

# Climate and Tropical Cyclone Activity: A New Model Downscaling Approach

KERRY EMANUEL

*Program in Atmospheres, Oceans, and Climate, Massachusetts Institute of Technology, Cambridge, Massachusetts*

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## ABSTRACT

While there is a pressing need to understand and predict the response of tropical cyclones to climate change, global climate models are at present too coarse to resolve tropical cyclones to the extent necessary to simulate their intensity, and their ability to simulate genesis is questionable. For these reasons, a “downscaling” approach to modeling the effect of climate change on tropical cyclones is desirable. Here a new approach to downscaling is introduced that consists of generating a large set of synthetic storm tracks whose statistics are consistent with the large-scale general circulation of the climate model, and then running a deterministic, coupled tropical cyclone model along each track, with atmospheric and upper-ocean thermodynamic conditions taken from the global climate model. As a first step in this direction, this paper explores the sensitivity of the intensity of a large sample of tropical cyclones to changes in potential intensity, shear, and ocean mixed layer depth, fixing other variables, including the space–time probability distribution of storm genesis. It is shown that a 10% increase in potential intensity leads to a 65% increase in the “power dissipation index,” a measure of the total amount of mechanical energy generated by tropical cyclones over their life spans. This is consistent with the observed increase of power dissipation over the past 50 yr. Storms are somewhat less influenced by equivalent fractional changes in environmental wind shear or ocean mixed layer depth.

## 1. Introduction

The relationship between global tropical cyclone (TC) activity and global climate is of obvious interest, both from a basic scientific and from a societal point of view. Globally, 90 tropical storms develop each year, with a standard deviation of 10 and no evidence of a long-term trend (Emanuel 2005). There is at present no understanding of what controls this number or why it is so stable. There is some evidence that tropical cyclone intensity is increasing as a result of global warming (Emanuel 2005; Webster et al. 2005), as is the duration of storms (Emanuel 2005). Regionally, there can be large variability of both the number and intensity of tropical cyclones. This is particularly well documented in the Atlantic where it has been linked to such phenomena as El Niño–Southern Oscillation (Goldenberg and Shapiro 1996). The regional control of Atlantic tropical cyclone activity, according to these studies, is statistically linked to, and probably physically caused

by, variability in deep tropospheric wind shear and tropical sea surface temperature. Trends in tropical cyclone intensity and duration are also well correlated with tropical sea surface temperature (Emanuel 2005).

Modeling the response of tropical cyclones to climate change has proven challenging. Global climate models do appear to be capable of generating tropical cyclones at approximately the correct rate, and in roughly the right places (Broccoli and Manabe 1990), but attempts to use global climate models to explore the sensitivity of storm frequency to climate change have produced such conflicting results (Broccoli and Manabe 1990; Haarsma et al. 1992; Bengtsson et al. 1996; Sugi et al. 2002; McDonald et al. 2005) as to cast serious doubt on their present utility for this purpose. At the same time, the horizontal resolution of the current generation of GCMs is far too coarse to allow them to simulate storms at their full, observed intensity. For this reason, recent attempts to use models to explore the climate sensitivity of tropical cyclones have used a downscaling approach. This approach was pioneered by Knutson et al. (1998) and furthered by Knutson and Tuleya (2004). They integrated the Geophysical Fluid Dynamics Laboratory (GFDL) hurricane model, a nested model with horizontal grid spacing as fine as 9 km, subject to

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*Corresponding author address:* Kerry Emanuel, Massachusetts Institute of Technology, Rm. 54-1620, 77 Massachusetts Ave., Cambridge, MA 02139.  
E-mail: emanuel@texmex.mit.edu

boundary conditions provided by a suite of GCMs, and run using a variety of convective representations. In their study, both the rate of genesis and the environmental wind were held fixed. A robust result, valid across the spectrum of models used for boundary conditions and with the variety of convective schemes used, is that the intensity distribution across many events shifts to higher intensity in a warmer climate.

The present study constitutes an extension of the work of Knutson and Tuleya (2004) to climate scenarios with variable wind shear and storm tracks, but as in the Knutson and Tuleya study, we hold fixed the space–time probability of genesis and examine the sensitivity of tropical cyclone intensity to specified changes in potential intensity, wind shear and ocean mixed layer properties. To accomplish this, we run a coupled hurricane intensity prediction model along 3000 synthetic Atlantic storm tracks. This model has the advantage of very high spatial resolution of the storm core and small run times, so that it is possible to create a large sample. In future work, we will take the same approach but generate synthetic tracks and shears directly from the output of GCMs.

In the next section, we briefly review our method for generating synthetic storm tracks and our intensity model, and we describe the experimental setup. Section 3 presents results of the study, and a summary is provided in section 4.

## 2. Synthetic tropical cyclone tracks and intensity model

The means of generating synthetic tropical cyclone tracks is the second of two methods described in detail in Emanuel et al. (2006). Here we provide a condensed summary of the technique.

Synthetic track origin points are generated simply by randomly drawing from a smoothed space–time probability distribution estimated from the post-1970 best-track Atlantic hurricane data (updated from Jarvinen et al. 1984). In all the experiments described here, this distribution is held fixed, lacking any generally accepted theory or modeling results for how such a distribution might change in response to global climate change. (Note that we do not here permit the genesis distribution to reflect natural interannual to interdecadal variability. While changes in the variability of genesis locations may be an important component of global climate change, we lack a clear understanding or prediction of how such variability itself may change.)

Once a storm is generated, it is then moved according to a suitably defined vertical average of the deep tropospheric environmental winds, plus a correction for

“beta drift” (Holland 1983); this is sometimes referred to as the “beta and advection model” (“BAMS”; Marks 1992). The track is continued until it reaches generously defined geographical boundaries at high latitudes or low longitudes; when the intensity model is subsequently run along each track, it usually predicts storm dissipation well before the end of a track is reached.

One method for producing environmental winds for determining each track would simply be to run a GCM for a long time, launching TC tracks as appropriate. This would necessitate the manipulation of a large data file containing GCM winds at several levels globally for a long time. Instead, we follow Emanuel et al. (2006) in generating synthetic time series of winds at 250 and 850 hPa that conform in certain key respects to the statistics of the GCM winds. Namely, we manufacture winds using discrete Fourier time series of random phase but that have the same monthly mean, variances, and covariances among the two scalar wind components at the two levels as the GCM winds, and that have an  $\omega^{-3}$  power spectrum, where  $\omega$  is frequency, to conform to observed flows at synoptic and greater scales. Again following Emanuel et al. (2006), we use winds only at 250 and 850 hPa to determine storm translation. The synthetic winds at these levels are also used to calculate vertical wind shear as input to the intensity model, as described presently.

For the purpose of the present study, we use wind statistics from the present climate, as determined from the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis data (Kalnay et al. 1996). In one of our sensitivity experiments, however, we will increase all the vertical shears in the model by 10%.

The effectiveness of this technique is tested by comparing statistics of tropical cyclone tracks generated using these winds to the equivalent statistics from historical tropical cyclone tracks. In particular, we compare the frequency distributions of 6-h zonal and meridional displacements. This comparison, shown in Emanuel et al. (2006), is quite good and gives us confidence in this technique.

After the tracks are generated, the Coupled Hurricane Intensity Prediction System (CHIPS) model (Emanuel et al. 2004) is run along each track, as described in Emanuel et al. (2006). This is an axisymmetric atmospheric model, phrased in potential radius coordinates (Schubert and Hack 1983), coupled to a simple, one-dimensional ocean model that captures most of the effects of upper-ocean mixing. Because the atmospheric model is axisymmetric, it excludes any direct effect of background vertical wind shear, and so this is parameterized in a way that empirically gives

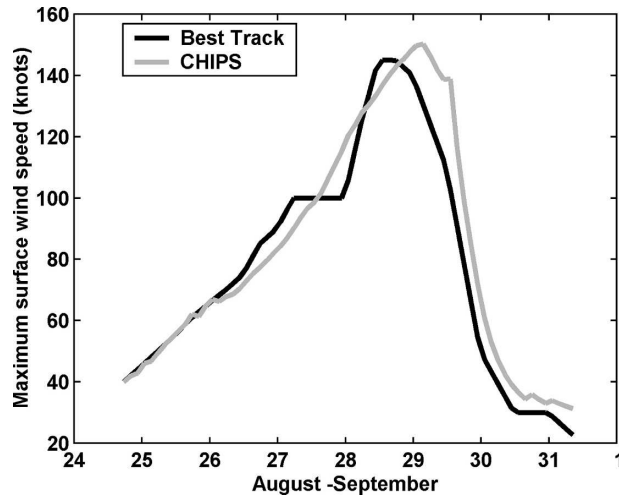


FIG. 1. Hindcast of the maximum wind speed (kt) in Hurricane Katrina (2005) using the CHIPS model (gray curve) compared to the observations (black). The initialization period, during which the model is aligned with the observations, lasts for the first 1.5 days.

good forecasts of the evolution of storm intensity (Emanuel et al. 2004). The potential radius coordinates allow fine resolution of the eye and eyewall using a relatively small number of radial nodes. When used for real-time intensity forecasts, the CHIPS model performs comparably to other deterministic and statistical intensity forecast methods (Emanuel et al. 2004). An example of the performance of this model is shown in Fig. 1, a hindcast of Hurricane Katrina of 2005. (The advantage of a hindcast is that it uses the observed rather than the forecast storm track and vertical wind shear.) For the present purpose, input to CHIPS is in the form of monthly mean climatological potential intensity (which combines the thermodynamic control on hurricane intensity of both the sea surface temperature and the environmental atmospheric temperature profile), ocean mixed layer depth, and thermal stratification of the ocean below the mixed layer, all interpolated to the position and time of the storm. The effect of using monthly mean climatological potential intensity instead of daily data was examined by Emanuel et al. (2004) and found to be minimal in most cases. Landfall and other effects are calculated using a high-resolution bathymetry database. Vertical wind shear is provided by the same synthetic time series used to generate the storm track.

For this study, we generated 3000 synthetic tracks in the North Atlantic region and performed four experiments, all using this set of tracks. In the first, or control experiment, we used normal values of potential intensity, shear, and upper-ocean properties as described

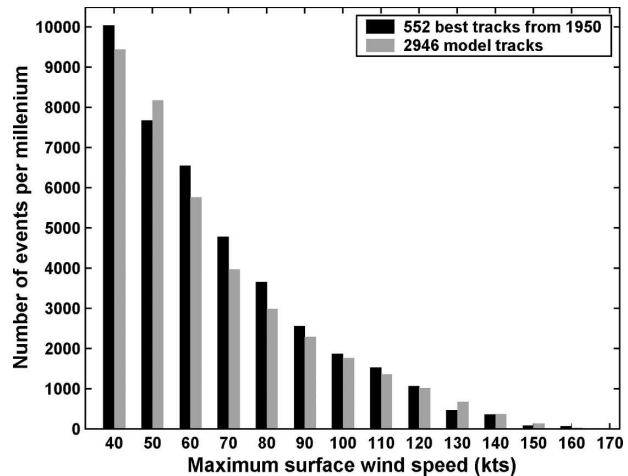


FIG. 2. Cumulative frequency distribution, expressed as the number of events per millennium whose peak wind speed (kt) exceeds the value on the abscissa, for tropical cyclones in the North Atlantic. The black bars are taken from Atlantic historical tropical cyclone data, encompassing all 552 events from 1950 to 2004, while the gray bars are calculated by running the CHIPS model on 3000 synthetic storm tracks. (Fifty-four storms failed to achieve a peak wind speed of 40 kt.)

above. The second experiment is identical to the first, but the potential intensity is increased everywhere by 10% of its normal value. The third is also identical to the first, but in this case the vertical wind shear, input to the intensity model, is increased everywhere by 10%. In the fourth and final experiment, the ocean mixed layer depth is increased everywhere by 10%. Results are described in the following section.

### 3. Results

#### a. Control experiment

Figure 2 presents a cumulative histogram of Atlantic peak storm intensity<sup>1</sup> from the control experiment, in which all inputs assume their normal values, and compares this to the record of Atlantic tropical cyclones since 1970, when satellite coverage became good enough to ensure that all storms were at least partially observed. [This is identical to Fig. 3 of Emanuel et al. (2006), except that a different random sample of tracks was used, and here we used 3000 tracks instead of the 1000 used in the former study. The total number of events used to construct Fig. 2 is less than 3000, because a few storms fail to reach the minimum intensity of 40

<sup>1</sup> As in Emanuel et al. (2006), we add 60% of the storm's translation speed to the peak circular wind to estimate the ground-relative peak wind speed.

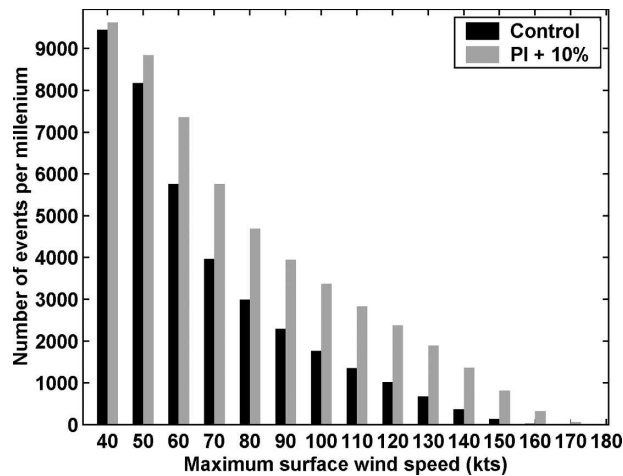


FIG. 3. Cumulative frequency distribution of storm peak wind speed, as in Fig. 2, but comparing the control experiment with an experiment in which the CHIPS model was run using the same 3000 tracks but with the potential intensity increased everywhere by 10%. All other input variables, such as shear and ocean properties, were the same as in the control.

kt.] The good agreement between observed and simulated cyclone statistics suggests that our approach is viable. The “power dissipation index” (“PDI”) was defined by Emanuel (2005) as

$$\text{PDI} \equiv \int_0^{\tau} V_{\max}^3 dt,$$

where  $V_{\max}$  is the maximum wind speed over the diameter of the storm at any given time,  $t$  is time, and  $\tau$  represents the storm’s lifetime. Here we average the power dissipation over all 3000 storms in the synthetic sample, and all 552 storms in the best-track data. The average value of PDI for the synthetic storms is  $2.38 \times 10^{10} \text{ m}^3 \text{ s}^{-2}$ , while for the actual storms it is  $2.40 \times 10^{10} \text{ m}^3 \text{ s}^{-2}$ .

#### b. Effect of increased potential intensity

In this experiment, the CHIPS model was run over the same tracks with the same evolution of vertical wind shear, but the potential intensity was increased everywhere by 10%. The resulting cumulative distribution of storm peak intensity is compared to the control in Fig. 3. There is a large increase in the frequency of high intensity events, and the sample PDI is  $3.92 \times 10^{10} \text{ m}^3 \text{ s}^{-2}$ , a 65% increase over the control. Figure 4 shows the number of events multiplied by the storm peak wind speed cubed, binned in 10-kt intervals of storm peak wind speed; this shows approximately how PDI is distributed with respect to storm lifetime maximum wind speed. Higher potential intensity clearly

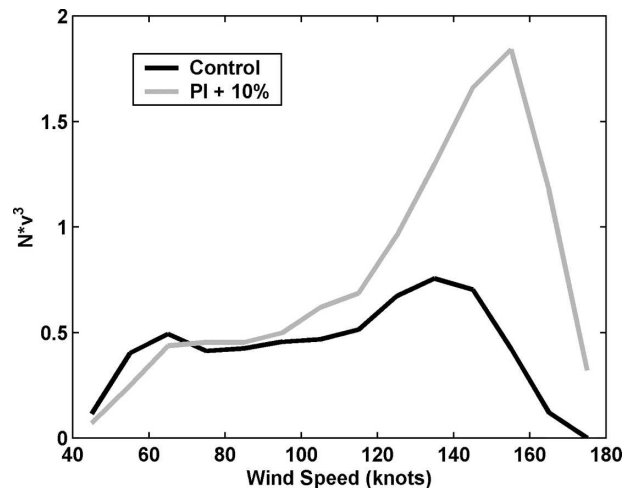


FIG. 4. The number of events in 10-kt bins, multiplied by the bin-mean storm lifetime peak wind speed cubed, as a function of the bin-mean storm lifetime peak wind speed, from 45 to 175 kt. The black curve is from the control experiment while the gray curve is from the experiment with potential intensity increased everywhere by 10%.

shifts the distribution toward more intense events. This increase is commensurate with the observed increases in PDI in several ocean basins over the past 50 yr (Emanuel 2005). Looking more closely at the storm statistics shows that wind speed averaged over the storm’s lifetime increases 15%, while the average cube of the wind speed increases by 60%, showing that the increase in wind speed is not uniform with intensity (which would have yielded a 50% increase in the average cube of the wind speed) but is skewed toward high-intensity events. Total storm lifetime increases only 3%, but average duration at hurricane intensity, for those storms that attain hurricane intensity, increases by 15%. The percentage of all hurricanes whose storm lifetime maximum wind speed classifies them as category 1 on the Saffir–Simpson scale (Simpson 1974) decreases from 43% to 34%, while the percentage that are category 4 and 5 increases from 25% to 40%. These changes are similar to those reported globally over the past 35 yr by Webster et al. (2005).

The cumulative frequency distribution of observed storm intensities normalized by potential intensity appears to be a universal, bilinear function (Emanuel 2000). This would predict that, all other things being equal, a 10% increase in potential intensity should yield a 10% increase in average wind speed, in contrast to the 15% increase obtained here. On the other hand, in doing this experiment we may not have held fixed the relevant *nondimensional* control parameters. For example, a nondimensional shear could be defined as the actual shear divided by the potential intensity. Increas-

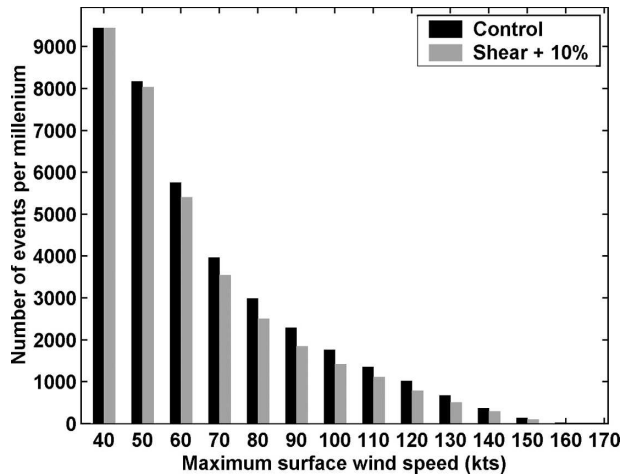


FIG. 5. Same as in Fig. 3, but with the vertical wind shear increased everywhere by 10%.

ing the latter by 10% would decrease the nondimensional shear, so defined, by about 10%. In the shear experiment described in the next subsection, such a decrease yields a 3.4% increase in average wind; this would explain much of the additional 5% increase in average wind speed observed when the potential intensity is increased by 10%. Similarly, although the actual upper-ocean thermal structure was not changed in this experiment, some nondimensional parameters relating to upper-ocean properties may have changed with potential intensity.

### c. Effect of increased wind shear

Vertical shear of the horizontal wind is observed to diminish hurricane intensity (DeMaria and Kaplan 1994). Although CHIPS cannot directly simulate the effect of shear, as it is an axisymmetric model, it does contain a parameterization of shear effects that has been developed and tuned to optimize the performance of the forecast version of the model. Use of this parameterization is critical to obtain reasonable forecasts of hurricane intensity.

In this experiment, the shear was simply increased everywhere by 10%, with other input variables assuming their normal values. The effect on the cumulative distribution of storm peak wind speeds is illustrated in Fig. 5. Increased shear clearly diminishes peak winds, and the PDI is correspondingly reduced from its control run value of  $2.38 \times 10^{10} \text{ m}^3 \text{ s}^{-2}$  to  $2.10 \times 10^{10} \text{ m}^3 \text{ s}^{-2}$ , a reduction of 12%. This corresponds to a decrease of 3% in the average storm wind speed and a decrease of 11% in the average cube of the wind speed. (The average storm lifetime decreases by less than 1%, and the average duration at hurricane intensity, for

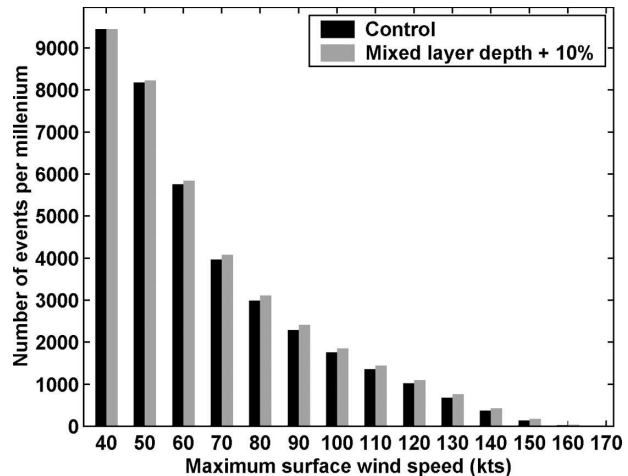


FIG. 6. Same as in Fig. 3, but with the ocean mixed layer depth increased everywhere by 10%.

those storms that attain hurricane intensity, decreases by 7%.)

The effect of increasing shear by 10% is substantially weaker than the effect of increasing potential intensity by the same percentage. On the other hand, the standard deviation of vertical wind shear is a large fraction of its mean value in the Tropics, and it is possible that climate change would lead to a larger fractional change in shear than in potential intensity.

### d. Effect of increased ocean mixed layer depth

Mixing of the upper ocean can have a large effect on individual storms (Bender and Ginis 2000). It is therefore of some interest to explore the sensitivity of a large sample of storms to changes in the thermal structure of the upper ocean. In this set of experiments, we increase the monthly mean ocean mixed layer depth (which is variable in space and from month to month) by 10% everywhere. The result is compared to the control run in Fig. 6. There is a small but systematic increase in storm intensity, with the per-storm PDI rising to  $2.47 \times 10^{10} \text{ m}^3 \text{ s}^{-2}$  from  $2.38 \times 10^{10} \text{ m}^3 \text{ s}^{-2}$  in the control experiment, a rise of 4%. While it is not known how upper-ocean thermal structure might evolve with climate change, there is some evidence of trends in upper-ocean temperature over the past few decades (Levitus et al. 2000).

## 4. Summary

A coupled atmosphere–ocean hurricane intensity model was run along approximately 3000 synthetically generated Atlantic tropical cyclone tracks, yielding a statistically large record of storm intensities. For the

control experiment, using monthly mean potential intensity and upper-ocean thermal structure, and variable wind shear conforming to reanalysis climatology, the cumulative frequency distribution of storm intensity is in good agreement with the distribution determined from historical tropical cyclone data. When the same model is run over the same tracks but with the potential intensity increased everywhere by 10%, there is a large increase in the incidence of high-intensity events, and the power dissipation index (PDI) increases by 65%. Increasing the shear or the ocean mixed layer depth by 10% results in much smaller changes in the PDI, of  $-12\%$  and  $+4\%$ , respectively. These results may serve as a guide to more comprehensive investigations of the effect of climate change on tropical cyclone activity.

An obvious next step is to create new sets of synthetic tracks taking the necessary global wind field statistics from the output of global climate models rather than from reanalysis data, as was done here. Likewise, the potential intensity and upper-ocean thermal structure can be taken from coupled model output and used with the new tracks to generate tropical cyclone wind frequency distributions. This work is underway. A sticking point in this approach is the estimation of the space-time genesis probability distribution, as there is still little by way of theory or observation to guide us on this problem.

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