projection that is inconsistent with that of the dynamical models (Fig. 2, bottom panels). The points do not exhibit a systematic pattern and have a significant bias (the value of the intercept in the regression equation is 186.8% and 238.7% vs 9.1% and 1.4% obtained when using both tropical Atlantic and tropical mean SSTs). We obtain a correlation coefficient of 0.14 and we explain 2% of the variance exhibited by the data. Moreover, the RMSE and MAE are almost an order of magnitude larger when compared to the statistical model that focuses on SST change pattern.

These results, in addition to the skill in reproducing the historical record of homogenized tropical storm frequency (Villarini et al. 2010), provide additional evidence in support of the idea that tropical Atlantic SST relative to tropical mean SST is a very important factor in the frequency of occurrence of tropical storms in the North Atlantic basin. That is, none of the dynamical modeling studies explored here supports the notion that tropical Atlantic SSTs on their own are the primary control on North Atlantic tropical storm frequency.

b. *Sensitivity of the projections of North Atlantic tropical storm activity to different climate models and climate change scenarios*

So, why is there such a spread in the projected changes of SST patterns, and thus in projections of tropical storm frequency? Since the statistical model is computationally efficient and provides results that compare reasonably well with those from the dynamical models, we can use it to explore the changes in basinwide tropical storm frequency for the entire twenty-first century and for each of the 24 available climate models (see Vecchi and Soden 2007 for a summary of the different models). In Fig. 3 we show the modeled time series for the Special Report on Emissions Scenarios (SRES) A1B scenario and eight different climate models. The time series exhibit large variability, with more active periods alternating to less active ones. We also notice differences across the different climate models. For instance, both the Geophysical Fluid Dynamics Laboratory (GFDL) and Met Office, Hadley Centre models exhibit very large interannual variability, while the Commonwealth Scientific and Industrial Research Organisation (CSIRO) and the Model for Interdisciplinary Research on Climate 3.2, high-resolution version [MIROC3.2(hires)] exhibit less variability. Moreover, some models present a more marked increase over the twenty-first century, while others show a decrease. Overall, we obtain a substantial range of results when computing the slopes of the regression lines over the periods 2001–50, 2051–2100, and 2001–2100 (Fig. 4). There is a tendency among the models toward decreasing trends during the twenty-first century, with most of the projections within ±5 tropical storms century^{-1}. For the period 2001–50 (2051–2100) we obtain statistically significant (at the 5% level) trends in 5 (7) cases (all of them decreasing). When considering the period 2001–2100, in 11 cases we obtain statistically significant decreasing trends and in 4 cases increasing trends (significant at the 5% level).

Apart from the SRES A1B scenario, we have also investigated the sensitivity of the modeling results to different IPCC SRES climate change scenarios [using 12 climate models, and also focusing on the GFDL Climate Model version 2.1 (CM2.1)]. The scenarios and the approximate CO_2 equivalent concentrations to which they correspond (in terms of radiative forcing by both anthropogenic greenhouse gases and aerosols by 2100) include: SRES A1FI: 1550 ppm; SRES A2: 1250 ppm; SRES A1B: 850 ppm; and SRES B1: 600 ppm. We also consider Stable_2000, which maintains CO_2, aerosols, etc. at 2000 levels for 100 yr. As shown in Fig. 5, these projection time

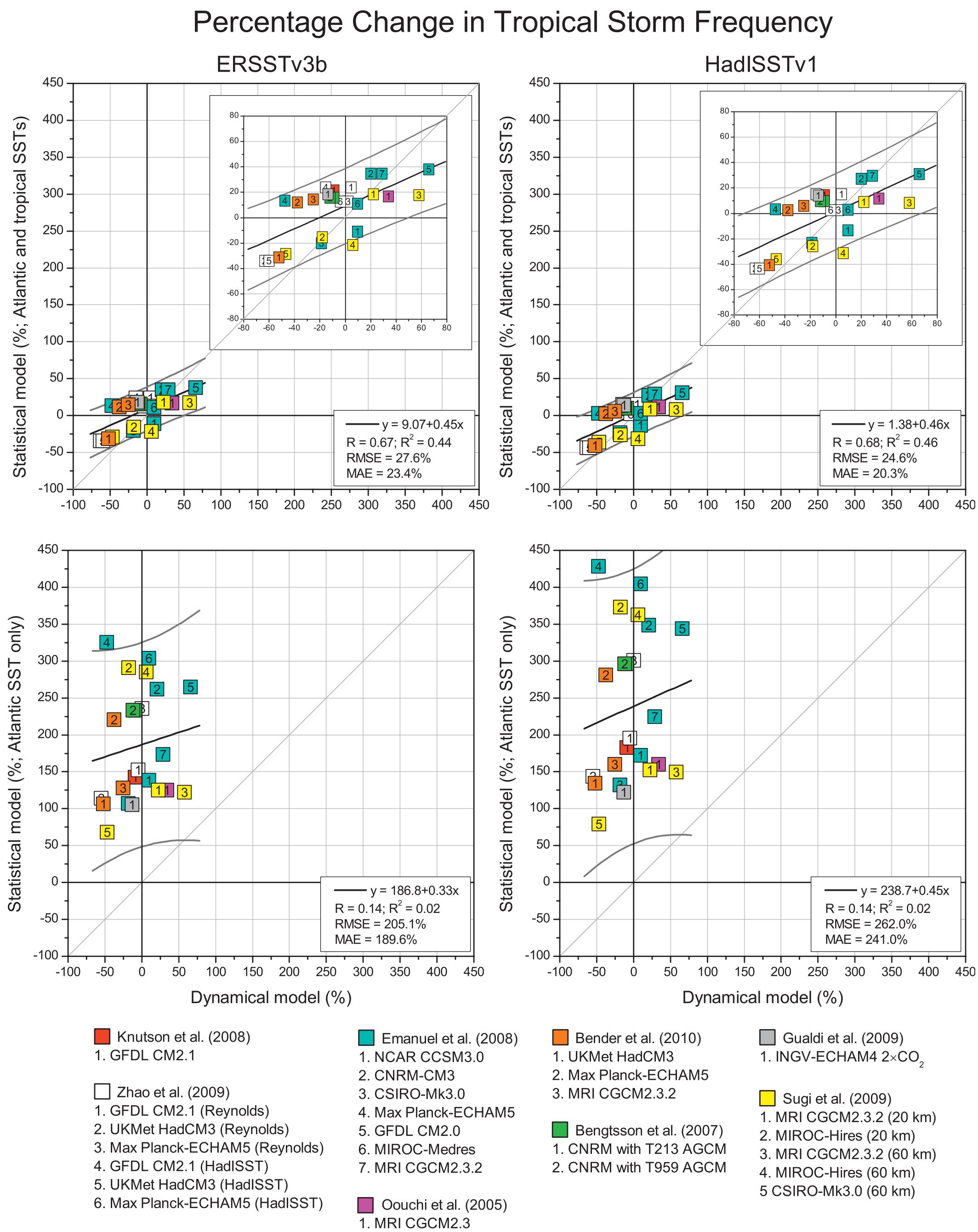

FIG. 2. Comparison of fractional tropical storm count changes between dynamical and statistical models. The statistical model uses (top) both tropical Atlantic and tropical mean SSTs and (bottom) only tropical Atlantic SST as covariates. Results are based on the models constructed using (left) NOAA's ERSSTv3b dataset and (right) the Met Office's HadISSTv1 dataset. The gray lines represent the 90% prediction intervals for the linear regression model.

series from GFDL CM2.1 exhibit little or no increasing trend (only the trend for the SRES A1B scenario for the period 2001–2100 is significant at the 5% level), ranging from 0 to 2 storms century^{-1} (based on 2001–2100 trends; black dots), but are not ordered according to the degree of global temperature increase or equivalent CO_2 forcing. Nonetheless, in these model scenarios one would still experience years and decades with higher activity alternating to years and decades of reduced activity, as have been experienced over the past 150 yr.

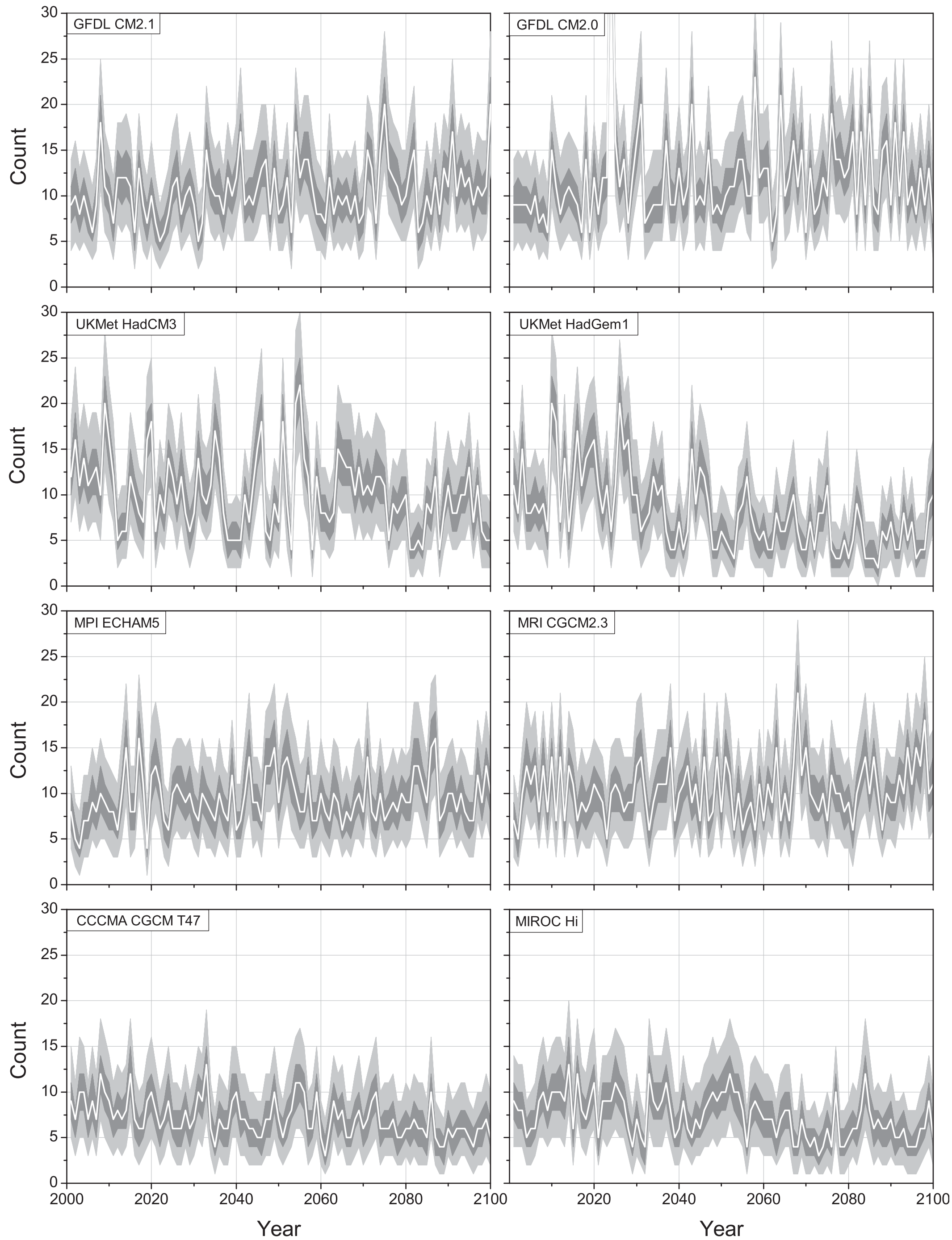

FIG. 3. Projections for the twenty-first century of the tropical storm counts for the North Atlantic basin under the SRES A1B scenario for eight different climate models using both tropical Atlantic and tropical mean SSTs as covariates in the statistical model (based on the model constructed using NOAA's ERSSTv3b dataset). The white line represents the median (50th percentile), the dark gray region represents the area between the 25th and 75th percentiles, and the light gray region represents the area between the 5th and 95th percentiles.

FIG. 4. Slopes of the regression lines for three periods (2001–50, 2051–2100, and 2001–2100) for all the 24 available climate models. These results are based on the projections for the twenty-first century of the tropical storm counts for the North Atlantic basin under the SRES A1B scenario, using both tropical Atlantic and tropical mean SSTs as covariates in the statistical model (based on the model constructed using NOAA's ERSSTv3b dataset). The solid black curves represent the probability density function for a Gaussian distribution fitted to the 24 climate models (gray dots; the mean μ and the standard deviation σ are included). In the box plots, the limits of the whiskers represent the 5th and 95th percentiles, the limits of the boxes represent the 25th and 75th percentiles, and the horizontal lines and the squares inside the boxes are the median and the mean, respectively.

When we consider the linear trend over two different periods (2001–50 and 2001–2100) from the entire 12-model suite, we do not find an obvious pattern across the different radiative forcing scenarios. The large inter-model spread in the various projections masks the tendency for the multimodel average to show a slight increasingly negative trend with increasing greenhouse gas forcing. There are three main reasons that could explain the very different outcomes from the different models in these scenarios: internal (unforced) climate variability within each model, differences in the prescription and model response to nongreenhouse gas forcings (e.g., aerosol, ozone, and changes in land use–land cover), and differences in model description and parameterization of the physical processes that lead to different sensitivity to greenhouse gas increases. We distinguish between the greenhouse gas and nongreenhouse gas forcings here in particular because the greenhouse gas forcing is relatively consistent across the different models, whereas the nongreenhouse gas forcings are specified, and responded to, in substantially different ways among the different models. Therefore, similar patterns of response across the models would suggest a dominant influence of the (common) greenhouse gas forcing.

We attempt to provide a first quantitative description of the relative contribution of each of these three components. The relative impact of internal climate variability versus total response to climate forcing agents was examined by computing the correlation coefficient between the 12-model response vectors for three different scenarios (SRES A2, A1B, and B1). In other words, we ask to what extent do the models that tend to show relatively smaller/larger changes in one scenario also show it in the other scenarios? If the pattern of ordering of the trends across scenarios is inconsistent, then we can infer that the spread is largely driven by either unforced climate variations or by differences in forcings and responses to nongreenhouse gas forcings. Focusing on the 2001–2100 trends in SRES A2, SRES A1B, and SRES B1 (Fig. 6 and Table 2), we obtain correlation coefficients of the model response across scenarios between 0.68 and 0.74, indicating that differences in the model response to total forcing in those scenarios explain about half of the variance in the tropical storm response, and with the remaining half originating from the unforced climate variability and the nongreenhouse gas forcing/response.

The importance of the internal variability is underscored by examining the variability in the slopes from an ensemble of 10 different GFDL CM2.1 model runs for the SRES A1B scenario that differ only in their initial conditions (Fig. 5, middle panel): over the period 2001–50, the variance for the 10 slopes is equal to 6.2, which is about 42% of the variance exhibited by the 12 climate models for the same scenario. Even though each model has a different internal variability and the results for the GFDL CM2.1 model cannot be generalized to all of the other ones, from these estimates we speculate that close to half of the variability in the results can be attributed to internal variability. As a third more direct way to estimate the impact of the internal climate variability of the models on the linear trends, we have examined the preindustrial control runs for all 12 models, resampling the data, creating 1000 12-member sets of 100-yr linear trends and comparing the spread of these to the spread of the 3 scenarios. In this case, we estimate the internal climate variability in the models as responsible for close to 50% of the spread in the projections. Based on these auxiliary calculations, we conclude that about half of the variability exhibited by the different models in these scenarios comes from internal climate variability, with the rest due to differences in the specification of or the response to radiative forcing.

To attempt to isolate the role of differences in nongreenhouse gas forcings in these models on the spread

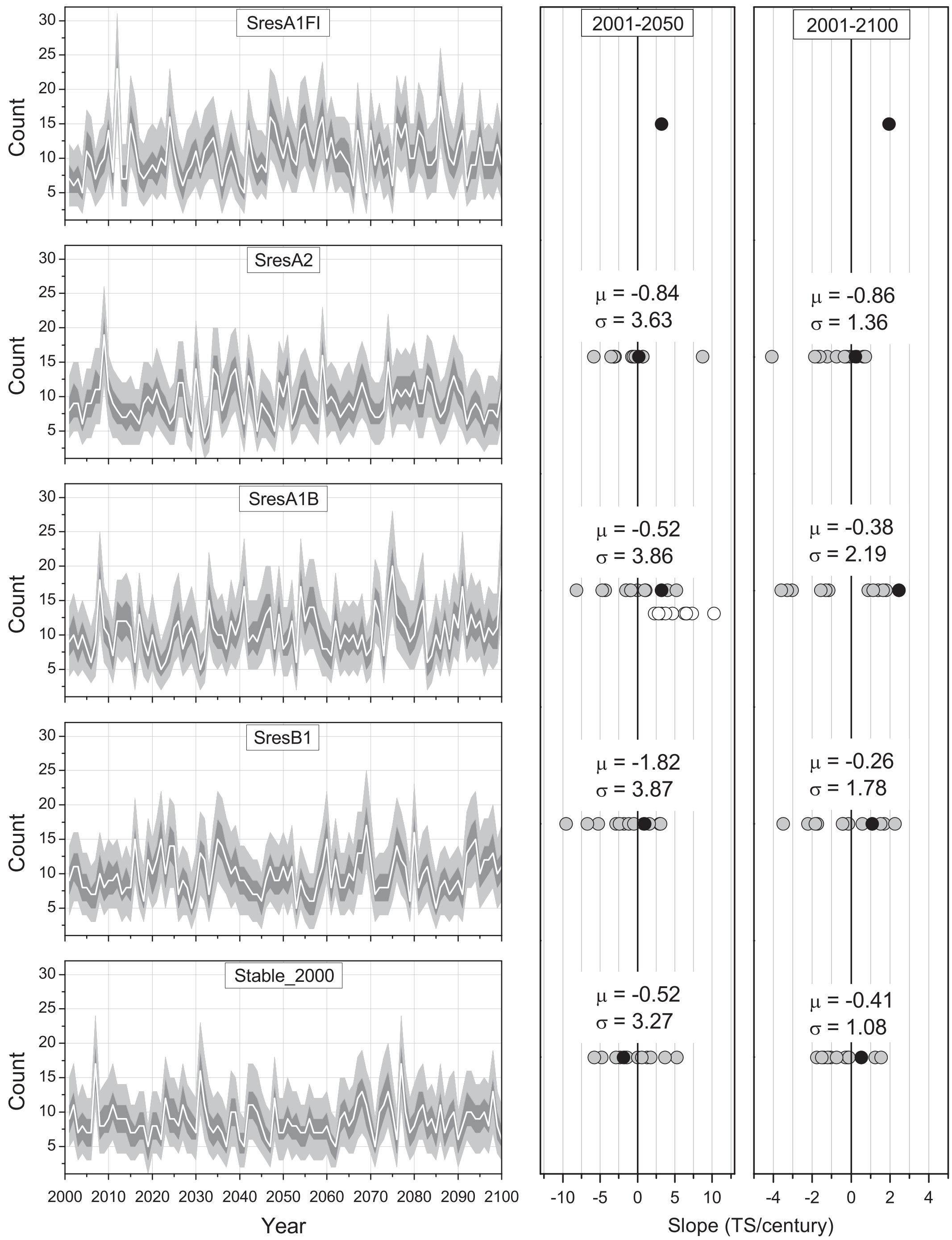

FIG. 5. (left) Projections for the twenty-first century of the tropical storm counts in the North Atlantic basin for five different climate change scenarios using the GFDL CM2.1 climate model, and tropical Atlantic and tropical mean SSTs as covariates in the statistical model (based on the model constructed using NOAA's ERSSTv3b dataset). The white line represents the median (50th percentile), the dark gray region represents the area between the 25th and 75th percentiles, and the light gray region represents the area between the 5th and 95th percentiles. Results are shown for the different scenarios and two time periods (middle) 2001–50 and (right) 2001–2100. The black points represent the results for the GFDL CM2.1, while the white points (for the SRES A1B scenario) are for 10 GFDL CM2.1 runs available for this scenario through 2050; the gray points represent the results for the 12 different climate models (the mean μ and the standard deviation σ are included).

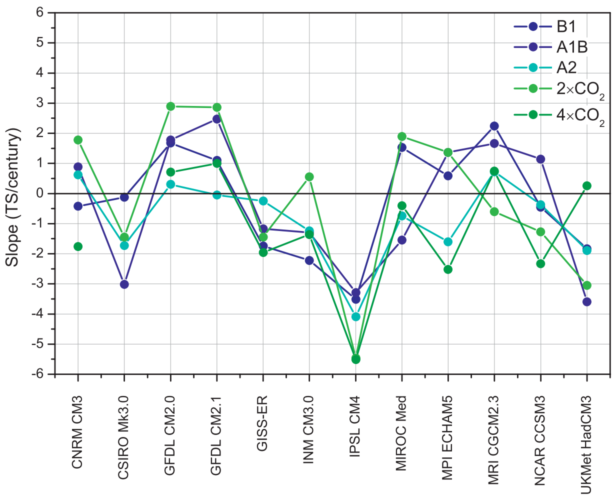

FIG. 6. Slopes from the linear fitting of the North Atlantic tropical storm counts over the period 2001–2100 for 12 climate models under 3 different SRES scenarios and for model runs for CO_2 doubling ($2 \times CO_2$) and quadrupling ($4 \times CO_2$) with respect to the preindustrial runs. These results are used to assess the extent to which the different slope responses among the models are due to deterministic (forcing/response related) differences vs internal climate variability (noise).

of tropical storm projections, we have also computed correlations based on model runs with only CO_2 changes (doubling or quadrupling with respect to preindustrial levels). Comparing the slopes from the 12 different models and including the 2 additional sets of CO_2-only runs, we obtain (Fig. 6 and Table 2) correlation coefficients of 0.61–0.74 (with the exception of 0.42 for A1B vs $4 \times CO_2$), which indicates that about 45% of the variance in the trend results can be described as a response to greenhouse gas changes in these models. To summarize, based on these analyses, we find that almost half of the variability among the projections of tropical storm frequency from different climate models results from internal (unforced) climate variability, almost another half results from differences in the models' responses to greenhouse gases, and thus, by process of elimination, a relatively smaller portion results from differences in the specification of and response to nongreenhouse gas–forcing agents in this set of experiments.

c. Sensitivity of the projections of U.S. landfalling tropical storm activity to different climate models and climate change scenarios

Most of the studies in the literature focus on changes in North Atlantic tropical storm frequency in a warmer climate, and there is still very limited information about possible changes in U.S. landfalling tropical storms. To

TABLE 2. Summary of the correlation between the slope values for the period 2001–2100 for 12 climate models under 3 different SRES scenarios and model runs for CO_2 doubling ($2 \times CO_2$) and quadrupling ($4 \times CO_2$) with respect to the preindustrial runs. Notice that the correlation coefficients between the $4 \times CO_2$ model run and the others are based on 11 models (the data for the CSIRO Mk3.0 is not available).

Correlation coef R	B1	A1B	A2	$2 \times CO_2$	$4 \times CO_2$
B1	1	—	—	—	—
A1B	0.681	1	—	—	—
A2	0.690	0.738	1	—	—
$2 \times CO_2$	0.723	0.720	0.711	1	—
$4 \times CO_2$	0.699	0.421	0.694	0.610	1
R^2	B1	A1B	A2	$2 \times CO_2$	$4 \times CO_2$
B1	1	—	—	—	—
A1B	0.464	1	—	—	—
A2	0.477	0.544	1	—	—
$2 \times CO_2$	0.523	0.518	0.506	1	—
$4 \times CO_2$	0.489	0.177	0.482	0.370	1

shed light on the possible effects of increasing temperatures on U.S. landfalling tropical storms, we use the statistical model developed by Villarini et al. (2010), and use as input the projected time series of tropical Atlantic and tropical mean SSTs for different climate change forcing scenarios and climate models.

In Fig. 7 we show the projected U.S. landfalling tropical storm frequency for 8 different climate models under the SRES A1B scenario. The consensus estimate is not for a marked increase in U.S. landfalling tropical storms projected for the twenty-first century; however, individual models project the possibility of trends between -2.64 to $+1.32$ tropical storms century^{-1} over the twenty-first century. Moreover, depending on the climate model, we observe a more or less marked interannual variability, associated with different spatiotemporal SST variability patterns. When looking at the 24 climate models together (Fig. 8), there is not a strong tendency toward either increasing or decreasing trends, with most of the models having a slope between ± 1.5 tropical storm (100 yr)$^{-1}$. The impact of internal climate variability on the estimate of trends in U.S. landfalling numbers can be seen in the decrease in spread from the 50- to the 100-yr trends.

When focusing on the impact of different climate change forcing scenarios on the U.S. landfalling tropical storm frequency, the picture does not change significantly from either basinwide or the multimodel exploration. As shown in Fig. 9 focusing on GFDL CM2.1, and similar to what was observed in Fig. 5, there are no marked increasing trends in these time series, with slopes between 0 and $+1$ storm century^{-1} for the period 2001–2100.

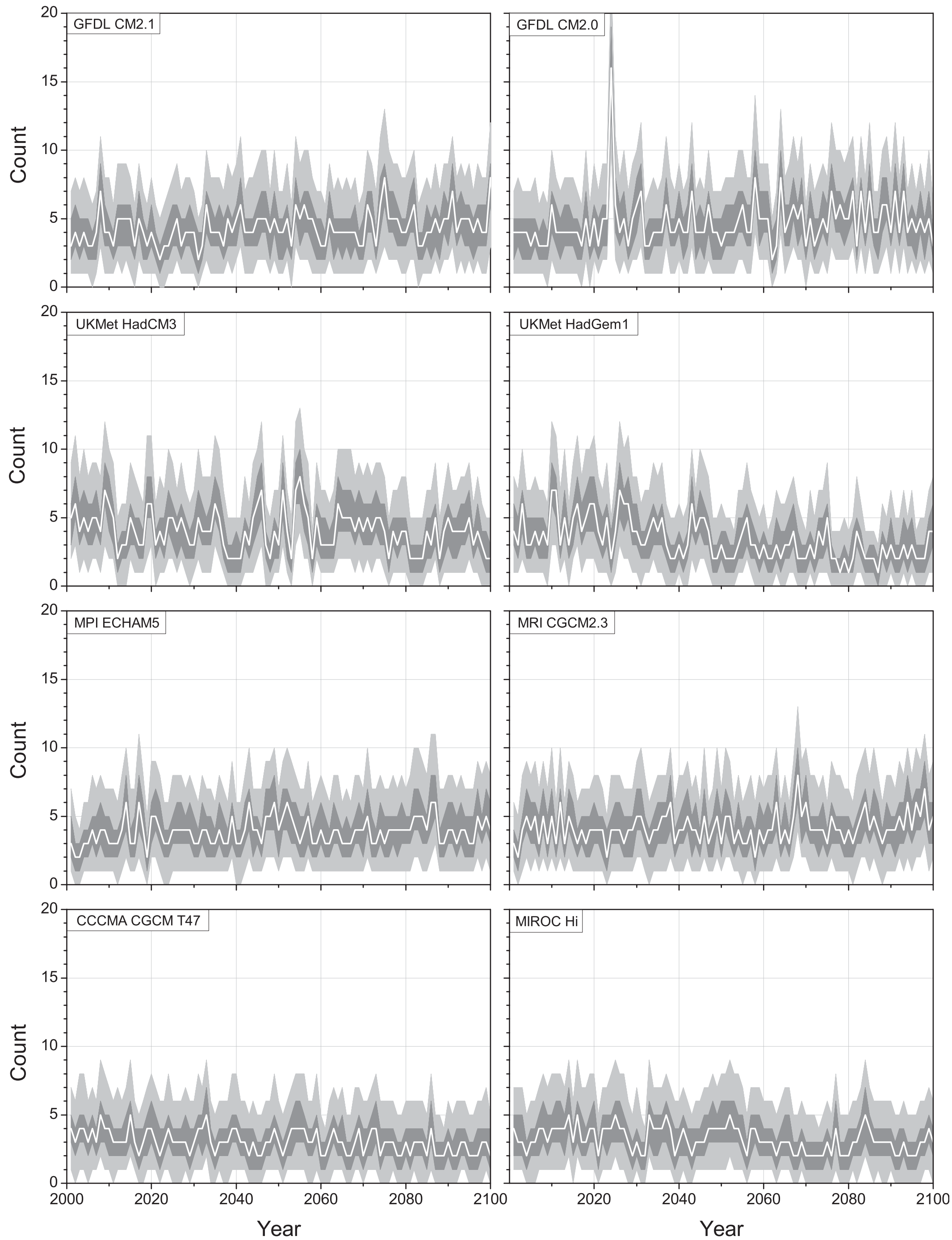

FIG. 7. Projections for the twenty-first century of the U.S. landfalling tropical storm counts under the SRES A1B scenario for 8 different climate models using tropical Atlantic and tropical mean SSTs as covariates in the statistical model (based on the model constructed using NOAA's ERSSTv3b dataset). The white line represents the median (50th percentile), the dark gray region represents the area between the 25th and 75th percentiles, and the light gray region represents the area between the 5th and 95th percentiles.

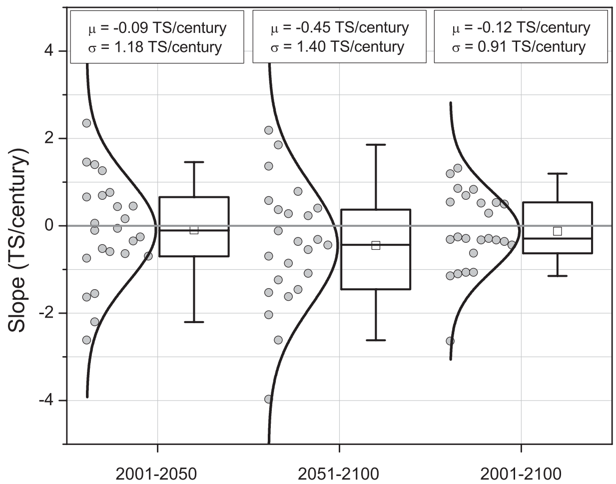

FIG. 8. Slopes of the regression lines for three periods (2001–50, 2051–2100, and 2001–2100) for all the 24 available climate models. These results are based on the projections for the twenty-first century of U.S. landfalling tropical storms under the SRES A1B scenario, using both tropical Atlantic and tropical mean SSTs as covariates in the statistical model (based on the model constructed using NOAA's ERSSTv3b dataset). The solid black curves represent the probability density function for a Gaussian distribution fitted to the 24 climate models (gray dots; the mean μ and the standard deviation σ are included). In the box plots, the limits of the whiskers represent the 5th and 95th percentiles, the limits of the boxes represent the 25th and 75th percentiles, and the horizontal lines and the squares inside the boxes are the median and the mean, respectively.

4. Discussion and conclusions

The main results of this study are as follows:

1) The disagreement among published results concerning increasing or decreasing North Atlantic tropical storm trends in a warmer climate can be largely explained (close to half of the variance) in terms of the different sea surface temperature projections (Atlantic minus tropical mean) of the different climate model projections used. Our results suggest that reducing the uncertainty in future projections of North Atlantic tropical storm frequency (for a given emission scenario) may depend as critically on reducing the uncertainty in projections of the tropical Atlantic warming relative to the tropical mean as than on improving dynamical or statistical downscaling techniques.
2) For the SRES A1B scenario and 24 climate models, over the twenty-first century there is a large spread among projected trends in tropical storm activity in the North Atlantic basin, with a mean of -0.83 tropical storm century^{-1} and a standard deviation of 2.48 tropical storms century^{-1}. As far as U.S. landfalling tropical storms are concerned, results based on 7 climate models point to a statistically significant increasing trend, while 6 point to a decreasing trend.
3) Exploring several climate change forcing scenarios (SRES A1FI, SRES A2, SRES A1B, SRES B1, and Stable_2000) and based on a set of different climate models, the response of tropical storms in the twenty-first century does not exhibit a clear monotonic relationship to increasing "equivalent" greenhouse gas forcing. This statement is valid for both the overall activity in the North Atlantic basin, as well as for the frequency of U.S. landfalling tropical storms. This lack of a systematic response to changes in greenhouse gas forcing reflects both the large internal climate variability that impacts even 100-yr projected trends, as well as disagreement among climate models as to whether the tropical Atlantic should warm more or less than the rest of the tropics from increasing greenhouse gases.

Based on the results from 12 climate models, we estimate that close to 50% of the variance in the trend results over the period 2001–2100 can be associated with internal climate variability in the models, with another 50% due to models' differences in response to greenhouse gas forcings, leaving only a much smaller percentage to be associated with the models' response to nongreenhouse gas forcings in this suite of experiments. For the upcoming IPCC Fifth Assessment Report, the influence of nongreenhouse forcings should be reexamined in the newer models, which may in a number of cases include larger influences (e.g., enhanced aerosol influence due to indirect effects). Our results to date suggest that, to the extent that the SRES forcing scenarios are relevant, there is a possibility of narrowing the range of uncertainty in the projections of Atlantic tropical storm frequency if we can better understand the mechanisms that control patterns of tropical SST changes in nature and the models (Xie et al. 2010). However, if our model-based estimates of internal (unforced) climate variability are robust, there is a considerable level of uncertainty in climate change projections that will remain effectively "irreducible," as no current prospects exist for skillful century-scale predictions of unforced climate variability.

For century-scale projections of tropical storm frequency, the sources of uncertainty that emerge as dominant (internal variability and structural model uncertainty) are quite dissimilar to those of global and regional temperature projections, which tend to be dominated by greenhouse gas emissions and structural model uncertainties (Hawkins and Sutton 2009).

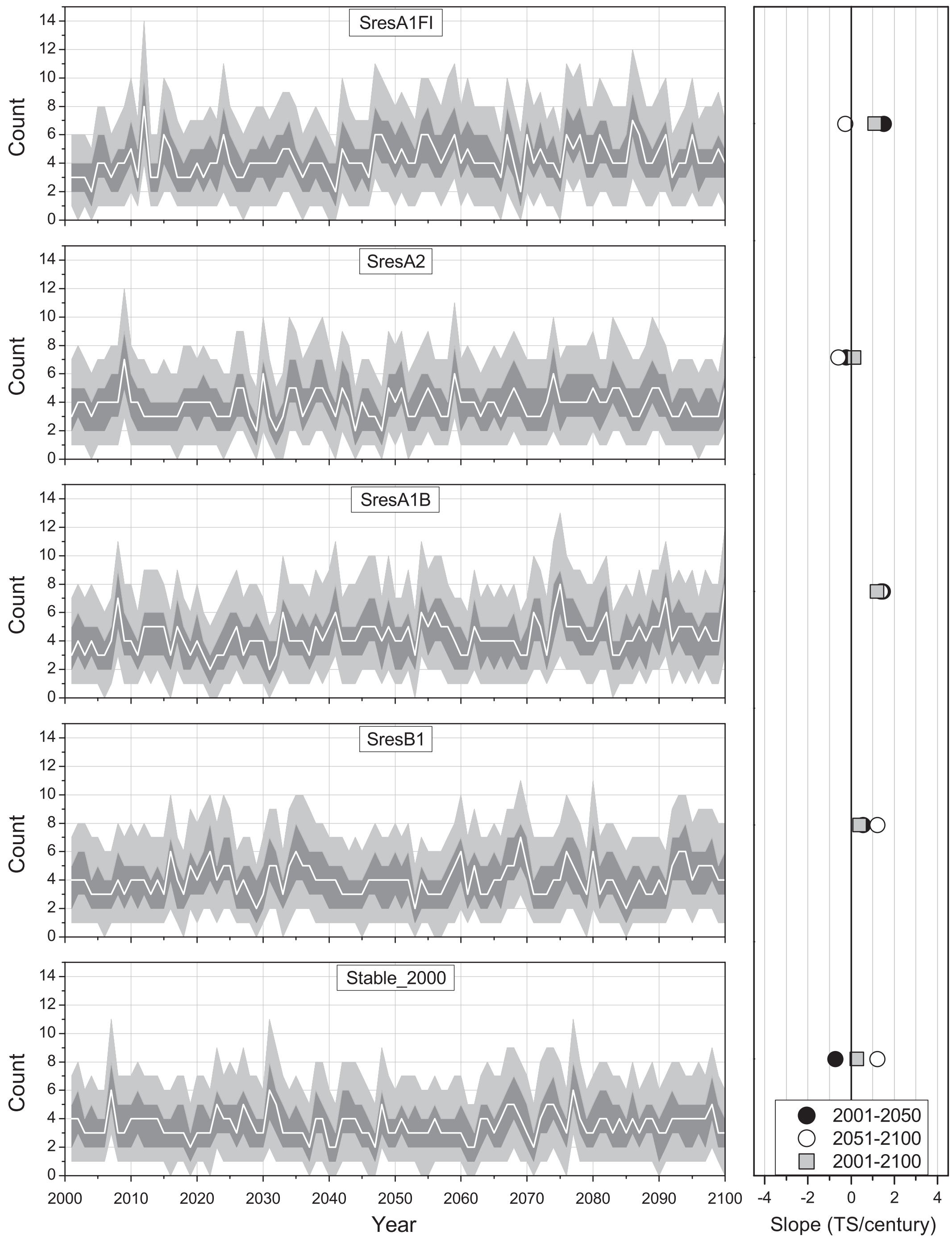

FIG. 9. (left) Projections for the twenty-first century of the U.S. landfalling tropical storm count for 5 different climate change scenarios using the GFDL CM2.1 climate model, and tropical Atlantic and tropical mean SSTs as covariates in the statistical model. The white line represents the median (50th percentile), the dark gray region represents the area between the 25th and 75th percentiles, and the light gray region represents the area between the 5th and 95th percentiles. (right) For the same five climate change scenarios, the slopes of the linear regression line for three periods (2001–50, 2051–2100, and 2001–2100) are shown. The results are based on the statistical model constructed using NOAA's ERSSTv3b dataset.

4) The statistical model used in this study was trained on a 131-yr record of North Atlantic tropical storms (Villarini et al. 2010). It is parsimonious and requires only tropical Atlantic and tropical mean SSTs as input to project the distribution of North Atlantic tropical storm counts for any given year. Because it is observationally based, reflects our current understanding of the main physical processes responsible for the formation of tropical storms in the North Atlantic, and because of its agreement with the dynamical results, we propose that the use of this model for prediction of tropical storms under different scenarios is justified.
5) These results provide further supporting evidence for the importance of *both* Atlantic and tropical SSTs in describing variations in tropical storm activity in the North Atlantic basin.
6) The projections from the various dynamical models are consistent with observational behavior as captured through the statistical model using tropical Atlantic and tropical mean SSTs. Moreover, a $\pm 40\%$ change by the late-twenty-first century is consistent with both the observed record and with the range of projections of SST patterns. Unfortunately, we are not able to use observations to falsify projected trends of magnitude $\pm 40\%$ at this point owing to the high levels of estimated internal variability. However, improved understanding of the physical mechanisms that control patterns of SST changes, in response to climate forcing agents, should result in better constraints on the range of uncertainties (Xie et al. 2010).

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REFERENCES

Bender, M. A., T. R. Knutson, R. E. Tuleya, J. J. Sirutis, G. A. Vecchi, S. T. Garner, and I. M. Held, 2010: Model impact of anthropogenic warming on the frequency of intense Atlantic hurricanes. *Science,* **327,** 454–458.

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.

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

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

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.

Hawkins, E., and R. Sutton, 2009: The potential to narrow uncertainty in regional climate predictions. *Bull. Amer. Meteor. Soc.,* **90,** 1095–1107.

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

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. A,* **365,** 2695–2716.

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.

Knutson, T. R., J. J. Sirutis, S. T. Garner, G. A. Vecchi, and I. Held, 2008: Simulated reduction in Atlantic hurricane frequency under twenty-first-century warming conditions. *Nat. Geosci.,* **1,** 359–364.

——, and Coauthors, 2010: Tropical cyclones and climate change. *Nat. Geosci.,* **3,** 157–163.

Landsea, C. W., G. A. Vecchi, L. Bengtsson, and T. R. Knutson, 2010: Impact of duration thresholds on Atlantic tropical cyclone counts. *J. Climate,* **23,** 2508–2519.

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

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 in cooperation with the National Hurricane Center, 193 pp.

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.

Pielke, R. A., 2005: Are there trends in hurricane destruction? *Nature,* **438,** E11, doi:10.1038/nature04426.

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

——, 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.

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.

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

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

Sugi, M., 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.

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

Vecchi, G. A., and B. J. Soden, 2007: Global warming and the weakening of the tropical circulation. *J. Climate,* **20,** 4316–4340.

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

Villarini, G., and J. A. Smith, 2010: Flood peak distributions for the eastern United States. *Water Resour. Res.,* **46,** W06504, doi:10.1029/2009WR008395.

——, G. A. Vecchi, and J. A. Smith, 2010: Modeling of the dependence of tropical storm counts in the North Atlantic basin on climate indices. *Mon. Wea. Rev.,* **138,** 2681–2705.

Xie, S., C. Deser, G. A. Vecchi, J. Ma, H. Teng, and A. T. Wittenberg, 2010: Global warming pattern formation: Sea surface temperature and rainfall. *J. Climate,* **23,** 966–986.

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.