

# Characteristics of tropical cyclones in high-resolution models in the present climate

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27 **Abstract.** The global characteristics of tropical cyclones (TCs) simulated  
28 by several climate models are analyzed and compared with observations. The  
29 global climate models were forced by the same sea surface temperature (SST)  
30 fields in two types of experiments, using climatological SST and interannu-  
31 ally varying SST. TC tracks and intensities are derived from each model's  
32 output fields by the group who ran that model, using their own preferred track-  
33 ing scheme; the study considers the combination of model and tracking scheme  
34 as a single modeling system, and compares the properties derived from the  
35 different systems. Overall, the observed geographic distribution of global TC  
36 frequency was reasonably well reproduced. As expected, with the exception  
37 of one model, intensities of the simulated TC were lower than in observations,  
38 to a degree that varies considerably across models.

## 1. Introduction

39 The impact of tropical cyclones (TCs) on society makes it important to understand how  
40 their characteristics might change in the future. Global climate models, also known as  
41 General Circulation Models (GCMs), are important tools for studying this problem. In a  
42 GCM, one has the ability to simulate the climate organically; if the model has sufficient  
43 resolution and physics to provide a plausible simulation of TCs as well, then one can use  
44 the model to examine how climate controls the statistical properties of TCs. One can  
45 explore, in particular, the behavior of TCs under different climate scenarios.

46 Many studies (e.g., *Manabe et al.* 1970; *Bengtsson et al.* 1982; *Vitart et al.* 1997; *Ca-*  
47 *margo et al.* 2005) have shown that GCMs, even at relatively low resolution, are capable of  
48 generating storms that have similar characteristics as observed TCs. More recently, stud-  
49 ies that have used higher resolution atmospheric GCMs forced with prescribed sea surface  
50 temperatures (SSTs) (e.g., *Bengtsson et al.* 2007a; *LaRow et al.* 2008; *Zhao et al.* 2009)  
51 have demonstrated these high-resolution models' remarkable ability to simulate realistic  
52 distributions of TCs.

53 In order to use GCMs for projections of possible future changes in TC activity, it is  
54 necessary to assess their ability to reproduce the characteristics of observed TCs in the  
55 present climate. These characteristics include the climatological spatial, temporal, and  
56 intensity distributions as well as the interannual variability of TCs. This work is an inter-  
57 comparison of the ability of 9 high-resolution GCMs to simulate TCs. The models have  
58 resolutions that vary from 28 to 130 km, with different parameterizations and dynamics.

59 Two of the models have done simulations at multiple resolutions, while a single resolution  
60 is available for our analysis of the other models.

61 The simulations analyzed were performed for the U.S. CLIVAR Hurricane Working  
62 Group. The objective of this working group was to have a better understanding of the  
63 differences among high-resolution models in simulating TC activity, in the present climate  
64 as well as in warmer climate scenarios. In order to do that, a set of common experiments  
65 with the same forcings and prescribed SST was performed by all modeling groups. Here  
66 we analyze the characteristics of TC activity in the simulations produced by the working  
67 group over SST distributions derived from observations taken in the late 20th century  
68 (1981-2005 for the climatology simulations and 1981-2009 for the interannual simulations).

69 Observed TC tracks and intensities are derived from atmospheric measurements — in  
70 situ and remote — by human forecasters. With climate models, it is necessary to apply  
71 objective tracking schemes to the model output fields to obtain the tracks and intensities.  
72 The criteria applied to the models can be different from those applied to observations; a  
73 model storm is not necessarily required to meet the same thresholds for intensity as an  
74 observed one would be in order to be classified as a TC. It has been found that when  
75 allowance is made for the fact that model TCs are weaker and larger than those observed,  
76 the resulting spatio-temporal distributions of TC tracks resemble those observed enough  
77 to be useful — for example, in seasonal forecasting — even in quite low-resolution models  
78 [*Camargo and Barnston, 2009; Camargo et al., 2010*].

79 In the present study, we examine the TCs derived from each model’s output by the group  
80 who ran that particular model, using their own preferred tracking scheme. We consider  
81 the combination of model and tracking scheme to be a “modeling system” and compare

82 the outputs from each system. In the interests of brevity, we will refer to these modeling  
83 systems below simply as “models”, taking the tracking scheme as implicit, though our  
84 expectations about the sensitivities of the results to tracking schemes are discussed in  
85 several points.

86 This approach implicitly makes allowances for the different resolutions and physics of  
87 each model, resulting in different TC intensities. It is consistent with the way each model  
88 has been used in previous single-model studies. Using each group’s own tracks also allows  
89 each model to be seen as each group intended, to the extent that tracking schemes have  
90 tunable parameters whose adjustment can allow some gross aspects of the statistics to  
91 be brought closer to those observed. An alternative approach that could be considered is  
92 to use a bias correction procedure to obtain values closer to observations as was done in  
93 *Murakami et al.* [2012] for TC frequency and in *Zhao and Held* [2010] for TC intensity.  
94 We will leave the bias correction analysis of TC activity for future work.

95 It is also of interest to compare the different models using the same tracking scheme,  
96 so that the differences in results are purely attributable to the differences in the models  
97 themselves. This has been done by *Horn et al.* [2014], who also used multiple tracking  
98 schemes to study the sensitivity of the analysis to the tracking scheme used. We focus our  
99 analysis on the following TC characteristics: TC frequency, intensity and lifetime. Other  
100 TC characteristics could potentially be explored in these models, such as TC size, which  
101 only recently has been receiving more attention in observations [*Dean et al.*, 2009; *Chavas*  
102 *and Emanuel*, 2010; *Knaff et al.*, 2014] and idealized models [*Chavas and Emanuel*, 2014].  
103 Analysis of the rainfall associated with TCs in a subset of the models considered here was  
104 presented in *Villarini et al.* [2014] and *Scoccimarro et al.* [2014].

105 This paper is organized as follows. The data, models, and experiments are discussed in  
106 section 2. Results from the climatological and historical forced simulations are described  
107 in section 3. Finally, conclusions are given in section 3.2.

## 2. Models and Data

108 The data used for this study consists of TC tracks from nine GCMs. The models were  
109 forced with two different SST boundary conditions, monthly climatologically averaged  
110 (seasonally varying) SSTs and monthly interannually varying SSTs. The SSTs were ob-  
111 tained from the Hadley Centre Sea Ice and Sea Surface Temperature (HadISST) data set  
112 [*Rayner et al.*, 2003] and the climatological SST was obtained by averaging the monthly  
113 data over the period 1981-2005, which was previously used in *Held and Zhao* [2011]. The  
114 number of years in the climatological simulations performed by each group varied from 5  
115 years to 20 years, as shown in Table 2.

116 Each group used the output of their simulations to detect and track the model TCs,  
117 using their own tracking algorithm. Tracks for these TCs were generated and their char-  
118 acteristics were analyzed here. The sensitivity of the models to the different tracking  
119 schemes is currently being analyzed by members of the working group.

120 Outputs from nine GCMs were analyzed in this study, as summarized in Table 1, namely:  
121 Community Atmosphere Model version 5.1, or CAM5.1 [*Wehner et al.*, 2014]; European  
122 Centre for Medium-Range Weather Forecasting - Hamburg, or ECHAM5 [*Roeckner et al.*,  
123 2003; *Scoccimarro et al.*, 2011]; Florida State University, or FSU [*LaRow et al.*, 2008];  
124 NASA Goddard Earth Observing System Model version 5, or GEOS-5 [*Rienecker et al.*,  
125 2008]; National Centers for Environmental Prediction Global Forecasting System, or GFS  
126 [*Saha et al.*, 2014]; NASA Goddard Institute for Space Studies, or GISS [*Schmidt et al.*,

127 2014]; Met Office Hadley Centre Model version 3 - Global Atmosphere 3.0 (GA3) con-  
128 figuration, or HadGEM3 [*Walters et al.*, 2011]; Geophysical Fluid Dynamics Laboratory  
129 High Resolution Atmosphere Model, or HiRAM [*Zhao et al.*, 2009]; and Meteorologi-  
130 cal Research Institute, or MRI [*Mizuta et al.*, 2012; *Murakami et al.*, 2012]. The model  
131 resolutions vary from 28 to 130 km.

132 The models have different tracking schemes, most of them with very similar character-  
133 istics, based on the original tracking schemes in *Bengtsson et al.* [1982] and *Vitart et al.*  
134 [2007]. These tracking schemes look for vortices with a minimum of sea level pressure, a  
135 maximum of low-level vorticity and a warm core [*Camargo and Zebiak*, 2002; *Walsh*, 1997;  
136 *Vitart et al.*, 2003; *Zhao et al.*, 2009; *Murakami et al.*, 2012]. The main difference among  
137 the schemes is how they define the warm core and the thresholds used to define the model  
138 TC. An exception is the HadGEM3, which uses a tracking scheme originally developed  
139 for extra-tropical (cold core) cyclones [*Hodges*, 1995] and modified to track warm core  
140 vortices [*Bengtsson et al.*, 2007a; *Strachan et al.*, 2013]. More detailed descriptions of the  
141 tracking schemes are given in the Appendix.

142 We compare the model TC characteristics with the observed TC data. For the North  
143 Atlantic and eastern and central North Pacific the best-track datasets from the National  
144 Hurricane Center are used [*Landsea and Franklin*, 2013; *NHC*, 2013]. In the case of the  
145 western North Pacific, North Indian Ocean and southern hemisphere, the TC data is from  
146 the best-track datasets from the Joint Typhoon Warning Center [*Chu et al.*, 2002; *JTWC*,  
147 2014].

### 3. Results



### 3.1. Climatology

148 We first examine the climatological simulations, in which all models are forced with the  
149 same monthly, climatological, seasonally varying SST fields. As there is no interannual  
150 variability in these SST fields, we can use them to assess the level of internal, unforced  
151 variability in the models' TC activity. We will also compare the mean TC activity in each  
152 model with the observations, globally and in different basins.

#### 3.1.1. TC Frequency

154 There are on average approximately 80 TCs observed every year across the globe  
155 [*Emanuel, 2003*]. Figure 1 shows the distribution of the number of TCs per year for  
156 all models along with the observations. There are large differences in the number of TCs  
157 between the different models. Different models run at approximately the same resolution  
158 do not have similar mean numbers of TCs (e.g., the LR CAM5.1, FSU, GFS, and GISS  
159 models all have resolutions of roughly 100 km, but the mean number of TCs per year  
160 varies from about 10 to over 100.)

161 At the same time, the absolute number of TCs in each model is somewhat dependent  
162 on the tracking scheme applied; higher thresholds result in fewer TCs. This is particularly  
163 evident in the CAM5.1 models, where the same thresholds were used for both the low  
164 resolution and high resolution simulations, resulting in a very low number of TCs in the  
165 LR CAM5.1 model. Application of strictly uniform tracking schemes, with no allowance  
166 for the different intensities in different models (whether due to resolution or other factors)  
167 would almost certainly produce even larger differences in the total numbers of TCs from  
168 model to model. By using each group's own tracking scheme, we allow some compensation  
169 for the different TC intensities, in order to allow more productive comparison between

170 other aspects of the results, such as the spatial and seasonal distributions of TC genesis  
171 and tracks, in the way that they would be shown in single-model studies by the individual  
172 groups.

173 The three resolutions of the HadGEM3 model show an increase in the number of TCs  
174 with increasing resolution, though it does not increase linearly. The tracking algorithm  
175 for all resolutions of the HadGEM3 model use the same threshold for the 850-hPa relative  
176 vorticity after being filtered to a standard spectral resolution of T42 as described in  
177 *Strachan et al.* [2013]. Thus, the increase in the number of TCs with increasing resolution  
178 is not an artifact of the tracking scheme.

179 Figure 2 shows the mean number of TCs formed per year in each ocean basin. The  
180 total number of TCs formed in each basin per year is shown at the top of the figure and  
181 the percentage of all TCs that formed in each basin is shown at the bottom. Due to the  
182 large differences in the total numbers of global TCs reported by each model, it is more  
183 illustrative to compare the percentages of the TCs that form in each basin, rather than  
184 the total number of TCs, to the observations.

185 There are clear differences among the models in the distribution of TCs across basins,  
186 particularly in the North Atlantic and Pacific. Several of the models (ECHAM5, GISS,  
187 and all resolutions of the HadGEM) have percentages much lower than that observed in  
188 the North Atlantic. Three of the models (ECHAM5, FSU, and GISS) have a significantly  
189 lower percentage than that observed in the Eastern North Pacific, while the CAM5.1 (at  
190 both resolutions) and GFS have a much higher percentage than observed in the Eastern  
191 North Pacific. In the Western North Pacific, the CAM5.1 models have smaller percentages  
192 than observed, and the ECHAM5 and GISS models have larger percentages than observed.

193 This is consistent with previous studies that have found that low-resolution models tend to  
194 have a large percentage of TCs in the Western North Pacific and very few TCs in the North  
195 Atlantic [*Camargo et al.*, 2005; *Camargo*, 2013]. Also of note is that the discrepancies in  
196 the partitioning between the Western and Eastern North Pacific in the CAM5.1 models  
197 are partially linked to a bias toward too many TCs in the Central North Pacific.

198 One interesting observation is that there are larger differences in TC distributions be-  
199 tween one model and another, than between versions of the same model at different  
200 horizontal resolutions. The TC distributions obtained by the versions of the CAM5.1  
201 with different resolutions are very similar, and the same is true of the HadGEM3 models.  
202 This suggests that the global and regional distributions of TCs is mainly determined by  
203 the characteristics of the models (e.g., parameterizations, convection scheme), with model  
204 resolution not being as important. While the tracking schemes are also different, our  
205 expectation is that the usage of different tracking schemes reduces the apparent differ-  
206 ences between models, particularly in overall TC frequency. As will be seen below, the  
207 intensities of the simulated TCs are quite different in different models, and the different  
208 thresholds in the tracking schemes adjust for this to a large degree. If the same tracking  
209 scheme (including the specific thresholds) used to detect TCs in HiRAM were applied to  
210 the GISS model, for example, very few TCs would be detected.

211 In order to study the geographic patterns of TC occurrence, we will use track density,  
212 defined as the number of TCs that pass through a  $5^\circ \times 5^\circ$  box per year. Figure shows  
213 the track density for all models and observations. The observed track density shows a  
214 region of very high density off the western coast of Central America and the eastern coast

215 of Asia, along with regions of high density in the North Atlantic, South Indian, and off  
216 the eastern coasts of Australia and India.

217 Consistent with the basin averages, the models have different patterns of track density.  
218 The GISS model has a similar pattern to the observations, with some key differences. The  
219 most striking difference is the lack of a region of high track density off the western coast  
220 of Central America, which is notoriously difficult to simulate with lower resolution GCMs  
221 [*Camargo et al.*, 2005]. Other differences include a higher density around India, the region  
222 of high density off the eastern coast of Asia extending further to the east, and a lower  
223 density in the North Atlantic. The HiRAM model has a remarkably similar pattern to the  
224 observations globally. The FSU model has higher density in the North Atlantic and South  
225 Indian along with lower density off the eastern coast of Central America. The ECHAM5  
226 model has very low density in the North Atlantic and South Indian, but similar density  
227 patterns to the observations in the Western Pacific and South Pacific. The ECHAM5  
228 model also has a localized region of very high density directly on the eastern coast of  
229 India. The high resolution CAM5.1 model has a region of very high density off the western  
230 coast of Central America that extends too far westward and has much lower density off  
231 the eastern coast of Asia than the observations. The low resolution HadGEM3 model has  
232 small regions of high density in the correct locations. The higher resolution HadGEM3  
233 models have higher density in these regions, which expand covering larger areas. The  
234 global mean densities in the low resolution CAM5.1 and GFS models are much lower  
235 than observed. Also shown is the multi-model mean (MMM) track density (using only  
236 the high-resolution version of the CAM5.1 and HadGEM3 models). The MMM pattern's

237 similarity to the pattern in observations is greater than those in many of the individual  
238 models, but the magnitudes of the maxima are not as high as in observations.

239 These results are consistent with the findings of *Strazzo et al.* [2013] which examined  
240 track densities of the FSU and HiRAM simulations. *Strazzo et al.* [2013] showed that the  
241 HiRAM density distribution is very similar to the observed distribution, while FSU model  
242 has a higher density in the North Atlantic than is found in observations.

243 In addition to track density, it is useful to study where the simulated TCs form, or  
244 genesis density. Figure 4 shows the genesis density of all the models and observations.  
245 Genesis density is defined as the number of TCs that form in a  $5^\circ \times 5^\circ$  box per year.  
246 The overall differences in the patterns of the genesis density between the models and  
247 observations are similar to the differences in the track density described above. Consistent  
248 with the observations, all the models have narrower meridional bands of high genesis  
249 density as compared to track density. This occurs because the TCs tend to form in  
250 low-latitudes and travel poleward, causing the track density to have a greater meridional  
251 spread than the genesis density. Similarly to the case of track density, the genesis density  
252 MMM pattern is closer to the observations than many of the individual models.

253 It can be easier to distinguish patterns in the distributions by examining certain spatial  
254 or temporal dimensions. Fig.5(a) shows the genesis as a function of latitude of each model  
255 and the observations. For the CAM5.1 and HadGEM3 models, only the highest resolution  
256 simulations are shown. The observations have a large peak at  $10^\circ$  north, a smaller peak at  
257  $10^\circ$  south, and no TC formation directly at the equator. All of the models have peaks at  
258 roughly the same latitudes as the observations, with the FSU and GEOS-5 model having  
259 a peaks closer to the equator, especially in the southern hemisphere, and the ECHAM5

260 model, having peaks poleward than the observations. In addition, the FSU model has a  
261 high number of storms forming very near the Equator in the southern hemisphere. The  
262 ECHAM5 model's southern hemisphere peak has a fatter tail and has non-zero genesis  
263 extending to higher latitudes than the observations and all other models. Although the  
264 GFS model has fewer TCs than in observations, the maxima in genesis location occur at  
265 roughly the same latitudes and with similar relative magnitude as the observations.

266 Fig.5(c) shows the genesis as a function of longitude for the models and observations.  
267 The observations have two sharp peaks at roughly 90E and 110W (corresponding to the  
268 maxima in the South Indian and western coast of Central America in Fig. 4), a broader  
269 peak at roughly 150E (corresponding to the maxima off the eastern coast of Asia in Fig.  
270 4), and near-zero genesis near and east of the dateline. Three of the models (GISS, FSU,  
271 and ECHAM5) have much lower Central American 110W peak than the observations,  
272 with the GISS model producing virtually no TCs. The FSU model has peaks at 55° (off  
273 the eastern coast of Africa) and 50W (North Atlantic) that are not present in any other  
274 model or the observations. The ECHAM5 model has a very strong peak at 85E (off the  
275 eastern coast of India). The HiRAM model exhibits a pattern remarkably similar to the  
276 observations.

277 Another metric of interest is the seasonal cycle of TC formation. Fig. 5(b) shows global  
278 genesis as a function of month for models and observations. The observations show a  
279 fairly smooth seasonal cycle with a clear maximum between August and September and a  
280 minimum around April. In general, the models have a significantly weaker seasonal cycle  
281 than the observations, i.e. the difference between the number of TCs in the second half of  
282 the year and the first half of the year is less than the same difference in the observations.

283 The TC seasonal cycles in different basins are shown in Fig. 6<sup>1</sup>. The basins in the  
284 northern hemisphere typically have a broad peak in the second half of the year and few  
285 TCs in the first half of the year, with exception of the North Indian Ocean. In the Western  
286 North Pacific, the GISS, HiRAM, FSU, HR HadGEM3, and ECHAM5 models are able  
287 to roughly reproduce the peak in the second half of the year, while the other models have  
288 no peak. In the Eastern North Pacific, the HiRAM3, HR HadGEM3, HR CAM5.1, and  
289 GFS models are able to reproduce the August peak while the other models have very low  
290 density throughout the year in this basin. However, HR CAM5.1 has a second peak in  
291 October and November that does not occur in the observations. In the North Atlantic,  
292 the HiRAM3, FSU, HR CAM5.1, and GFS models reproduce the second half of the year  
293 peak. Also of note is that the FSU model has a peak in the Western North Pacific that is  
294 roughly three months later than in observations, while it has a peak in the North Atlantic  
295 roughly one month earlier than observed. Most models are able to capture the bimodal  
296 distribution in the North Indian Ocean, with exception of the ECHAM5. All models are  
297 able to reproduce the observed peak in the early part of the year in the South Pacific and  
298 Australian basins. In contrast, in the South Indian basin, the CAM5.1 and FSU models  
299 have the wrong seasonality with a peak in the second half of the year.

### 300 **3.1.2. TC Intensity**

301 Along with the frequency of TCs, it is important to examine TC intensity. Although the  
302 global climate models here are considered “high-resolution”, it is not expected that they  
303 would be able to reproduce the most intense TCs (category 4 and 5 hurricanes), which  
304 would require even higher resolution to be able to simulate those intensities (see e.g.,

305 *Bender et al.* [2010]). A significant fraction of the models has TCs that reach category 4,  
306 but only one model has TCs that reach category 5.

307 The accumulated cyclone energy (ACE) of a TC is the sum of the squares of the TC's  
308 maximum wind speed, summed over all 6-hour intervals in which the maximum wind  
309 speed is at least tropical storm strength (35 kt). Adding the ACE of individual TCs can  
310 produce a total ACE for a spatial or temporal region, e.g., a basin ACE or a seasonal  
311 ACE. Thus, a larger value of total ACE could correspond to stronger TCs, more TCs,  
312 and/or TCs that last longer. Figure 7 shows the total ACE (averaged per year) for each  
313 basin. The top panel shows the total ACE of each basin and the bottom panel shows  
314 the percentage of the global ACE that occur in each basin. The observations have large  
315 values of ACE in the Western North Pacific (40%) , followed by the eastern North Pacific,  
316 North Atlantic and South Indian Ocean (15%), with the Australian and South Pacific  
317 contributing with about 5% of the global ACE and a very low value of ACE in the North  
318 Indian Ocean. All models are able to reproduce the large ACE percentage in the Western  
319 North Pacific, with the ECHAM5 and FSU models having a very low ACE percentage in  
320 the Eastern North Pacific. The ECHAM5 and GISS models have a relatively large ACE  
321 percentage in the South Pacific, while the HadGEM3 models (all resolutions) have an  
322 anomalously high ACE percentage in the South Indian Ocean.

323 The top panel of Fig. 8 shows the distribution of the maximum wind speed achieved  
324 by each TC in all models and the observations. The vertical lines represent boundaries of  
325 the Saffir-Simpson hurricane intensity scale [*Saffir, 1977*]. The models seem to separate  
326 into four regimes of intensities. The HR CAM5.1 has an intensity distribution similar to  
327 observations, with a significant number of category 2 hurricanes and even the ability to



328 produce the most intense TCs, i.e. categories 4 and 5 storms. The HiRAM, FSU, and  
329 HR HadGEM3 models have many tropical storms and category 1 TCs and some category  
330 2 TCs. The ECHAM5, GEOS-5, and GFS models have mostly tropical storms. The  
331 GISS model's TCs are almost all of tropical depression intensity, with only a very small  
332 number of weak tropical storms. The difference between the intensity distributions among  
333 the models cannot simply be a result of the models' different resolutions. For example,  
334 the GEOS-5 model has a horizontal resolution similar to the HiRAM model, but has  
335 significantly weaker TCs. On the other hand, the FSU model has some of the strongest  
336 TCs, but does not have one of the highest resolutions among the models.

337 In order to better understand the effect of model resolution on simulated TC intensities,  
338 it is instructive to examine the differences in the intensity distributions of the same models  
339 run with multiple horizontal resolutions. Histograms of the maximum wind speeds for  
340 the CAM5.1 and HadGEM3 models using various different resolutions are shown in the  
341 bottom panels of Fig. 8. As expected, both the CAM5.1 and HadGEM3 models show an  
342 increase in the mean TC intensity with higher resolution. The increase in intensity of the  
343 HR HadGEM3 and HR CAM5.1 models can be also seen as an elongation of the tails of  
344 the distributions into higher TC categories.

### 345 **3.1.3. TC Lifetime**

346 TC lifetime distributions in models and observations are shown in Fig. 9, with the TC  
347 lifetime histograms of the CAM5.1 and HadGEM3 models in different resolution given in  
348 the two bottom panels. There is a large variation in the TC lifetime among the models.  
349 The ECHAM5, GISS, and HR HadGEM3 models have TCs lasting longer than 40 days,  
350 while the GFS model has very few TCs lasting more than 10 days. This is most likely

351 due to the different tracking schemes used, as they consider different criteria for when to  
352 form and end a TC. Of particular note is that for the models with simulations in multiple  
353 resolutions, the TCs in the higher resolution simulations have a slightly longer average  
354 duration than in the low-resolution ones. This is probably also an artifact of the tracking  
355 scheme, as if the same intensity thresholds are used for high-resolution simulations, which  
356 generate more intense storms, this will lead to longer-living storms.

### 3.2. Interannual Variability

357 In the previous section, we analyzed the model simulations forced with climatological  
358 SSTs, which characterizes the typical TC properties in the models, but does not simulate  
359 the TC interannual variability. Well known modes of climate variability in the atmosphere  
360 and ocean, most notably the El Niño-Southern Oscillation (ENSO), have been shown to  
361 affect the frequency and characteristics of TCs [*Camargo et al.*, 2010; *Iizuka and Matsuura*,  
362 2008; *Bell et al.*, 2013]. In order to evaluate the ability of the models to accurately simulate  
363 the interannual variability of TCs, the models were also run while forced with historical  
364 monthly varying SST, as opposed to climatological mean SSTs. The number of ensemble  
365 members and years of the simulations are shown in Table 3.

366 Figure 10 shows the total number of TCs globally per year for the models and obser-  
367 vations (top panel), as well as for the Western North Pacific, Eastern North Pacific, and  
368 North Atlantic, separately<sup>2,3</sup>. The global number of TCs in the models is similar to the  
369 observed numbers in all the models, but the global interannual variability is not well cap-  
370 tured by the models. The three individual basins shown here present a greater similarity  
371 between the observations and model results, with the exception of the GISS model which

372 has very few TCs in the North Atlantic and Eastern North Pacific and the FSU model  
373 which has very few TCs in the Eastern North Pacific.

374 In order to quantify the ability of the models to reproduce the interannual variability  
375 of observed TCs in different basins, we calculate the correlation coefficients between the  
376 model-simulated and observed ACE per year in each basin for each model in Table 4.  
377 Since the GISS model's TCs have very weak intensities that seldom exceed the ACE  
378 threshold of 35 kt, we define another metric, the model-ACE (MACE), as the sum of  
379 the squares of the TC's maximum wind speed, sampled at 6-hourly intervals without  
380 any intensity threshold (as was done in *Camargo et al.* [2005] for low-resolution models).  
381 The correlations of the models' yearly MACE in each basin with the yearly ACE of the  
382 observations are also shown in Table 4. The correlations in the North Atlantic and Pacific  
383 basins are much higher than the other basins. In particular, the FSU and HiRAM models  
384 have a correlation coefficient of 0.7 in the North Atlantic and the GEOS-5 model has  
385 a correlation coefficient of 0.7 in the Western North Pacific basin. Similar result are  
386 obtained when calculating the correlation of the number of TCs per year globally and per  
387 basin (shown in Table 6), the highest and significant values of the correlations occur in  
388 the North Atlantic for all models and in other basins (eastern and western North Pacific)  
389 only for the HIRAM model.

390 Figure 11 shows the differences in genesis density between composites of El Niño and La  
391 Niña years. The seasons for the El Niño and La Niña composites are defined separately  
392 for the northern and southern Hemispheres in Table 5<sup>4</sup>. The observations have a larger  
393 and stronger peak in genesis density off of the western coast of Central America in El  
394 Niño months than La Niña months. As the GISS and FSU models have very few TCs in

395 this region, they are unable to reproduce this difference, while the HiRAM and GEOS-5  
396 models are able to reproduce the difference.

397 A well known impact of ENSO on TC development is for average formation location  
398 to shift to the south and east in the Western North Pacific and to shift to the south  
399 and west in the Eastern North Pacific during El Niño years [*Chia and Ropelewski, 2002*].  
400 Figure 12 shows the mean position of TC formation in the Western and Eastern North  
401 Pacific in La Niña and El Niño years. In the Western North Pacific, the models are able  
402 to reproduce the southeast shift in El Niño years, with exception of the FSU model which  
403 has an eastern shift, with no meridional change. In the Eastern North Pacific, all the  
404 models are able to simulate the southwest shift in El Niño years.

405 This work has described an intercomparison of several high-resolution atmospheric mod-  
406 els of the present climate, forced with both climatological and historical SSTs, in their  
407 ability to simulate the characteristics of TCs seen in observations. Model TCs were com-  
408 pared to observational TCs in terms of frequency as well as spatial, temporal, and intensity  
409 distributions. A range of tracking schemes were applied by each individual group to derive  
410 TC tracks and intensities for all models, consistent with the way in which results from  
411 these models have been shown previously in single-model studies.

412 Overall the models were able to reproduce the geographic distribution of TC track  
413 density in the observations, with the HiRAM model, in particular, demonstrating the  
414 most similarity to observations. TC formation off the western coast of Central America  
415 was the most difficult region to correctly simulate, with the HiRAM, HR CAM5.1, and  
416 HadGEM3 models demonstrating superior performance.

417 The models tend to have a weaker seasonal cycle in this region than is found in ob-  
418 servations, as some of the models are too active in the southern hemisphere basins (e.g.,  
419 FSU in the South Indian Ocean, ECHAM5 in the Australian and South Pacific, GEOS-5  
420 in the South Pacific) in the first half of the year. The models reproduce the observational  
421 seasonal cycle to varying degrees in each basin, with the HiRAM model showing arguably  
422 the best match to observations overall.

423 There is a wide range in TC intensities between the different models. Some, but not  
424 all, of this difference can be seen as a consequence of resolution, with higher resolution  
425 models being able to simulate stronger TCs. This effect can be most readily seen in the  
426 CAM5.1 and HadGEM3 models which were run at multiple resolutions.

427 Many previous studies have predicted a decrease in TC frequency and an increase in  
428 TC intensity in a warmer climate [*Knutson et al.*, 2010]. The prediction of a decrease  
429 in TC frequency is mainly from modeling studies, where GCM simulations of a warmer  
430 climate produce fewer TCs than the present climate, with a few notable exceptions (e.g.,  
431 *Emanuel* 2013). Although some of the current models still have biases in reproducing  
432 the mean global number of TCs, they are able to reproduce other characteristics of the  
433 TC activity. These biases could be potentially corrected using statistical methods as was  
434 done in *Zhao and Held* [2010] and *Murakami et al.* [2012]. On the other hand, some  
435 of the models (especially HiRAM) are able to simulate the TC climatology remarkably  
436 well. It is particularly encouraging that in the simulations forced with historical SSTs, the  
437 models were able to reproduce the interannual variability of TC frequency in the North  
438 Pacific and Atlantic basins, with the HiRAM and GEOS-5 models showing particularly

439 high correlation with observations in those basins. All models were also able to reproduce  
440 the general geographic shift in TC formation location during El Niño and La Niña years.

## Appendix A: Tracking Schemes

441 Here we give a description of the tracking schemes used by the various modeling groups.  
442 In general the tracking schemes look for features in which there is a minimum of sea level  
443 pressure, a maximum in vorticity and the existence of a warm core. The schemes vary  
444 in the definition of the thresholds for the different variables and in the definition of the  
445 warm core, but all tracking schemes have similar characteristics that can be traced back  
446 to the original papers of *Bengtsson et al.* [1982] and *Vitart* [1998].

447 The GFDL tracking scheme [*Vitart*, 1998; *Zhao et al.*, 2009] was used to track storms  
448 in the HiRAM, GFS, and CAM5.1 models. In the case of the CAM5.1 it was modified to  
449 run on a highly parallel systems [*Prabhat et al.*, 2012]. The original Vitart scheme was  
450 used in the FSU and GEOS-5 models, while for the ECHAM5 model, the Vitart scheme  
451 was modified by the Walsh wind speed resolution dependent thresholds [*Walsh*, 1997].  
452 The GFDL tracking scheme identifies TCs by locating grid points that have a relative  
453 vorticity maxima exceeding  $3.5 \times 10^{-5} s^{-1}$  within a 6 degrees latitude x longitude box;  
454 a local minimum of sea level pressure within 2 degrees of the vorticity maximum and a  
455 local maximum anomaly in temperature between 300 and 500hPa, at least 1°C warmer  
456 than the surrounding environment, withing 2 degrees of the sea level pressure maximum.  
457 The resulting points are combined into trajectories by associating the closest successive  
458 detections within 400km of each other. The tracks are required to last at least 3 days and  
459 have a maximum suraface wind speed greater than 12 m/s during at least 2 days (not  
460 necessarily consecutive).

461 The GISS model used the *Camargo and Zebiak* [2002] detection scheme. This scheme,  
462 derived originally for seasonal forecasting using low-resolution models, is similar to the  
463 others in most respects, but obtains model-dependent thresholds by analyzing the tails of  
464 the probability distribution functions of specific variables found in each model's output:  
465 850hPa vorticity, anomalous integrated temperature (850 to 300hPa), surface wind speed.  
466 The algorithm then finds grid points in which these variables are higher than the model-  
467 dependent thresholds and where there is a local minimum in sea level pressure, a positive  
468 local temperature anomaly (850 to 300hPa), a larger temperature anomaly in 850 hPa  
469 than in 300 hPa and higher wind speeds in 850hPa than in 300hPa. These points are then  
470 joined into tracks if they occur within 5 degrees of each other. Only tracks that last at  
471 least 1.5 days are considered. These tracks are then extended forwards and backwards in  
472 time by tracking a vorticity maximum which is above a relaxed vorticity threshold.

473 The MRI models tracking scheme is described in *Murakami et al.* [2012], six criteria are  
474 considered: (i) a maximum relative vorticity above  $8 \times 10^{-5} s^{-1}$ , (ii) maximum wind speed  
475 at 850hPa larger than 13m/s, (iii) sum of temperatures at 300, 500, and 700hPa higher  
476 than 0.8K, (iv) maximum wind speed at 850hPa is higher than at 300hPa, (v) in the North  
477 Indian Ocean only, the radius of the maximum mean wind speed must be less than 200  
478 km from the storm center, (vi) the storm last at least 36 hours. If the storm satisfies the  
479 criteria intermittently, multiple storms are considered, only one single time-step failure is  
480 allowed.

481 The HadGEM3 model tracking scheme is based on the Hodges method [*Hodges,*  
482 1995, 1996, 1999] developed originally to track extra-tropical cyclones. The application of  
483 the Hodges method to tropical cyclones is described in *Bengtsson et al.* [2007a] and *Strat-*

484 *chan et al.* [2013], where the warm core criteria was refined. The 850hPa relative vorticity  
485 is used on a spectral resolution of T42, making this method resolution independent. All  
486 vorticity centers with intensity greater than  $0.5 \times 10^{-5} s^{-1}$  at T42 are tracked, if they last  
487 at least 2 days then they are further analyzed. The 850hPa vorticity is then applied on  
488 a finer resolution (T63), and must reach at least a value of  $6 \times 10^{-5} s^{-1}$ , and is required  
489 to have a positive center at 850, 500 and 200hPa. There also must be a difference in the  
490 850hPa to 200hPa vorticities of at least  $6 \times 10^{-5} s^{-1}$  to provide evidence of a warm core,  
491 with a reduction in the T63 vorticity with height checked between consecutive pressure  
492 levels. These criteria must be valid for at least 1 day.

493 **Acknowledgments.** The authors would like to thank all members of the U.S. CLIVAR  
494 Hurricane Working Group for their contribution to this significant effort. We also would  
495 like to thank Naomi Henderson for making the model data available for the working  
496 group and managing the dataset. DAS, SJC and AHS acknowledge support of NSF  
497 AGS 1143959. SJC, AHS and DK acknowledge support for the GISS model runs and  
498 analysis from NASA grant NNX09AK34G. ES acknowledges support from the Italian  
499 Ministry of Education, University and Research and the Italian Ministry of Environment,  
500 Land and Sea under the GEMINA project. M.W. was supported by the Director, Office  
501 of Science, Office of Biological and Environmental Research of the U.S. Department of  
502 Energy under Contract No. DE-AC02-05CH11231 as part of their Regional and Global  
503 Climate Modeling Program. CAM5 simulations used resources of the National Energy  
504 Research Scientific Computing Center (NERSC), also supported by the Office of Science  
505 of the U.S. Department of Energy, under Contract No. DE-AC02-05CH11231. The model  
506 data used in this paper is part of the US CLIVAR Hurricane Working Group dataset.



507 Currently the data is only available for Working Group members, in a near future, the  
508 data will be made available for the scientific community.

## Notes

1. The HadGEM3 models only tracked TCs for specific seasons (May–November for the Northern Hemisphere and October–May for the Southern Hemisphere).
- 509 2. The FSU model interannual simulation was only performed between June and November of each year and the tracking scheme was only done in the North Atlantic and North Pacific basins.
3. The GEOS-5 model used different physical parametrizations (minimum entrainment threshold for parameterized deep convection in the modified Relaxed Arakawa-Schubert convection scheme, as well as a different time step) in the climatological and interannual simulations, which led a very different TC global frequency between those runs.
4. Using the warm and cold ENSO (El Niño Southern Oscillations) definitions of the Climate Prediction Center, available at [http://www.cpc.ncep.noaa.gov/products/analysis\\_monitoring/ensostuff/ensoyears.shtml](http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ensoyears.shtml).

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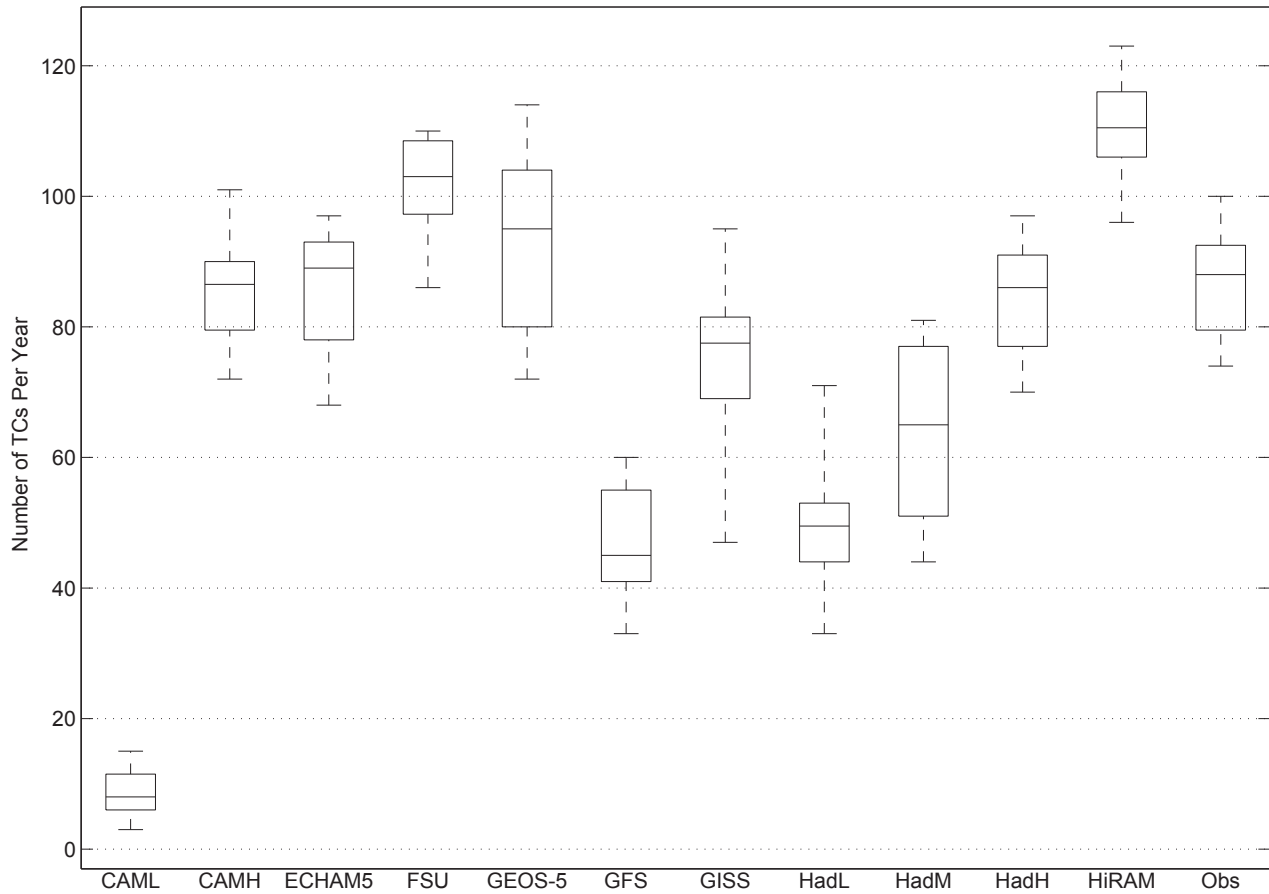
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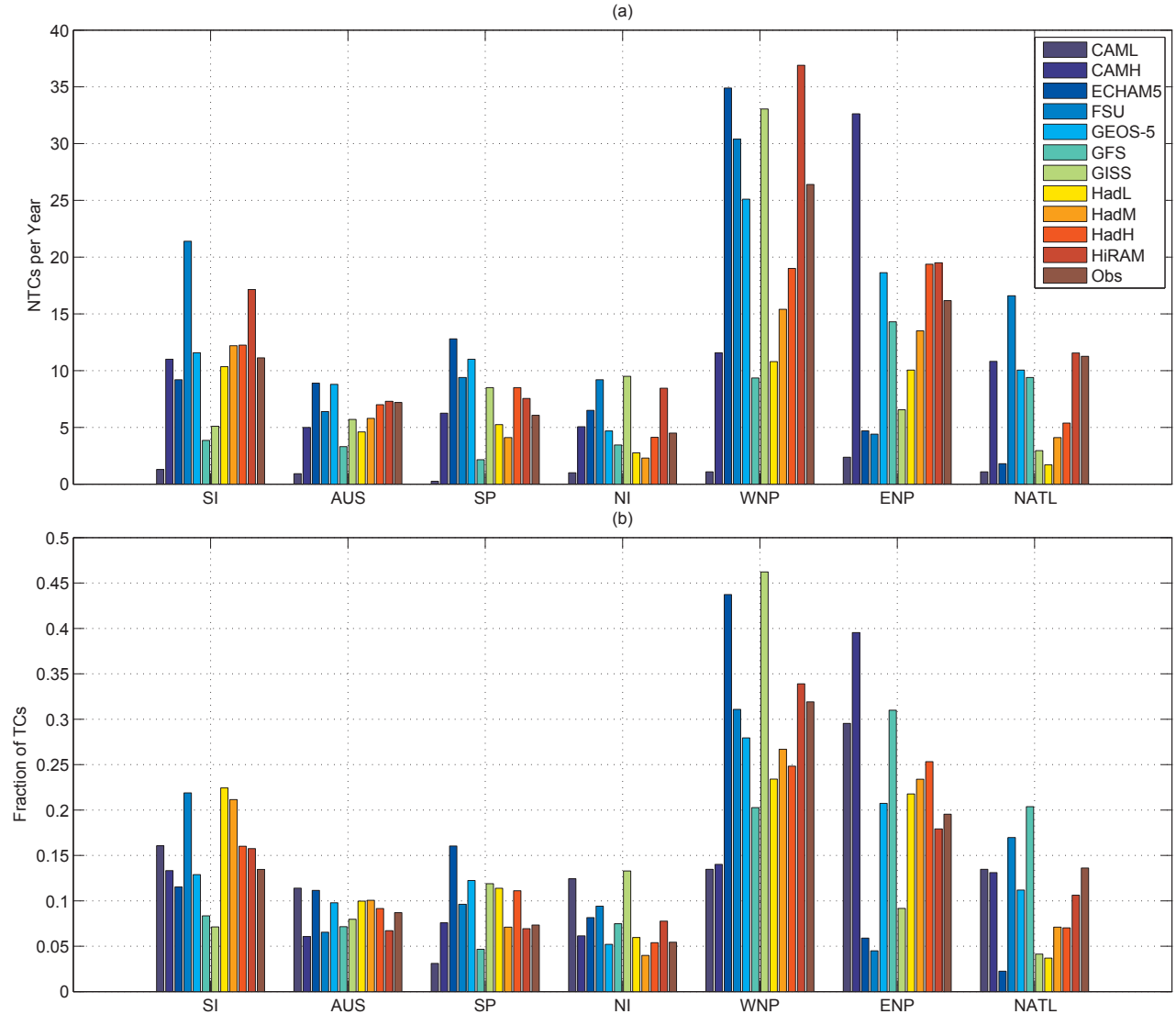
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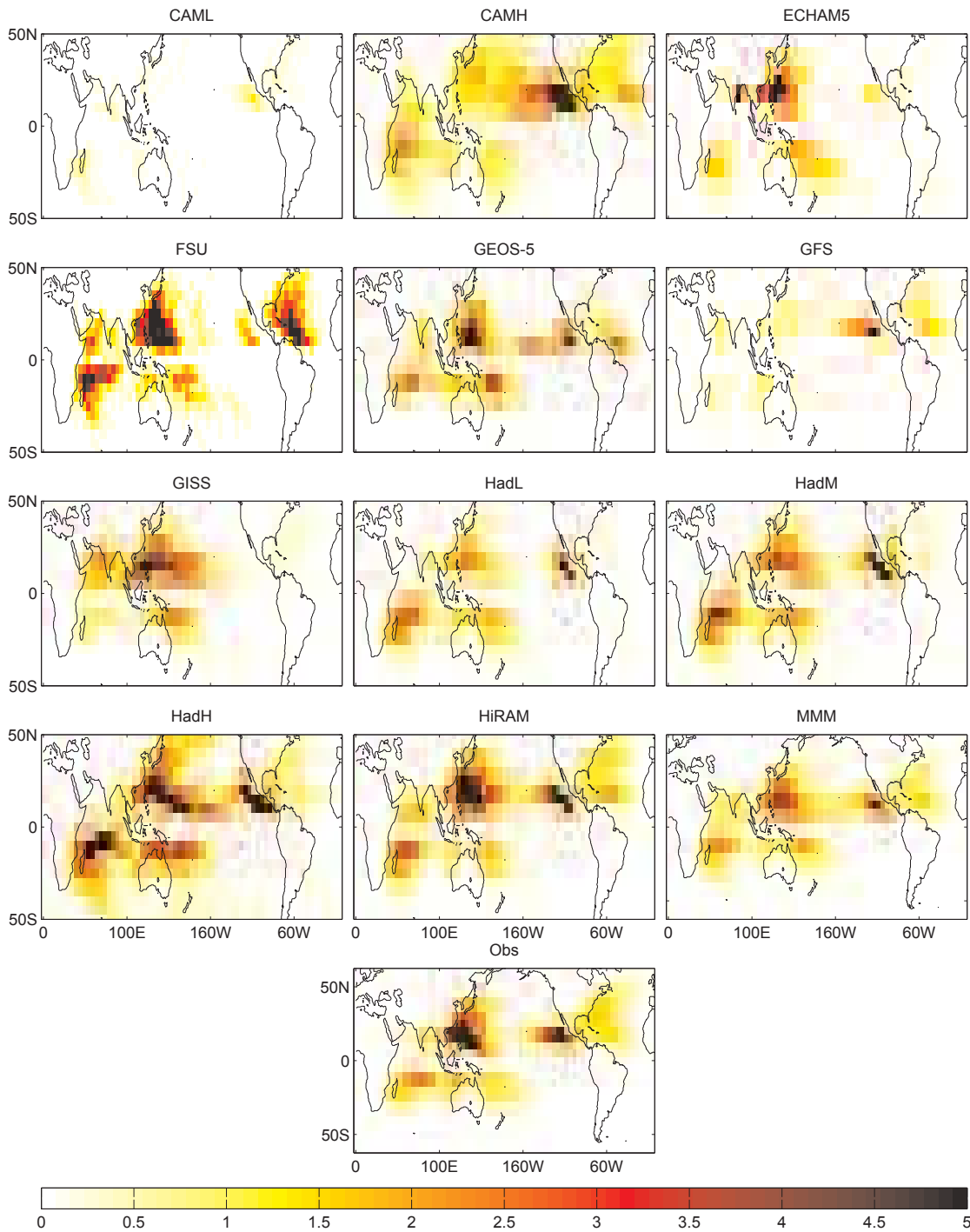
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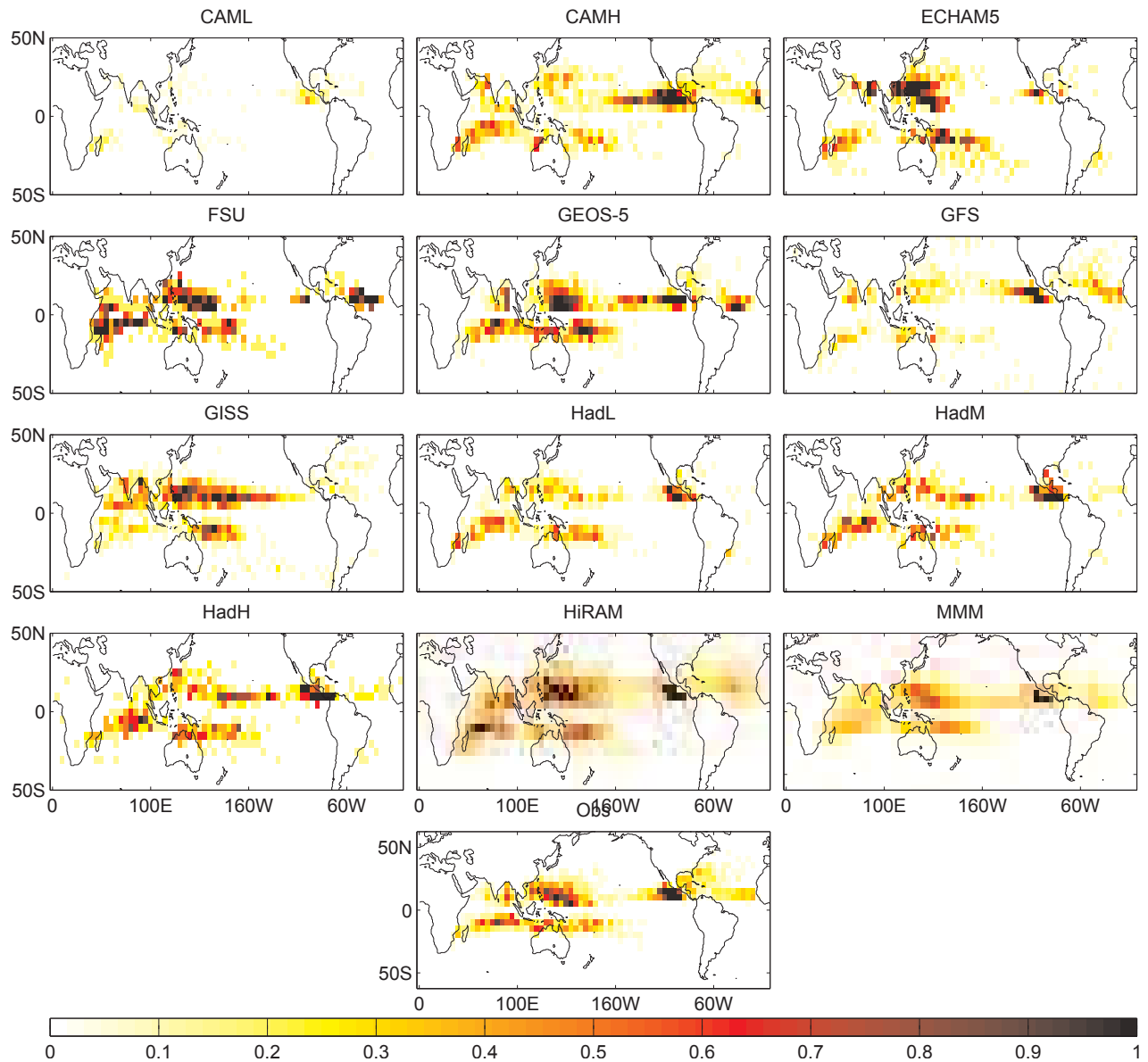
**Figure 1.** Distributions of the number of TCs per year for models and observations. The horizontal line inside the boxes shows the median number of TCs per year, the top and bottom of the boxes represent the 75th and 25th percentiles respectively, with the whiskers extending to the maximum and minimum number of TCs per year in each case. CAML: Low-resolution CAM5.1, CAMH: High-resolution CAM5.1, HadL: Low-resolution HadGEM3, HadM: Medium-resolution HadGEM3, HadH: High-resolution HadGEM3.



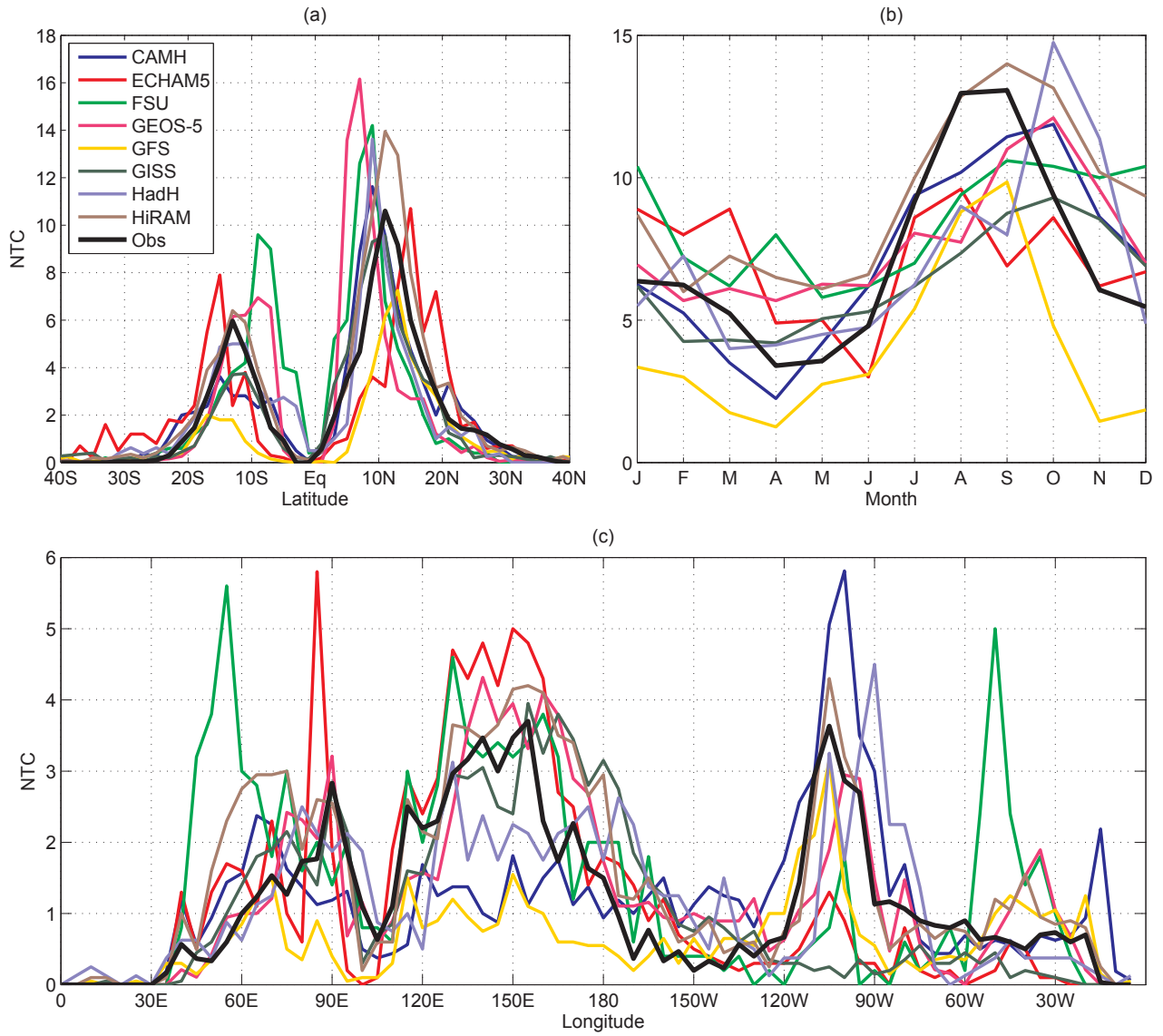
**Figure 2.** Mean number of TCs formed in each basin for models and observations. (a) shows the total number of TCs, (b) shows the percentage of TCs in each basin. The basins are defined as: SI (South Indian), AUS (Australian), SP (South Pacific), NI (North Indian), WNP (Western North Pacific), ENP (Easter North Pacific), NATL (North Atlantic). The model names follow the definitions in Fig. 1.



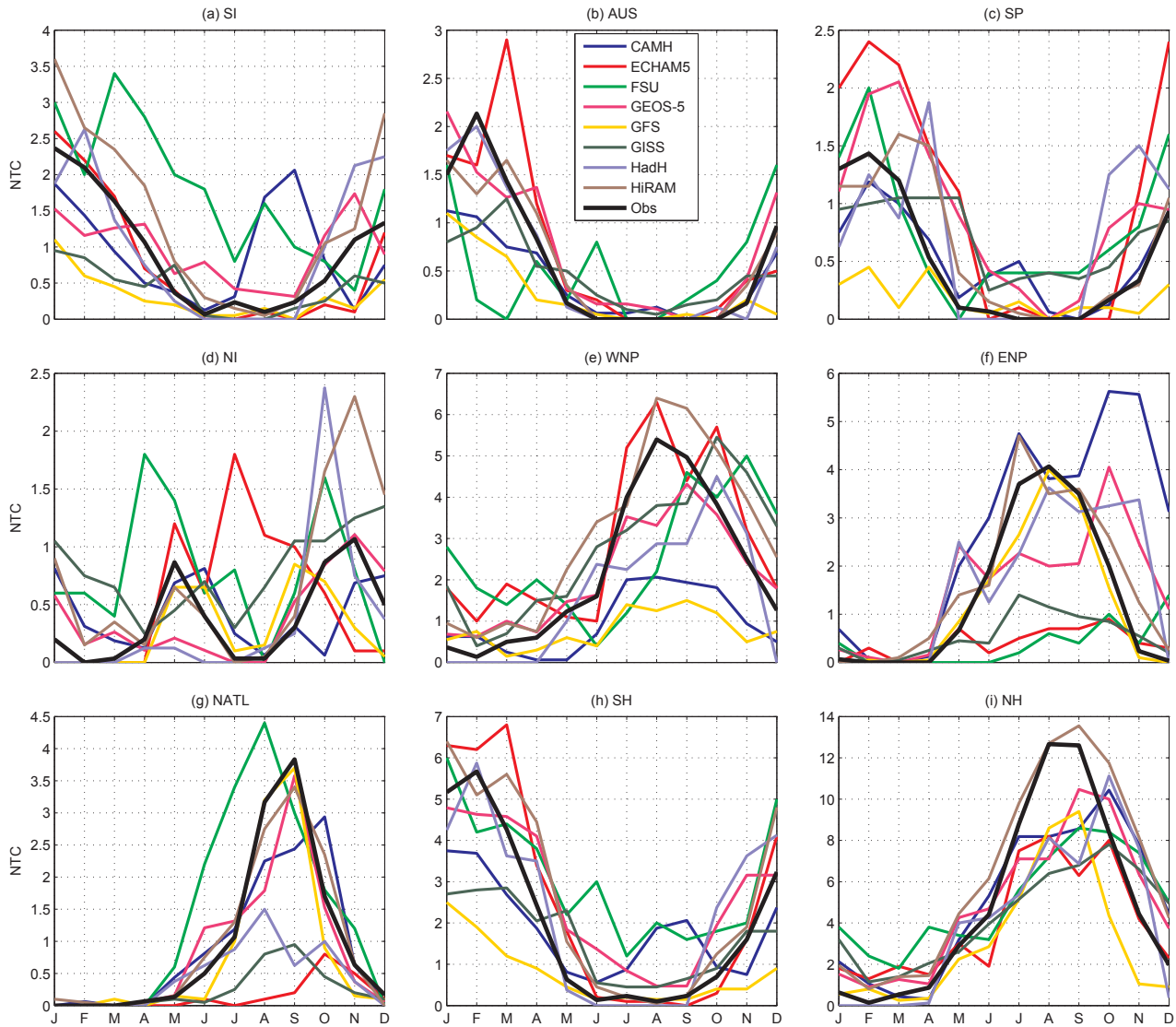
**Figure 3.** TC track density in models and observations. Track density is defined as the number of TC transits per  $5^\circ \times 5^\circ$  box per year. The total number of transits in each grid point and model is obtained and then divided by the number of years in each model simulation. The multi-model mean (MMM) track density is also shown. In the case of CAM5.1 and HadGEM3 only the high-resolution version was included in the multi-model mean.



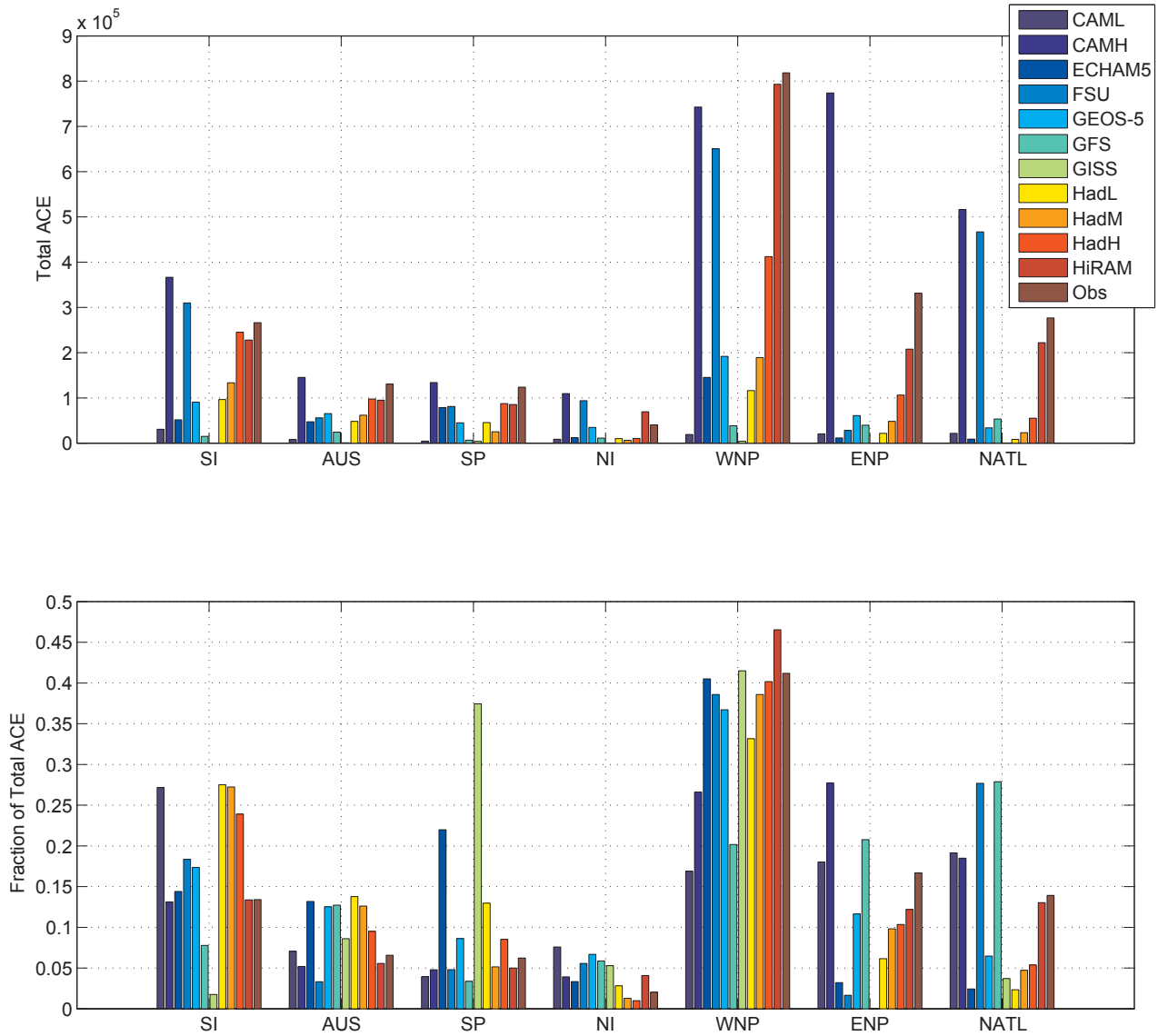
**Figure 4.** TC genesis density in models and observations. Genesis density is defined as the number of TC formation per  $5^\circ \times 5^\circ$  box per year. The total number of transits in each grid point and model is obtained and then divided by the number of years in each model simulation. The multi-model mean (MMM) track density is also shown. In the case of CAM5.1 and HadGEM3 only the high-resolution version was included in the multi-model mean.



**Figure 5.** Mean number of TC genesis per year in models and observations as a function of latitude (a), month (b), and longitude (c). The latitude (longitude) counts are per 2 (5) degrees bins.

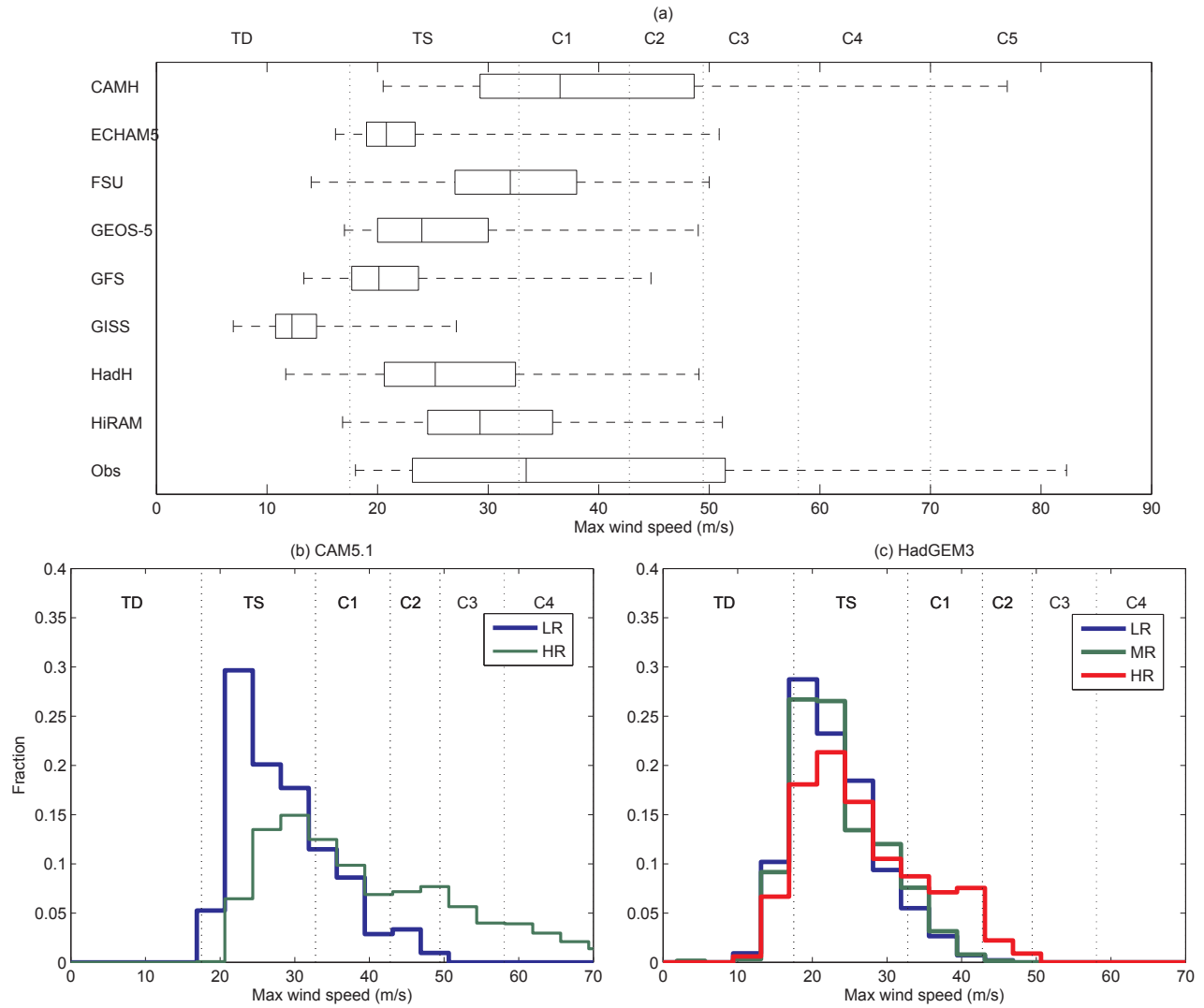


**Figure 6.** Mean TC genesis per year and month in models and observation in various basins (as defined in Fig. 2) and in the southern (SH) and northern (NH) hemispheres

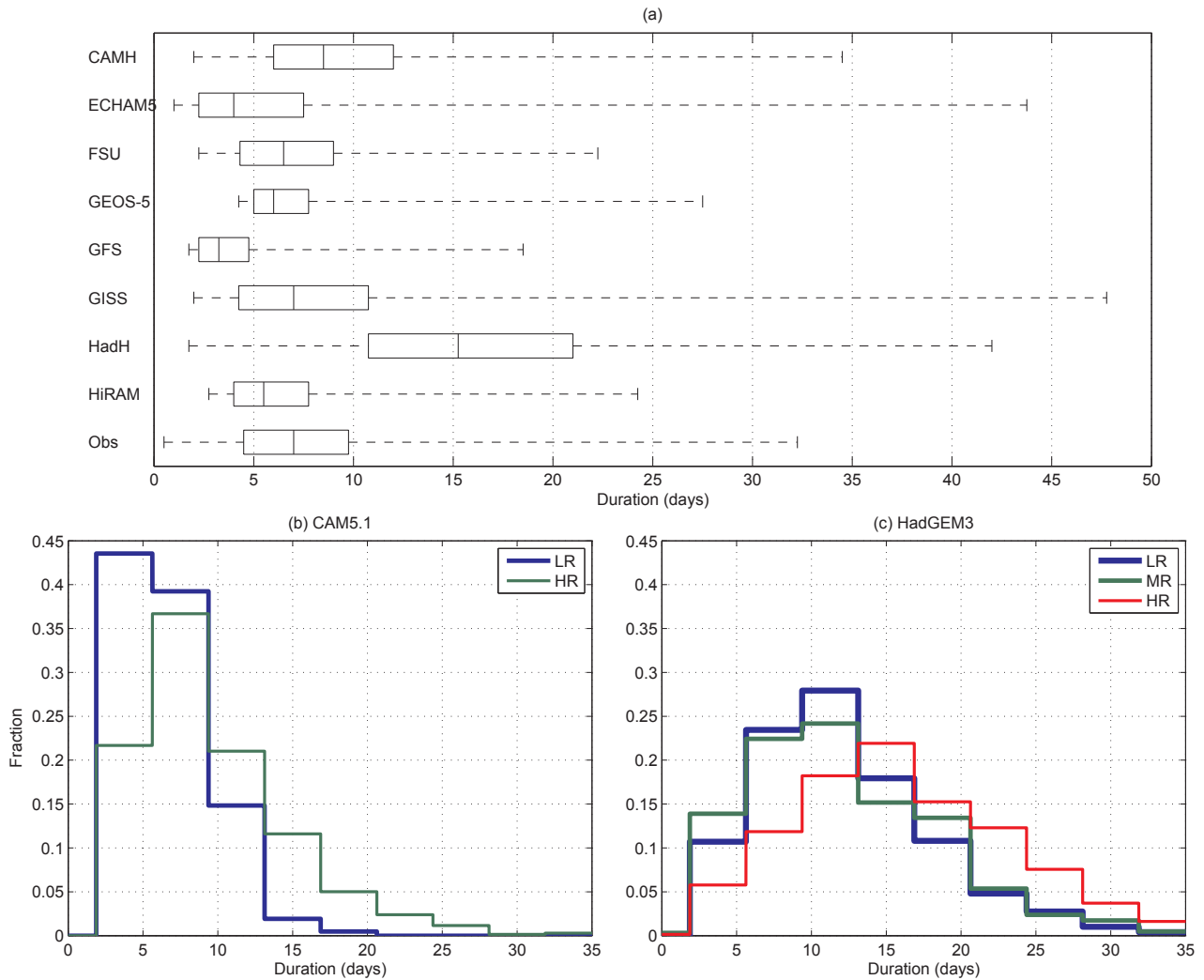


**Figure 7.** Accumulated cyclone energy (ACE) for models and observations (top panel). The bottom panel shows the percentage of the ACE in each basin for models and observations. Basins and models are defined as in previous figures.

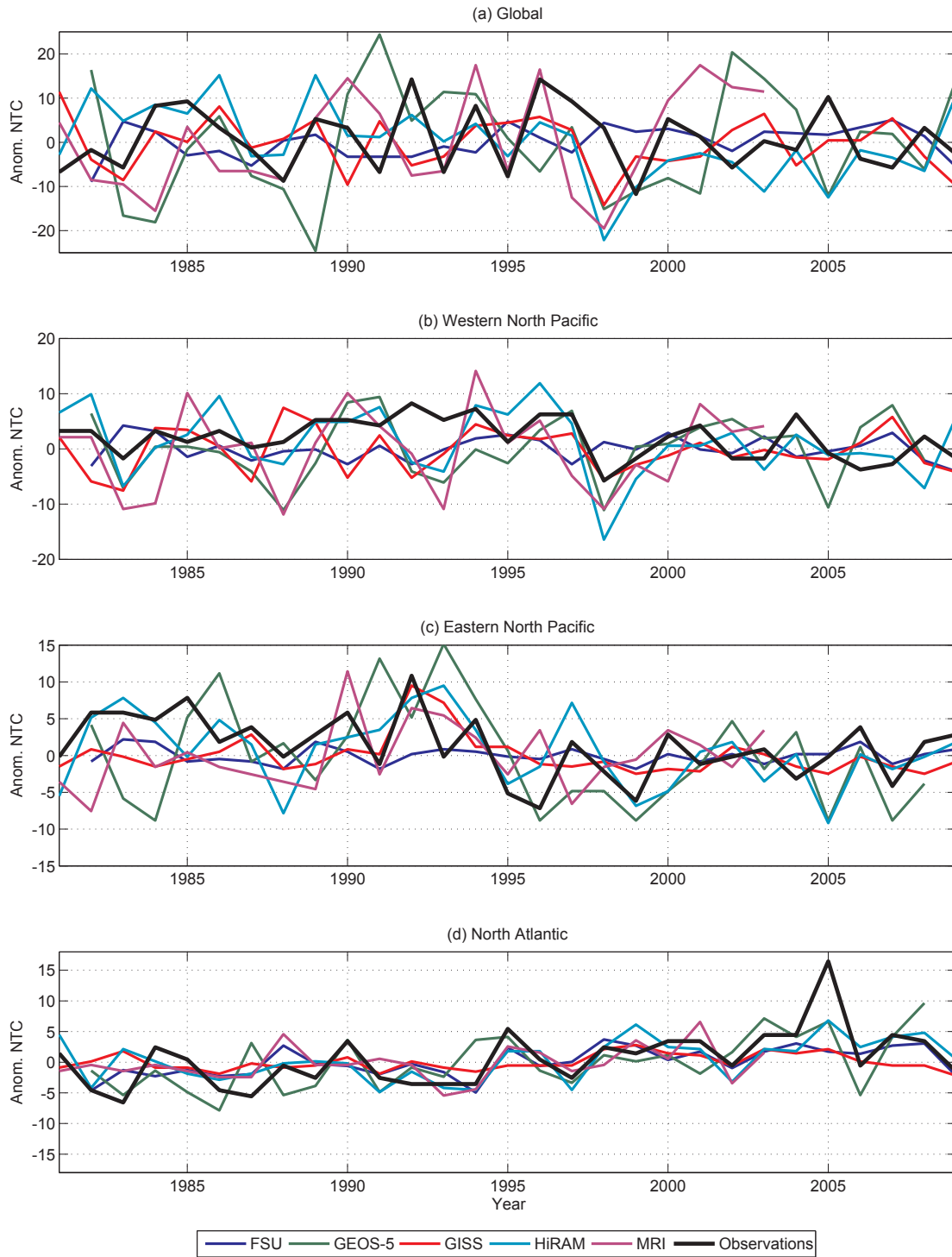




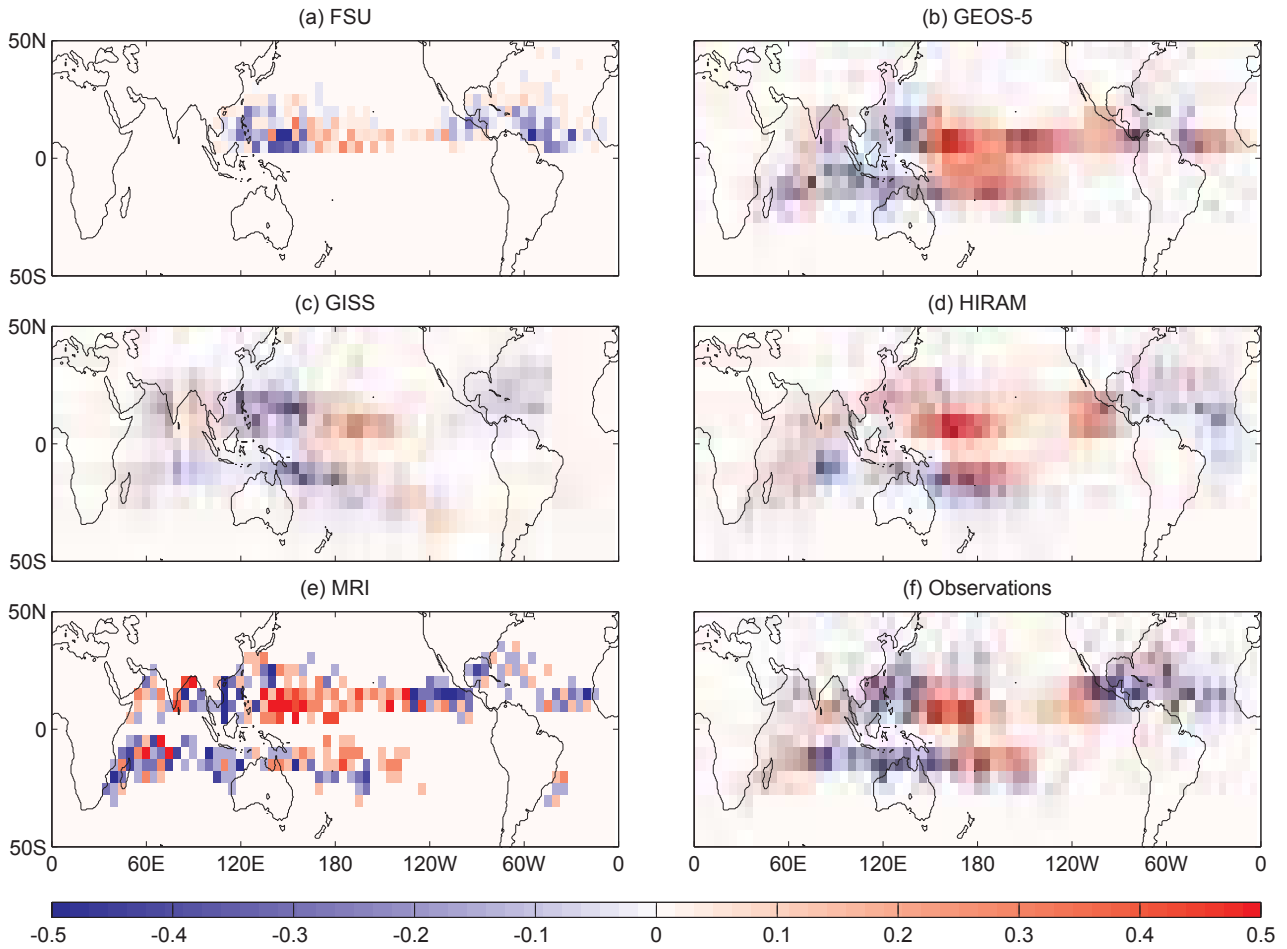
**Figure 8.** Distributions of TC maximum intensity in models and observations (a). The vertical line shows the median of each distribution, the left and right edges of the box represent the 75th and 25th percentiles respectively, and the whiskers extend to the maximum and minimum values in each case. Histograms of TC maximum intensity for two horizontal resolutions of the CAM5.1 model (b) and three model resolutions of the HadGEM1 model (c). The vertical lines show the boundaries of the Saffir-Simpson hurricane classification scale. TD: Tropical Depression, TS: Tropical Storm, C1-C5: Category 1-5 hurricanes. LR: Low resolution, MR: Medium resolution, HR: High resolution.



**Figure 9.** (a) Distributions of TC lifetime (or duration) for models and observations. The vertical line shows the median of each distribution, the left and right edges of the box represent the 75th and 25th percentiles respectively, and the whiskers extend to the maximum and minimum values in each case. The histograms of TC durations in the CAM5.1 and HadGEM3 models for different resolutions are shown in (b) and (c), respectively. LR: Low resolution, MR: Medium resolution, HR: High resolution.

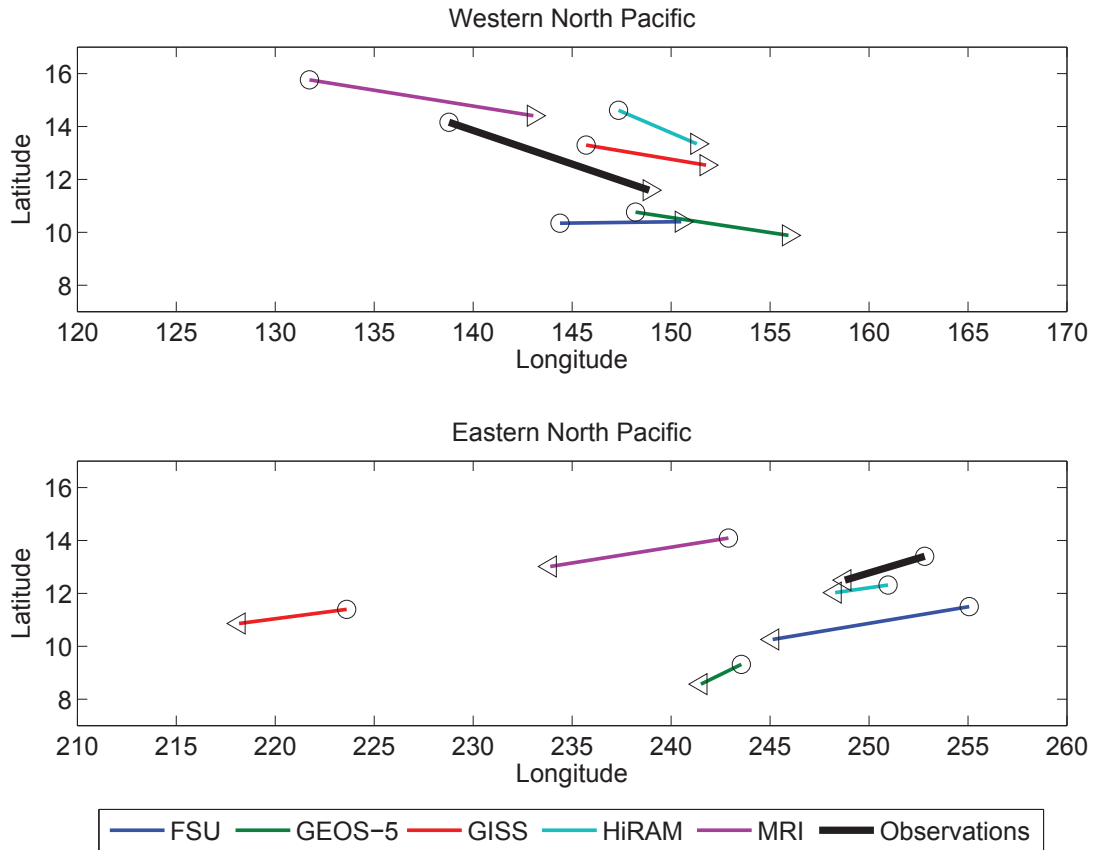


**Figure 10.** Anomalous number of TCs per year (number of TCs per year minus the mean number of TCs for all years) (a) in the globe and in a few of the Northern Hemisphere basins (Western North Pacific (b), Eastern North Pacific (c), and North Atlantic (d)). For the models, when more than one ensemble simulation was available, the ensemble mean anomlay number of TCs in each year is shown.



**Figure 11.** Difference of TC genesis density in El Niño and La Niña in models and observations.

The genesis density is defined as the mean TC formation per  $5^\circ \times 5^\circ$  box per year.



**Figure 12.** Mean TC genesis location in the western and eastern North Pacific in El Niño (triangles) and La Niña (circles) years in models and observations.

**Table 1.** Models characteristics and references for models and tracking schemes. LR: Low Resolution, MR: Medium Resolution, HR: High Resolution. References: Wehner: *Wehner et al.* [2014]; Prabhat: *Prabhat et al.* [2012]; RS: *Roeckner et al.* [2003] and *Scoccimarro et al.* [2011]; Walsh: *Walsh* [1997]; LaRow: *LaRow et al.* [2008]; Vitart: *Vitart et al.* [2003]; Rienecker: *Rienecker et al.* [2008]; Saha: *Saha et al.* [2014]; Zhao: *Zhao et al.* [2009]; Schmidt: *Schmidt et al.* [2014]; Camargo: *Camargo and Zebiak* [2002]; Walters: *Walters et al.* [2011]; HB: *Hodges* [1995] and *Bengtsson et al.* [2007a, b]; MM: *Mizuta et al.* [2012] and *Murakami et al.* [2012]; Murakami: *Murakami et al.* [2012].

Model	Resolution	Approx Res (km)	Reference	Tracking Scheme
LR CAM5.1	100 km	100	Wehner	Vitart/Prabhat
HR CAM5.1	1/4°	28	Wehner	Vitart/ Prabhat
ECHAM5	T159	84	RS	Vitart/Walsh
FSU	T126	106	LaRow	Vitart/Zhao
GEOS-5	1/2°	56	Rienecker	Vitart/Zhao
GFS	T126	106	Saha	Vitart/Zhao
GISS	1°	111	Schmidt	Camargo
LR HadGEM3	N96	130	Walters	HB
MR HadGEM3	N216	60	Walters	HB
HR HadGEM3	N320	40	Walters	HB
HiRAM	50 km	50	Zhao	Vitart/Zhao
MRI	TL319	60	MM	Murakami

**Table 2.** Number of years in the climatological simulations for each model.

Model	Years
LR CAM5.1	24
HR CAM5.1	16
ECHAM5	9
FSU	5
GEOS-5	20
GFS	20
GISS	20
LR HadGEM3	20
MR HadGEM3	10
HR HadGEM3	9
HiRAM	20

**Table 3.** Models' interannual simulations ensemble members and years.

Model	Number of Ensembles	Years
FSU	3	1982-2009
GEOS-5	2	1982-2009
GISS	3	1981-2009
HiRAM	3	1981-2009
MRI	1	1981-2003



**Table 4.** Correlations of yearly ACE and model-ACE in each basin ( $r_{AA}$ ) and correlations the yearly observed ACE the model modified MACE ( $r_{AM}$ ). The correlations are shown as  $r_{AA}/r_{AM}$ . Asterisks denote correlations that are statistically significant. Basins are defined as: SI (South Indian), AUS (Australian), SP (South Pacific), NI (North Indian), WNP (Western North Pacific), ENP (Easter North Pacific), NATL (North Atlantic).

Model	SI	AUS	SP	NI	WNP	ENP	NATL
FSU	-	-	-	-	0/0	0.5*/0.5*	0.7*/0.7*
GEOS-5	0/0	-0.1/-0.2	0.5*/0.4*	-0.2/-0.2	0.7*/0.7*	0.4*/0.5*	0.6*/0.6*
GISS	0/0	-0.3/0	-0.2/-0.2	-0.2/0.2	0.3/0.2	0/0.7*	0/0.4
HiRAM	0.2/0.2	0.4*/0.4*	0.1/0.1	-0.1/-0.1	0.5*/0.5*	0.6*/0.6*	0.7*/0.7*
MRI	0.2/0.2	-0.4*/-0.4*	0.1/0.1	-0.1/-0.1	0.3/0.3	0.4*/0.4*	0.6*/0.6*

**Table 5.** El Niño and La Niña seasons for the northern and southern hemispheres, using the warm and cold ENSO (El Niño Southern Oscillations) definitions of Climate Prediction Center. The northern (southern) hemisphere seasons definitions as based on the state of ENSO in the August - October (January - March) seasons. Note that the southern hemisphere TC seasons are defined from July to June, encompassing 2 calendar years.

Northern Hemisphere		Southern Hemisphere	
El Niño	La Niña	El Niño	La Niña
1982	1983	1982/83	1980/81
1986	1985	1986/87	1984/85
1987	1988	1987/88	1988/89
1991	1995	1991/92	1995/96
1994	1998	1994/95	1998/99
1997	1999	1997/98	1999/00
2002	2000	2002/03	2000/01
2004	2007		2005/06
2006			2007/08
2009			

**Table 6.** Correlations of NTC per year or season (southern hemisphere) in the globe by basins. Basins are defined as: SI (South Indian), AUS (Australian), SP (South Pacific), NI (North Indian), WNP (Western North Pacific), ENP (Easter North Pacific), NATL (North Atlantic). Asterisks denote correlations that are statistically significant.

Model	Global	SI	AUS	SP	NI	WNP	ENP	NATL
FSU	-0.13	–	–	–	0	-0.25	0.42	0.61*
GEOS-5	-0.21	0.20	0.07	0.32	-0.10	0.24	0.27	0.61*
GISS	-0.01	0.12	0.15	-0.26	-0.12	0.21	0.42	0.45
HiRAM	0.22	0.34	0.39	0.07	0.11	0.55*	0.51*	0.69*
MRI	0.15	0.36	0.32	-0.02	-0.37	0.35	0.22	0.55*