

Resolution dependence of tropical cyclone formation in CMIP3 and finer  
resolution models

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## Abstract

Detection of tropical lows is performed in a suite of climate model simulations using objectively-determined detection thresholds that are resolution-dependent. It is found that there is some relationship between model resolution and tropical cyclone formation rate even after the resolution-dependent tropical cyclone detection threshold is applied. The relationship is investigated between model-simulated tropical cyclone formation and a climate-based tropical cyclone Genesis Potential Index (GPI). It is found that coarser-resolution models simulate the GPI better than they simulate formation of tropical cyclones directly. As a result, there appears to be little relationship from model to model between model GPI and the directly-simulated cyclone formation rate. Statistical analysis of the results shows that the main advantage of increasing model resolution is to give a considerably better pattern of cyclone formation. Finer resolution models also simulate a slightly better pattern of GPI, and for these models there is some relationship between the pattern of GPI simulated by each model and that model's pattern of simulated tropical cyclone formation.

19 1. Introduction

20 Recent fine-resolution modelling results have shown considerable ability to  
21 simulate the climatological observed global formation rate of tropical cyclones;  
22 for a recent review, see Knutson et al (2010a). These models have also now  
23 shown an ability to generate a realistic distribution of tropical cyclone intensity  
24 (Bender et al. 2010; Lavender and Walsh 2011; Murakami et al. 2011a). While  
25 coarser-resolution models have only a limited ability to simulate tropical  
26 cyclone intensity, they have demonstrated good performance in simulating the  
27 interannual variation of tropical cyclone formation (Vitart and Anderson 2001;  
28 LaRow et al. 2008; Zhao et al. 2009). The quality of such simulations is  
29 important for skilful dynamical seasonal predictions of tropical cyclone  
30 formation as well as for projections of future climate. Since it is crucial that a  
31 climate model used for the prediction of future climate gives a good simulation  
32 of the current climate (e.g. Delsole and Shukla 2010), an evaluation of the  
33 ability of such models to reproduce the current tropical cyclone climatology is  
34 important. This is particularly vital at the scale of individual tropical cyclone  
35 formation basins, where models have shown less ability to simulate observed  
36 cyclone formation rates, and where the response to global warming of tropical  
37 cyclone formation varies considerably from model to model (Knutson et al.  
38 2010a,b).

39           In many cases, it is not clear why models produce different basin-scale  
40 formation rates for tropical cyclones. There are many factors in the real climate  
41 that produce variations in tropical cyclone formation rate: vertical wind shear  
42 (Palmen 1956; Gray 1968; McBride and Zehr 1981); the presence of substantial  
43 pre-existing convective development (e.g. Hendricks et al. 2004); temporal and  
44 geographical variations in sea surface temperature (Gray 1968; Vecchi and  
45 Soden 2007; Murakami et al. 2011b); and variations in mid-tropospheric  
46 relative humidity (Bister and Emanuel 1997). The combined effects of these  
47 variables on tropical cyclone formation rates has motivated the development of  
48 climatological or seasonal genesis parameters, indices that are derived from the  
49 best climatological fit to observed tropical cyclone formation for variables that  
50 are known to affect tropical cyclone formation on shorter time scales (e.g. Gray  
51 1975, Royer et al. 1998; Emanuel and Nolan 2004; Camargo et al. 2007;  
52 Camargo et al. 2009; Tippett et al. 2011). While all of these physical factors are  
53 present in model simulations and influence simulated tropical cyclone formation  
54 rates, there are additional model-dependent factors that can influence formation  
55 rates: for instance, the model specification of horizontal diffusion and the details  
56 of the model's convective parameterization (e.g. Vitart et al. 2001).

57           Identifying the reasons for these different model responses is the main  
58 goal of an intercomparison process. There are many possible strategies for  
59 determining the reasons for model responses. In principle, the use of a common

60 set of physical parameterisations among a group of models should reduce the  
61 number of degrees of freedom between the models that would be causing  
62 different responses. In practice, even if models employ a similar  
63 parameterisation of cumulus convection, there is no guarantee that the effect of  
64 using this parameterisation would be the same in two different models, as  
65 interactions of the cumulus scheme with other elements of the physics in  
66 different models could generate different simulation outcomes. In addition,  
67 implementing these changes across a suite of climate models is time consuming  
68 and would also usually require re-tuning the model after the new  
69 parameterisation scheme is introduced.

70         Alternatively, some insight can be gained by comparison of the  
71 performance of groups of models that contain common elements. For example,  
72 Lin et al. (2006) evaluated the performance of 14 AR4 climate models in  
73 generating the Madden-Julian Oscillation (MJO; Madden and Julian 1971).  
74 This intercomparison strengthened previous conclusions (Tokioaka et al. 1988;  
75 Wang and Schlesinger 1999) that the best models for simulating the MJO were  
76 ones with convective closures or triggers linked to moisture convergence.  
77 Physically, an important factor for a good MJO simulation appears to be the  
78 preconditioning of the atmosphere through moistening rather than quick release  
79 of available potential energy. This concept has been applied in a number of

80 subsequent improvements of model simulation of the MJO (Fu and Wang 2009;  
81 Seo and Wang 2010).

82         This comparison approach has the advantage of simplicity but it does rely  
83 on the evaluation of the model performance being conducted in a consistent  
84 manner, using the same model output metrics for every model in the  
85 comparison. In general, the use of consistent evaluation metrics is an important  
86 first step in any intercomparison of climate model results but has not been  
87 employed to date in the analysis of most climate simulation of tropical cyclones  
88 (Walsh et al. 2007). This paper outlines initial results from a multi-model  
89 intercomparison project, the Tropical Cyclone climate Model Intercomparison  
90 Project (TC-MIP; Walsh et al. 2010). Like all intercomparison projects, it aims  
91 to improve the simulation of the chosen phenomenon through identification of  
92 common model features that have led to improved simulations. Ideally, such  
93 intercomparisons should have many models available for analysis, so that clear  
94 groups of better-performing models can emerge from the analysis of the results.  
95 One drawback of this approach for the generation of tropical cyclones by  
96 climate models is that relatively few global models have been run for the long,  
97 very fine resolution simulations required to generate a good tropical cyclone  
98 climatology. Such resolution is needed for best results because of the small  
99 scale of tropical cyclones compared to the typical resolution of a climate model;  
100 ultimately, a horizontal resolution as fine as a few kilometres may be required  
101 (Chen et al. 2007). Nevertheless, coarse resolution climate models have shown a

102 surprising ability to generate realistic tropical cyclone formation rates, although  
103 the storms so generated clearly have lower intensities than many observed  
104 storms. Thus, in addition to selected recent fine-resolution modelling results, we  
105 also examine results from the CMIP3 archive (<http://cmip-pcmdi.llnl.gov/>).

106 Analysis of detected tropical cyclones for model results contained in the  
107 CMIP3 archive has been performed previously by a number of authors (e.g.  
108 Yokoi et al. 2009). In general, though, these results were either focused on a  
109 particular region or did not use systematic, model-independent common metrics  
110 for the specific purpose of comparing the model climatology of tropical  
111 cyclones with observations. Camargo et al. (2005) analysed the results of three  
112 GCMs with horizontal resolutions of approximately 2.5 degrees using a model-  
113 and basin-dependent tropical cyclone detection routine. They found that the  
114 models were able to reproduce basic features of the observed tropical cyclone  
115 climatology. Camargo et al. (2007) used the same cyclone detection method for  
116 the analysis of the output of several GCMs and compared the detection tropical  
117 cyclone numbers to those estimated from an empirical index of tropical cyclone  
118 formation, the Emanuel and Nolan (2005) Genesis Potential Index (GPI). They  
119 found that there was little relationship from model to model between the GPI  
120 and model-simulated cyclone formation; a model with a high GPI did not  
121 necessarily have a high tropical cyclone formation rate. In the present study, we  
122 examine global model results and employ common metrics for model

123 evaluation, including a resolution-dependent, model-independent tropical  
124 cyclone detection technique. Section 2 gives a list of models and of  
125 observations used for model validation, Section 3 describes the analysis  
126 methodology, Section 4 details the results and Section 5 provides a discussion  
127 and concluding remarks.

128

## 129 2. Models and validation data sets

130 As mentioned above, two sets of model results are examined here. To provide a  
131 baseline comparison, the CMIP3 model archive is analysed. Table 1 gives some  
132 details of the models, including their resolution as stored in the archive and their  
133 convection schemes. In addition, two finer-resolution, more recent model results  
134 are analysed for current climate conditions. The MRI/JMA 20-km global mesh  
135 model (Mizuta et al. 2006) is run using a timeslice method for model years  
136 1979-2003. In the timeslice method, the SSTs from a coarser-resolution model  
137 run are used to force a fine-resolution atmospheric general circulation model  
138 (AGCM). The model is hydrostatic, with 60 vertical levels, uses a semi-  
139 Lagrangian time integration scheme and a prognostic Arakawa-Schubert  
140 cumulus convection scheme (Randall and Pan 1993). The CMCC\_MED model  
141 (Scoccimarro et al. 2011) is a fully coupled GCM without flux adjustments,  
142 using an atmospheric spectral resolution of T159 (equivalent to a horizontal  
143 resolution of about 80 km; Roeckner et al 2003). The parameterization of



144 convection is based on the mass flux concept (Tiedtke 1989), modified  
145 following Nordeng (1994). The global ocean model used is a 2 degree  
146 resolution global ocean model (Madec 1998) with a meridional refinement near  
147 the equator to 0.5 degrees. The CMCC\_MED model output used in this work  
148 are obtained running the model over the period 1970-1999 using 20th century  
149 (20C3M) atmospheric forcings as specified by the IPCC ([http://www-](http://www-pcmdi.llnl.gov/ipcc/about/_ipcc.php)  
150 [pcmdi.llnl.gov/ipcc/about/\\_ipcc.php](http://www-pcmdi.llnl.gov/ipcc/about/_ipcc.php)). Results from these two recent models are  
151 likely to be more similar to model results that will be obtained from a similar  
152 analysis of the CMIP5 model archive (<http://cmip-pcmdi.llnl.gov/cmip5>). Thus  
153 another purpose of this paper is to establish a model intercomparison  
154 methodology that can be applied to a suite of finer-resolution climate model  
155 results, when these become available.

156 Model tropical cyclone formation is compared with the IBTrACS best  
157 track data (Knapp et al. 2010), a global compilation of the best estimated  
158 tropical cyclone positions and intensities. The observed cyclones are analysed  
159 over a twenty-year period corresponding to the current climate (1980-1999).  
160 Data used to construct observed versions of model diagnostic parameters is  
161 taken from the NCEP-2 reanalyses (Kanamitsu et al. 2002) over the same  
162 period. For selected fields, comparisons are also made with the ERA40  
163 reanalyses (Uppala et al. 2005). Both reanalysis data sets are at a horizontal grid  
164 spacing of 2.5 degrees.

165

## 166 3. Methods

167 It is important in an intercomparison project that aims to evaluate the ability of  
168 climate models to generate tropical cyclones that it is agreed what constitutes a  
169 tropical cyclone in the climate model output. One metric would be simply to  
170 apply the criterion applied to observed tropical cyclones, that the storms must  
171 have 10-minute average wind speeds of  $17.5 \text{ ms}^{-1}$  or greater at a height of 10m  
172 above the surface. This may not be appropriate for climate model output,  
173 though, as there are numerous cyclonic disturbances generated by a model that  
174 satisfy this criterion that are not tropical cyclones, for example, mid-latitude  
175 cyclones. Thus additional structural criteria that identify simulated tropical  
176 cyclones need to be imposed. Typically, these have been in the form of  
177 assuming that low-level wind speed, usually at 850 hPa, exceeds that in the  
178 upper troposphere, and that temperature anomalies in the center of the storm are  
179 larger in the upper troposphere than in the lower troposphere. Due to the  
180 thermal wind equation, these conditions are essentially equivalent, but they are  
181 often both imposed because of the ability of mid-latitude storms to sometimes  
182 mimic one or the other of these two conditions (e.g. Shapiro and Keyser 1990).

183 Here, the resolution-dependent method of Walsh et al. (2007) is used to  
184 track cyclones. This method assumes that simulated tropical cyclones are best  
185 compared with fine-resolution observations that have been degraded to the

186 resolution of the model, in a manner analogous to that usually performed for  
187 other comparisons of observations to model simulations of variables such as  
188 precipitation. When observed tropical cyclones are regridded to the relatively  
189 coarse resolution of a climate model, their maximum wind speeds become less,  
190 and so also the detection threshold for tropical cyclone winds falls from the  
191 observed value of  $17.5 \text{ ms}^{-1}$  to lower values (Fig. 1). The advantage of this  
192 technique is that it provides a baseline, model-independent comparison of  
193 simulated tropical cyclone formation rates. This detection technique also  
194 assumes a number of other thresholds:

- 195 • Points with vorticity more cyclonic than  $1 \times 10^{-5} \text{ s}^{-1}$  are first  
196 identified; this threshold serves merely to eliminate isolated points  
197 of weak cyclonic vorticity, thus speeding up the detection routine;
- 198 • A centre of low pressure is then found;
- 199 • At the centre of the storm, there must be a warm core, specified as  
200 the sum of the temperature anomalies at the centre of the storm  
201 versus the surrounding environment, and the temperature anomaly  
202 at 300 hPa must be greater than zero; in addition, the mean wind  
203 speed over a specified region at 850 hPa must be greater than that  
204 at 300 hPa.
- 205 • The resolution-dependent 10 m windspeed threshold is then  
206 imposed.

- 207           • Detected storms need to satisfy these conditions for at least 24  
208           hours.

209   The solid line given in Fig. 1 is the one that is employed here to set the  
210   resolution-dependent detection threshold. Other symbols shown on Fig. 1  
211   correspond to different vortex specifications, as explained in Walsh et al.  
212   (2007).

213           A number of atmospheric variables have been previously shown to  
214   influence the rate of tropical cyclone formation. The Emanuel and Nolan (2004)  
215   genesis parameter is here employed as a means of comparing the effects of  
216   several of these variables simultaneously:

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

217

218   where  $\eta$  is the absolute vorticity at 850 hPa in  $s^{-1}$ , H is the relative humidity at  
219   700 hPa in percent,  $V_{pot}$  is the potential maximum wind speed in  $ms^{-1}$  and  
220    $V_{shear}$  is the magnitude of the vertical wind shear between 850 hPa and 200  
221   hPa, also in  $ms^{-1}$ .

222           A number of standard statistical measures were applied to the analysis of  
223   the climate variables that compose the GPI, collected in the form of Taylor  
224   diagram (Taylor 2001). In addition, in our analysis, for the first time a Taylor  
225   diagram is constructed comparing observed tropical cyclone formation rates to

226 simulated rates. One difference in the analysis contained here from the standard  
227 Taylor diagram is that the zonal mean value of each quantity is removed before  
228 the correlation is performed, giving an anomaly correlation. This is a more  
229 sensitive statistic than the standard pattern correlation as it removes the high  
230 pattern correlation that is caused simply by the variables having substantial  
231 variation with latitude caused by the known equator to pole climatological  
232 gradients.

233         The results shown here are similar to those already described in Walsh et  
234 al. (2010), but there are two differences from the results described in that paper.  
235 Firstly, a bug was fixed in the data interface section of the detection routine,  
236 which improved the ability of the routine to detect weak tropical cyclones. In  
237 addition, a further improvement to the method was made, in that for the CMIP3  
238 model results the “background” climatological mean sea level pressure (mslp)  
239 was increased. This further improved the detection of weak storms by enabling  
240 them to stand out from the background more clearly, resulting in an improved  
241 detection of storms in the CMIP3 model results.

242

#### 243 4. Results

244 Figure 2 compares results of the GPI diagnosed from the higher-resolution  
245 CMIP3 simulations for the January through March climatology, to the GPI

246 diagnosed from NCEP2 reanalyses with a horizontal resolution of 2.5 degrees.  
247 While there appears to be considerable variation between the model simulations  
248 of GPI, most models generate a pattern similar to that derived from the NCEP  
249 reanalyses. Some systematic differences can be seen between the model results  
250 and the NCEP2 GPI, though. For instance, many models have excessive GPI in  
251 the South Atlantic, and many models have regions of GPI that extend too far  
252 east into the South Pacific. These simulated GPI values can be quite large: for  
253 instance, in the MPI ECHAM5 model, maximum values in excess of 40 (per  
254 2.5x2.5 degree grid box per 20 years) are found, compared with maximum  
255 values derived from the NCEP2 reanalysis in the same region of 10-15. The  
256 excessive simulated GPI values are likely associated with the known dry bias in  
257 the mid-tropospheric relative humidity from the NCEP reanalyses (Bony et al.  
258 1997). This would strongly affect the GPI values since they depend on the cube  
259 of the 700 hPa relative humidity. This result was also noted by Camargo et al.  
260 (2007).

261 Figure 3 gives a Taylor diagram corresponding to the plots in Fig. 2, and  
262 this diagram also includes the lower-resolution CMIP3 models. Values are  
263 shown for both January-March (JFM) and July-September (JAS). The statistics  
264 are evaluated between latitudes 40S and 40N and the anomaly correlation rather  
265 than the pattern correlation is plotted, as described in section 3. Models with  
266 horizontal grid spacings finer than 2.8 degrees are indicated in red. In general,

267 with the exception of one outlier, the finer-resolution models give superior  
268 performance, with better correlations and with standard deviations more similar  
269 to the NCEP2 reanalyses, indicated by the red line. Most models have higher  
270 GPI than that diagnosed from the NCEP2 reanalyses, as also seen in Fig. 2.  
271 Similarly, Figure 4 shows the relationship between the GPI index and model  
272 resolution for JFM, with the GPI value averaged over the latitudes specified  
273 above. A linear regression line is fitted to the model results, and the NCEP2  
274 and ERA40 reanalyses GPI values are given for comparison. With the exception  
275 of a few outliers, in general the finer-resolution models more closely approach  
276 the reanalysis values, although there is little dependence of GPI value on  
277 resolution. Interestingly, most GPI values from the models are lower than that  
278 diagnosed from the ERA40 reanalyses but higher than those from the NCEP2  
279 reanalyses, consistent with the NCEP2 values having a dry bias in the mid-  
280 troposphere.

281 Figure 5 shows the detected January-March formation of tropical  
282 cyclones in the models compared with the best-track data, in the same order of  
283 models as Figure 2 (note that not all models listed in Table 1 had sufficient  
284 output archived to enable cyclone tracking to be performed). It is clear that most  
285 finer-resolution models (finer than 2.8 degrees) simulate a reasonable pattern of  
286 cyclone formation. In addition, Figure 6 shows results from coarser resolution  
287 models, where the simulated pattern of formation is less adequate. In contrast to

288 the results for the GPI, there is little or no simulated cyclone formation in the  
289 South Atlantic. In addition, a number of the finer-resolution models are  
290 simulating excessive formation in the northwest Pacific at this time of year,  
291 compared with the best-track data.

292 It is evident from Figures 5 and 6 that the lowest resolution models tend  
293 to have less cyclone formation, and Figure 7 summarizes this result. The  
294 correlation between formation and resolution for the CMIP3 models is -0.5,  
295 which is statistically significant at the 95% level. Note, though, that this could  
296 also be regarded as a threshold effect. For instance, Figure 7 shows that once the  
297 models have resolutions finer than about four degrees, it could be argued that  
298 there is actually little relationship between resolution and formation rate for this  
299 set of CMIP3 models, since some finer-resolution models also have relatively  
300 low simulated cyclone numbers. Figure 8 shows the Taylor diagram of cyclone  
301 formation for JFM and JAS compared with the observed best track data,  
302 corresponding to Fig. 5 and 6. Also included in this diagram are the results from  
303 the two higher-resolution (post-CMIP3) models listed in section 2, indicated by  
304 a red x. It is clear from this analysis that the higher-resolution CMIP3 models  
305 have the best pattern correlations compared with the observed formation, and  
306 the post-CMIP3 models have among the best correlations of all, although they  
307 do not necessarily have the smallest model biases. This may suggest that the  
308 main advantage of finer resolution is to generate a better pattern of formation.



309 Note that the anomaly correlations for the GPI index (Fig. 3) are substantially  
310 higher than those for the directly simulated cyclone formation (Fig. 8),  
311 reinforcing the point that it is fundamentally easier for the models to simulate a  
312 good pattern of large-scale climate variables that are known to influence  
313 tropical cyclone formation rates than of tropical cyclone formation itself.

314 Turning to Northern Hemisphere results, Figure 9 shows GPI results for  
315 July-September compared with simulated cyclone formation. For brevity, only  
316 selected model results are shown. Once again, there is a large variation in the  
317 results, with some models capturing well the pattern of diagnosed genesis, and  
318 other models performing less well. The accompanying Taylor diagram is shown  
319 previously in Fig. 3. Once again the fine-resolution models appear to be  
320 capturing the NCEP2 GPI a little better, although there are a number of outliers.  
321 As in January-March, most models have values of GPI that are larger than  
322 observed, and many models simulate GPI values over the North Pacific that are  
323 higher than diagnosed from the NCEP2 data. A number of models (not shown)  
324 also have excessive GPI in the regions near Indonesia, again consistent with the  
325 dry bias in the NCEP reanalyses. These models also tend to be those that  
326 overestimate GPI across the Pacific.

327 Figure 9 also shows the simulated formation rates for July-September, for  
328 selected models; the accompanying Taylor diagram is given in Fig. 8. Some  
329 systematic biases in model formation compared with the observations are

330 apparent. Most models simulate considerably lower formation than observed in  
331 the North Atlantic, while simulated formation in the eastern north Pacific is  
332 usually lower than observed also. In contrast, simulated formation in the north-  
333 west Pacific appears to be more accurate. There is a similar relationship  
334 between cyclone formation and resolution in JAS as in JFM for the CMIP3  
335 models, with a similar correlation of -0.54 (not shown). The corresponding  
336 Taylor diagram (Fig. 8) shows that once again the highest-resolution models  
337 have in general higher pattern correlations, although again not necessarily the  
338 smallest biases, as there is a considerable scatter in the simulated formation  
339 rates.

340 To examine the ability of the models to simulate the observed  
341 geographical pattern of cyclone tracks, Figure 10 shows annual tropical cyclone  
342 tracks compared with the best track data, for finer-resolution models. As for  
343 formation, there are a number of systematic differences from the observed  
344 tracks that are common to many of models. Even so, the models are able to  
345 capture important aspects of the observed geographical variation of tracks: for  
346 example, most models simulate the observed minimum in cyclone track density  
347 in the central north Pacific, caused by the high climatological vertical wind  
348 shear in this region. Some models simulate a collection of short tracks in the  
349 South Atlantic, where cyclones are not observed frequently (Pezza and  
350 Simmonds 2005). The best track data have a higher track density overall than

351 most models, and many more tracks at higher latitudes than the models. In the  
352 North Atlantic, model tracks mostly tend to be restricted to low latitudes, with  
353 few tracks approaching the eastern United States, unlike the observed track  
354 pattern. This can also be seen in the northwest Pacific, with few simulated  
355 storms striking Japan. At least part of this difference may arise from the lack of  
356 an objective criterion in the observed best track data that is systematically  
357 imposed to indicate extratropical transition (Kofron et al. 2010), which if  
358 imposed would shorten the observed tracks in the mid-latitudes. In addition, it is  
359 noted that the CMIP3 archive consists largely of daily-mean data, and the  
360 tracking in the present study was performed on those data. Further analysis of  
361 these data (S. Yokoi, personal communication, 2011) suggests that in mid-  
362 latitude regions, the faster translation speed of these storms makes them more  
363 difficult to detect in daily average data, thus leading to the lack of tracks at  
364 higher latitudes.

365         While there may be some relationship between model formation rates and  
366 resolution, little or no inter-model global relationship was found between  
367 tropical cyclone formation and the GPI, or between model resolution and the  
368 GPI (not shown; see also Camargo et al. 2007). Nor was there are strong inter-  
369 model global relationship between TC formation and the various components of  
370 the GPI (wind shear, relative humidity or MPI; not shown). Since there is some  
371 relationship between model resolution and TC formation, this suggests that it is

372 more difficult to improve the simulation of the large-scale variables that  
373 comprise the GPI simply by increasing resolution than it is to improve the  
374 model simulation of tropical cyclone formation by increased resolution. Some  
375 support for this hypothesis comes from Fig. 11, which shows TC formation  
376 normalized by GPI versus resolution. Comparing this result to Figs. 4 and 7,  
377 low resolution models tend to have reasonable to high GPI values but low TC  
378 formation. Thus in Fig. 11, the response shown in Fig. 7 is exacerbated. Coarse-  
379 resolution models have low values of this quantity, as for these models GPI  
380 tends to be more similar to that of the high-resolution models while the directly-  
381 simulated TC formation is low. While this relationship is statistically significant  
382 for the CMIP3 models, it clearly depends on other model-dependent factors  
383 apart from resolution. As an example of this effect, statistics show that the  
384 better resolution models are clearly performing better at simulating the observed  
385 wind shear (not shown), even though this is not translating into a genuine  
386 statistically-significant inter-model relationship between simulated wind shear  
387 and TC formation.

388         It is well known that observed tropical cyclones arise from regions of  
389 persistent deep tropical convection (e.g. Charney and Eliassen 1964; Evans and  
390 Shemo 1996). Nevertheless, there also appears to be little inter-model  
391 relationship between precipitation and TC formation rates: models with lower  
392 total precipitation rates appear to be giving slightly more tropical cyclone

393 formation (not shown), although this relationship is not statistically significant.  
394 The finer resolution models also appear to have somewhat better simulation of  
395 precipitation overall (Fig. 12). In addition, there appears to be little relationship  
396 between convective precipitation rates, as specified by the model convective  
397 scheme, and tropical cyclone formation (not shown). Nor does there appear to  
398 be an inter-model relationship between the ratio of convective precipitation to  
399 total precipitation and the tropical cyclone formation rate (not shown). On the  
400 other hand, of the higher-resolution models, the MIROC hires model has high  
401 resolution but a rather low generation rate of tropical cyclones, combined with a  
402 low fraction of convective precipitation. This may be related to the results of  
403 McDonald et al. (2005), who found that there appeared to be a relationship  
404 between model-generated convective rainfall and tropical cyclone formation, at  
405 least for higher-resolution models. In the results shown here, there does not  
406 appear to be a strong correlation between this variable alone and seasonal  
407 formation rates of tropical cyclones.

408         While the analysis indicates that it is difficult to find relationships that are  
409 robust between models, relationships between variables within a single model  
410 can be strong. As Fig. 3 shows, anomaly correlations between the individual  
411 model GPI patterns and the NCEP-derived GPI are high, with an average when  
412 taken across all models and seasons of about 0.6. Since the GPI was originally  
413 developed by tuning the NCEP-derived GPI values to the best track data, this

414 implies that anomaly correlations between individual model GPI patterns and  
415 the best track observed patterns of formation are also strong. Nevertheless, the  
416 individual model GPI is less reliable as a predictor of that model's pattern of  
417 simulated cyclone formation, with anomaly correlations when averaged across  
418 all models and seasons of about 0.3. Higher-resolution models mostly have  
419 higher anomaly correlations between model GPI and model cyclone formation,  
420 however (not shown).

421

## 422 5. Discussion

423

424 Several studies have shown that simulated tropical cyclone frequency  
425 increases with increased resolution, all other things being equal (Murakami and  
426 Sugi 2010; Gentry and Lackmann 2010). Figure 13 shows the relationship  
427 between annual model formation and resolution, using the Walsh et al. (2007)  
428 detection criterion. There is a statistically significant relationship between  
429 model formation of TCs and resolution, even when in this case the detection  
430 threshold is adjusted downwards for models of coarser horizontal resolution,  
431 thus making it easier to detect cyclones in such models. Even after this is done,  
432 simulated tropical cyclone formation in these coarse-resolution models remains  
433 low. Increased horizontal resolution thus may have an effect on tropical cyclone  
434 formation that is in addition to that of resolution only, as this would be

435 accounted for solely by the increasing threshold imposed by the detection  
436 technique. If a fixed threshold rather than a resolution-adjusted threshold were  
437 employed, this relationship would of course be even stronger, as has been  
438 shown previously by others. For instance, for storms simulated by the GISS  
439 model, with a resolution of 4.5 degrees, the maximum wind speed recorded for  
440 a simulated tropical cyclone is only just over  $20 \text{ ms}^{-1}$ . Thus if the observed  
441 detection threshold of  $17.5 \text{ ms}^{-1}$  were imposed on the output of this model, even  
442 fewer storms would be detected than those shown in Fig. 13. More generally, if  
443 the formation and intensification of simulated tropical cyclones is related to a  
444 non-linear feedback process between the ocean and the atmosphere (Rotunno  
445 and Emanuel 1987), it can be argued that this process would operate more  
446 efficiently in a finer-resolution model. The higher wind speeds generated by the  
447 finer resolution model would enhance any such feedback process, and an  
448 increased number of model grid points in closer proximity to the storm centre  
449 would help amplify this process. An alternative explanation, though, is that the  
450 lack of detection of storms in low resolution models may be simply a result of  
451 the tracking algorithms not being able to track the storms properly at these  
452 resolutions, combined with the coarse temporal resolution of the CMIP3 results  
453 analysed here (Camargo and Sobel 2004).

454         There appears to be little relationship between the choice of convective  
455 parameterisation and the model generation rate of tropical cyclones (Fig. 13).

456 Models employing various versions of the Arakawa-Schubert convection  
457 scheme (green squares) give a wide range of TC formation rates, as do models  
458 employing mass-flux or Zhang-McFarlane type schemes. While it is clear that  
459 the use of a particular convection scheme can give a systematic change in  
460 tropical cyclone formation rate within a single model (e.g. Yoshimura et al.  
461 2011), there are other factors that can cause changes in tropical cyclone  
462 formation rates. For instance, the two versions of the GFDL model that were  
463 run as part of the CMIP3 model suite (models 7 and 8 in Table 1) have the same  
464 convective parameterizations but are based on different dynamical cores, and  
465 yet the tropical cyclone formation rate of the two models as analysed here  
466 differs by more than a factor of two. Thus, in agreement with the results of  
467 Camargo et al. (2007), dynamical factors appear to be playing a strong role in  
468 the intermodal differences in tropical cyclone formation rate.

469         The Taylor diagrams shown here for the different variables show that  
470 simulation of tropical cyclone formation is in general considerably worse than  
471 the model simulation of any variable that composes the GPI. The GPI is often  
472 well-simulated by coarse-resolution models (compare Fig. 3 to Fig. 8, for  
473 instance). We interpret this as further demonstrating the importance of  
474 resolution for the simulation of tropical cyclone formation. A coarse-resolution  
475 model may be able to generate a reasonable GPI pattern, derived as it is from  
476 large-scale variables, but is less well able to generate the actual rate of tropical



477 cyclone formation. While this result might suggest that given limited computing  
478 resources, for making climate change predictions of tropical cyclone formation  
479 indices like the GPI should be used in preference to direct simulation of tropical  
480 cyclones, these indices have their own uncertainty issues. They are tuned to the  
481 current climate and it is debatable whether such a functional relationship would  
482 hold in a warmer world in exactly the same way. Note also that most models  
483 have larger GPI rates than observed. The original formulation of the GPI was  
484 tuned using the NCEP reanalyses, which are known to be drier than observed in  
485 the tropics (Bony et al. 1997), which would explain this bias in the GPI derived  
486 from the CMIP3 models.

487       Most models simulate little cyclone formation in the Atlantic, despite  
488 having reasonable GPI patterns in many cases. Table 2 compares results in the  
489 western North Pacific basin to those in the Atlantic. While GPI values are  
490 considerably lower in the Atlantic than in the western North Pacific, simulated  
491 formation rates in the Atlantic decrease even more than does the GPI. In  
492 addition, the ratios of both simulated GPI and tropical cyclone formation  
493 between the Atlantic and western North Pacific are both well below the  
494 observed ratio of formation of about 1:2. In the results analysed here, high-  
495 resolution models appear to have higher formation rates in this basin than  
496 coarse-resolution models. For the two post-CMIP3 models (Table 2), simulated  
497 Atlantic formation is higher than the CMIP3 average, although still below the

498 observed numbers. Daloz et al. (2011) showed a strong relationship between the  
499 able of models to generate Atlantic Easterly Waves (AEWs) and the model  
500 generation of tropical cyclones. It is likely that the ability of models to generate  
501 AEWs, the main precursor for tropical cyclone formation in the Atlantic basin,  
502 is related to the resolution of the model (Thorncroft and Hodges 2001). This  
503 implies that climate model resolution may be particularly important in the  
504 Atlantic basin for a good simulation of tropical cyclone formation.

505 In summary, we find the following results from the initial stage of this  
506 intercomparison:

- 507 • There is some relationship between model resolution and tropical cyclone  
508 formation rate even after a resolution-dependent tropical cyclone  
509 detection threshold is applied. This may imply some non-linearity in the  
510 simulated tropical cyclone formation process different from the largely  
511 linear dependence of the resolution-adjusted detection threshold
- 512 • Coarse-resolution models simulate the Genesis Potential Index better than  
513 they simulate the formation of tropical cyclones directly. As a result,  
514 there appears to be little inter-model relationship between model GPI and  
515 model directly-simulated formation rate. In contrast, there are some  
516 relationships within individual, finer-resolution models between patterns  
517 of simulated tropical cyclone formation and genesis potential index  
518 patterns.

- 519       • The main advantage of finer model resolution, apart from giving a  
520            somewhat better simulation of tropical cyclone formation rate, is to give a  
521            better pattern of formation rate.

522

523   Ideally, it would be preferable if such climate model intercomparisons were  
524   conducted using a larger suite of fine-resolution simulations similar to the two  
525   post-CMIP3 models used here. In addition, performing common perturbation  
526   experiments to determine the model responses to idealized forcings will shed  
527   light on the model responses to climate change. This approach is envisaged as  
528   part of the U.S. Clivar Working Group on Hurricanes  
529   (<http://www.usclivar.org/hurricanewg.php>), for which the analysis methodology  
530   established here will be employed.

531

532

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737 climatology, interannual variability, and response to global warming  
738 using a 50km resolution GCM. *J Climate* 22: 6653–6678.
- 739  
740

741 Table 1. List of CMIP3 models analysed, along with their resolutions and  
742 convective parameterisations (MF: Mass flux-type scheme; MFK mass flux  
743 with Kuo-type closure; ZM: Zhang and McFarlane (1995); MFGR: Gregory and  
744 Rowntree (1990); RAS: Relaxed Arakawa-Schubert (Moorthi and Suarez 1992);  
745 PCAS: Arakawa-Schubert with prognostic closure (Randall and Pan 1993);  
746 MFT: Mass flux scheme following Tiedtke (1989) and Nordeng (1994)).

747

<b>No.</b>	<b>Model</b>	<b>Institution</b>	<b>Resolution (deg.)</b>	<b>Convective Parameterisation</b>
1	BCCR-BCM2.0	Bjerknes Centre for Climate Research	2.8 x 2.8	MFK
2	CGCM3.1(T47)	Canadian Centre for Climate Modelling & Analysis	3.75 x 3.75	ZM
3	CGCM3.1(T63)	Canadian Centre for Climate Modelling & Analysis	2.8 x 2.8	ZM
4	CNRM-CM3	Météo-France / Centre National de Recherches Météorologiques	2.8 x 2.8	MFK
5	CSIRO-Mk3.0	CSIRO Atmospheric Research	1.9 x 1.9	MFGR
6	CSIRO-Mk3.5	CSIRO Atmospheric Research	1.9 x 1.9	MFGR
7	GFDL-CM2.0	US Dept. of Commerce / NOAA / Geophysical Fluid Dynamics Laboratory	2.5 x 2.0	RAS
8	GFDL-CM2.1	US Dept. of Commerce / NOAA / Geophysical Fluid Dynamics Laboratory	2.5 x 2.0	RAS
9	GISS-AOM	NASA / Goddard Institute for Space Studies	4.0 x 3.0	MF
10	GISS-EH	NASA / Goddard Institute for Space Studies	5.0 x 4.0	MF
11	GISS-ER	NASA / Goddard Institute for Space Studies	5.0 x 4.0	MF
12	FGOALS-g1.0	LASG / Institute of Atmospheric Physics	2.8 x 3.0	ZM
13	INM-CM3.0	Institute for Numerical Mathematics	5.0 x 4.0	Modified Betts (1986)
14	IPSL-CM4	Institut Pierre Simon Laplace	3.75 x 2.5	Modified Emanuel (1991)
15	MIROC3.2(hires)	University of Tokyo, National Institute for Environmental Studies, and JAMSTEC	1.1 x 1.1	PCAS
16	MIROC3.2(medres)	University of Tokyo, National Institute for Environmental Studies, and JAMSTEC	2.8 x 2.8	PCAS
17	ECHAM5/MPI-OM	Max Planck Institute for Meteorology	1.9 x 1.9	MFT
18	MRI-CGCM2.3.2	Meteorological Research Institute	2.8 x 2.8	PCAS
19	NCAR-CCSM3	National Center for Atmospheric Research	1.4 x 1.4	ZM
20	NCAR-PCM1	National Center for Atmospheric Research	2.8 x 2.8	ZM
21	UKMO-HadCM3	Hadley Centre for Climate Prediction and Research / Met Office	3.75 x 2.5	MFGR
22	UKMO-HadGEM1	Hadley Centre for Climate Prediction and Research / Met Office	1.9 x 1.25	Modified MFGR

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749

750 Table 2. Comparison of observed, CMIP3 and finer-resolution models average

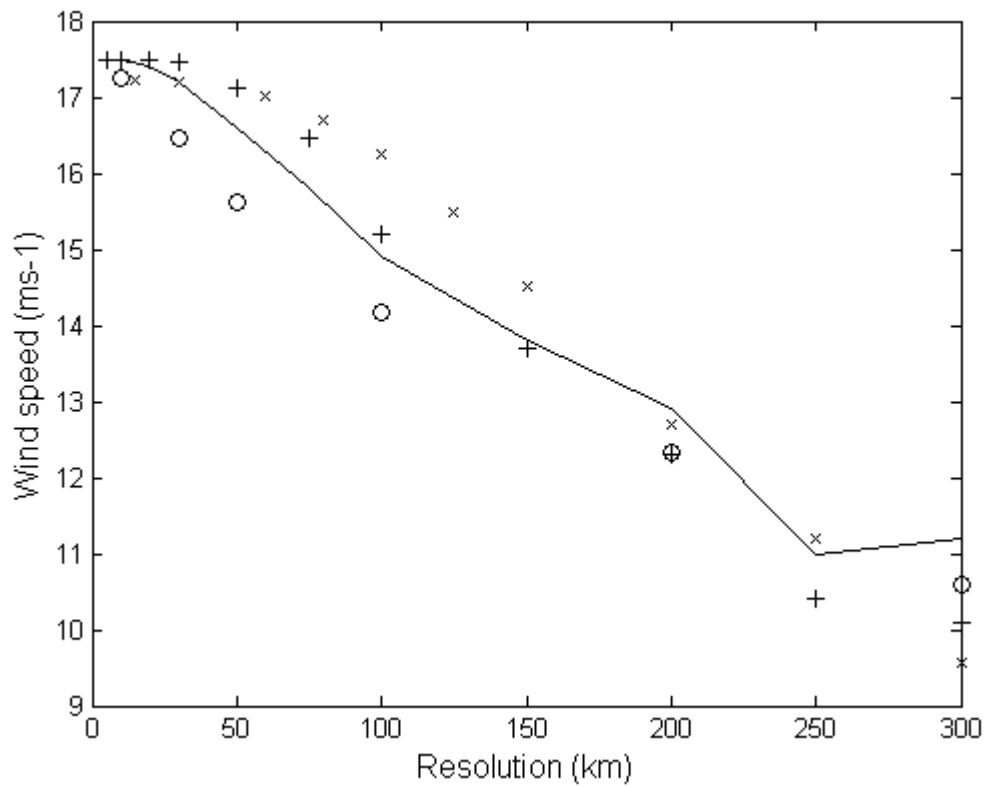
751 TC formation by basin with GPI values, July-September

	Western North Pacific	Atlantic
Observed	15	7
CMIP3 Simulated	9.3	0.9
GPI	4.5	0.9
MRI 20 km	8.9	2.8
CMCC MED	17	1.5

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756 Figure 1. Variation with resolution of 10 m wind speed detection threshold for  
757 tropical cyclones, for various vortex specifications as described in Walsh et al.  
758 (2007).

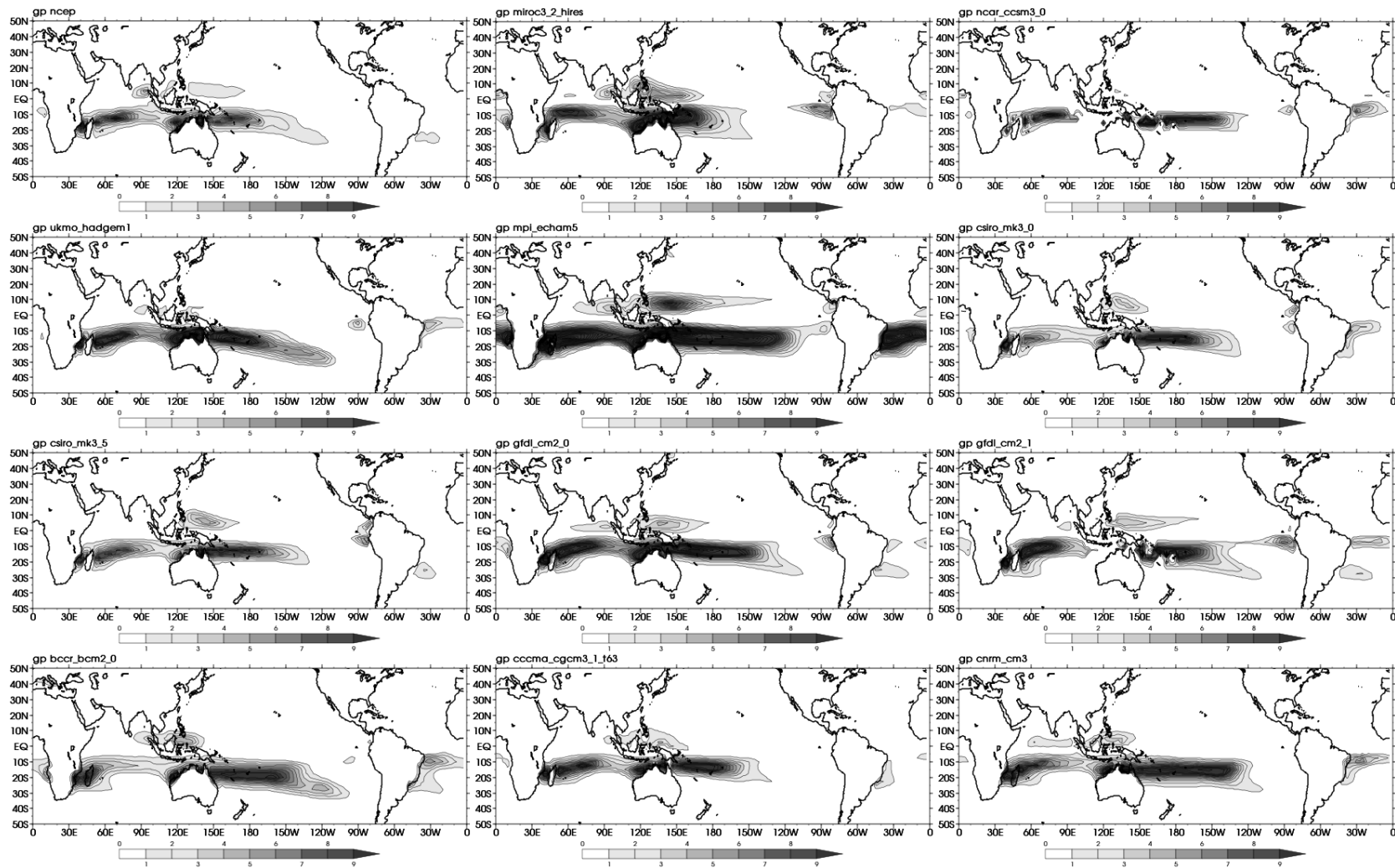
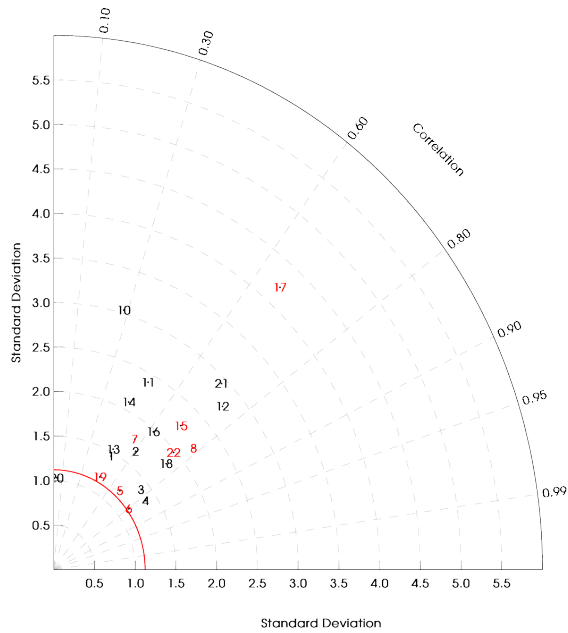


Figure 2. Emanuel genesis parameter fields derived from NCEP2 reanalyses (top left) and higher-resolution CMIP3 models, January-March. Formation rate is per 2.5x2.5 degree grid box per 20 years.

### JFM



### JAS

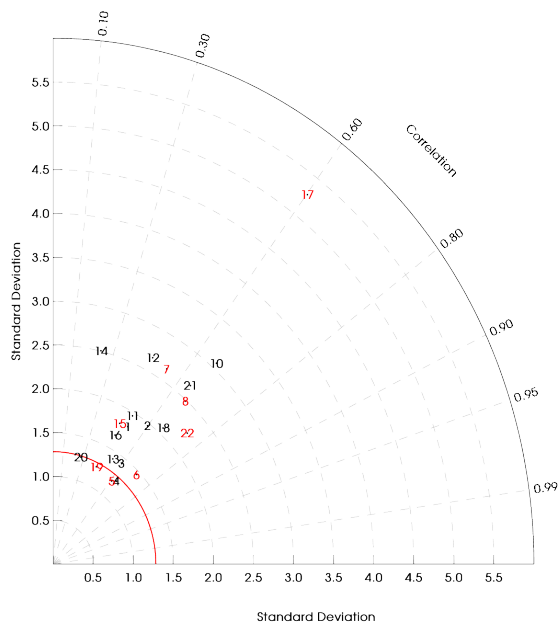


Figure 3. Taylor diagram of model GPI versus NCEP reanalyses, (top) JFM and (bottom) JAS. Model numbers are the same as in Table 1, with higher-resolution models in red. The standard deviation of the NCEP reanalyses is indicated by the red line.

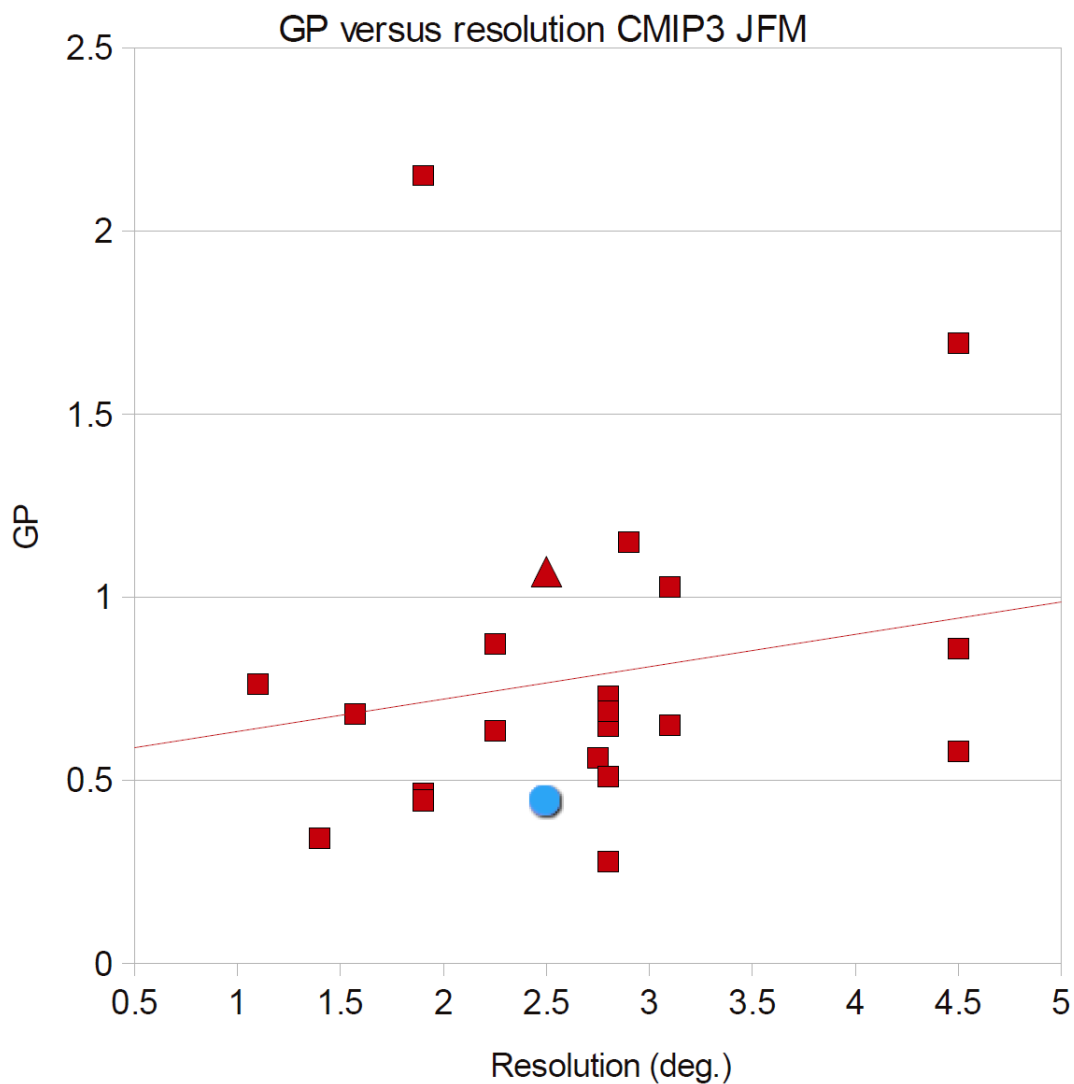


Figure 4. Emanuel and Nolan GPI versus resolution for the CMIP3 models, JFM. GPI value derived from NCEP2 reanalyses is indicated by a circle, and the value from the ERA40 reanalyses is indicated by a triangle.



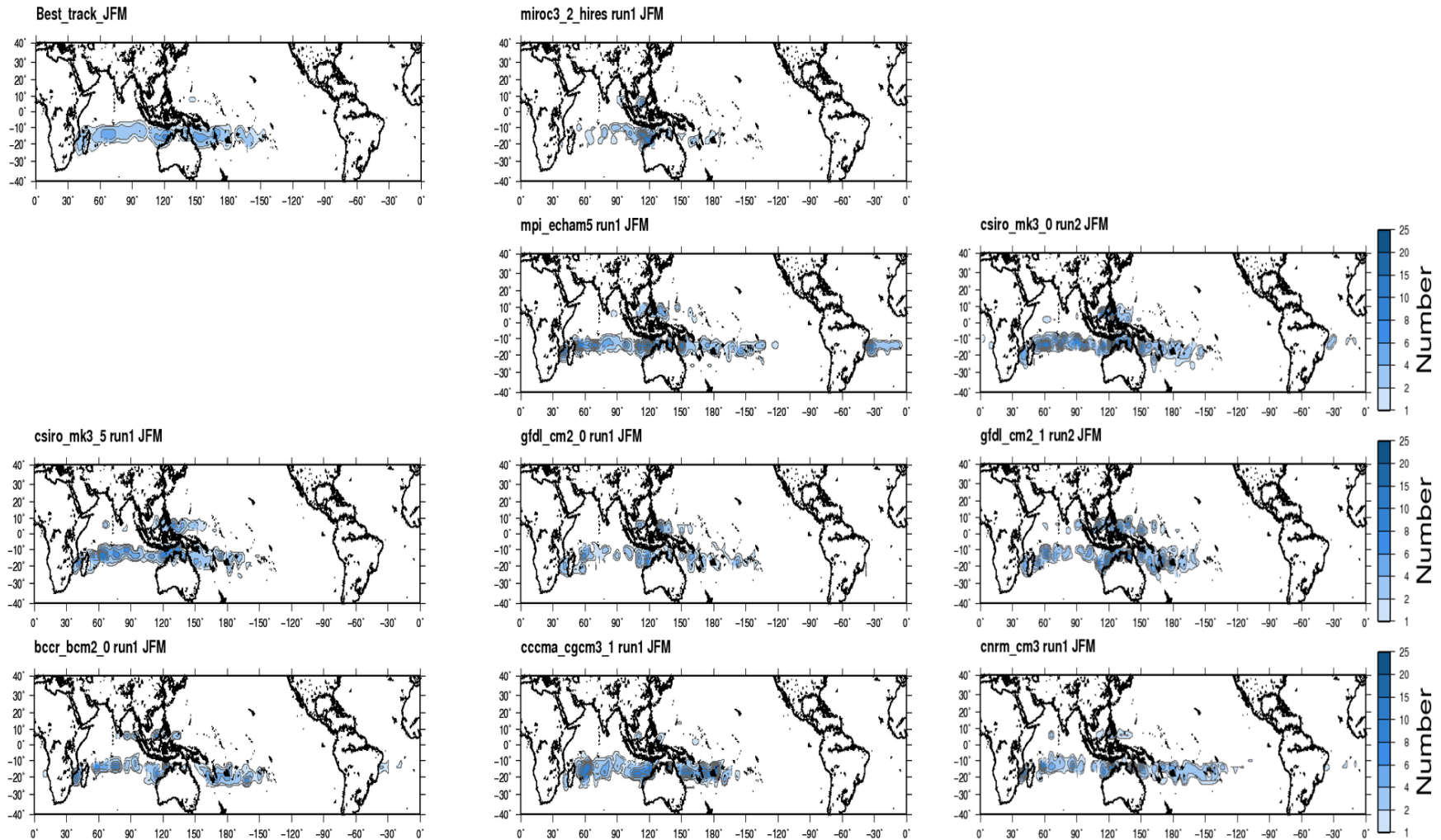


Figure 5. Tropical cyclone genesis for higher-resolution models (January-March), same units as Fig. 2, for iBTracs best track data (top left) and model tropical cyclone detections, after the method of Walsh et al. (2007).

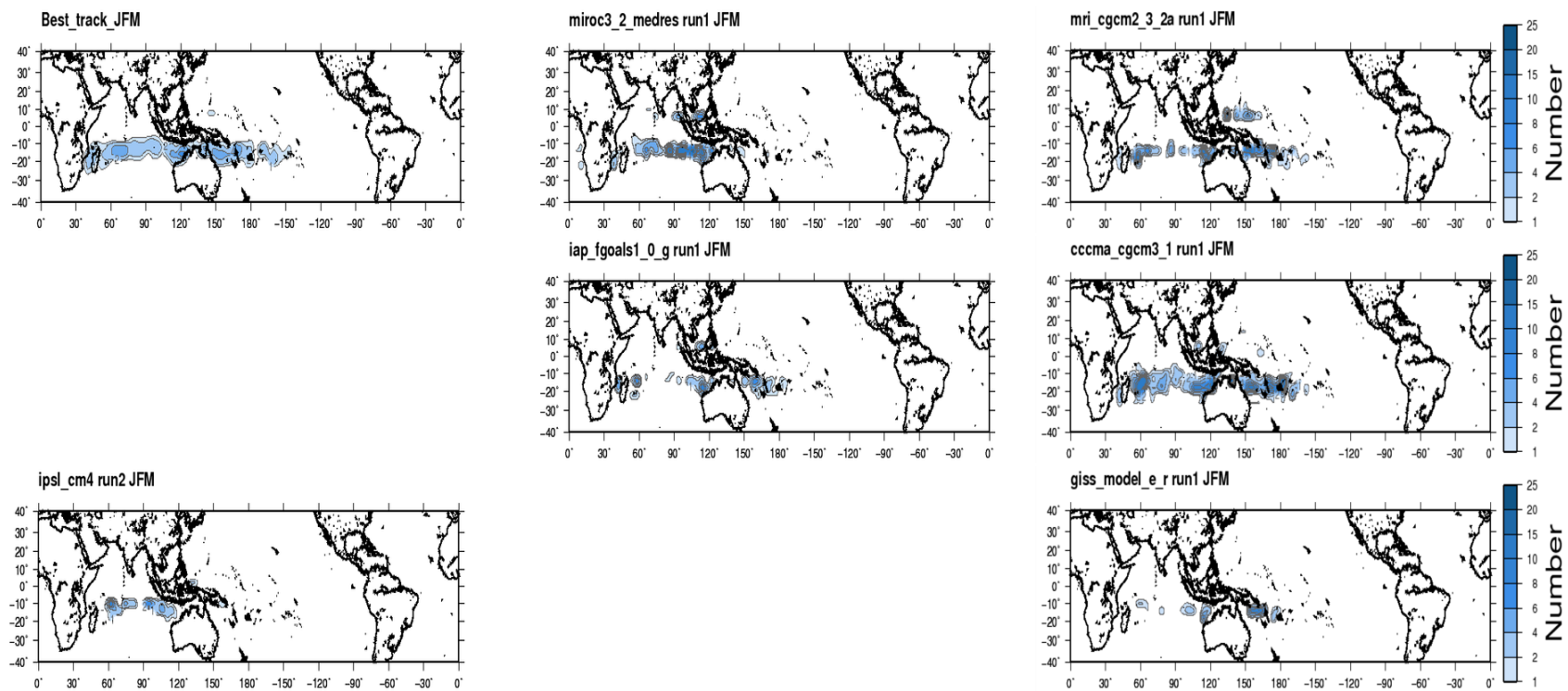


Figure 6: The same as Fig. 5 for lower-resolution models.

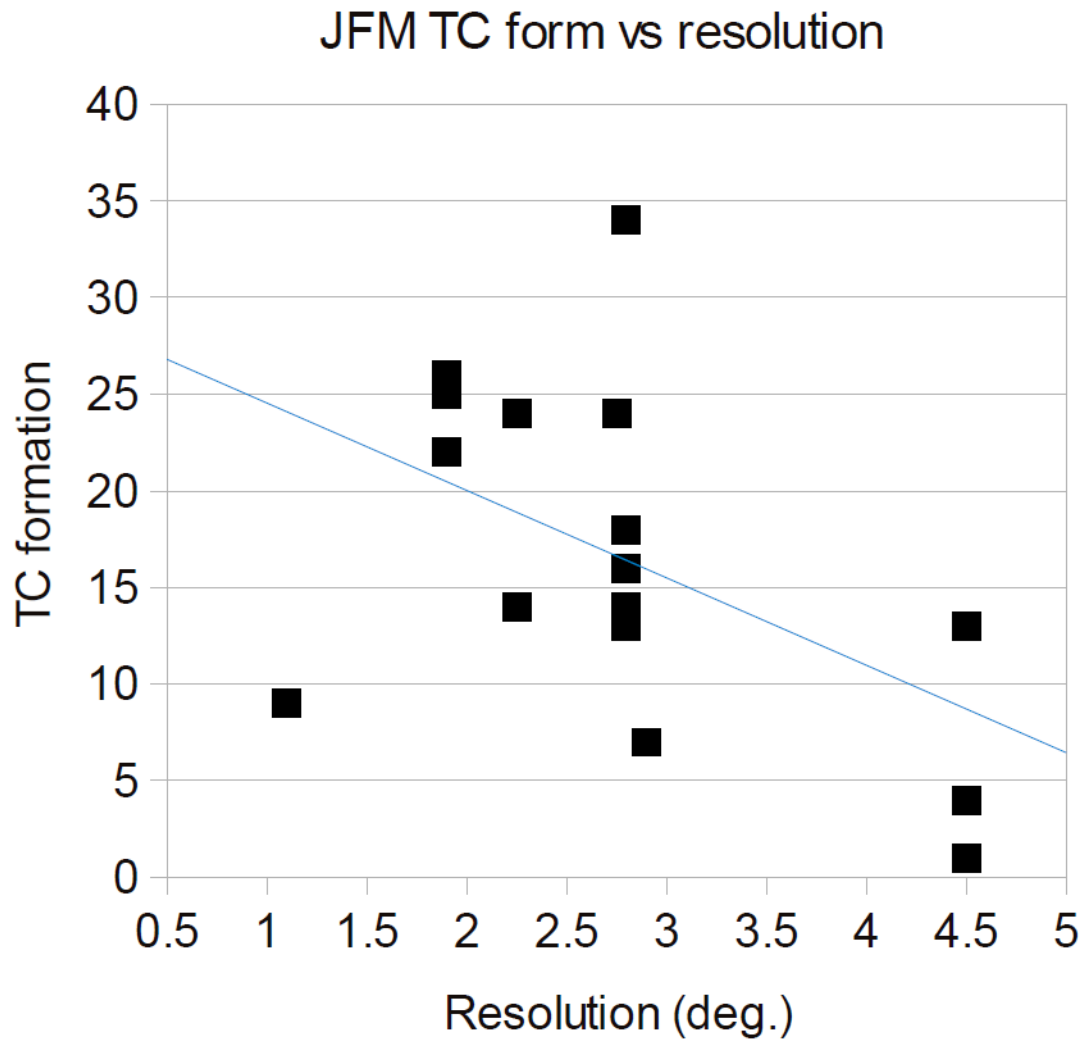
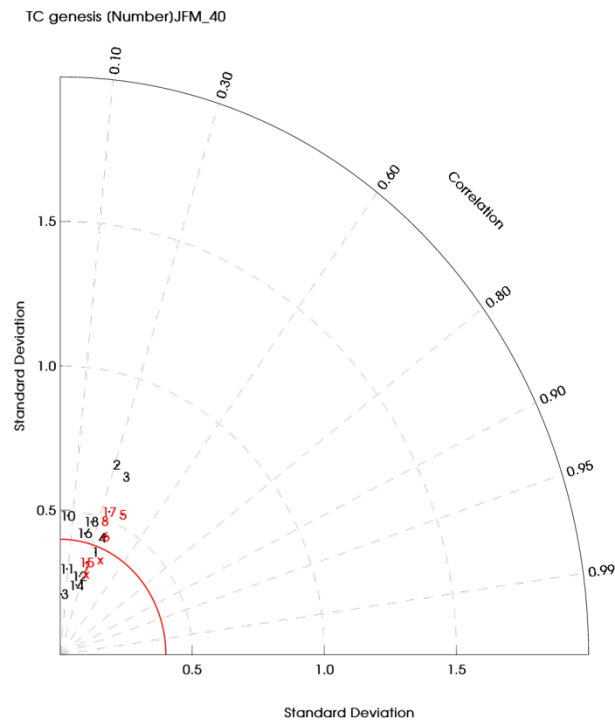


Figure 7: JFM simulated TC formation for CMIP3 models versus resolution. A line of best fit is included.

## JFM



## JAS

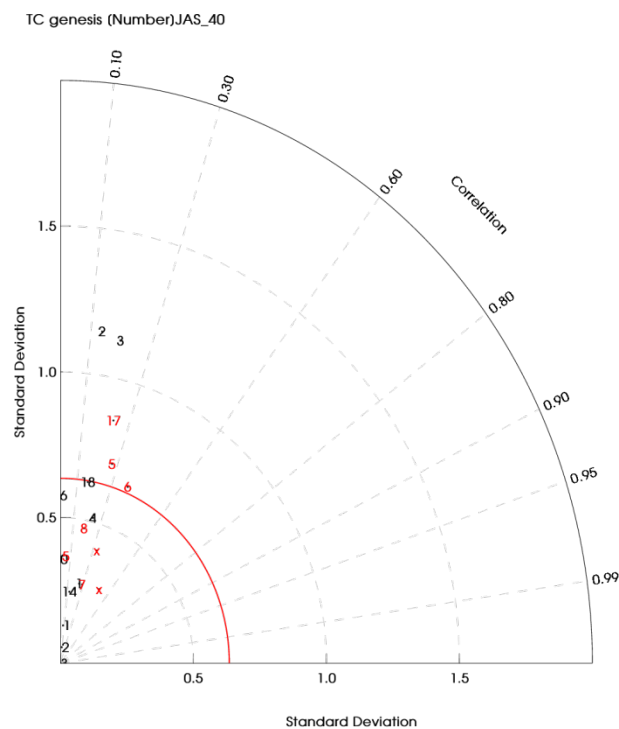


Figure 8. Taylor diagram for tropical cyclone formation versus best track data corresponding to the models shown in Figs. 5 and 6: (top) JFM and (bottom) JAS. Higher-resolution CMIP3 models are indicated in red. Two finer-resolution recent models are indicated with a red x.

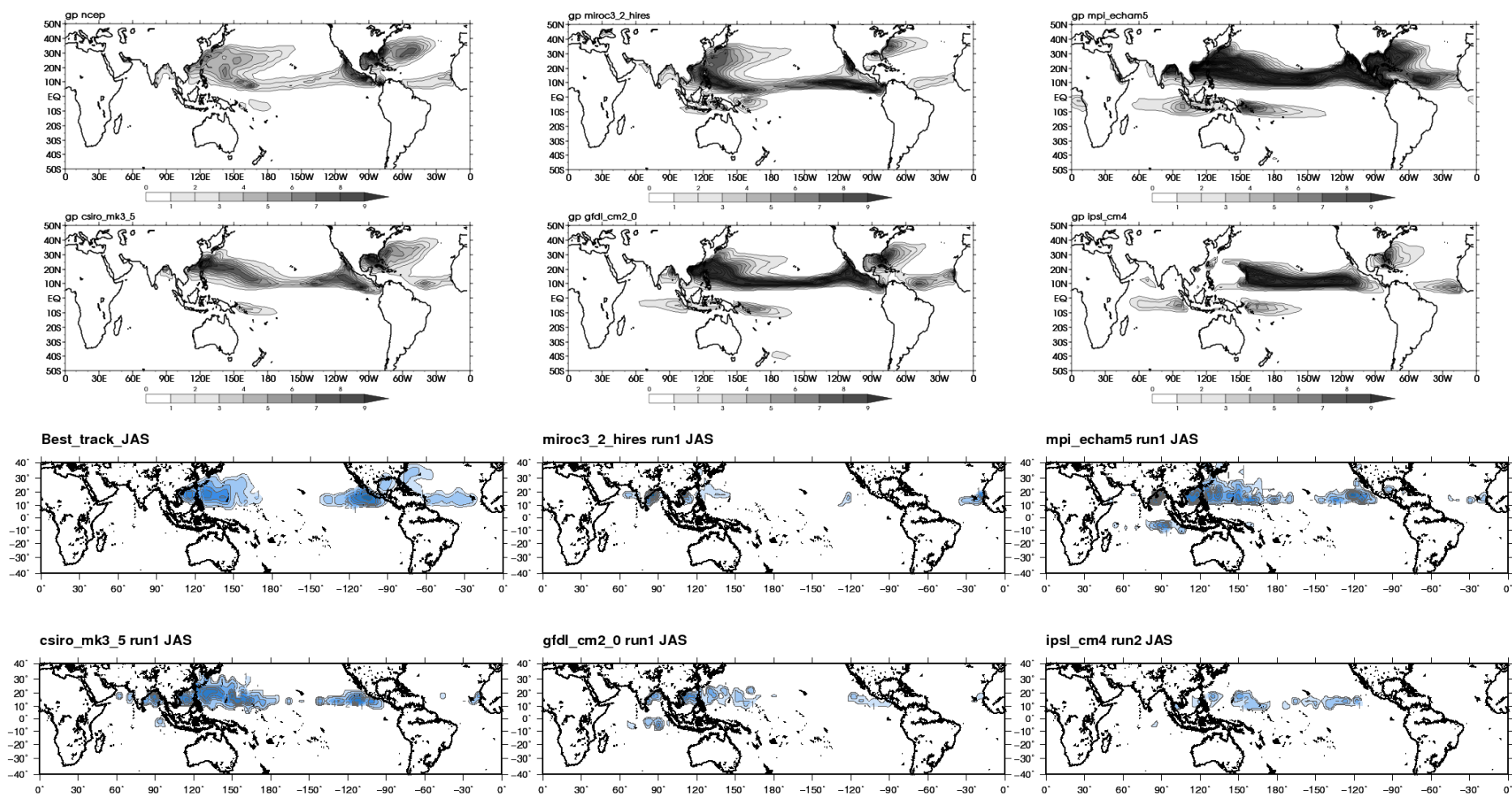


Figure 9. The same as Figure 2 for July-September (upper two rows), for selected fine and coarse-resolution models, including a comparison to model cyclone formation rates (lower two rows).

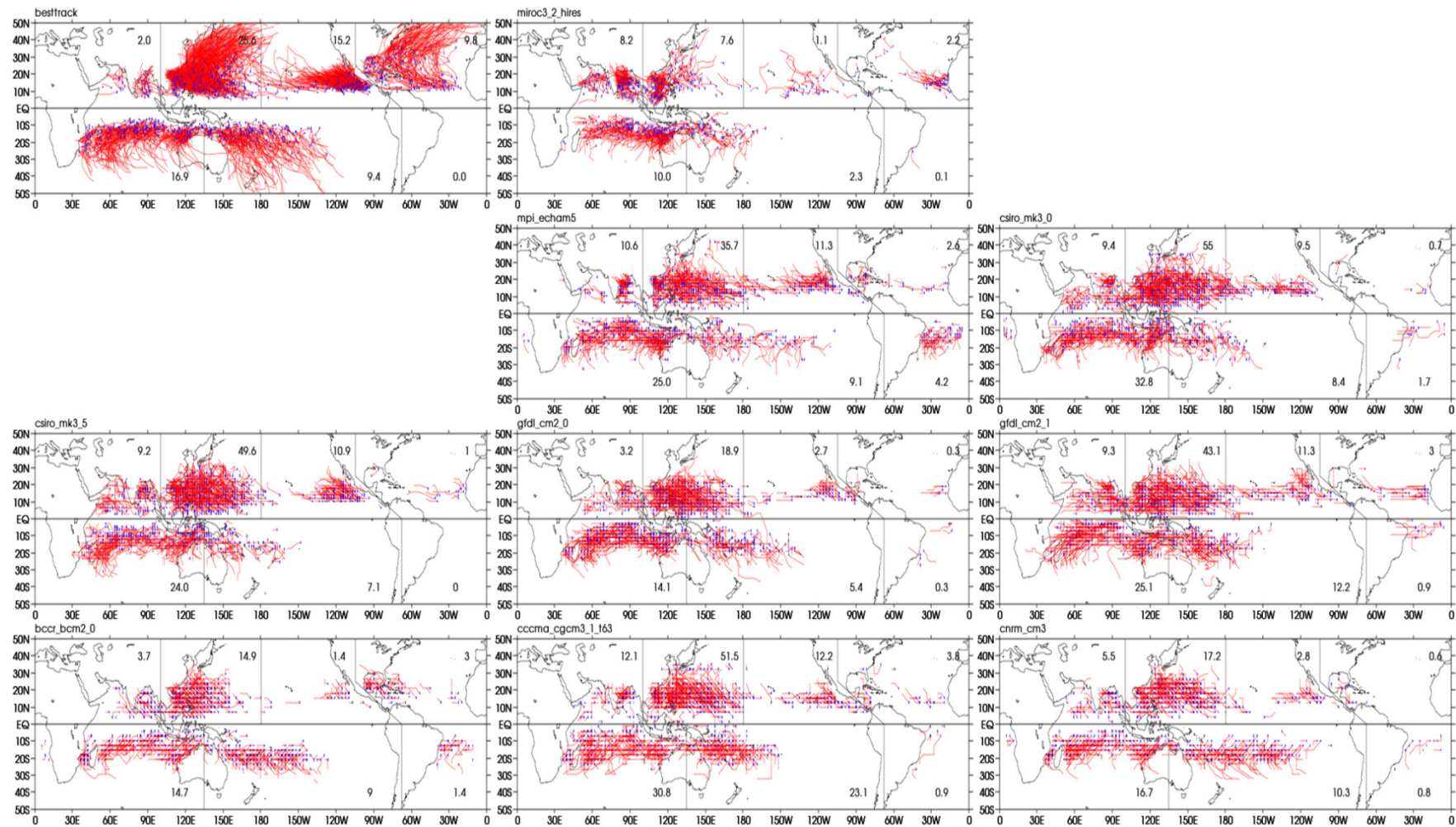


Figure 10: Annual tropical cyclone tracks for finer-resolution models. Observed and model-simulated formation rates for each basin are also given.

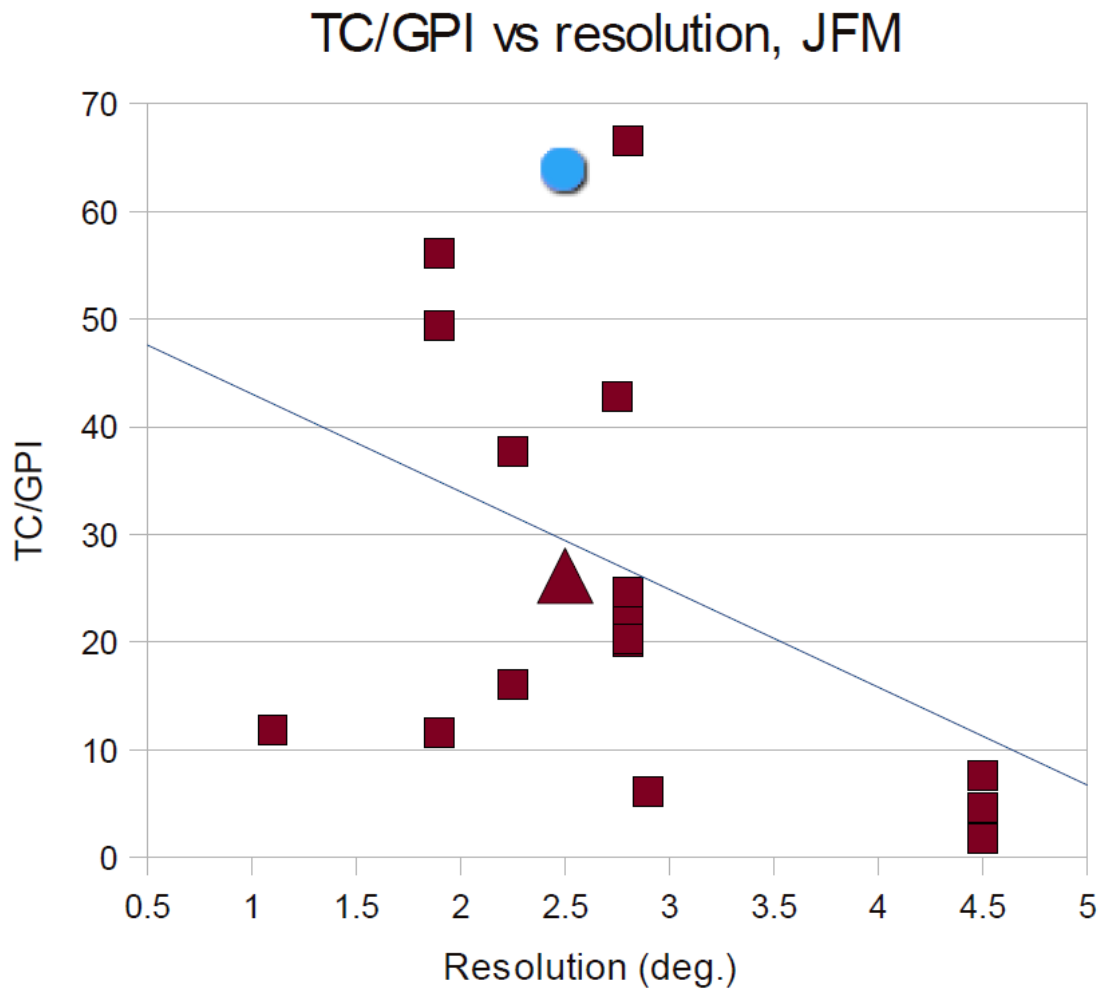


Figure 11. Cyclone formation rate normalized by GPI, as a function of resolution, for JFM. Included also is the same quantity for the best track values divided by the NCEP2 reanalyses-derived GP (circle) and by the ERA40 reanalyses-derived GP (triangle).

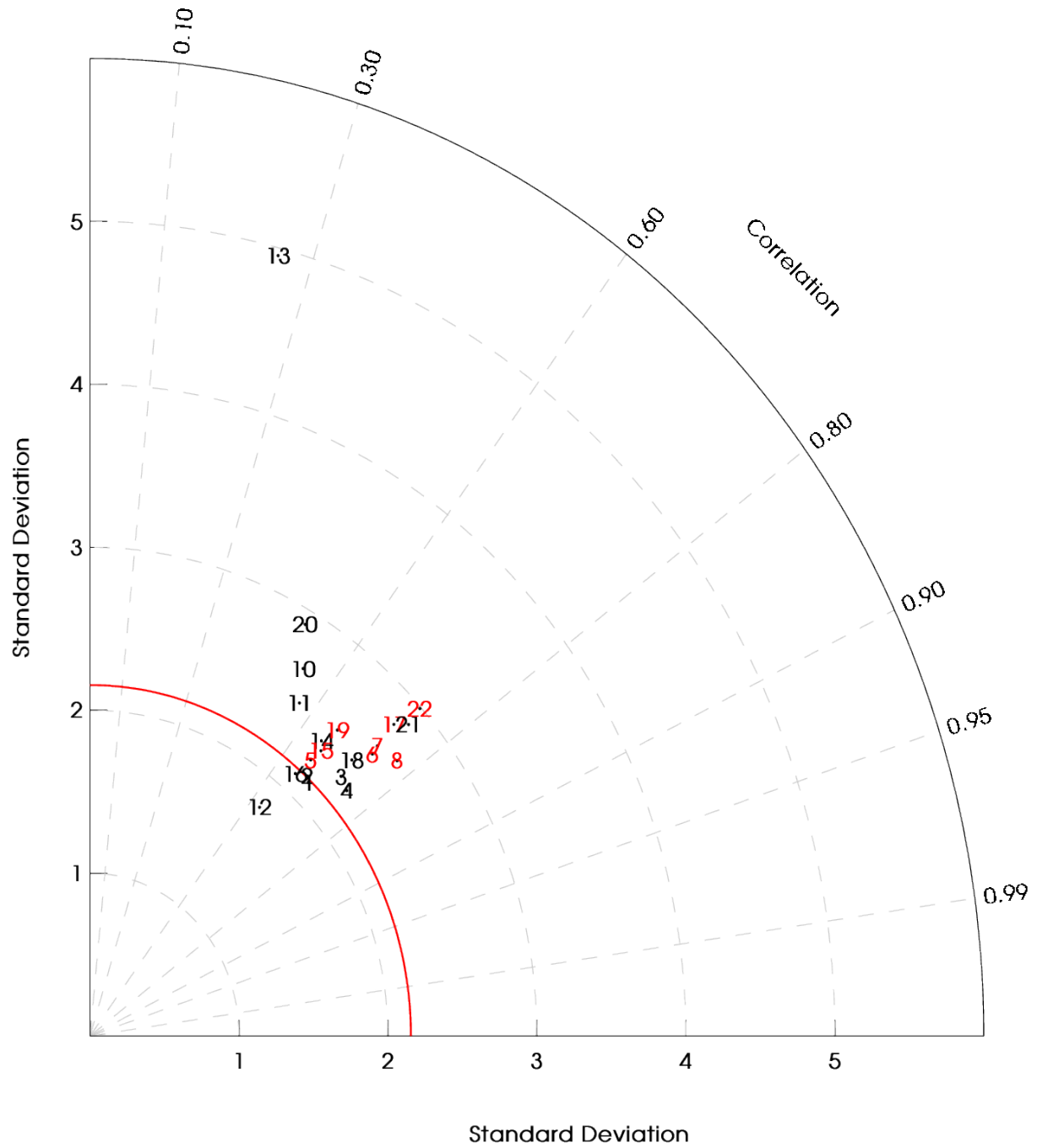


Figure 12. Taylor diagram for JAS total precipitation.



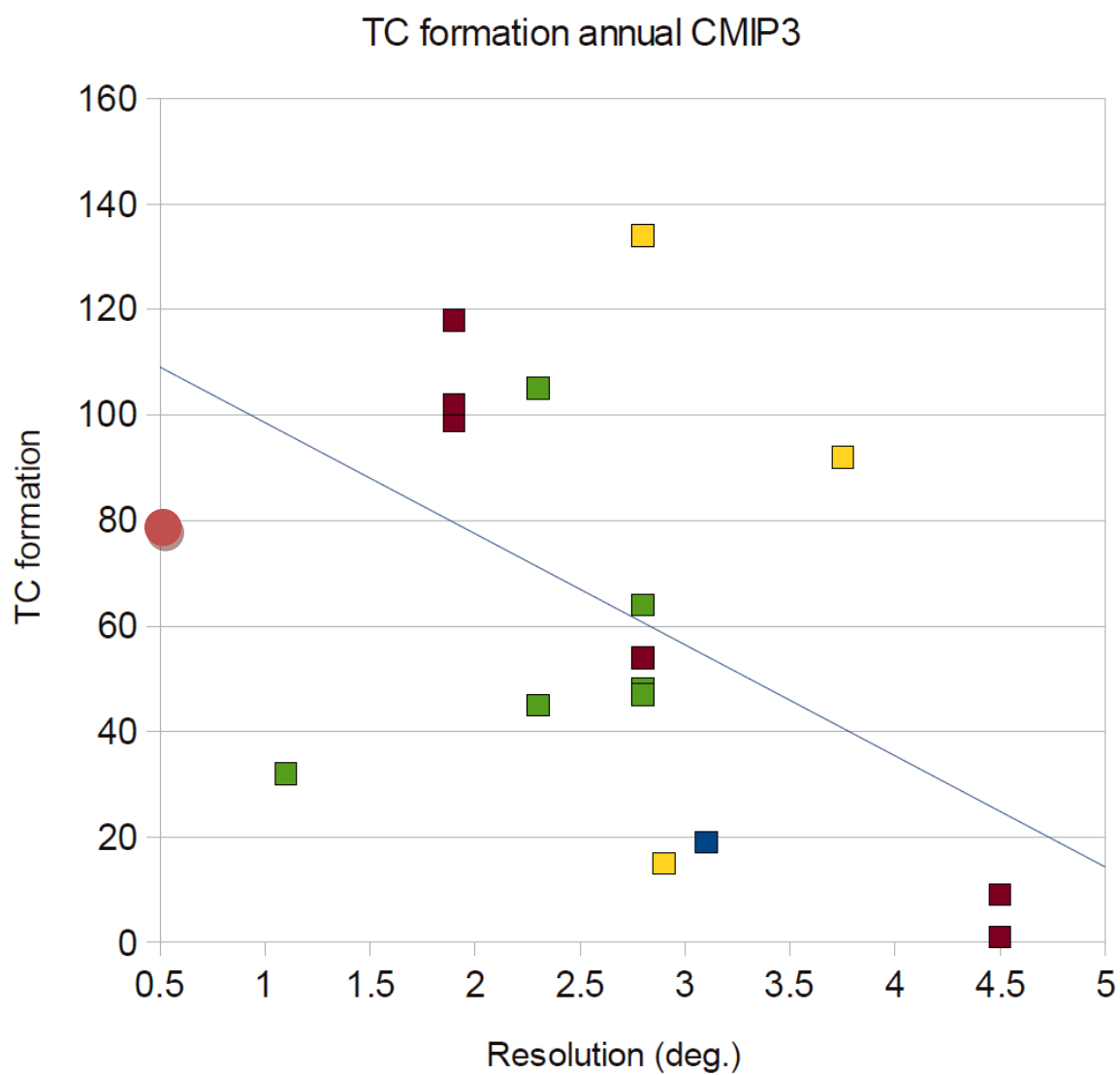


Figure 13. CMIP3 model resolution (in degrees of latitude) versus diagnosed model TC genesis, with the detection threshold adjusted for resolution.

Observed annual formation is shown by the red circle; green are models that employ versions of the Arakawa-Schubert convection scheme; yellow are

models that use the Zhang-McFarlane scheme; brown are models that use mass-flux schemes; and blue are models with other convection schemes.