CLIMATOLOGY

Estimation of the maximum annual number of North Atlantic tropical cyclones using climate models

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Using millennia-long climate model simulations, favorable environments for tropical cyclone formation are examined to determine whether the record number of tropical cyclones in the 2005 Atlantic season is close to the maximum possible number for the present climate of that basin. By estimating both the mean number of tropical cyclones and their possible year-to-year random variability, we find that the likelihood that the maximum number of storms in the Atlantic could be greater than the number of events observed during the 2005 season is less than 3.5%. Using a less restrictive comparison between simulated and observed climate with the internal variability accounted for, this probability increases to 9%; however, the estimated maximum possible number of tropical cyclones does not greatly exceed the 2005 total. Hence, the 2005 season can be used as a risk management benchmark for the maximum possible number of tropical cyclones in the Atlantic.

INTRODUCTION

The 2005 Atlantic hurricane season produced a record-breaking 28 named tropical cyclones (TCs), 15 of which reached hurricane intensity (*1*). Excluding 2005, the recorded maximum over the entire Atlantic TC record commencing in 1851 is 20 TCs (in 1933). However, this database is notoriously incomplete due, in large part, to many storms having been entirely missed by the observational network before the satellite era (*2*). Results also suggest an increase in the number of "shorties;" that is, short-lived storms that exist for 2 days or less in the recent record due to improvements in observational techniques (*3*, *4*). Nevertheless, efforts to extend the Atlantic TC record using available data before the satellite era have not shown an incidence of TCs exceeding that of 2005 (*2*, *5*–*7*).

Because the 2005 season produced the largest number of TCs in the Atlantic basin regardless of the best estimate used to correct for missing storms in the earlier part of the record, we examine whether 28 TCs are close to the maximum possible number for the present climate of that basin. If the TC formation rate in 2005 were found to be close to the maximum possible occurrence, then that year could be used as a benchmark for risk management. However, if it were found that the number of TCs in 2005 could be considerably exceeded, then this would require a different risk management strategy. It should be pointed out that this study only considers the number of storms and does not account for other important factors required for risk analysis, such as the intensity and the duration of the storms.

Risk assessments of TC incidence in the Atlantic basin and elsewhere have typically relied upon statistical approaches, whereby a probability distribution is constructed from observed TC records and an estimate is then made of the characteristics of the extreme tails of the distribution (*8*–*12*). The accuracy of these estimates is limited by the short length of the reliable observed record, particularly for estimates of extremes. Some quantitative information can also be obtained from paleotempestology, the science of the reconstruction of storm occurrence in the past from paleoclimate records, which provides an important addition to the observational record and can relate past events to variations in the climate [for example, (*13*, *14*)]. However, this technique only provides estimates of past storms at particular locations and is unable to provide basin-wide information. In addition, paleoclimate estimates may also include periods of time when the baseline climate was different for physical reasons and not just because of statistical variability, which would then require a separate risk assessment.

Here, we analyze basin-wide fluctuations in TC numbers under present-day climate conditions using climate models. These models are based on physical equations that represent the processes in the atmosphere, land, and ocean. We use millennia-long climate model simulations of current climate conditions to examine the potential variations in climate that could occur over the Atlantic basin. Rather than evaluating the ability of the models to simulate the generation of TCs directly, we examine year-to-year variations in statistical relationships between large-scale climate conditions and TC formation rate, known as genesis potential indices (GPIs). This approach allows us to analyze whether TC climate conditions can be more favorable than those in 2005 over a longer period of time than we have available in observations.

RESULTS

The interannual variability in North Atlantic TCs over the full 1851–2016 period is shown in Fig. 1 for all TCs and long-lived TCs only (>2.0 days; see Materials and Methods). For comparison, the data used by Landsea *et al.* (*3*) are also shown. These data only include long-lived TCs and account for "missing" storms before 1965 using the method described by Vecchi and Knutson (*2*). Even with these adjustments to the data, the year 2005 stands out as an exceptional year for TC activity, equaled only by 1887 and 1933, if we assume that the correction for missing storms as documented by Vecchi and Knutson (*2*) is correct. We analyze both the full and the long-lived TC datasets here. The full TC dataset results are discussed in detail, and the results from only long-lived TCs are summarized in the main text, with figures included in the Supplementary Materials.

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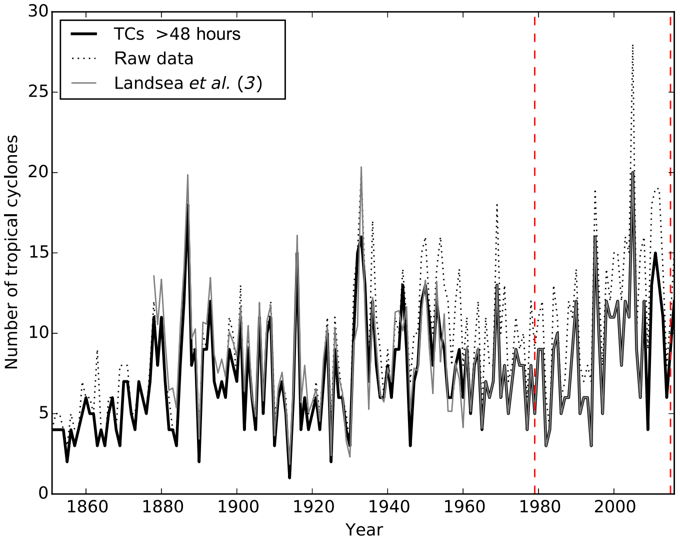

Fig. 1. Interannual variability of North Atlantic TCs. Interannual observed TC numbers using all TCs (black dotted), long-lived TCs (>2.0 days; black solid), and tracks used by Landsea *et al.* (*3*) (gray solid). Red dashed lines indicate the period of comparison with the reanalysis-derived GPIs.

The statistical relationships between climate conditions and TC formation rates are formulated using three different TC GPIs. The year-to-year GPIs are calculated in two millennial climate model simulations, including 5000 years from the Commonwealth Scientific and Industrial Research Organisation (CSIRO) model (*15*, *16*), with constant present-day forcing and 1000 years from the EC-Earth model with varied forcing from the last millennium (see Materials and Methods for model information) (*17*). The GPIs were scaled to the observed data and captured the annual cycle and relationship between year-to-year climate variations and TC formation (see Materials and Methods and figs. S1 and S2).

The indices extracted from the CSIRO and EC-Earth model simulations occasionally approach the 2005 value of 28 TCs, but only rarely (fig. S3 and Table 1): For the CSIRO model, for the 5000 years of model output analyzed here with three different indices, only once does the value reach the observed number in 2005. The indices calculated in EC-Earth also reach the observed value of 28 once in one of the three indices and come within one TC an additional two times. When the long-lived TC dataset is used, the observed value (20 TCs) is reached more often but still only seven and four times in the CSIRO and EC-Earth calculated indices, respectively (fig. S4 and table S1).

It could be argued that a fairer comparison to the climate model output might be the TC numbers derived from the GPIs calculated using reanalysis data for that year, rather than the TC numbers derived from the best-track data, where reanalysis data are a combined form of observational data and climate model simulation, thus representing a best estimate of the observed weather and climate (see Materials and Methods). This is because actual TC formation is subject to variations caused by stochastic processes—that is, even given exactly the same climate forcing, it is possible to generate different numbers of TCs, an issue that is addressed quantitatively below. As a result, the GPIs were similarly calculated in two reanalysis datasets: ERA-Interim reanalysis (ERA) (*18*) and NCEP-2 reanalysis (NCEP) (*19*).

Table 1. Frequency of when the observed number of TCs in 2005 is exceeded. The percentage of years the modeled GPIs exceed the observed 2005 number of 28.0 and the calculated 2005 reanalysis GPIs over the entire North Atlantic basin. Values in parentheses include an internal variability of two TCs in the model-calculated GPIs. The number of years of simulation is included for each model.

Dataset for comparison	GPI	Model		
		CSIRO (5000 years)	EC-Earth (1000 years)	MRI (m050) (61 years)
Observed (all TCs)	EN	0% (0.4%)	0% (0.5%)	0% (0%)
	TIP	<0.05% (0.4%)	0.1% (1.1%)	0% (1.6%)
	CGI	0% (0.6%)	0% (0.5%)	0% (0%)
ERA	EN	1.9% (9.0%)	2.4% (9.2%)	4.9% (9.8%)
	TIP	1.0% (6.0%)	1.9% (6.9%)	1.6% (8.2%)
	CGI	3.7% (11.1 %)	4.7% (13.5%)	4.9% (14.8%)
NCEP	EN	0.9% (5.8%)	0.9% (6.5%)	0% (6.6%)
	TIP	1.1% (6.3%)	2.0% (7.0%)	1.6% (8.2%)
	CGI	2.0% (8.4%)	2.2% (9.2%)	1.6% (9.8%)

The blue and green arrows in the histograms (Fig. 2 and fig. S5) show the year 2005 GPI values calculated from the reanalysis data. If we assume that these GPI values represent what the models should be compared to as a proxy for the TC formation rate in 2005, then we note that less than 5% of all model years have GPI values that equal or exceed the 2005 values independent of whether the short-lived storms are removed or not (Table 1 and table S1), with an average exceedance probability of 2% across all GPIs. The maximum GPI value seen within the CSIRO and EC-Earth model results (fig. S3) is 28.0 and 28.5, respectively, comparable with the observed number in 2005. This value exceeds the year 2005 GPI calculated in the reanalysis data by 30% but is very rare. Even a 10% (about two TCs) exceedance of the 2005 reanalysis-calculated GPIs occurs less than 1% of the time.

The above analysis shows that the diagnosed number of TCs for 2005 from the reanalyses is somewhat lower than the observed number of TCs (see arrows in Fig. 2 and fig. S5). The peak in observed TC numbers in 2005 is evident in the interannual variability (Fig. 3 and fig. S6), and this is greater than the GPI values for the same year. In the reanalysis-forced GPIs, there is a reasonable correlation with observations (see Materials and Methods), but although the year 2005 has a high value in all three indices, it is not an outlier. This suggests the possibility that GPIs, as currently formulated, are missing some essential physical parameters that would enable them to capture the full range of TC numbers seen in the best-track observations. A consequence of this would be that, because the 2005 conditions occur more frequently using the reanalysis GPIs than observed 2005 TC numbers, the reanalysis GPI values would be expected to be higher than what was observed in 2005 to produce, on average, the 2005 TC activity. This may mean that the climate models are even less likely to simulate values greater than the 2005 GPI values than what is shown in Fig. 2. Another possible explanation is that, even if the GPIs did have a complete representation of TC physics in their parameters,

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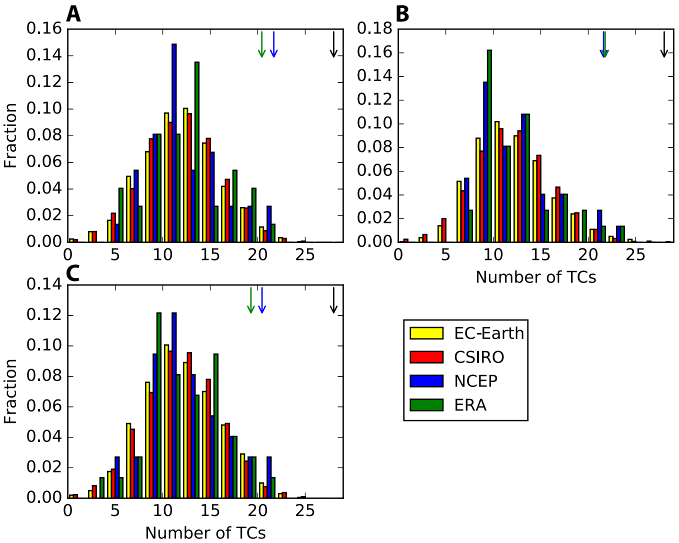

Fig. 2. Variability in annual numbers of North Atlantic TCs calculated in reanalysis and model data. Histograms of normalized variance-scaled GPIs calculated on a 5° × 5° grid for the EC-Earth model (yellow), the CSIRO model (red), NCEP-2 reanalyses (blue), and ERA-Interim reanalyses (green) for (**A**) the Emanuel and Nolan index (EN) (*27*), (**B**) the Tippett index (TIP) (*29*), and (**C**) the Bruyère *et al.* index (CGI) (*28*). Arrows show 2005 GPI values (actual and unbinned) for the reanalyses and observed number of TCs (black).

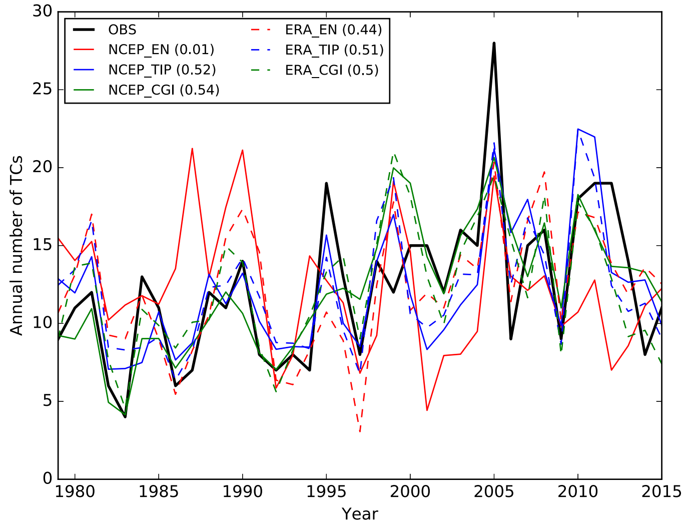

Fig. 3. Interannual variability of North Atlantic TCs. Interannual observed TC numbers (from IBTrACS, black line) and variance-scaled genesis indices calculated in ERA-Interim (dashed lines) and NCEP-2 reanalyses (solid lines). Values in parentheses indicate interannual correlations (r^2) between GPIs and IBTrACS.

the nonlinear and chaotic nature of the climate system might add an additional stochastic (internal) element that amplifies an already climatically favorable year into a record year like 2005.

To estimate the effect of stochastic processes in the climate system on TC numbers, the GPIs are calculated for 100 ensemble members of the same climate model [Meteorological Research Institute (MRI)] (see Materials and Methods for model information) (*20*) for the year 2005. This ensemble is a series of simulations using the same sea surface temperature (SST) forcing but with slightly different initial atmospheric conditions. Because of the chaotic nature of the climate system, the resulting evolution of the weather systems generated by the model will differ among the ensemble members. We are able to make an estimate of the stochastic component of the climate by taking the ratio of the SD of the GPIs when forced with the same SSTs, in this case observed 2005 values, to the SD when forced with interannually varying SSTs from one ensemble member for 1951–2011. This gives a stochastic component of about 50% of the total interannual variability. After calibration of the mean (see Materials and Methods), the stochastic component is estimated to be slightly lower, at 30 to 45% depending on the GPI calculated. This is consistent with the results of Done *et al.* (*21*), who found an internal variability of around 40% using a regional climate model ensemble.

To estimate the possible effect of stochastic variability on the possible maximum number of TCs, we assume that the internal variability ranges between 30 and 50% and we account for this in the results. With an observed SD of 4.8 and 3.9 over the full and long-lived TC datasets, respectively, this equates to an additional variability of 1.4 to 2.4 TCs for the full dataset and 1.2 to 2.0 TCs for the long-lived TC dataset. For the purpose of this study, we will add an internal variability of two TCs (see Materials and Methods). Values in parentheses in Table 1 document the number of times a model-calculated genesis parameter exceeds the observed 2005 level (28 cyclones) when an additional factor of two cyclones is added to the GPI variance. This shows that the 2005 occurrence is still a rare event. The result is significant as it implies that the well-documented data from the year 2005 could serve as an approximate benchmark for maximum TC incidence in the Atlantic basin, an important consideration for TC risk management. For completeness, the model GPIs with the added internal variance are compared against the 2005 reanalysis GPIs (values in parentheses in Table 1 and table S1). As expected, this results in an increase in the percentage of years exceeding 2005 but still remains below 15% across all indices and models (average exceedance probability of 8.7% over all indices).

A related issue is that, even given the same climate forcing, the number of TCs may vary more than the GPIs, due to the nonlinear, chaotic nature of the TC formation process. To address this issue, we further analyze the results of the MRI simulations, this time directly detecting the TCs generated within the model (see Materials and Methods). Direct detection is a justifiable assessment method for this model because of its comparatively finer horizontal resolution and (in principle) its better representation of TC processes.

It is a well-known issue that many climate models underestimate the observed numbers of TCs in the Atlantic basin (*22*). The MRI model has the same problem, as indicated in Fig. 4A and fig. S7A, which shows the number of TCs forming at or south of 30°N for one ensemble member (m050) over the full 61 years analyzed. The average number of simulated TCs here is 2.7 (1.8 when only long-lived TCs are included). Because of the stochastic nature of the direct simulation of TCs, the peak year for TC formation in this ensemble member is 1955, not 2005. In contrast, we found no peak in the GPIs in 1955, again demonstrating how stochastic variability can amplify TC formation.

Figure 4B and fig. S7B show the results for each of the 100 realizations using observed 2005 SSTs. The numbers simulated for 2005 remain well below the observed numbers, with a mean of 5.0 TCs (3.5 for long-lived TCs) and an SD of 2.4 (1.7 for long-lived storms). Nevertheless, this is almost twice the long-term MRI model mean shown by the single ensemble member (Fig. 4A and fig. S7A), which

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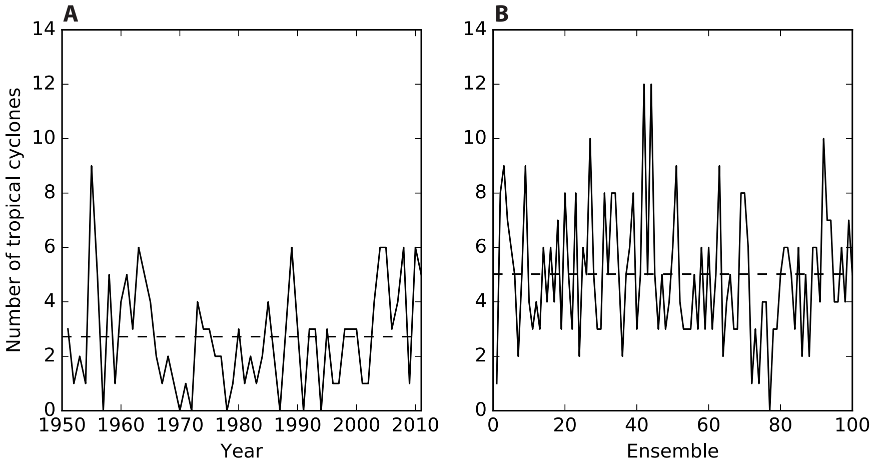

Fig. 4. Number of Atlantic TCs simulated by the MRI model. The number of directly simulated TCs in the MRI model for (**A**) the ensemble member m050 and (**B**) each ensemble member forced by 2005 SSTs. The mean TC occurrence for each is shown by the horizontal dashed lines.

indicates that the model is partially capturing the amplifying effect on TC numbers by the climate of 2005. The SD is 47% of the mean, again similar to the estimate of the internal Atlantic TC variability provided using the GPIs and by Done *et al.* (*21*). The maximum number of TCs formed in the 100-member ensemble is 12 when all TCs are included and 8 when only long-lived TCs are included, or 2.4 and 2.3 times the average value for 2005 for the full and long-lived TCs, respectively. According to this result, over a period of 100 years, a value 2.4 times the mean could occur simply by random variation. Because the mean of observed Atlantic TC formation is about 12.2 using all TCs over the 1979–2015 period, this means that, on the basis of the results of Fig. 4, a value of 29 TCs could occur during a period of 100 years of average climate conditions due to random variation. When this is repeated for the long-lived TCs, a value of 21 TCs could occur. Nevertheless, this is a short period of time compared to the variability estimates from the other millennia-long simulations discussed previously, so the potential sampling error is larger.

DISCUSSION

To be confident that there are likely to be years with TC formation well in excess of the formation observed in 2005, there would need to be clear evidence of this from our analysis, but we do not find this evidence. When we compare the observed TC formation rate for 2005 to the millennial model–calculated GPI variations, the model-generated GPIs only very rarely (<0.5%) equal or exceed the observed number of 28 TCs. When the stochastic variability is taken into account, this increases to 1.1% (Table 1). This is increased further to a maximum of 3.2% (with added stochastic variability) when only long-lived storms (>2.0 days) are considered. If we assume instead that we should be comparing the 2005 reanalysis–driven GPI values to the model-driven GPIs to see how often the model-generated GPIs exceed these values, then the model-driven GPIs exceed these values on average 2% of the time, but maximum GPI values from the model do not exceed the 2005 reanalysis values by a substantial margin (Fig. 2 and fig. S5). Adding the stochastic variability results in an average probability of exceedance of 2005 GPIs of 9%. Repeating the analysis for long-lived storms only results in only a small increase in the probability of exceedance and hence helps to reinforce our conclusions.

For the purposes of risk management, it is therefore likely that 2005 represents a reasonable benchmark for the maximum number of TCs that might occur in the Atlantic basin in the current climate. Note that this study does not include or estimate variations in total destructive potential of TCs through analysis of parameters related to TC intensity. Such an analysis, if it could be performed, would further constrain the risk assessment of year-to-year variations in TCs in the Atlantic basin.

MATERIALS AND METHODS

Observational and reanalysis data

The observed TC data for the North Atlantic region (between 0° and 40°N, including the American and African coast) came from the International Best Track Archive for Climate Stewardship v03r10 (IBTrACS) (*23*). This is an updated version of the Atlantic TC database used by Landsea *et al.* (*3*), and recent improvements have resulted in several storms being added to the earlier periods. Data were obtained for the full 1851–2016 period available (Fig. 1). For the subsequent analysis, we used the 37 years, from 1979 to 2015, to correspond with the available reanalysis data. There were 451 TCs over the 37-year period; that is, 12.2 per year on average, with an SD of 4.8. On the basis of the analysis by Landsea *et al.* (*3*), the analysis was repeated with only long-lived storms existing for more than 2.0 days, due to the likely omission of short-lived storms in the earlier part of the record. There were, on average, 9.0 long-lived TCs per year and an SD of 3.9.

The reanalysis products have assimilated the observational data, including ground-based and satellite measurements, and therefore served as the best estimate of observed data. We used two different reanalyses: the NCEP-DOE AMIPII (NCEP) (*19*) and the ERA-Interim (ERA) (*18*) datasets for 1979–2015. Monthly data were obtained on a 2.5° × 2.5° grid and were interpolated to 5° × 5° for comparing with model output.

Model data

First, we used the CSIRO Mk2 coupled ocean–atmosphere climate model, as previously documented by Gordon and O'Farrell (*16*). The model version and experimental design are the same as previously published by Hunt and Watterson (*15*). The atmospheric model has

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nine vertical levels and a horizontal resolution of 350 km × 625 km, rather coarse by the standards of contemporary climate models. The model was set up for a "present" climate with a fixed atmospheric CO_2 concentration of 330 parts per million. This equilibrium simulation thus only reflects the internal variability generated in the coupled climate model system. The simulation was run for 10,000 years, but only the last 5000 years were analyzed here. Note that, in this project, we did not detect TCs directly as generated by the model. The model generated some low-pressure systems that have some of the structural characteristics of TCs. Nevertheless, because of the coarse resolution of the model, its simulation of TCs is unlikely to be very skillful. Instead, we derived the basin-wide climate variables simulated by the model and applied them to the GPIs defined below.

EC-Earth is developed by a consortium of European research institutions (*17*). The atmospheric component of EC-Earth is based on Integrated Forecasting System (IFS), which is developed at the European Centre for Medium-Range Weather Forecasts (ECMWF), coupled with the land model H-TESSEL. The IFS and H-TESSEL components were also used to produce ERA-Interim reanalysis. The ocean component is based on Nucleus for European Modelling of the Ocean (NEMO) (*24*), including the sea ice model LIM3 (*25*). EC-Earth model has relatively high resolution, a horizontal resolution of 125 km, and the atmosphere has 62 vertical levels; the ocean model NEMO has a horizontal resolution of 110 km with 46 vertical levels. Here, we used the last millennium simulation with EC-Earth v3.1. The initial condition started from an equilibrium state at 850 CE after 300 years of spin-up, and the imposed forcings were changed from 850 to 1850. This millennium simulation provides a 1000-year transient climate, contains both externally forced variability and internal variability, and is thus closer to a real climate condition than an equilibrium climate simulated by the CSIRO model.

The third model we used was the MRI Atmospheric General Circulation Model version 3.2 (MRI-AGCM3.2) (*20*). The model atmosphere has a high horizontal resolution of 60 km with 64 vertical levels. A randomly varying ensemble of 100 members was performed for the historical period 1951–2011, forced by the prescribed SST, sea ice concentration, global mean concentrations of greenhouse gases, and three-dimensional distributions of ozone and aerosols. The data from these simulations are freely available to download from the Database for Policy Decision Making for Future Climate Change (d4PDF) (*26*). We analyzed two subsets of these data here. First, we analyzed one ensemble over the full 61 years (ensemble member m050) to provide an assessment of the model's TC climatology over the Atlantic. Second, we analyzed all 100 ensembles for the year 2005 to determine whether, given exactly the same climate forcing, random variation in formation rates could cause years of high TC formation.

Genesis parameters and direct detection of TCs

Genesis parameters (GPIs) are equations that relate variations in observed atmospheric data to changes in the TC formation rate. The parameters in the equations are based on the best statistical fit to the observed TC formation rate variations and provide a succinct way of encapsulating the effect of atmospheric and oceanic climate on TC formation. These are required because we do not have a full understanding of TC genesis and there is no complete theory for genesis. Three different genesis parameters were calculated in this study. These are the GP (here, EN so as not to confuse with the general acronym GPI) by Emanuel and Nolan (*27*), the CGI by Bruyère *et al.* (*28*), and the TCS (here, TIP) by Tippett *et al.* (*29*) defined below. Because these indices were developed for different datasets and time periods, we scaled the indices to the mean number of TCs observed in the North Atlantic (12.2 per year for all TCs and 9.0 per year for long-lived TCs). The EN index is defined as follows

$$\mathrm{EN} = |10^5\eta|^{\frac{3}{2}}\left(\frac{H}{50}\right)^3\left(\frac{V_{\mathrm{pot}}}{70}\right)^3(1+0.1V_{\mathrm{shear}})^{-2} \tag{1}$$

where η is the absolute vorticity at 850 hPa (s^{-1}), H is the relative humidity at 700 hPa (%), V_{pot} is the potential intensity (m s^{-1}) calculated using a routine provided by Emanuel (ftp://texmex.mit.edu/pub/emanuel/TCMAX/), and V_{shear} is the vertical shear from 850 to 200 hPa (m s^{-1}). The CGI index is defined as

$$\mathrm{CGI} = \left(\frac{V_{\mathrm{pot}}}{70}\right)^3(1+0.1V_{\mathrm{shear}})^{-2} \tag{2}$$

This uses just two components from the EN (V_{pot} and V_{shear}). Bruyère *et al.* (*28*) found that this formulation results in improved correlations of interannual variability and trends compared to the original EN and updated GPI (*27*, *30*). Because the CGI does not include a vorticity term to remove TCs that form close to the equator, its values are set to zero between 0° and 5°N, as done in the original paper. The TIP index is defined as

$$\mathrm{TIP} \;=\; \exp\left(b + b_\eta\eta + b_H H + b_T T + b_v V + \log(\cos\phi)\right) \tag{3}$$

where η is the clipped absolute vorticity at 850 hPa in 10^5 s^{-1} ($\eta = \min(\eta, 3.7)$), T is the SST $- \overline{\mathrm{SST}}^{[20^\circ\mathrm{S}\text{-}20^\circ\mathrm{N}]}$ in °C, ϕ is the latitude, H is the relative humidity at 600 hPa (%), and V is the vertical shear from 850 to 200 hPa (m s^{-1}). The constants used are those from line 6 of table 1 of Tippett *et al.* (*29*) and as used by Menkes *et al.* (*31*)

$$b = -5.8;\;\; b_n = 1.03;\;\; b_H = 0.05;\;\; b_T = 0.56;\;\; b_V = -0.15$$

The annual cycle from both the GPIs calculated in the reanalyses and models is shown in fig. S1 when scaled to the full TC dataset. The calculated GPIs all do a reasonable job of reproducing the observed annual cycle of North Atlantic TC formation, but values in all GPIs are too high outside of the peak North Atlantic TC season of August to October (ASO), resulting in lower values during the peak ASO period. The similarities in the GPIs calculated in the reanalyses and the models are clear, with TIP giving the lowest out-of-season values and CGI the highest. The year-to-year (interannual) variability in the reanalysis-calculated GPIs and observed number of TCs is shown in Fig. 3, with r^2 values for the correlations included. The EN index has the poorest correlation, consistent with the results of Bruyère *et al.* (*28*), and this is poor in particular for the NCEP data (r^2 = 0.01). The CGI and TIP indices are able to capture the relationship between year-to-year climate variations and TC formation, with r^2 values above 0.5. It is worth noting here that the CGI was tested and developed for the Atlantic region only; hence, it is no surprise that it performs well over this region. However, the TIP index is a globally developed index and performs comparably well.

When the GPIs were rescaled for the long-lived TCs, the annual cycle (fig. S2) and interannual variability (fig. S6) were generally slightly poorer when compared to the observed data, and there was a

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slight decrease in correlations in all indices except the CGI calculated in ERA. This is due to the data originally used to formulate these GPIs including these short-lived TCs.

For the MRI model data, in addition to a GPI analysis, we also detected TCs directly in the four-time daily output of the model, using the method of Walsh (*32*) and Horn *et al.* (*33*). The detection wind speed threshold was chosen to be 16 m s^{-1}, almost identical to the threshold for observed TCs and appropriate for the resolution of the model (*34*). For comparison with the long-lived TCs, systems that were tracked for 2.0 days or less were removed.

Variance-scaling

In our initial analysis, we "mean-scaled" the results; that is, corrected the output of the GPIs to ensure that their means were the same as the observed formation rate over the Atlantic, as derived from the best-track data for the period 1979–2015, while allowing their variances to be determined by the raw values of the genesis parameters themselves. Figures S8 and S9 show that the variations in the GPIs calculated from the models are very constrained around the mean. The variability in the models was less than in the reanalyses, and the year 2005 calculated from reanalyses fell outside the range of the distribution for both the CSIRO and EC-Earth models (figs. S8 and S9). This is even more evident when compared to the observed year-to-year variance of TC formation from best-track data.

To address this issue, we rescaled the variance of the derived genesis parameters to match the variance of best-track formation rate over the Atlantic basin. The model time series was divided by its SD to give a standardized time series, which was then multiplied by the SD of the observed time series. We then adjusted the variance and mean to match the observed time series. Adjusting the variance of the model time series should provide a more adequate comparison of the distribution obtained from the two different samples (Fig. 2 and fig. S5). To avoid biasing the results by the inclusion of 2005, an event that is a clear outlier in the observed record, we excluded that year from the calculation of the rescaled variance. Note that one of the limitations of this methodology is that we get some years with negative TC formation, which is unphysical (for example, fig. S3).

We calculated the stochastic (internal) variability using the analysis of MRI data (see Results). To account for the internal variability in the model, this value (two TCs) was added to the observed variance and the variance scaling was recalculated.

SUPPLEMENTARY MATERIALS

Supplementary material for this article is available at http://advances.sciencemag.org/cgi/content/full/4/8/eaat6509/DC1

Fig. S1. Annual variability in North Atlantic TCs.
Fig. S2. As in fig. S1 but scaled to long-lived TCs.
Fig. S3. Interannual variability of modeled GPIs.
Fig. S4. As in fig. S3 but scaled to long-lived TCs.
Fig. S5. As in Fig. 1 but scaled to long-lived TCs.
Fig. S6. As in Fig. 3 but for long-lived TCs.
Fig. S7. As in Fig. 4 but for long-lived TCs (>2.0 days).
Fig. S8. Distribution of mean-scaled numbers of North Atlantic TCs calculated in reanalysis and model data.
Fig. S9. As in fig. S8 but scaled to long-lived TCs.
Table S1. As in Table 1 but for long-lived TCs only.

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