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Key Points:
- We downscale 4 CMIP5 models to generate long-term synthetic TC data sets
- Relationship between power dissipation index and SST is weaker than expected
- Support for the use of paleohurricane landfall records to infer basin-wide TC trends

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An analysis of long-term relationships among count statistics and metrics of synthetic tropical cyclones downscaled from CMIP5 models

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Abstract In a changing climate, the impact of tropical cyclones on the United States Atlantic and Gulf Coasts will be affected both by how intense and how frequent these storms become. The observational record of tropical cyclones in the Atlantic Basin is too short (A.D. 1851 to present) to allow for accurate assessment of low-frequency variability in storm activity. In order to overcome the limitations of the short observational record, we downscale four Coupled Model Intercomparison Project Phase 5 models to generate synthetic tropical cyclone data sets for the Atlantic Basin that span the interval of A.D. 850–2005. Using these long-term synthetic tropical cyclone data sets, we investigate the relationship between power dissipation and ocean temperature metrics, as well as the relationship between basin-wide and landfalling tropical cyclone count statistics over the past millennium. Contrary to previous studies, we find only a very weak relationship between power dissipation and main development region sea surface temperature in the Atlantic Basin. Consistent with previous studies, we find that basin-wide and landfalling tropical cyclone counts are significantly correlated with one another, lending further support for the use of paleohurricane landfall records to infer long-term basin-wide tropical cyclone trends.

1. Introduction

In a changing climate, the impact of tropical cyclones (TCs) on the United States Atlantic and Gulf Coasts will be affected both by how often these storms occur and how powerful these storms become. TCs are extremely costly natural disasters for the United States, historically causing both significant fatalities and economic damage [*Pielke*, 2007; *Rappaport*, 2014]. It is therefore useful to investigate the impact of climate change on the frequency and intensity of TCs in the United States. Recent climate assessment reports have devoted considerable attention to the issue of how TCs may be affected by climate [*Intergovernmental Panel on Climate Change*, 2012, 2013; *Melillo et al.*, 2014]. Some specific studies investigating connections between climate and TCs include *Gray* [1968], *Gray* [1984], *Emanuel* [1995], *Bove et al.* [1998], *Emanuel* [2005], *Mann et al.* [2007], *Knutson et al.* [2010], *Kozar et al.* [2013], and *Lackmann* [2014].

A considerable amount of research has been conducted investigating connections between TC behavior and sea surface temperature (SST) or potential intensity (PI). *Gray* [1968] discusses the important influence of SST on the buoyancy of cumulus clouds, particularly in the main development region (MDR) of the North Atlantic and other basins. Further, *Emanuel* [1995] indicates that SST may be related to a number of TC traits, including the time scale over which TCs develop, the ratio of a mature storm's outer scale to the radius of maximum winds, the maximum azimuthal wind speed of mature TCs, and the central pressure of mature storms. *Emanuel* [2005] discusses the idea that it is not only SST but also air temperature that influences the strength and intensity of TCs. In particular, Emanuel states that PI, which depends on both SST and the entire temperature profile of the troposphere, is the most appropriate measure of the thermodynamic environment for a TC. It should be noted that the relationship between PI and SST is mostly indirect, and *Emanuel and Sobel* [2013] showed that the change in PI per unit change in SST depends strongly on the nature of the climate forcing.

Additionally, *Emanuel* [2005] investigates the potential destructiveness of TCs and the possible losses such storms could inflict upon coastal regions of the United States. *Emanuel* [2005] defines the power dissipation index (PDI) as an index of the potential destruction that a TC or hurricane may cause:

$$\mathrm{PDI} \equiv \int_0^{\tau} V_{\max}^3 dt. \tag{1}$$

In this equation, $V_{\max}$ is the maximum sustained wind speed at 10 m and τ is the lifetime of the storm. Using the SST from the Hadley Centre Sea Ice and SST data set, and calculating PDI from "best track" data sets obtained from the U.S. Navy's Joint Typhoon Warning Center and the National Oceanographic and Atmospheric Administration's (NOAA's) National Hurricane Center, Emanuel finds a strong direct relationship between PDI from TCs and the tropical SST. His results indicate that further warming of the planet may increase the damaging power of TCs, greatly increasing TC-related losses this century [*Emanuel*, 2005].

Vecchi et al. [2008] acknowledge the existence of a strong correlation between Atlantic TC PDI and MDR SST from 1946 to 2007 as well. However, their work points out that a similarly strong relationship exists between PDI and relative SST—that is, the Atlantic tropical SST relative to the global mean tropical SST, which bears a more direct relationship to PI than does absolute SST. *Swanson* [2008] also notes that variations in Atlantic TC activity depend strongly on relative SST. Variable warming in the Atlantic MDR relative to the global tropics is likely to result from natural multidecadal variability or anthropogenic aerosol forcing but is less likely to be the result of greenhouse gas forcing [*Vecchi et al*., 2008; *Knutson et al.*, 2010] (although the latter rests on the models correctly reproducing forced changes in tropical Pacific ocean-atmosphere dynamics, something that has been questioned in the literature, e.g., most recently *Steinman et al.* [2015]). Thus, the correlation between the relative SST and PDI for the Atlantic Basin may indicate that the recent increase in intensity of Atlantic TCs is the result of factors other than increases in concentrations of greenhouse gases [*Vecchi et al*., 2008; *Swanson*, 2008; *Knutson et al.*, 2010]. In our work, we aim to further investigate the relationship between PDI as a measure of TC activity in the Atlantic Basin and PDI and various ocean surface temperature metrics.

It is also instructive to investigate how a changing climate could affect TC numbers. Using a data set of TCs downscaled from a National Center for Atmospheric Research (NCAR) Climate System Model, version 1.4 (CSM 1.4) simulation, which is forced by both natural and anthropogenic forcings and spans the past millennium (A.D. 850–1999), *Kozar et al.* [2013] find that the alignment of TC landfalls with basin-wide TC activity on multidecadal time scales lends support for the use of paleohurricane records in analyzing long-term changes in TC activity. Here we revisit that analysis using synthetic TC data sets downscaled from an assortment of simulations using state-of-the-art Coupled Model Intercomparison Project Phase 5 (CMIP5) climate models.

2. Methods

Although past investigations have made great strides toward identifying connections between climate patterns and TC activity in the Atlantic Basin, such studies can be rather limited in scope due to the brevity of the observational record, which spans only from approximately A.D. 1851 to the present [*Kozar et al.*, 2013]. In addition, *Kozar et al.* [2013] point out that there is some disagreement in the literature about the reliability of the observational record. For example, *Landsea* [2007] argues for a potentially significant undercount bias in the observational record, particularly early in the observational record, due to the lack of observational data from satellites and other modern tools and data sources. *Landsea et al.* [2010] further expand on this idea, indicating that very short lived storms may have been unaccounted for early in the observational record. Additionally, *Vecchi and Knutson* [2008] find very mixed evidence for changes in Atlantic TC frequency during the twentieth century. *Chang and Guo* [2007] investigate the issue of long-term TC counts as well but find that, although there may be a slight undercount bias prior to World War I, the number of TCs that may not be recorded is likely no greater than 10 storms per decade. Using a statistical model to relate annual frequency of TCs to climate state variables, *Mann et al.* [2007] reach a similar conclusion as *Chang and Guo* [2007].

Because the observational record of TC activity in the Atlantic is short and potentially biased, it is difficult to accurately assess low-frequency variability in storm activity; thus, it is desirable to turn to other means of assessing this variability. Using monthly mean thermodynamic state variables, including SST and vertical profiles of temperature and humidity, as well as daily mean values of interpolated 250 hPa and 850 hPa

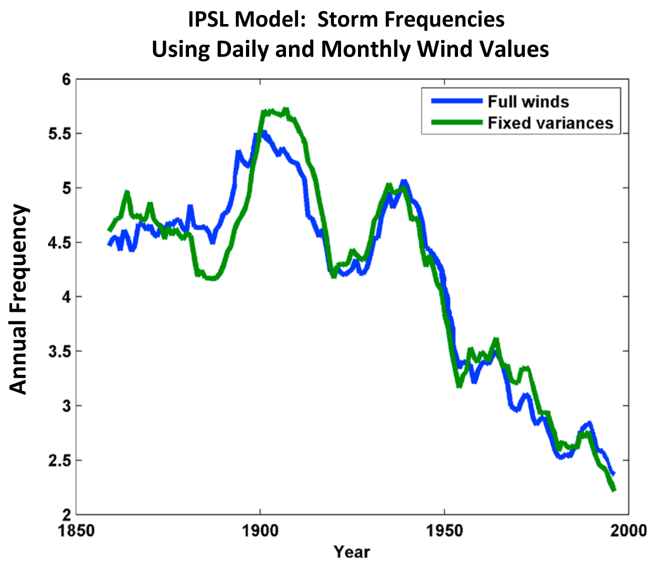

Figure 1. Downscaled time series of storm annual frequency from the IPSL model using daily wind.

winds, *Kozar et al.* [2013] downscale a simulation from the NCAR CSM 1.4 model spanning the past millennium to generate a long-term synthetic TC data set consistent with a plausible long-term past climate scenario. Caveats related to the use of the NCAR CSM 1.4 in the *Kozar et al.* [2013] study include too much vertical wind shear in the Atlantic Basin, cooler than expected North Atlantic SSTs, and a lack of lower stratospheric cooling, as seen recently in the observational record [*Emanuel et al.*, 2013; *Vecchi et al.*, 2013].

The downscaling method used by *Kozar et al.* [2013], developed in *Emanuel et al.* [2006] and *Emanuel et al.* [2008], is applied here to several of the more recent state-of-the-art CMIP5 models to perform further analysis of TC activity in the Atlantic Basin. Downscaling to create TC data sets involves three main steps: genesis of storms, generating tracks for storms, and intensification of storms. These parts of the downscaling process are described in detail in *Emanuel et al.* [2006] and *Emanuel et al.* [2008].

In this work, our sets of synthetic TCs are downscaled from CMIP5 models. We simulate the period from A.D. 850 to 2005, using the CMIP5 last millennium and historical experiments. Details of these experiments and their forcings are available publicly from the Program for Climate Model Diagnosis and Intercomparison; additionally, a summary of the project and experiment design is provided by *Taylor et al.* [2012]. Our choice of models is dictated by the availability of the necessary thermodynamic (SST, vertical temperature profiles, and humidity profiles) and kinematic (250 hPa and 850 hPa wind components) state variables for the time period from A.D. 850 to 2005. CMIP5 models used in this work include the Max-Planck-Institute Earth System Model (MPI), the Coupled Climate System Model 4.0 (CCSM4), the Institut Pierre Simon Laplace Earth System Model (IPSL), and the Model for Interdisciplinary Research on Climate (MIROC).

There are a few caveats related to the CMIP5 models used in this work. First, for our downscaling, it is ideal to have daily values of the kinematic state variables produced by the model. However, only the MPI model provides the daily wind fields required for this work. In order to allow us to analyze results from more than one model, we use the less ideal monthly values of the wind fields from the CCSM4, IPSL, and MIROC models. In these cases, we allow winds to vary over the seasonal cycle while fixing the variances and covariances at 1980 values. The choice of using 1980 values for fixed variances and covariances is arbitrary.

Although it is preferable to have daily values of the 250 and 850 hPa wind fields for our downscaling process, we have investigated the sensitivity of the downscaling process to the use of monthly wind values and find that results using monthly winds are reasonable and similar to those produced using daily wind values. For example, consider the comparison of annual storm frequencies from the IPSL model in Figure 1. Here we compare downscaled results for the annual number of TCs using daily wind values, denoted “full winds” (blue), and downscaled results for the annual number of storms using monthly winds with fixed variances (green) for the time period from A.D. 1850 to 2005. As can be seen from the figure, the downscaled results from the two different methods track one another well. Results were similar for the CCSM4 and MIROC models and suggest that it is reasonable to use monthly values of wind fields with fixed variances and covariances for cases in which daily wind fields are not available.

Finally, it is important to note a major caveat with respect to the MIROC model results, as values of SST from the MIROC model show an unexpected upward drift throughout the preanthropogenic era (A.D. 850–1850). This problematic drift is a known issue with the last millennium run of the MIROC model [*Bothe et al.*, 2013] and at this point is unresolved. Thus, we place little emphasis on results from the MIROC simulation at this time.

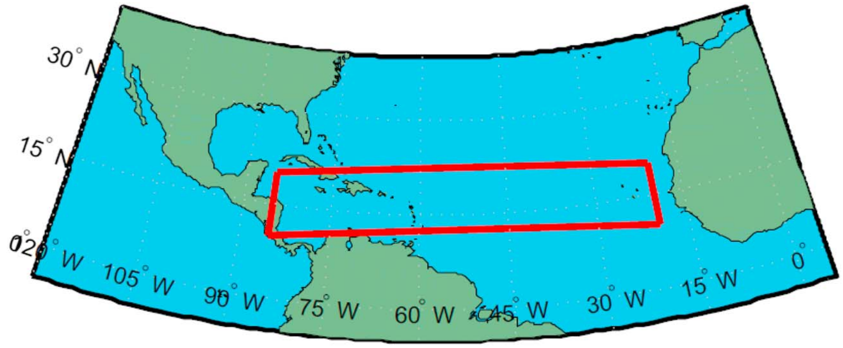

Figure 2. Map of the main development region in the Atlantic; MDR is outlined by the red box.

3. Results: PDI and Ocean Surface Temperature Metrics

As noted above, there have been a number of studies investigating the relationship between PDI and Atlantic SST. In particular, *Emanuel* [2005] indicates a strong direct relationship between PDI and Atlantic SST based on reanalysis data from 1950 to 2005. Here we compare PDI from storms in long-term (A.D. 850–2005) synthetic TC data sets to long-term records of SST from CMIP5 models. Although there are other important measures of TC destructiveness or power, such as size and strength of a storm, here we will focus on central intensity of storms, using PDI as a proxy for the power of each TC.

Our goal is to establish whether or not a relationship between PDI and SST similar to what was found in *Emanuel* [2005] can be seen for spans of time greater than 56 years. In this work, we use SSTs, vertical ocean temperature profiles, and synthetic TCs downscaled from four CMIP5 models—MPI, CCSM4, IPSL, and MIROC.

The MDR is defined to be the region bordered by 10 and 20°N and 20 and 85°W (see Figure 2). In Figure 3, the smoothed time series of annually accumulated PDI from the synthetic TC data sets and the MDR SST from

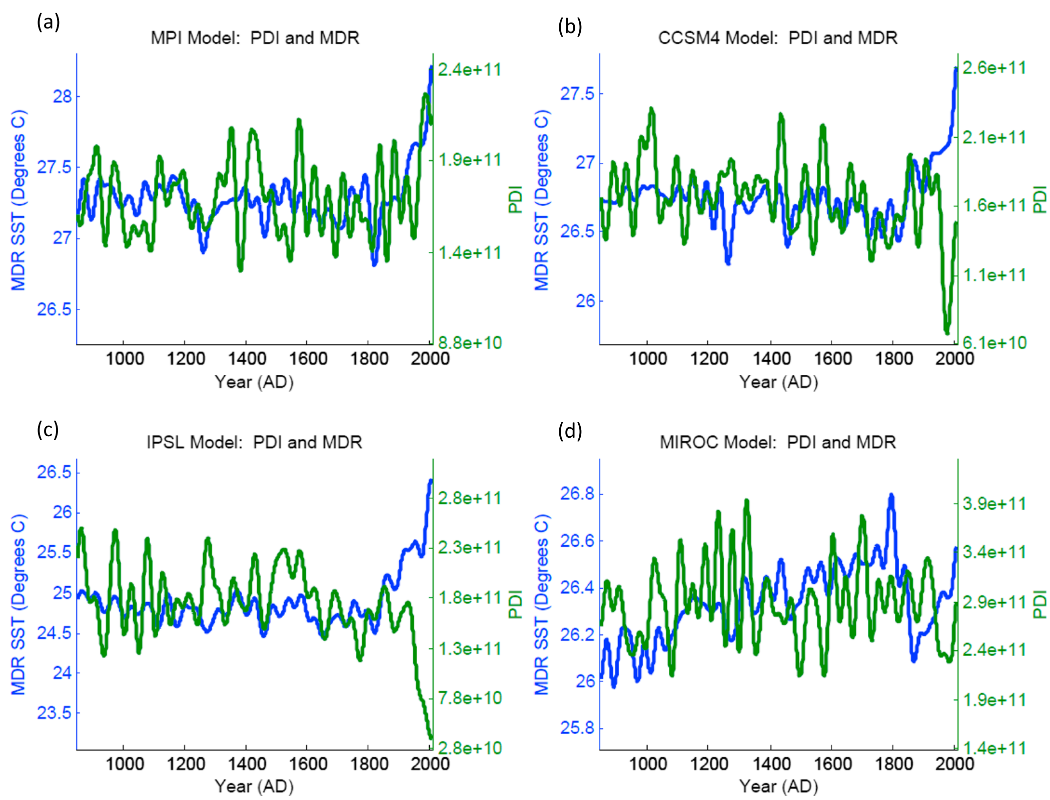

Figure 3. Time series of MDR SST (blue, °C) and annually accumulated PDI (green) for (a) the MPI model, (b) the CCSM4 model, (c) the IPSL model, and (d) the MIROC model.

Table 1. Squared Pearson's Linear Correlation Coefficients (r^2) Between Smoothed Ocean Temperature Metrics (MDR SST—MDR, Relative SST—REL, and Potential Intensity—PI) and PDI for the Full Past-Millennium Time Series (Full—A.D. 850–2005), Preanthropogenic Time Series (Preanth—A.D. 850–1800), and Anthropogenic Time Series (Anth—A.D. 1800–2005)[a]

		MPI	CCSM4	IPSL	MIROC
Full	MDR	0.10	0.01	*0.15*	0.01
	REL	0.00	**0.38**	**0.37**	0.09
	PI	*0.17*	*0.13*	*0.16*	0.01
Preanth	MDR	0.01	0.11	*0.13*	0.03
	REL	0.00	**0.31**	**0.32**	0.08
	PI	0.04	0.00	0.01	0.00
Anth	MDR	0.28	0.10	0.46	0.05
	REL	0.17	0.47	0.18	0.11
	PI	0.35	**0.88**	*0.76*	0.04

[a]Values that are significant at the $P = 0.01$ level are shown in bold. Values that are significant at the $P = 0.05$ level are shown in italics.

each of the models are shown. Here and in subsequent discussion of smoothed data unless otherwise noted, the long-term data sets have been smoothed using a low-pass filter [*Mann*, 2008; *Kozar et al*., 2013] to emphasize time scales that are multidecadal or longer. The low-pass filter has a half-power cutoff at $f = 0.025$ c/yr, equivalent to a 40 year period.

Squared Pearson's linear correlation coefficients (r^2) between smoothed MDR SST and PDI from each model are given in Table 1, for the full time series (A.D. 850–2005), the preanthropogenic era time series (A.D. 850–1800), and the anthropogenic era time series (A.D. 1800–2005). The degrees of freedom for the full smoothed time series is approximately $N = 29$; thus, r^2 values greater than 0.10 are significant at the $P = 0.05$ level, and those greater than 0.18 are significant at the $P = 0.01$ level. The degrees of freedom for the preanthropogenic smoothed time series is approximately $N = 24$; thus, r^2 values greater than 0.12 are significant at the $P = 0.05$ level, and those greater than 0.22 are significant at the $P = 0.01$ level. The degrees of freedom for the anthropogenic smoothed time series is approximately $N = 5$; thus, r^2 values greater than 0.57 are significant at the $P = 0.05$ level, and those greater than 0.79 are significant at the $P = 0.01$ level.

Building on work from *Emanuel* [2005], *Emanuel* [2007] reports an r^2 value of 0.75 between smoothed MDR SST and PDI values in the Atlantic Basin using observational and reanalysis data for the 56 year period from 1950 to 2005. Using CMIP5 model data over much longer time periods, we do not find nearly as strong of a relationship between MDR SST and PDI. This can be seen in both the time series plotted in Figure 3, and their corresponding r^2 values are given in Table 1. Only the r^2 values for the full and preanthropogenic time series from the IPSL model are significant at the $P = 0.05$ level. Even in these cases, only 15% (full time series) and 13% (preanthropogenic time series) of the variance in PDI values is explained by the relationship between PDI and MDR SST. Given that there is consensus among all four of our CMIP5 models that more than 80% of the variance in PDI values is unexplained by varying MDR SSTs, we choose to investigate the relationship between PDI and other surface temperature metrics from our models for the Atlantic Basin.

Thus, we consider the relationship between relative SST and PDI in the Atlantic Basin. Here relative SST is defined as

$$\text{REL SST} = \text{Atlantic MDR SST} - \text{Mean Tropical SST}. \quad (2)$$

The smoothed time series of relative SST and annually accumulated PDI from the synthetic TC data sets for each of the models are shown in Figure 4. We find that, in some cases, r^2 values between relative SST and Atlantic PDI for the four models indicate a stronger relationship than the relationship between MDR SST and Atlantic PDI (Table 1). In the case of relative SST, r^2 values for both the full time series and preanthropogenic time series from both the CCSM4 and IPSL models are significant at the 99% level. Although these r^2 values indicate that more than 30% of the variance in PDI values may be related to varying relative SST, there is very little consensus across our models for the relative SST and Atlantic PDI relationship. Results from the MPI and MIROC models indicate almost no relationship between relative SST and Atlantic PDI (Table 1).

Finally, we also consider the relationship between PDI and PI. As noted above, *Emanuel* [2005] suggest that PI is the most appropriate measure of the thermodynamic environment for a TC; we are thus interested to see if

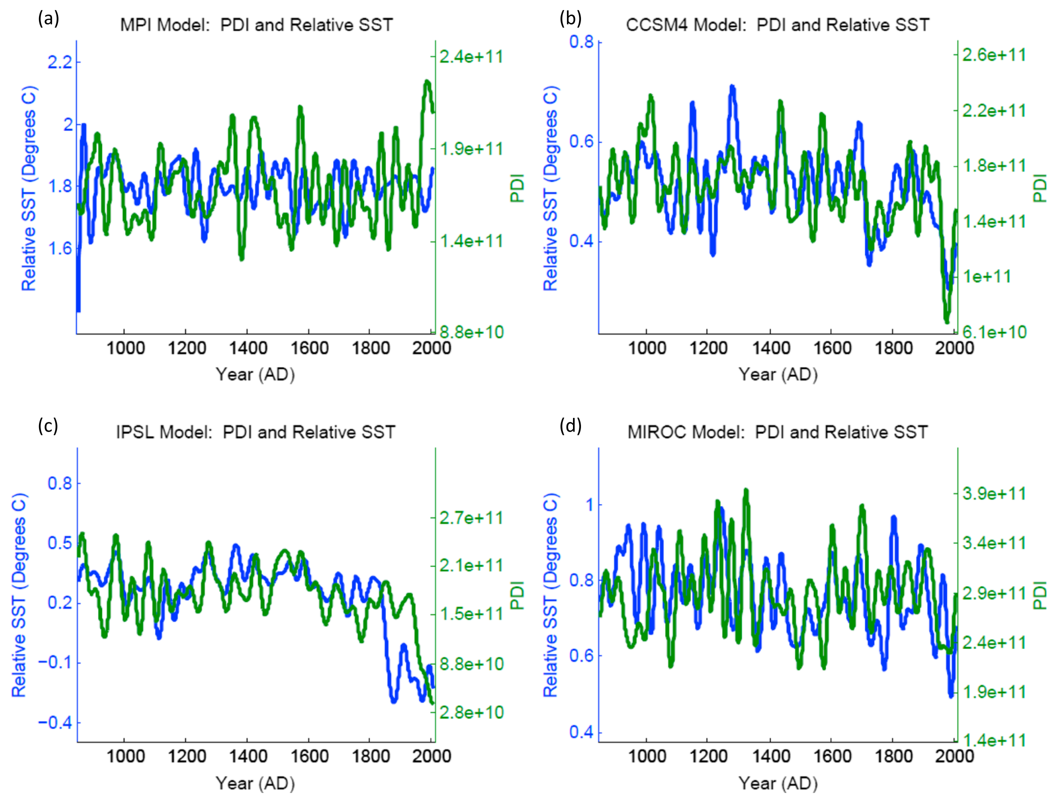

Figure 4. Time series of relative SST (blue, °C) and annually accumulated PDI (green) for (a) the MPI model, (b) the CCSM4 model, (c) the IPSL model, and (d) the MIROC model.

we can find a relationship between PDI from our synthetic TCs and PI as calculated from the models. Here PI is defined as in *Emanuel* [2007]:

$$V_p^2 = \frac{C_k}{C_D}\frac{T_s - T_o}{T_o}\left(k_0^* - k\right), \tag{3}$$

where V_p is the potential maximum wind speed or PI, C_k is the surface exchange coefficient for enthalpy, C_D is the surface exchange coefficient for momentum, T_s is the SST, T_o is an entropy-weighted mean outflow temperature [*Emanuel*, 1986, equation (19)], k_0^* is the enthalpy of air in thermodynamic equilibrium with the ocean, and k is the specific enthalpy of air near the surface. Here the potential intensity has been calculated using the algorithm developed by *Bister and Emanuel* [2002]. The smoothed time series of PI and annually accumulated PDI from the synthetic TC data sets for each of the models are shown in Figure 5.

As with relationships between MDR SST and PDI, and relative SST and PDI, we find mixed results when considering the r^2 values associated with the relationships between PDI and PI on various time scales for our four models. We find that r^2 values between PDI and PI for the full time series are significant at the 95% level for the MPI, CCSM4, and IPSL models (Table 1), although the most variance explained by any of these relationships is still only 17%. Additionally, we find significant relationships between PDI and PI for the CCSM4 and IPSL anthropogenic time series; however, results indicate almost no relationship between PDI and PI for the preanthropogenic time series (Table 1).

The lack of consensus across our models toward any significant relationships between PDI and various Atlantic Ocean surface temperature metrics over long periods of time suggests the lack of a robust relationship between ocean temperature metrics and TC intensity in the Atlantic Basin. However, we hypothesize that a stronger relationship between PDI and ocean temperature metrics may be evident on shorter time scales. Emanuel reports r^2 values between PDI and MDR SST for a time period of 56 years. For the purpose of comparing our results to Emanuel's findings, we now divide the preanthropogenic portion of our time series into 56 year periods, analyzing R values between PDI and MDR SST at running 56 year intervals. Note

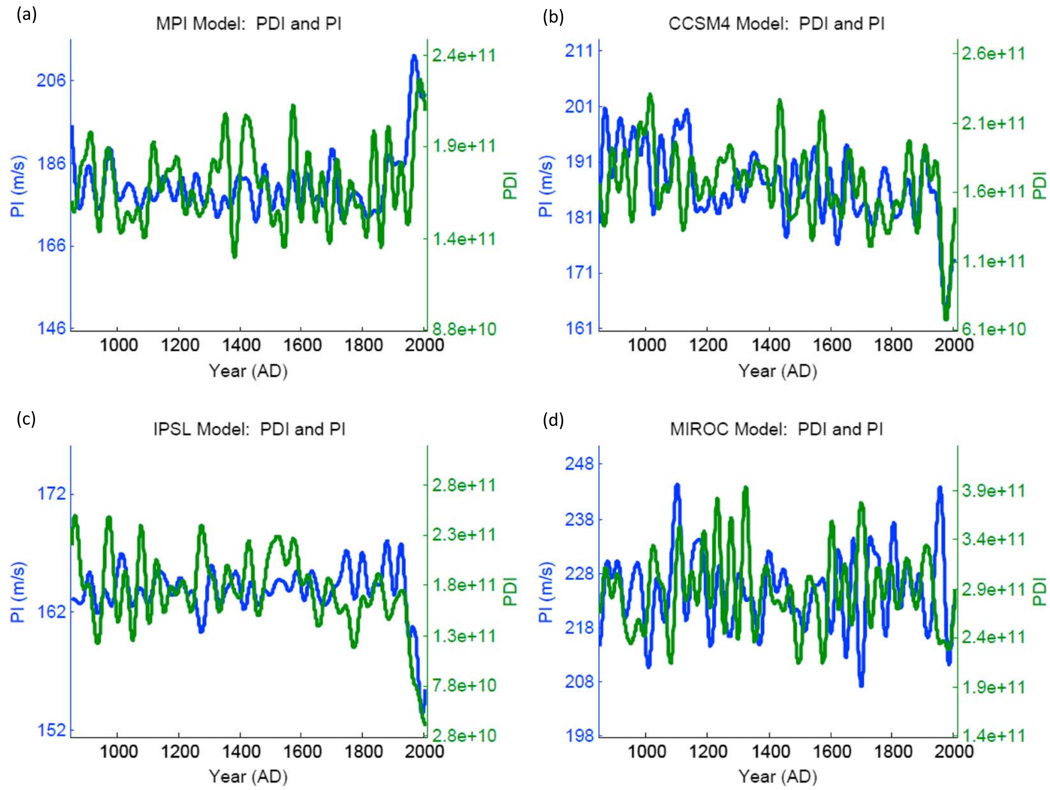

Figure 5. Time series of PI (blue, m/s) and annually accumulated PDI (green) for (a) the MPI model, (b) the CCSM4 model, (c) the IPSL model, and (d) the MIROC model.

that here, for consistency with Emanuel's previous work, we investigate R values, or the Pearson's correlation, rather than r^2 values, or squared Pearson's linear correlation coefficients, as above.

Figure 6 shows the distribution of R values for 56 year time intervals between PDI and MDR SST from the CMIP5 simulations for the preanthropogenic era. Here the 56 year time series of PDI and MDR SST being compared are smoothed using a triangular filter, as in *Emanuel* [2007], allowing for a more direct comparison to Emanuel's work. This filtering technique reduces noise in the time series from interannual variability and emphasizes time scales of 3 years or greater. In addition to the distribution of R values for 56 year intervals over the preanthropogenic era, several other reference points are included on each plot in Figure 6. For each model, the zero line, the distribution mean, the R value from *Emanuel* [2007] for the 56 year time period from 1950 to 2005 ($R = 0.87$), and the R value for each model from the 56 year time period from 1950 to 2005 are marked.

We can see from Figure 6 that, in general, R values found between PDI and MDR SST in our CMIP5 models are far lower than the R value found by *Emanuel* [2007]. Additionally, there seems to be very little agreement between the R value reported in *Emanuel* [2007] and the R values from the CMIP5 models for the same time period. The variability in the R values for our four models, and their disagreement with the observed R value found in *Emanuel* [2007], highlights that fact that, as in all modeling work, our model results are likely affected by model biases and are somewhat less reliable than observed data. In spite of this, however, we do note that the mean of the R value distribution for each model is greater than zero. Combined with the consensus from all four models that no significant relationship between MDR SST and PDI is evident on long time scales (Figure 3 and Table 1), the positive means of the R value distributions from all of our models suggest that, although it is weaker than expected, there is generally a positive correlation between PDI and MDR SST but only for short time scales.

4. Results: TC Count Statistics

Investigating the changing intensities of TCs and the potential relationship of those intensities to climate variables is an issue of great importance, but it is also interesting to consider the TC frequency for a basin.

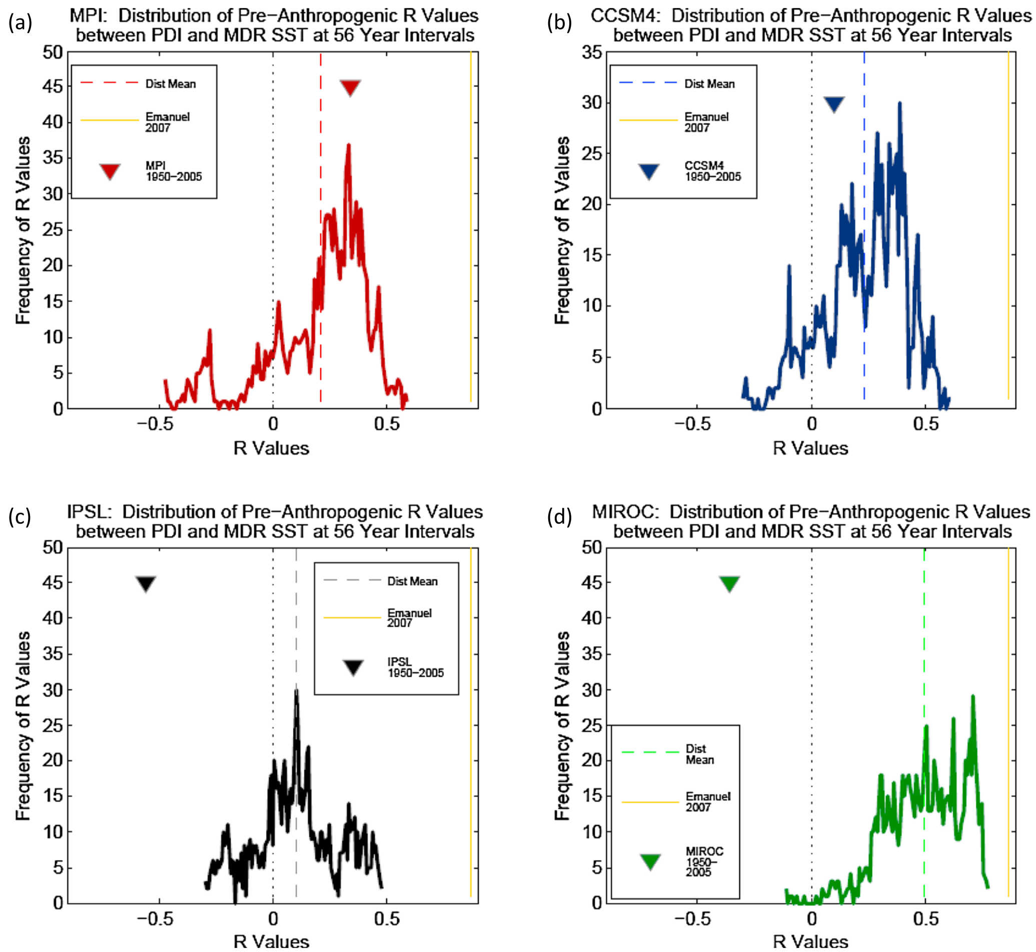

Figure 6. Distribution of *R* values between PDI and MDR SST in the Atlantic Basin at 56 year intervals during the preanthropogenic era for (a) the MPI model, (b) the CCSM4 model, (c) the IPSL model, and (d) the MIROC model. For each model, the zero line is marked using a black dotted line, the distribution mean for each model is marked using a colored dashed line, the *R* value Emanuel found in his study for the 56 year time period from 1950 to 2005 is marked by a solid yellow line, and the *R* value for each model from the 56 year time period from 1950 to 2005 is marked by a triangle.

The multiple long-term synthetic TC data sets at our disposal in this work provide an excellent tool for analyzing the relationship between basin-wide and landfalling TC counts for the Atlantic Basin. Through our analysis of TC counts, we hope to gain further insight into the usefulness of paleohurricane records for analyzing long-term changes in TC activity within the Atlantic Basin.

We begin our investigation into the relationships between different subsamples of TC counts by considering the r^2 values that describe those relationships. Similar to the r^2 values that described the relationships between TCs and the environment in Table 1, Figure 7 displays the r^2 values that describe the relationships between various subsamples of smoothed TC count statistics for each model. The time series corresponding to each relationship in Figure 7 are shown in Figures 8 and 9. Here a TC refers to a storm with winds of at least 40 kts, a hurricane refers to a storm with winds of at least 64 kts, and a major hurricane refers to a storm with winds of at least 96 kts. In Figure 7, r^2 values greater than 0.10 are significant at the $P = 0.05$ level; r^2 values greater than 0.18 are significant at the $P = 0.01$ level. For every model, correlations between basin-wide TCs and total landfalling TCs, and basin-wide hurricanes and total landfalling hurricanes, are significant at the $P = 0.05$ level; all of these except for the correlation between basin-wide TCs and total landfalling TCs from the IPSL model are significant at the $P = 0.01$ level (Figure 7). Correlations between basin-wide and total landfalling major hurricanes are significant at the $P = 0.01$ level for the CCSM4, IPSL, and MIROC models. To test the robustness of these relationships, we have run 10,000 bootstraps of each pair of data sets and computed the r^2 values for each of the 10,000 random samples. The spread of these 10,000 r^2 values are illustrated by histograms in Figure 7. As can be

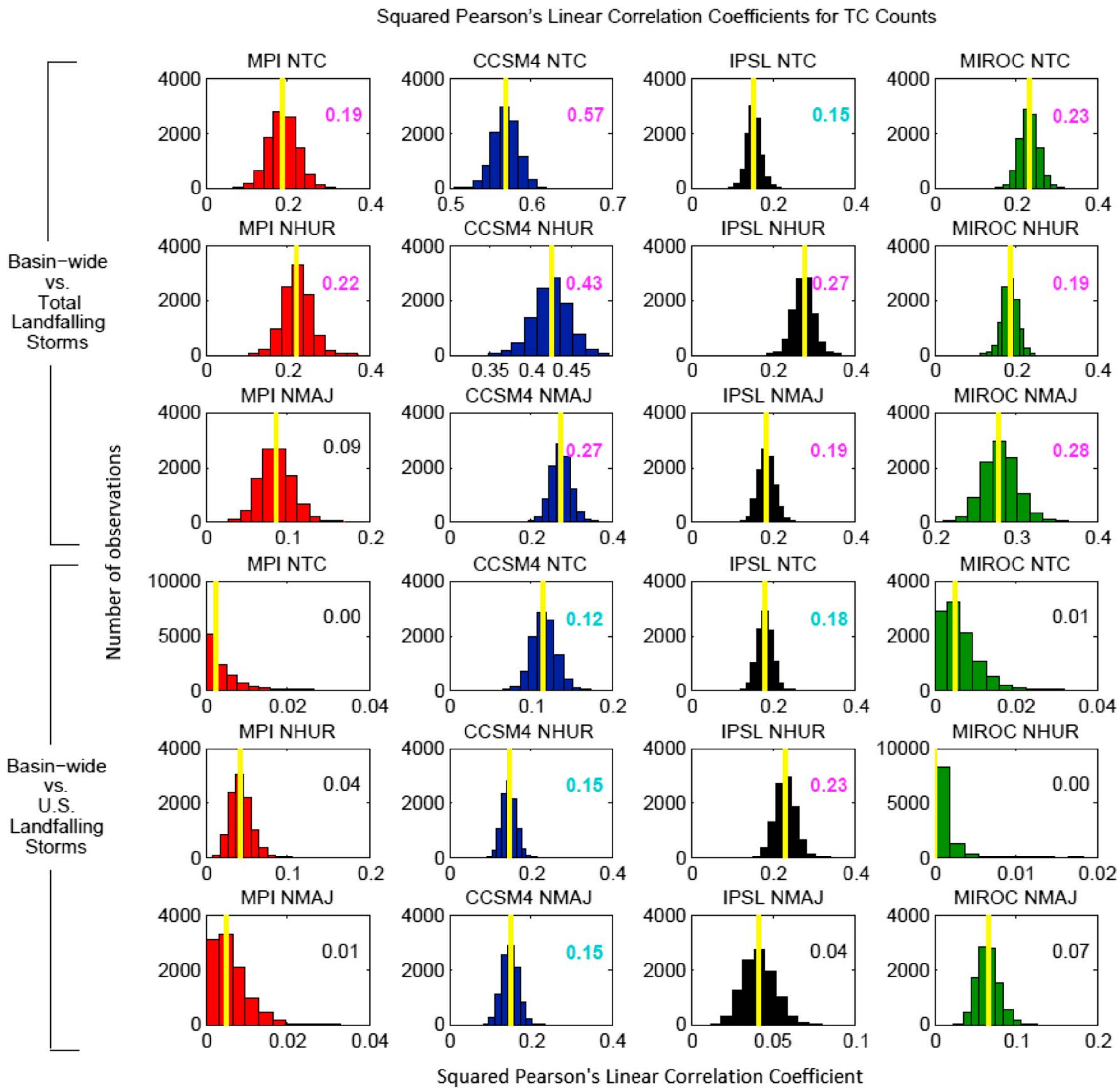

Figure 7. Squared Pearson's linear correlation coefficients (r^2; yellow line on each plot—numerical value included in upper right-hand portion of plot) between various smoothed TC count statistics. Values that are significant at the $P = 0.01$ level are shown in magenta. Values that are significant at the $P = 0.05$ level are shown in cyan. The degrees of freedom for the smoothed time series is approximately $N = 29$; thus, r^2 greater than 0.10 are significant at the $P = 0.05$ level, and those greater than 0.18 are significant at the $P = 0.01$ level. Abbreviations on the plot can be read as follows: NTC = number of TCs, NHUR = number of hurricanes, and NMAJ = number of major hurricanes. Count statistics between basin-wide and total landfalling storms are shown in the top 12 plots; count statistics between basin-wide and U.S. landfalling storms are shown in the bottom 12 plots. Histograms represent the spread of r^2 values from 10,000 bootstraps run on each data set.

seen in the figure, the means of the bootstrapped r^2 values correspond to the actual r^2 values from our data; we thus conclude that the correlation between basin-wide and landfalling storms is robust.

Weaker relationships exist between basin-wide TCs, hurricanes, and major hurricanes and their counterparts making landfall specifically in the United States (Figure 7). We see that the correlations between basin-wide and U.S. landfalling storms across all categories of storms are significant at the $P = 0.05$ level for the CCSM4 model. For the IPSL model, the correlation between basin-wide and U.S. landfalling TCs is significant at the $P = 0.05$ level, while the correlation between basin-wide and U.S. landfalling hurricanes is significant at the $P = 0.01$ level. None of the correlations between basin-wide and U.S. landfalling storms are significant for the MPI or the MIROC models.

The weaker correlations between basin-wide and U.S. landfalling storms as opposed to the correlations between basin-wide and total landfalling storms are not surprising, given that less of the Atlantic Basin coastline

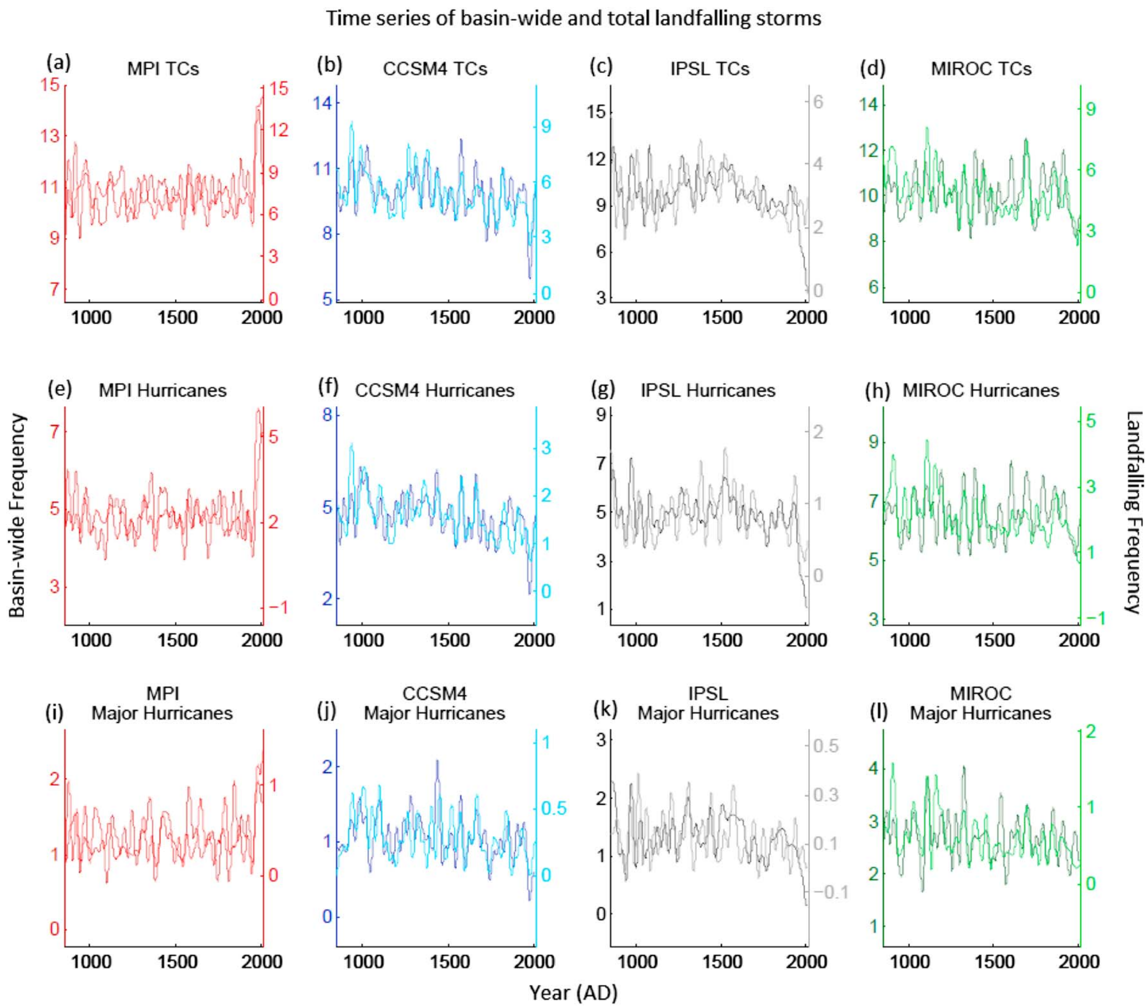

Figure 8. Basin-wide and total landfalling TCs for (a) the MPI model, (b) the CCSM4 model, (c) the IPSL model, and (d) the MIROC model. Basin-wide and total landfalling hurricanes for (e) the MPI model, (f) the CCSM4 model, (g) the IPSL model, and (h) the MIROC model. Basin-wide and total landfalling major hurricanes for (i) the MPI model, (j) the CCSM4 model, (k) the IPSL model, and (l) the MIROC model. Basin-wide time series are shown by dark lines; landfalling time series are shown by light lines.

is included in the former. However, we also note that there is quite a bit of variability in basin-wide and U.S. landfalling correlations among our four CMIP5 models. This variability across the models can be largely explained by different spatial biases found in the tracks of the synthetic TCs downscaled from each model.

To illustrate spatial biases in TCs from our models, points of genesis for tracks from each of the models, as well as from observational data, are shown in Figure 10. Figure 10a shows points of genesis for 400 randomly chosen storms from the Atlantic hurricane database (HURDAT). Genesis points are randomly chosen throughout the observational record, from 1851 to 2005. In Figures 10b–10e, points of genesis for 400 randomly chosen synthetic TCs from 1851 to 2005 are plotted for each of the CMIP5 models we are considering. By comparing the maps, it is evident that the distribution of tropical cyclogenesis for each of the models is in some way spatially biased compared to the observed genesis points; this spatial bias is not the same across the four models. The spatial biases we see in Figure 10 almost certainly affect our TC count statistics. Using a clustering technique to describe TC trajectories in the North Atlantic, *Kossin et al.* [2010] find that both frequency of TC landfalls and their region of impact are strongly dependent upon the spatial characteristics of storm tracks; similar results have also been noted in other basins, such as the North Pacific [*Camargo et al.*, 2007]. The varying spatial biases observed in the synthetic TC tropical cyclogenesis distributions for the different models provide some explanation for the varying strengths of the correlations between basin-wide and U.S. landfalling storm counts across the models.

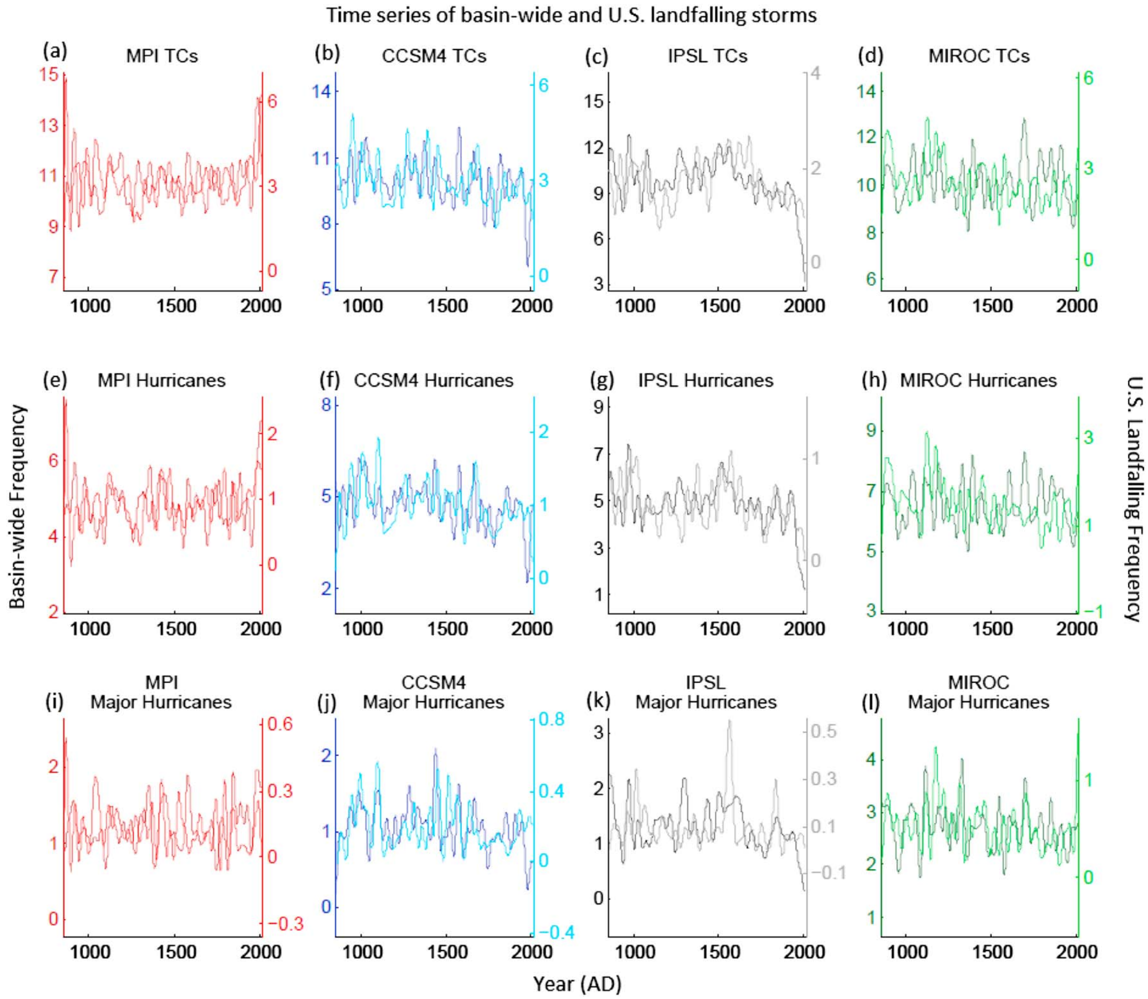

Figure 9. Basin-wide and U.S. landfalling TCs for (a) the MPI model, (b) the CCSM4 model, (c) the IPSL model, and (d) the MIROC model. Basin-wide and U.S. landfalling hurricanes for (e) the MPI model, (f) the CCSM4 model, (g) the IPSL model, and (h) the MIROC model. Basin-wide and U.S. landfalling major hurricanes for (i) the MPI model, (j) the CCSM4 model, (k) the IPSL model, and (l) the MIROC model. Basin-wide time series are shown by dark lines; U.S. landfalling time series are shown by light lines.

5. Summary and Conclusions

Here we investigate correlations between TC intensity and ocean temperature metrics as well as correlations between basin-wide and landfalling TC counts from A.D. 850 to 2005. Results from this study are, in some cases, different than expected and in other cases, nearly as expected.

Based on *Emanuel* [2005] and *Emanuel* [2007], we expected that we may be able to find a strong relationship between PDI and MDR SST for long-term synthetic TC data sets downscaled for the Atlantic Basin from four different CMIP5 models. In reality, we found only a very weak, or in some cases, a nonexistent, direct relationship between PDI and MDR SST in our synthetic TC data sets for the past millennium. A similarly weak relationship between PDI and relative SST was found and between PDI and PI. However, it is important to note that in our analysis of long-term relationships between PDI and ocean temperature metrics, we smoothed the data using a low-pass filter. If a direct relationship between PDI and ocean temperature metrics is only apparent for shorter time scales, our use of smoothed data for the past millennium simulations may contribute to the lack of a direct relationship between these variables on such time scales.

Using a triangular filter [*Emanuel*, 2007] to analyze our synthetic TC data sets for shorter time periods of 56 years during the preanthropogenic era, we found that relationships between PDI and ocean temperature metrics in general, and PDI and MDR SST in particular, were still far weaker than the direct relationship

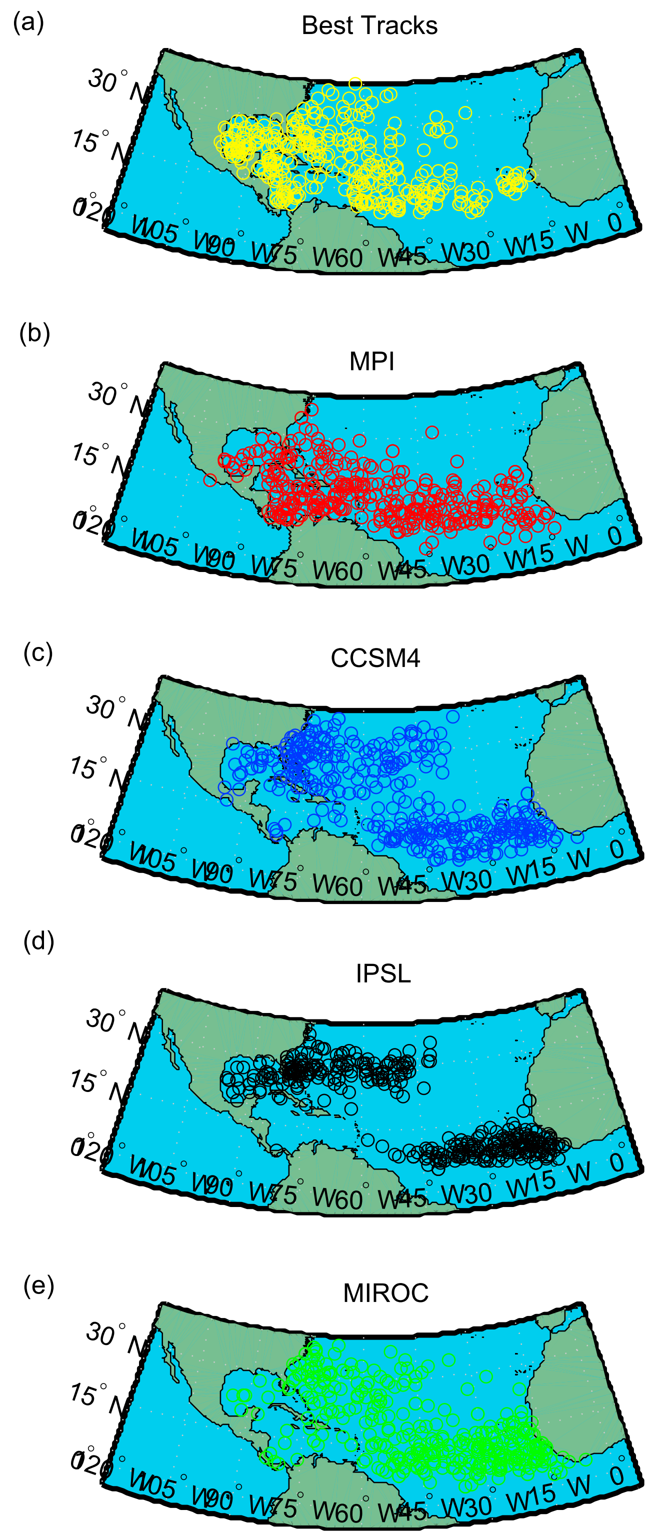

Figure 10. Maps of (a) observed TC genesis points from HURDAT and synthetic TC genesis points from (b) MPI, (c) CCSM4, (d) IPSL, and (e) MIROC models. Observed genesis points are from 400 randomly chosen tracks from HURDAT between the years 1851 and 2005. The same number of genesis points for the same time period are randomly chosen and plotted in Figures 10b–10e.

between PDI and MDR SST found in *Emanuel* [2007] for a time period of identical length. However, using our model-derived synthetic TC data sets, we found that distributions of *R* values between PDI and ocean temperature metrics for running 56 year periods throughout the preanthropogenic era had positive means. Given the consensus of our four models about the lack of a strong direct relationship between PDI and MDR SST, but the overall positive mean of *R* value (Pearson's correlation) distributions for the preanthropogenic era, we conclude that a relationship between PDI and MDR SST may indeed exist, but it is likely a much weaker relationship than that found in *Emanuel* [2007].

Complementing work by *Kozar et al.* [2013], our analysis of long-term basin-wide and landfalling TC count statistics provides additional support for the use of paleohurricane records in analyzing long-term basin-wide TC trends. We find significant correlations between basin-wide and landfalling TCs for nearly all categories of storms across all four of our models. Though affected by spatial biases in synthetic TC tracks from the CMIP5 models, we find that, for some models, significant correlations also exist between basin-wide and U.S. landfalling storms. Indications are that basin-wide storm activity is indeed directly related to landfalling storm counts; thus, we have increased confidence that paleohurricane records can be highly useful in analyzing long-term TC activity for the Atlantic Basin [*Donnelly*, 2005; *Scileppi and Donnelly*, 2007; *Woodruff et al.*, 2008; *Mann et al.*, 2009; *Park*, 2012; *Toomey et al.*, 2013].

Unsurprisingly, a number of caveats related to downscaling apply to the work presented here. For example, although we required daily wind values for our downscaling method, we are here forced to interpolate based on monthly mean wind values from the model output for three of our four models. Additionally, the MIROC model used for one of the downscaled synthetic TC data sets here has a clear and problematic drift in SST across the preanthropogenic era, causing us to place less emphasis on results from this model than others. Such imperfections in model data directly affect our downscaling process. Nevertheless, using the state-of-the-art CMIP5 last millennium climate model simulations, we are able to perform more comprehensive analyses of model-simulated climate/hurricane relationships than in previous studies. Our approach moreover provides a fruitful avenue for future research, whereby multimodel ensembles of long-term climate model simulations, combined with appropriate TC downscaling approaches, can lead to an increasingly improved understanding of the relationship between climate and TC activity.

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