

Impact of model resolution on tropical cyclone simulation using the HighResMIP-PRIMAVERA multi-model ensemble

Article

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1 **Impact of model resolution on tropical cyclone simulation using the**
2 **HighResMIP-PRIMAVERA multi-model ensemble**

3

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33 **Abstract**

34 A multi-model, multi-resolution set of simulations over the period 1950-2014 using a
35 common forcing protocol from CMIP6 HighResMIP have been completed by six
36 modelling groups. Analysis of tropical cyclone performance using two different
37 tracking algorithms suggests that enhanced resolution towards 25 km typically leads
38 to more frequent and stronger tropical cyclones, together with improvements in
39 spatial distribution and storm structure. Both of these factors reduce typical GCM
40 biases seen at lower resolution.

41 Using single ensemble members of each model, there is little evidence of systematic
42 improvement in interannual variability in either storm frequency or Accumulated
43 Cyclone Energy compared to observations when resolution is increased. Changes in
44 the relationships between large-scale drivers of climate variability and tropical
45 cyclone variability in the Atlantic are also not robust to model resolution.

46 However using a larger ensemble of simulations (of up to 14 members) with one
47 model at different resolutions does show evidence of increased skill at higher
48 resolution. The ensemble mean correlation of Atlantic interannual tropical cyclone
49 variability increases from ~0.5 to ~0.65 when resolution increases from 250 km to
50 100 km. In the North West Pacific the skill keeps increasing with 50 km resolution to
51 0.7. These calculations also suggest that more than six members are required to
52 adequately distinguish the impact of resolution within the forced signal from the
53 weather noise.

54

55 **1. Introduction**

56 Tropical cyclone impacts globally are important for life and economies, being the
57 largest driver of losses among natural hazards (Landsea, 2000; Aon Benfield, 2018).
58 They also contribute significantly to regional seasonal rainfall totals (Jiang et al.
59 2010; Scoccimarro et al. 2014; Guo et al. 2017; Franco-Diaz et al. 2019) and hence
60 form an important part of the mean climate. In order to achieve improved forecasts,
61 risk assessment and projections of future changes of tropical cyclones, better
62 understanding of the drivers of interannual variability, and hence potential future
63 changes in frequency or intensity, are key. Such understanding can only come from
64 a combination of observations and modelling.

65 Previous assessments of tropical cyclone performance within global multi-model
66 simulation comparisons have been hampered by a variety of factors (Camargo and
67 Wing, 2016). Use of models from the Coupled Model Intercomparison Projects
68 (CMIP3 and CMIP5; Walsh et al. 2013; Camargo et al. 2013) typically implies that
69 model grid spacing is greatly restricted, typically to coarser than 100 km, and often
70 considerably coarser, when effective resolution determined from the kinetic energy
71 spectrum is considered (Klaver et al. 2019). This has consequences for both the
72 model mean state and tropical cyclone characteristics. Specific projects such as the
73 Tropical Cyclone-Model Intercomparison Project (TC-MIP; Walsh et al. 2011) and
74 the US Climate and Ocean: Variability, Predictability and Change (CLIVAR)
75 Hurricane Working Group (Walsh et al. 2014) have investigated higher resolutions,
76 but the simulations (and tracking algorithms) were not designed to be uniform and
77 hence the results can be difficult to interpret (Camargo et al. 2013; Shaevitz et al.
78 2014; Nakamura et al. 2017). There is also a need for multiple ensemble members in

79 order to separate the forced signal from the weather noise (e.g. Zhao et al. 2009;
80 Roberts et al. 2015; Mei et al. 2019).

81 There have also been many studies of the impact of horizontal resolution on tropical
82 cyclones (Zhao et al. 2009; Manganello et al. 2012; Wehner et al. 2014; Kodama et
83 al. 2015; Murakami et al. 2015; Roberts et al. 2015; Yoshida et al. 2017; Chauvin et
84 al. 2019). These mainly used individual climate models, but due to differences in
85 experimental design, tracking algorithm, model parameters and other factors it can
86 be difficult to understand how generally applicable the results are likely to be for
87 other models.

88 The CMIP6 High Resolution Model Intercomparison Project (HighResMIP; Haarsma
89 et al. 2016), in a new experimental design for CMIP6 (Eyring et al, 2016), that
90 provides a common protocol for a multi-model, multi-resolution ensemble. Some
91 aspects of the simulation have been deliberately simplified (for example aerosol
92 effects are imposed via specified optical properties), so that a comparison of model
93 performance is made more manageable. This protocol extends the period of
94 atmosphere-only simulations to 1950-2014 (compared to the standard CMIP6 period
95 of 1979-2014; Eyring et al. 2016), in order to assess a longer period of variability and
96 drivers of change and increase the tropical cyclone (TC) sample sizes for
97 climatology.

98 The European Union Horizon 2020 project PRIMAVERA has six different
99 contributing global atmospheric models, each run using the HighResMIP protocol at
100 both a standard CMIP6-type resolution (typically 100 km) and at a significantly higher
101 resolution (towards 25 km), to investigate the impact this has on the simulation of
102 climate variability and extremes, including tropical cyclones. It is a unique opportunity

103 to understand the robustness of such changes across a range of models and
104 resolutions. Two tracking algorithms—TRACK (Hodges et al. 2017) and
105 TempestExtremes (Ullrich and Zarzycki 2017; Zarzycki and Ullrich 2017)—have
106 been applied uniformly across all models and reanalyses to provide an indication in
107 the uncertainties in the TC identification.

108 The key science questions addressed in this study are:

- 109 1. Are there robust impacts of higher resolution on explicit tropical cyclone
110 simulation across the multi-model ensemble using different tracking
111 algorithms?
- 112 2. What are the possible processes responsible for any changes with resolution?
- 113 3. How many ensemble members are needed to assess the skill in the
114 interannual variability of tropical cyclones?

115 In section 2 we describe the models, forcing and reanalysis datasets used in this
116 study, together with the tracking algorithms and other datasets. In section 3 we
117 describe our multi-model, multi-resolution assessment of tropical cyclone
118 performance, both as a global overview and then with focus on the North Atlantic.
119 Here we also describe the impact of a larger ensemble size and the impact on skill
120 for interannual variability. In section 4 we discuss the implications of our results and
121 future work.

122

123 **2. Model description, forcing, datasets and tracking algorithms**

124 Six PRIMAVERA modelling groups have configured global models at (at least) two
125 horizontal resolutions and completed the Tier 1 CMIP6 HighResMIP atmosphere-
126 only simulations (Haarsma et al. 2016) for 1950-2014. The models and resolutions
127 are detailed in Table 1, including the ratio of the lower to higher grid spacing at the
128 equator (Table 2). The effective resolution of the models (relating to the kinetic
129 energy spectra) is described in Klaver et al. (2019) and is also included. Further
130 HighResMIP experiments (Tier 2 coupled simulations and Tier 3 future projections)
131 have also been completed, but the analysis of these is outside the scope of this
132 work.

133 Detailed documentation on all models can be found in the following references, and is
134 briefly summarised in Appendix A: ECMWF-IFS, Roberts et al. (2018); CMCC-CM2,
135 Cherchi et al. (2019); CNRM-CM6, Voldoire et al. (2019); MPI-ESM1-2, Gutjahr et al.
136 (2019); EC-Earth3P, Haarsma et al. (2019); HadGEM3-GC3.1, Vidale et al. (in prep)
137 and Roberts et al. (2019a). The HighResMIP protocol recommends minimal changes
138 in model parameters between low and high resolution simulations in order that
139 differences caused by resolution alone are emphasised. Table 3 describes all the
140 model parameters that are explicitly changed with resolution.

141 The inclusion of stochastic physics schemes, which attempt to represent the
142 dynamical aspects of sub-grid scale processes, is becoming common for weather
143 and seasonal forecasting (Palmer et al. 2009; MacLachlan et al. 2015; Walters et al.
144 2019), and is now being included in some global climate models (Batté and Doblus-
145 Reyes, 2015; Walters et al. 2019). Amongst the models used in this study, only the
146 HadGEM3-GC31 and ECMWF-IFS contain such schemes. The influence of these
147 schemes is designed to automatically decrease as model resolution becomes finer

148 (i.e. by self-tuning rather than explicit parameter change, Sanchez et al. 2016), and
149 hence needs to be considered when assessing “model resolution” impacts.
150 Stochastic schemes have been shown to increase tropical cyclone mean frequency
151 by up to 30% at some resolutions in multiple models (e.g. Met Office and ECMWF
152 models; Vidale et al., in prep), at least partly via moistening the tropical environment
153 in the regions where the TCs have genesis (Watson et al. 2017).

154 All the models use an atmospheric initial condition at 1950 from the ECMWF
155 Reanalysis of the 20th Century (ERA-20C; Poli et al. 2016). Components of the land
156 surface with longer memory (such as soil temperature and moisture) are initialised
157 differently by each group – however, since the focus here is on the later 1979-2014
158 period of the simulations, this should have minimal impact on the results.

159 a. Forcing

160 The HighResMIP experimental design has been followed for the forcing datasets
161 (Haarsma et al. 2016), including using simplified aerosol optical properties apart from
162 one model (see below). These optical properties are a combination of a model
163 constant background natural aerosol (typically diagnosed from a pre-industrially-
164 forced simulation), together with time-varying volcanic and anthropogenic aerosol
165 from the Max Planck Institute Aerosol Climatology version 2 (MACv2-SP; Stevens et
166 al. 2015) scheme. The latter uses sulphate aerosol patterns to scale the aerosol
167 forcing magnitude over time. Note that this forcing by design excludes natural
168 aerosol (including dust) variability and hence the simulations do not explicitly account
169 for any variability driven by such forcing (Reed et al. 2019), apart from that which is
170 integrated in the SST forcing itself. The exception to this is the CNRM-CM6-1 model,
171 which uses its own aerosol scheme (Voldoire et al. 2019; Chauvin et al. 2019). A

172 comparison of performance between MACv2-SP and prognostic aerosol is included
173 in Vidale et al. (in prep).

174 The sea surface temperature (SST) and sea-ice forcings used in the HighResMIP
175 protocol are based on the daily, $\frac{1}{4}$ degree Hadley Centre Global Sea Ice and Sea
176 Surface Temperature (HadISST.2.2.0; Kennedy et al. 2017) dataset, with area-
177 weighted regridding used to map this to each model grid. Mean differences between
178 this dataset and the standard monthly Program for CLimate Model Diagnosis and
179 Intercomparison (PCMDI) SST used in Atmospheric Model Intercomparison Project
180 (AMIP-II; Taylor et al. 2000) are shown in Vidale et al. (in prep). The CMIP6 (Eyring et
181 al. 2016) historic, time-varying forcings for solar (Matthes et al. 2017), ozone
182 concentration (Hegglin et al. 2016) and greenhouse gases (GHG) (Meinshausen and
183 Vogel 2016) are used. The land surface properties and land use remain constant,
184 representative of the year 2000 using a repeating seasonal cycle.

185 b. Datasets

186 (1) Reanalyses

187 The following reanalysis datasets are used: the European Centre for Medium-
188 Range Weather Forecasts (ECMWF) Interim Re-analysis project (ERA-Interim; Dee
189 et al., 2011; 1979-2014); Fifth Generation ECMWF Reanalysis (ERA5; Copernicus
190 Climate Change Service, 2017; 1979-2014); NASA Modern-Era Retrospective
191 analysis for Research and Applications, Version 2 (MERRA2; Gelaro et al. 2017;
192 1980-2014); National Center for Atmospheric Research - Climate Forecast System
193 Reanalysis (NCAR-CFSR; Saha et al. 2014; 1979-2014); Japanese 55-year
194 Reanalysis (JRA55; Kobayashi et al. 2015; 1959-2014). An overview of the

195 properties of these reanalysis datasets is given in Table 4. Tropical cyclones in these
196 datasets (apart from ERA5) have been compared in Hodges et al. (2017) and
197 Murakami et al. (2014b).

198 (2) Observations

199 Observed tropical cyclone tracks for the North Atlantic and Eastern Pacific basins
200 are obtained from the National Oceanic and Atmospheric Administration (NOAA)
201 National Hurricane Center's best-track Hurricane Database (HURDAT2 (Jan 2018
202 version); Landsea and Franklin, 2013). Observed tropical cyclone data for all
203 remaining basins are obtained from the US Navy's Joint Typhoon Warning Centre
204 (JTWC) best-track database (Chu et al., 2002). We define an observed tropical
205 cyclone as having a 1-min maximum sustained wind speed of 34 kt (17.5 m s^{-1}) or
206 higher, to give a globally-uniform criteria, and we exclude subtropical storms (SS)
207 from observations when they have SS as their officially designated maximum
208 classification. We use these datasets in preference to IBTrACS (Knapp et al. 2010)
209 for the consistency of 1-min averaging periods for all TCs around the world.

210 (3) Models

211 Model simulation output can be obtained via the Earth System Grid Federation
212 (ESGF) nodes from the following: Roberts (HadGEM3-GC31; 2017a, 2017b, 2017c),
213 Roberts et al. (ECMWF-IFS; 2017a, 2017b), Voldoire (CNRM-CM6-1; 2017, 2018),
214 Scoccimarro et al. (CMCC-CM2-(V)HR4; 2017a, 2017b), EC-Earth Consortium (EC-
215 Earth3P; 2018a, 2018b), von Storch et al. (MPI-ESM1-2; 2017, 2019). The storm
216 tracks derived from these datasets and analysed here are available from Roberts
217 (2019b, 2019c).

218 c. Analysis information

219 The analysis presented here focuses on the 1979-2014 period due to both the
220 satellite observations providing a more homogeneous observational reference
221 dataset, and the availability of multiple reanalysis datasets for validation.

222 The Accumulated Cyclone Energy (ACE) index (Bell et al. 2000) is an integrated
223 measure of tropical cyclone activity, and is calculated for model and observed
224 tropical cyclones using the same method as Camp et al. (2015). For observed
225 tropical cyclones, ACE is the sum of the square of the maximum sustained 10 m
226 wind speed every 6 hours whilst the cyclone is at least tropical storm strength (34
227 kts; 17.5 m s^{-1}). For model and reanalysis tropical cyclones, the wind speeds are
228 lower than observed (Williams et al. 2015), and therefore the wind speed threshold is
229 removed entirely, and instead we calculate ACE throughout the lifetime of the storm
230 during its warm core phase using winds at 925 hPa to better compare the seasonal
231 cycle and interannual variability with observations (henceforth ACE_{925}), as in Camp
232 et al. (2015). The ACE metric has been found to be a more robust measure for
233 interannual variability than simple storm counts (e.g. Villarini and Vecchi, 2012;
234 Scoccimarro et al. 2018), partly because it may reduce the impact of observational
235 methods and short-lived storms (Landsea 2010).

236 In general, models at the resolutions shown here are not able to represent very
237 intense wind speeds (see Davis (2018) for theoretical/numerical limits), but are more
238 able to generate strong minima in surface pressure (Manganello et al. 2012). Hence
239 in order to better stratify the model storms by intensity, we use a surface pressure

240 scale for the model intensity, rather than wind speed (Caron and Jones 2012;
241 Roberts et al. 2015). The categories are defined in Table 5.

242 d. Tracking algorithms (trackers)

243 The tropical cyclones are diagnosed from models and reanalyses using two feature
244 tracking algorithms (henceforth trackers): TRACK (Hodges et al. 2017) and
245 TempestExtremes (Ullrich and Zarzycki 2017; Zarzycki and Ullrich 2017). These are
246 described in detail in Appendix B, and briefly summarised here. TRACK is based on
247 tracking vorticity features on a common T63 spectral grid with criteria for warm-core
248 and lifetime. TempestExtremes tracks features using sea level pressure on the
249 model grid, with criteria for warm-core and lifetime. Models and reanalyses are all
250 tracked in the same way with the same parameters - for both trackers, the parameter
251 choices are primarily derived from comparing tracked reanalysis datasets and
252 observations (Hodges et al. 2017; Zarzycki et al. 2017), although with differing
253 emphasis (Appendix B). One notable difference between the application of the
254 trackers is the dependence on the model grid - TRACK transforms each model
255 output to a common T63 grid for tracking, while TempestExtremes operates on the
256 native model grid. No wind speed thresholds are applied to either tracker. A more
257 detailed comparison between several trackers to better understand the cause of the
258 differences, including using application of classification schemes to the systems
259 (McTaggart-Cowan et al. 2013; Yanase et al. 2014), is ongoing (Roberts et al. in
260 prep).

261 We chose to use two trackers in order to obtain complementary viewpoints of model
262 performance. We expect results to depend on the details of each trackers' criteria, as
263 is found in other feature tracking comparisons, for example Horn et al. (2014) for

264 TCs, Neu et al. (2013) for extra-tropical cyclones and Shields et al. (2018) for
265 atmospheric rivers. In cases where both trackers broadly agree, we can be more
266 confident that our conclusions are not dependent on tracker details.

267 **3. Results**

268 *a. Global TC activity and track density*

269 Realistic simulation of the frequency and spatial distribution of tracks of tropical
270 cyclones is an important prerequisite for understanding the risk of landfall and
271 climate impacts, as well as for potential changes in regional mean precipitation.

272 A simple initial assessment of TC frequency from models, reanalyses and
273 observations is shown in Figs. 1,2, illustrating the total number of storms in the
274 northern and southern hemispheres (NH, SH) and the distribution in each NH ocean
275 basin. It is informative to show this using two different trackers since there are
276 several aspects that might be misinterpreted when just a single tracker is used. With
277 TRACK (Fig. 1) there is a distinct increase in TC frequency with resolution for
278 HadGEM3-GC31, CMCC-CM2-(V)HR4 and EC-Earth3P models, while all models
279 and reanalyses typically have a smaller asymmetry of NH:SH TCs than is seen in the
280 observations. The proportions of storms in each ocean basin agree reasonably well
281 with observations, though for most models the relative frequency in the North Atlantic
282 is less than observed while in the North Indian it is more. The overall NH TC
283 frequency for the high resolution models typically approaches or exceeds that
284 observed.

285 Using TempestExtremes (Fig. 2) a somewhat different picture emerges compared to
286 the above. Now there are only two models (HadGEM3-GC31 and CNRM-CM6-1)

287 which have NH frequencies approaching or exceeding the observed. There is now a
288 more systematic increase in TC frequency with resolution, and the hemispheric
289 asymmetry is more consistent with that observed.

290 Several conclusions can be drawn from this simple comparison of models and
291 trackers. Great care is needed when interpreting absolute TC frequency from a
292 single tracker, since this will depend on many factors, including the tracker criteria
293 and analysis grid. Features such as the hemispheric asymmetry could lead to the
294 conclusion that the models produce too many SH TCs, but at least in part this seems
295 to depend on how such storms are initially characterised (by vorticity or sea level
296 pressure); observational issues could also contribute to the difference between
297 models and observations, for example because SH tropical depressions and sub-
298 tropical cyclones are not included in Best Track data whereas they are in the NH
299 (Strachan et al. 2013; Hodges et al. 2017).

300 Evaluation of the models' ability to simulate the spatial distribution of tropical cyclone
301 tracks globally is shown in Fig. 3. This shows track density derived from TRACK and
302 observations, defined by the mean number of tracks per month through a 4° cap at
303 each point during May-November in the NH and November-May in the SH on a
304 common grid. For each pair of plots, the bias in the higher resolution model is shown
305 first, followed by the difference between higher and lower resolution model.

306 Key aspects include:

- 307 • Most models show a reduction in the negative density bias in the North
308 Atlantic, North Western and Eastern Pacific when resolution is increased;

- 309 • Many models have an excess of activity in the Southern Hemisphere,
310 including in the South Atlantic, which is enhanced at higher resolution, as
311 discussed above;
- 312 • There is a common negative bias in the Western Pacific which would indicate
313 a lack of simulated TCs making landfall in the Philippines and Southern
314 China;
- 315 • Two models (HadGEM3-GC31 and CMCC-CM2-(V)HR4, both grid point
316 models) show a larger change with resolution, including: a positive bias near
317 the equator extending across the Pacific which is enhanced at higher
318 resolution, and larger positive biases extending into the mid-latitudes;
- 319 • The MPI-ESM1-2 model has very few TCs in any basin.

320 Results from TempestExtremes (not shown) have similar biases to Fig. 3, with
321 slightly larger negative biases in the tropics and reduced positive biases in the extra-
322 tropics, consistent with the lower frequencies shown in Figs. 1, 2. The resolution
323 differences are also similar, enhanced in HadGEM3-GC31 and CNRM-CM6-1 where
324 the lower resolution has fewer TCs, and hence the key aspects are common to both
325 trackers apart from the Southern Hemisphere activity.

326 The models tend to fall into groups of responses. The HadGEM3-GC31 and CMCC-
327 CM2-(V)HR4 models show similar biases and differences with resolution, as do the
328 EC-Earth3P and ECMWF models. The latter is probably unsurprising given the
329 common basis of their dynamical cores, while the former are the only grid point
330 models.

331 A summary of the impact of horizontal resolution on the TC spatial distribution is
332 shown in Fig. 4, using the warm core segments of the cyclone tracks only. The multi-
333 model ensemble mean resolution difference (top) and Root Mean Square Error
334 (RMSE) difference compared to the observed track density (bottom) are shown for
335 both TRACK and TempestExtremes. Both trackers have very consistent increases in
336 track density with higher horizontal resolution, and this leads to decreases in RMSE
337 of more than 50% in the North Atlantic, Eastern and North Western Pacific and the
338 Southern Indian and Australian regions (blue regions in Fig. 4 (c,d)).

339 There is a slight southwards shift of activity in the Eastern Pacific at higher resolution
340 with the TRACK tracker, which causes a larger error, and the positive error towards
341 the mid-latitudes is more evident when using TRACK than TempestExtremes,
342 consistent with the longer tracks as seen in the track densities in Fig. 3.

343 In summary, enhanced horizontal resolution generally reduces some typical TC
344 biases found in CMIP-class models, and the relative improvements are consistent
345 across two trackers. Biases remain in the southern sector of the North Western
346 Pacific at high resolution which will impact on TC landfall statistics there. The North
347 Atlantic remains a challenging region to simulate (Camargo et al. 2013), perhaps
348 partly due to low rates of intensification (see later and Manganello et al. 2012) as
349 well as sensitivity to model physics (Bruyère et al. 2017; Chauvin et al. 2019), though
350 the low biases are generally improved at higher resolution. Ongoing work suggests
351 that one reason for increased TC frequency in all basins with higher horizontal
352 resolution is a higher conversion rate of pre-TC “seeds” into TCs (Vecchi et al.
353 2019).

354 *b. Tropical cyclone intensity*

355 Many recent studies have indicated that although changes in aspects of future
356 tropical cyclone climatology are uncertain, it is likely that strong storms could
357 become stronger due to increased energy availability (in the form of increasing SSTs
358 and column water vapour; Walsh et al. 2016). Elsner et al. (2008) suggest there is
359 already evidence for this in the historic record, while Kossin et al. (2014) suggest an
360 observed poleward shift to the latitude of maximum intensity, though the uniformity of
361 the observational record is questionable (Barcikowska et al. 2012; Ren 2011).
362 However, modelling such changes is challenging for multi-decadal global climate
363 simulations, in which the horizontal resolution is such that few models can simulate
364 strong (Cat4/5) hurricanes, particularly in terms of surface wind speeds (Murakami et
365 al. 2012; Murakami et al. 2015; Wehner et al. 2014). Without this capability, drawing
366 conclusions on changing intensities determined by wind speed is somewhat
367 questionable, and hence here we focus on minimum surface pressure instead.

368 Figs. 5 shows the intensity scatter and best fit (maximum 10 m wind speed vs
369 minimum MSLP at peak storm intensity) for models, reanalyses and observations,
370 for the North Atlantic, North Western and Eastern Pacific basins respectively. In each
371 basin there is a systematic shift of the model intensities to higher values as
372 resolution is increased (moving from dashed to solid lines) which is as expected; all
373 the models struggle to achieve storm intensities much greater than Cat 2-3 using 10
374 m wind speeds apart from the CNRM-CM6-1-HR model. This model is an outlier,
375 matching observations extremely closely in the Atlantic and somewhat
376 overestimating them in the NW Pacific.

377 Such strong wind speeds are beyond the expected capability of the resolved
378 dynamics of a model at this resolution according to Davis (2018). The TC intensities

379 in CNRM-CM6-1-HR are also quite different from the previous CNRM-CM5-1 model
380 (Voldoire et al. 2012). Understanding how this model is able to generate such strong
381 TCs is the subject of an ongoing study (Chauvin et al., 2019; Chauvin et al. in prep),
382 but preliminary results suggest that the new CBR turbulence scheme (Cuxart et al.
383 2000) and the coefficients therein play an important role in enhancing the TC
384 strength via convection. This could be viewed as either a parameterisation of an
385 unresolved process, or as an outcome of parameter choices and hence perhaps as
386 the right result for the wrong reason.

387 The models are able to capture the difference in storm intensities in each basin, with
388 more frequent stronger storms in the NW Pacific and North Atlantic and typically
389 weaker storms in the Eastern Pacific. It is also evident here that the reanalyses also
390 struggle to sample the more intense TC activity.

391 It should be noted that TC intensity is artificially higher in these SST-forced
392 simulations, and it has been shown that interaction with the ocean (i.e. the TC-ocean
393 negative feedback) plays a pivotal role in reducing it (Zarzycki 2016; Scoccimarro et
394 al. 2017). Hence coupled model simulations are likely to produce weaker TCs.

395 In order to examine where the TCs have their peak intensity, Fig. 6 shows the joint
396 pdf of the mean sea level pressure (MSLP) and latitude of tropical cyclones at peak
397 intensity for all the models, reanalyses using TRACK, and observations. The
398 observations indicate that the TCs at their peak tend to be found at latitudes between
399 10-30°N with some weaker storms found further north. The low resolution models
400 cannot capture very low MSLP and hence the MSLP distribution with latitude is more
401 uniform or even with a peak at higher latitudes. This likely reflects lower growth rates
402 and also that at mid-latitudes the model resolution becomes more suitable for the

403 scale of the dynamics. In some of the higher resolution models the low latitude
404 “bulge” is more consistent with the observations, although they still have too much
405 activity at higher latitudes. The equivalent TempestExtremes figure (not shown) is
406 broadly similar, though the density of storms at higher latitudes is reduced due to the
407 shorter tracks.

408 In attempting to understand the behaviour of model storm intensity further, Fig.
409 7(a,b) shows normalised pdfs of winds at both 925 hPa and 10 m from each TC at
410 peak storm intensity for Northern Hemisphere storms. The CMCC-CM2-VHR4 and
411 CNRM-CM6-1 HR models have maximum 925 hPa winds reaching around 80 ms^{-1}
412 (Fig. 7a), while most of the other HR models achieve around 65 ms^{-1} . For 10 m
413 winds, the CNRM-CM6-1 HR model has wind speeds in excess of 60 ms^{-1} , while
414 CMCC-CM2-VHR4 reaches 55 ms^{-1} and other models more typically 40 ms^{-1} . The
415 equivalent figure for TempestExtremes is very similar.

416 This would indicate that, in order for a model to attain Cat4-5 10 m wind speeds, it
417 both requires high winds at 925 hPa, and for that momentum to be efficiently
418 exchanged with the near surface via the boundary layer. More detailed process-level
419 analysis will be required to understand whether this is a well-modelled physical
420 process improvement (perhaps relating to boundary layer, convection or surface
421 drag schemes), or whether they are an indication of marginally resolving grid-scale
422 features.

423 To illustrate that the storms produced in the models do indeed reflect the observed
424 tropical cyclone structure, Fig. 8 shows composite structures of the 10 m tangential
425 wind speeds and MSLP from the low and high resolution model groups and
426 reanalyses, stratified in columns by intensity based on minimum surface pressure.

427 The structures are broadly consistent across models, with the core becoming smaller
428 and more intense at higher resolution as expected. The CNRM-CM6-1 HR and
429 CMCC-CM2-VHR4 models have a larger proportion of storms contributing to the
430 composites at the highest intensity, consistent with the results described above, and
431 hence the more robust composites. Note that for some models and categories, the
432 sample of storms can become very small.

433 In summary, the higher resolution models are able to produce more intense TCs in
434 terms of 10m wind speed and surface pressure. Only the CNRM-CM6-1-HR model is
435 able to simulate above Cat3 10 m wind speeds, and hence these models do not
436 have the capabilities of some other models at around 25 km resolution (Murakami et
437 al. 2012; Murakami et al. 2015; Wehner et al. 2014).

438 *c. North Atlantic mean frequency and seasonal cycle*

439 The May-November mean tropical cyclone frequency in the North Atlantic from
440 models and reanalyses using TRACK and TempestExtremes, and observations,
441 over 1979-2014 (using the longer 1950-2014 period for the models shows only minor
442 differences), is shown in Table 6, together with a breakdown to intensity classes (as
443 measured by minimum SLP during storm lifetime). Common features include:

- 444 ● The frequencies and standard deviations are mostly reduced using
445 TempestExtremes compared to TRACK, as seen previously, and this is
446 mainly due to a reduction in the weaker storms;
- 447 ● All models (apart from HadGEM3-GC31-MM) have standard deviations which
448 are lower than observations and reanalyses; this has implications when

- 449 considering climate risks from interannual-decadal tropical cyclone variability,
450 and is sensitive to tracker;
- 451 ● All the higher resolution models have an increase in storms at higher
452 intensities, with CMCC-CM2-VHR4 and CNRM-CM6-1-HR beginning to reflect
453 similar distributions to the observations and surpassing reanalyses in this
454 respect;
 - 455 ● The CNRM-CM6-1 model has a high frequency even at low resolution using
456 TRACK with little change between resolutions, but many of these are weak
457 storms, and with TempestExtremes the CNRM-CM6-1-LR has much lower
458 frequency;
 - 459 ● Apart from MPI-ESM1-2, all the higher resolution models have mean TRACK
460 TC frequency within the standard deviation of the observations (and the range
461 as represented by the reanalyses datasets).

462 As seen previously, the use of TempestExtremes tends to considerably reduce the
463 numbers of storms found, with the largest differences found in the weaker storm
464 categories. Appendix B discusses potential reasons why the trackers may act in this
465 way. There is some evidence that the difference between trackers reduces at higher
466 resolution, which is an expected result given that higher resolution simulates
467 stronger storms and tracker variability is dominated by weak, short-lived systems
468 (Zarzycki and Ullrich, 2017). The particular reasons for why some storms are
469 detected by one tracker and not another are outside the scope of this study but
470 remain a target for future work.

471 The seasonal cycle of ACE and frequency for the North Atlantic is shown in Fig. 9 for
472 all models and reanalyses (using TRACK and ACE₉₂₅) and observations over 1979-
473 2014. The peak in activity in observations is between August-September, and the
474 ECMWF-IFS, CNRM-CM6-1 and EC-Earth3P models mirror this well. HadGEM3-
475 GC31 and CMCC-CM2-(V)HR4 have a slightly delayed peak in September-October,
476 and also have too much activity early in the season, which is also true of the
477 frequency distribution. The timing of peak activity does not seem to change with
478 model resolution for either frequency or ACE₉₂₅. For most models the seasonal cycle
479 based on TempestExtremes (not shown) scales the frequency and ACE₉₂₅
480 consistent with earlier results, but for HadGEM3-GC31-HM the phase error above
481 almost disappears, which perhaps suggests that the late-season activity with TRACK
482 is due to weaker storms.

483 *d. Interannual variability and ensemble size*

484 Future projections of the frequency and variability of tropical cyclones strongly
485 depend on how the forcing environment (e.g. global and local drivers such as SST,
486 ENSO, humidity) will change in the future (Zhao and Held, 2012; Murakami et al.
487 2012; Roberts et al. 2013; Sun et al. 2017). However, our confidence in model
488 projections of future variability is increased if we can show that past performance
489 agrees well with observations, and particularly if models have similar dependencies
490 to both global and regional drivers as are observed. In this section we examine the
491 importance of ensemble size and model resolution to the skill in interannual
492 variability.

493 Previous studies have shown, in individual models, that higher model resolution with
494 small ensemble sizes (Zhao et al. 2014; Roberts et al. 2016) and larger ensemble

495 sizes at one resolution (Yoshida et al. 2017; Mei et al. 2019) are both important to
496 capture skill in interannual variability of TCs as compared to observations. The larger
497 ensemble sizes mean that the TC internal variability (weather noise) can be
498 averaged out to give increasing correlation with observations (Mei et al. 2019).

499 In the present study the ensemble size is generally small (1-3 members) across the
500 multi-model dataset, however for the HadGEM3-GC31 model this has been
501 enhanced. A total of 14 members have been produced for the period 1979-2014, at
502 both LM and MM resolutions (nominally 250 km, 100 km resolution, as part of the
503 H2020 Blue-Action project (<http://blueaction.eu>), together with five members at 50km
504 resolution. A stochastic perturbation is applied to the initial conditions to generate the
505 ensemble. Fig. 10 shows the correlation of each set of combinations of (non-
506 independent) n ensemble members within the whole ensemble for 1979-2014 for
507 both frequency and ACE₉₂₅ in the North Atlantic, NW Pacific and E Pacific using
508 TRACK (solid lines) and TempestExtremes (dashed lines); the box indicates the
509 inter-quartile range, while the whiskers show the range of the data, and the lines join
510 the mean correlation achieved for each ensemble size. The significance levels at
511 95% and 99% are also indicated, based on 36 years of data.

512 For ACE₉₂₅ and frequency (apart from the NW Pacific), the 100 km model has higher
513 correlation than the 250 km model in all three basins using all ensemble members. It
514 seems that at least 6-8 members selected from this ensemble size are needed for
515 the correlations at these two resolutions to become distinct (as measured by non-
516 overlapping inter-quartile ranges). The 100 km ensemble mean correlation for
517 frequency and ACE₉₂₅ in the North Atlantic seem to asymptote at around 0.75 and
518 0.70 respectively, which for example compares to a range of correlation between

519 0.4-0.85 using particular combinations of three member ensembles. Note that the
520 combinations are not independent, hence the reduction in range for larger ensemble
521 sizes. Since the 50 km model only has five ensemble members it is difficult to
522 compare this to the lower resolutions, but there are indications that there is
523 potentially extra ACE₉₂₅ skill in this model in the NW Pacific, in contrast to little or no
524 improvement in hindcast skill in a coupled seasonal forecast model with similar
525 resolutions (Scaife et al. 2019).

526 The correlations shown in Fig. 10 using TRACK and TempestExtremes become
527 more similar as resolution is increased, and indeed mostly overlay each other at HM
528 resolution. This could indicate that: (1) as resolution increases, the tracker details
529 become less important and a more common set of TCs is detected; (2) the influence
530 of the weaker TCs on the interannual variability signal reduces as resolution
531 increases. For the North Atlantic, Fig. 10 also shows that ACE is a more robust
532 measure of variability (e.g. Villarini and Vecchi, 2012; Scoccimarro et al. 2018), since
533 the LM curves are closer together in Fig. 10b compared to Fig. 10a. This reflects the
534 much smaller number of TCs detected by TempestExtremes and hence the weaker
535 signal in terms of variability detected with that tracker using frequency alone, but the
536 more integral ACE measure combining frequency, intensity and lifetime is able to
537 better sample the variability.

538 Mei et al. (2019) suggest that an ensemble of 20 members should be sufficient to
539 skilfully simulate hurricane frequency in the North Atlantic (as opposed to tropical
540 cyclone frequency shown here). Fig. 10 suggests that more than 10 members are
541 required to fully distinguish the skill at different model resolutions for the tropical
542 cyclones used here, and that such an ensemble size represents most of the skill in

543 the system (noting that some ensemble members can reach skills of over 0.8 here,
544 perhaps indicating where the curve might asymptote to given enough members).

545 Since our ensemble size is much smaller in most models used here, can we say
546 anything robust about variability and multi-model resolution? Fig. 11 shows the
547 running 30 year correlation over the 1950-2014 period against observations for the
548 North Atlantic, where each timeseries has been detrended over the whole period.
549 There is little clear signal that the higher resolution models obtain an improved
550 correlation for this period using one ensemble member. It is notable that nearly all
551 correlations improve over time, perhaps indicating that:

- 552 ● The models are better in periods of increased activity and/or can detect trends
553 in activity;
- 554 ● Uncertainty in the SST forcing further into the past, and the methods used in
555 HadISST.2.2.0.0 (Kennedy et al. 2016) to reconstruct the daily, $\frac{1}{4}$ degree
556 dataset;
- 557 ● Uncertainty in the tropical cyclone frequency and ACE variability before the
558 global satellite era due to changes in observations and procedures;

559

560 The thicker lines in Fig. 11 show model ensemble means (of up to 3 members)
561 where available, and these typically increase the correlation compared to using only
562 one member. However, for two models the lower resolution ensemble (thick dashed
563 lines) has a greater correlation than the high resolution ensemble (thick solid lines),
564 suggesting either that three members is insufficient to show an improvement with

565 resolution (consistent with Fig. 10), or else that other models could have a different
566 resolution dependence than that shown in Fig. 10.

567 Table 7 shows the correlation of interannual variability with observations over the
568 period 1979-2014 for one ensemble member for each model-resolution, for both
569 tropical cyclone frequency and ACE₉₂₅. For reanalyses it is clear that the ACE₉₂₅
570 correlation is more robust and consistent than frequency (as shown in Villarini and
571 Vecchi, 2012, and Fig. 10(a,b)) and hence we focus on ACE. The models with an
572 ensemble (of size 3 and above) have significant correlations about 0.5, while for the
573 models with only one member only CNRM-CM6-1 at both resolutions nears 0.5.

574 The correlation of the TC interannual variability against selected individual drivers is
575 shown in Table 8 for models and reanalyses. While it is difficult to assess the
576 correlations with only one ensemble member, the models with at least 3 members
577 have ensemble mean correlations that are consistent with the range seen in the
578 reanalyses. Hence there is no reason to believe that the simulated TC variability has
579 drivers different from the observations. The range of correlations using only one
580 member may be simply indicative of internal variability, or else reflect that different
581 models have TC genesis in different regions of the North Atlantic - different drivers
582 influence particular regions, so if cyclogenesis is shifted (for example equatorwards
583 or westwards) then these correlations will differ from the observed.

584

585 *e. Impact of mean state in the Atlantic*

586 Simple relationships between simulated mean state, model bias and TC climatology
587 are generally difficult to establish (e.g. Camargo et al. 2013; Murakami et al, 2014a;

588 Tang and Camargo, 2014; Kim et al. 2018) and are often model dependent. Here we
589 briefly examine whether the models show any gross biases in key parameters known
590 to be important for TC performance.

591 The mean 850-250 hPa wind shear over the June-October period for 1979-2014 is
592 shown in Fig. 12 for models and reanalyses. Each model tends to have its own
593 pattern of shear, and there seems little systematic change with resolution. The
594 CNRM-CM6-1 model has the weakest shear across the North Atlantic, which is
595 consistent with their large number of TCs produced at both resolutions using
596 TRACK. The HadGEM3-GC31 model has its minimum shear further south than
597 observed, and this may be linked with the low latitude of the African Easterly Jet
598 (AEJ) in that model (Fig. 13). The MPI-ESM1-2 and ECMWF-IFS models have
599 slightly higher shear (in the Eastern Atlantic) at higher resolution. The shear over
600 West Africa and the Eastern Atlantic is too high in CMCC-CM2-(V)HR4.

601 In general the latitudes of the AEJ (Fig. 13a) are consistent with the shear, with
602 several models (MPI-ESM1-2 for example) having the mean jet somewhat further
603 north than indicated by the reanalyses, while HadGEM3-GC31-LM is too far to the
604 south. Some previous work (Patricola et al. 2018) has suggested that African
605 Easterly Waves (AEWs) play little role in setting North Atlantic tropical cyclone
606 numbers, while Thorncroft and Hodges (2001) and Roberts et al. (2016) showed
607 some relationship with TC variability at higher resolutions for storms with genesis in
608 the eastern Atlantic. The mean number of African Easterly Waves (AEWs) is shown
609 in Fig. 13b, and the maximum vorticity of these waves in Fig. 13c, calculated
610 following the Bain et al. (2014) simple Hovmöller algorithm calculated on a common
611 grid. There is little evident resolution sensitivity in mean AEW number, and no

612 obvious relation with each model having its own character. All the models are within
613 the range of the reanalyses. There is a more systematic increase in the vorticity of
614 the AEWs with model resolution and perhaps this helps to improve the storm
615 distribution in the eastern Atlantic (Fig. 3) by enabling earlier genesis.

616

617 **4. Conclusions**

618 The CMIP6 HighResMIP experimental design enables a more systematic
619 assessment of the role of horizontal resolution in the simulation of global tropical
620 cyclones over the period 1950-2014 across multiple models. The results from six
621 modelling groups within the European PRIMAVERA project have been analysed in
622 this work, with resolutions spanning from around 200 km to 25 km. There are several
623 seemingly consistent changes when resolution is increased:

- 624 ● Increased tropical cyclone frequency and seasonal ACE index in the North
625 Atlantic
- 626 ● Improved capability to represent the spectrum of tropical cyclone intensities
- 627 ● Improved distribution of tropical cyclone tracks (and genesis regions)

628 These conclusions seem to be robust to (at least two) different trackers used in this
629 study, TRACK and TempestExtremes. These improvements are consistent with
630 previous studies using multi-decadal simulations of individual climate models at
631 similar 25 km resolutions (e.g. Zhao et al. 2008; Caron et al. 2011; Murakami et al.
632 2012; Wehner et al. 2014; Murakami et al. 2015; Roberts et al. 2016).

633 Correlations of interannual ACE variability with observations seem to be more robust
634 than using simple storm frequency, but there is no obvious relationship between
635 increased resolution and improved correlation using only one ensemble member.

636 Using the HadGEM3-GC31 model and several resolutions with an ensemble of 14
637 members does indicate that increasing resolution from 200 km to 100 km improves
638 model skill for North Atlantic interannual variability. In this case, at 100 km resolution
639 the ensemble mean correlation tends towards $\sim 0.75/0.7$ (frequency/ACE), with a
640 sub-sample of ensemble size of 6-8 suggestive of being sufficient to be a robust
641 measure. Hence for this simulation protocol and model, we can explain $\sim 50\%$ of the
642 variance in observed tropical cyclone interannual ACE variability. In the NW Pacific,
643 there is evidence that 50 km resolution offers a further increase in skill.

644 Future work is needed to discover what factors are missing that could allow more of
645 the variance to be explained. This may lie within the HighResMIP protocol itself
646 (which, for example, excludes interannual variations in natural aerosol, and uses one
647 specific set of SST-sea ice forcing datasets), or could lie with the models themselves
648 (via model bias, lack of key processes, requirement for even higher resolution or
649 limitations in physics such as convection schemes).

650 Further investigation of the CNRM-CM6-1 model is required to understand how it is
651 able to achieve such outstanding surface wind speeds compared to all other models,
652 which allows this model to represent the full tropical cyclone intensity spectrum. The
653 other models in this study are not able to simulate above Cat3 intensities as
654 measured by 10 m wind speeds. Davis (2018) suggest that somewhat higher
655 intensities should be possible in theory at 25 km resolution, and indeed other models
656 have shown such capability (e.g. Wehner et al. 2014; Murakami et al. 2015).

657 Use of the CMIP6 HighResMIP coupled model simulations can be used to further
658 assess drivers of variability and intensity when the atmosphere and ocean are able
659 to fully interchange fluxes. This configuration may also be useful to understand likely
660 future changes in tropical cyclone characteristics, and is addressed in Roberts et al.
661 (2019d).

662 Additional assessment of different tracking trackers is needed to better understand
663 their strengths, weaknesses and sources of difference but this needs to be done
664 fairly with some well constrained criteria for evaluation. Using multiple trackers is
665 also likely to be important when assessing future climate simulations, which also
666 form a part of the HighResMIP experimental design.

667

668

669 APPENDIX A

670 Brief model descriptions.

671 Brief descriptions of the different models used in this study are included here, in
672 particular aspects that are relevant to tropical cyclones. A summary of the model
673 components is shown in Table 1, and all the parameter changes between model
674 resolutions are shown in Table 3.

675 The standard HadGEM3-GC31 model configuration is described in Williams et al.
676 (2018), with the atmosphere configuration (GA7.1) further described by Walters et al.
677 (2019) and the HighResMIP configuration in Vidale et al (in prep) and Roberts et al.
678 (2019). The dynamical core uses a semi-implicit semi-Lagrangian formulation to

679 solve the non-hydrostatic, fully-compressible deep-atmosphere equations of motion
680 (Wood et al., 2014) on a regular latitude-longitude grid, with 85 levels with a top at 85
681 km. This model has been used to generate a larger ensemble size (of up to 14
682 members) to examine the robustness of some results. Each resolution has at least
683 three ensemble members over 1950-2014. In addition, over the 1979-2014 period,
684 stochastic perturbation of the initial conditions is used and 10 additional members
685 are produced for LM and MM models, and two more members for HM.

686 The ECMWF-IFS model used for HighResMIP is documented in Roberts et al.
687 (2018) and references therein. The atmospheric component of the Integrated
688 Forecasting System (IFS cyc43r1) model is based on a hydrostatic, semi-
689 Lagrangian, semi-implicit dynamical core with computations alternated between
690 spectral and reduced Gaussian grid-point representations each time step. The
691 vertical discretization is based on a hybrid sigma-pressure coordinate, with 91 levels
692 in the vertical, with top at 0.01 hPa. Additional ensemble members have been
693 generated by random perturbations to the initial stochastic perturbed parameterized
694 tendencies (SPPT) scheme.

695 The EC-Earth3P model is documented in Haarsma et al. (2019, in prep). The
696 atmospheric component of the Integrated Forecasting System (IFS cyc36r4) model
697 is based on a hydrostatic, semi-Lagrangian, semi-implicit dynamical core. The
698 vertical discretization is based on a hybrid sigma-pressure coordinate, with 91 levels
699 in the vertical, with top at 0.01 hPa.

700 The MPI-ESM1-2 model is documented in Gutjahr et al (2019) and references
701 therein. The atmospheric submodel of MPI-ESM1.2 is ECHAM6.3, with a dynamical
702 core based on a vorticity and divergence form of the primitive equations, solved

703 using a spectral-transform method. The vertical discretization uses a hybrid sigma-
704 pressure coordinate system with 95 vertical levels with a top at 0.01 hPa.

705 The CNRM-CM6-1 model is documented in Voldoire et al. (2019) for CMIP6 DECK
706 experiments. It is based on four main components for atmosphere, surface and
707 ocean and sea ice. The atmospheric component is based on the spectral
708 atmospheric model ARPEGE-Climat version 6.3. There are 91 vertical levels
709 following a hybrid σ pressure discretization with 15 levels in the boundary layer.
710 Since the previous version of the model, changes have been introduced in the
711 parameterizations and mainly concern the convection (Piriou et al. 2007, Gueremy et
712 al. 2011), microphysics (Lopez 2002) and turbulence (Cuxart et al. 2000). The
713 surface component SURFEX (Masson et al. 2013) includes 3 surface types: ocean,
714 land and lakes.

715 A general description of CMCC-CM2 models family used in CMIP6 can be found in
716 Cherchi et al. (2019). In the present study, the CMCC-CM2-(V)HR4 configuration is
717 used, specifically developed for HighResMIP. This model differs from the standard
718 resolution CMCC-CM2 configuration (CMCC-CM2-SR5; Cherchi et al., 2019) in that it
719 makes use of the Community Atmosphere Model vn4 (CAM4; Neale et al., 2010), in
720 alternative to CAM5. This choice allowed a substantial reduction of computational
721 costs, especially beneficial for the high-resolution (CMCC-CM2-VHR4) experiments,
722 and it made possible the implementation of the MACv2-SP “simple plume” scheme for
723 the anthropogenic aerosols (Stevens et al., 2017), following the HighResMIP protocol.
724 Specific aspects concerning the CMCC-CM2-(V)HR4 ability in reproducing the
725 characteristics of TCs in the West North Pacific are documented in Scoccimarro et
726 al. 2019.

727

728 APPENDIX B

729 Brief tracking algorithm (tracker) descriptions

730 Brief descriptions of the two trackers used to find tropical cyclones within the model

731 simulations are included here, for TRACK (Hodges et al. 2017), and

732 TempestExtremes (Ullrich and Zarzycki, 2017; Zarzycki and Ullrich 2017). There are

733 no changes in the trackers used between models and resolutions. Note that the

734 variables used are on the Analysis grid (Table 2) for each model.

735 TRACK uses relative vorticity as the feature-tracking variable. The vorticity over 850,

736 700, 600 hPa is averaged on the analysis grid, and then spectrally filtered to a

737 common T63 grid using triangular truncation to retain wavenumbers 6-63. The

738 tracking proceeds by identifying the off-grid vorticity maxima, by applying a

739 maximization scheme (Hodges 1995), if they exceed a value of $5 \times 10^{-6} \text{ s}^{-1}$ in each

740 time frame (SH scaled by -1). These are initially linked together using a nearest-

741 neighbor approach and then refined by minimizing a cost function for track

742 smoothness, subject to adaptive constraints on displacement distance and track

743 smoothness (Hodges 1999). Only tracks that last at least 2 days (eight time steps)

744 are retained for further analysis. Identification criteria post tracking are used to

745 isolate warm-core tropical cyclones: 1) T63 relative vorticity at 850 hPa must attain a

746 threshold of $6 \times 10^{-5} \text{ s}^{-1}$; 2) the difference in vorticity between 850 and 250 hPa (at T63

747 resolution) must be greater than $6 \times 10^{-5} \text{ s}^{-1}$ to provide evidence of a warm core; 3) the

748 T63 vorticity centre must exist at each level (850, 700, 600, 500, 250 hPa) for a

749 coherent vertical structure; 4) 1-3 must be jointly attained for at least four

750 consecutive timesteps (one day) and only apply over the oceans; 5) tracks must start
751 between 30°S-30°N.

752 TempestExtremes uses sea level pressure (SLP) as its feature-tracking variable on
753 the native analysis grid. Candidates are initially identified by minima in SLP, and a
754 closed contour criteria is applied, requiring an increase in SLP of at least 2 hPa
755 within 5.5° of the candidate node. A decrease in geopotential height difference (250 -
756 500 hPa) of 6 m within 6.5° of the candidate within 1° of the candidate with maximum
757 geopotential height. Candidates are then stitched in time to form paths, with a
758 maximum distance between candidates of 8°, consisting of at least ten candidates
759 per path and with a maximum gap size of three (number of time steps where no
760 identification occurred). For at least ten timesteps the underlying topographic height
761 must be at most 1500 m, and for at least four timesteps it must be at most 10 m, and
762 the storm must form between 10-40°. The storm must also travel at least 8°.

763 The TRACK configuration is tuned to capture roughly the number of tropical storms
764 including possibly tropical depressions and sub-tropical storms found in
765 observations, primarily using the ECMWF operational analyses (Bengtsson et al.
766 2007). The TempestExtremes configuration was developed by performing a
767 sensitivity analysis and optimizing against high-resolution reanalysis products as
768 described in Zarzycki and Ullrich (2017). It has attempted to keep the false alarm
769 rate to acceptable levels, which may have the effect of reducing the detection of
770 weaker storms.

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794

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1158 Tables

Institution	MOHC, UREAD, NERC	EC-Earth KNMI, SHMI, BSC, CNR	CERFACS	MPI-M	CMCC	ECMWF
Model name	HadGEM3- GC31	EC- Earth3P	CNRM- CM6-1	MPI-ESM1- 2	CMCC- CM2- (V)HR4	ECMWF- IFS
Resolution names	LM, MM, HM	LR, HR	LR, HR	HR, XR	HR4, VHR4	LR, HR
Model atmosphere	MetUM	IFS cyc36r4	ARPEGE6.3	ECHAM6.3	CAM4	IFS cyc43r1
Atmos dynamical scheme (grid)	Grid point (SISL, lat-lon)	Spectral (linear, reduced Gaussian)	Spectral (linear, reduced Gaussian)	Spectral (triangular, Gaussian)	Grid point (finite volume, lat-lon)	Spectral (cubic octohedral, reduced Gaussian)
Atmos grid name	N96, N216, N512	T1255, T1511	T1127, T1359	T127, T255	1°x1°, 0.25°x0.25°	Tco199, Tco399
Atmos mesh spacing (0N), km	208, 93, 39	78, 39	156, 55	100, 52	100, 28	50, 25
Atmos mesh spacing (50N), km	135, 60, 25	71, 36	142, 50	67, 34	64, 18	50, 25
Atmos nominal res (CMIP6)	250, 100, 50	100, 50	250, 50	100, 50	100, 25	50, 25
Atmos model levels (top)	85 (85 km)	91 (0.01 hPa)	91 (78.4 km)	95 (0.01 hPa)	26 (2 hPa)	91 (0.01 hPa)

1159 Table 1: Summary of models and their properties as used in PRIMAVERA project to
 1160 complete the CMIP6 HighResMIP *highresSST-present* experiments. SISL = semi-
 1161 implicit, semi-Lagrangian.

LR-MR- HR / Model	HadGEM3 -GC31 LM, (MM), HM	EC- Earth3P LR, HR	CNRM- CM6-1 LR, HR	MPI-ESM1-2 HR, XR	CMCC-CM2- (V)HR4 HR4, VHR4	ECMWF- IFS LR, HR
Lbox	217, (96.7), 40.8	107, 54.2	207, 75.3	134, 66.9	153, 38.2	123, 62.8
Effective resolution (LR, (MR), HR)	590, (330), 135	375, 165	625, 230	605, 190	490, 150	290, 125
Resolution ratio (low/high) using Lbox (Eff resol)	5.32 (4.37)	1.98 (2.2)	2.75 (2.71)	2.0 (3.18)	4.0 (3.2)	1.95 (2.32)
Analysis grid	Native	Regridded 0.7x0.7, 0.35x0.35	Regridd ed 1.4x1.4, 0.5x0.5	Native	Native	Regridded 1x1, 0.5x0.5

1163 Table 2: Information about model resolutions as used in this study. The effective
1164 resolution is taken from Klaver et al. (2019) and derived from examining model
1165 kinetic energy spectra, as is the Lbox value (calculated as a weighted grid box
1166 distance). Ratio of the low and high model resolution, calculated from both Lbox and
1167 the effective resolution. The analysis grid is the grid of the data as published on
1168 ESGF and as used for this analysis.

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Model	Timestep (min)	Parameter changes (reason)	Parameter values by resolution (low to high)
HadGEM3-GC31 LM, MM, HM	20, 15, 10	USSP launch factor (QBO period)	1.3, (1.2), 1.2
EC-Earth3P LR, HR	45, 15	No changes	
CNRM-CM6-1 LR, HR	15, 15	No changes	
MPI-ESM1-2 HR, XR	3.3, 1.5	Horizontal diffusion damping term (stability)	1.5, 0.5
CMCC-CM2 HR4, VHR4	30, 15	No changes	
ECMWF-IFS LR, HR	30, 20	Autoconversion threshold for rain over ocean RCLCRIT_SEA (net surface energy balance)	2.5×10^{-4} , 2.0×10^{-4}

1173 Table 3: Summary of parameter differences between horizontal resolutions of the
 1174 PRIMAVERA models used in HighResMIP *highresSST-present* simulations.

1176

Reanalysis	ERA-Interim	MERRA2	JRA55	NCEP-CFSR	ERA5
Model grid (resolution)	TL255 (80 km)	Cubed sphere (50 km)	TL319 (55 km)	T382 (38 km)	TL1279 (31 km)
Assimilation	4D-Var	3D-Var GSI+IAU	4D-Var	3D-Var GSI	4D-Var
Atmos model levels (top)	L60 (0.1 hPa)	L72 (0.01 hPa)	L60 (0.1 hPa)	L64 (0.26 hPa)	L137 (0.01 hPa)
Analysis grid	480x241	576x361	288x145	720x361	1440x720

1177

1178 Table 4: Properties of the reanalysis datasets used in this study. Abbreviations: 4D-
 1179 Var, 4D variational data assimilation; 3D-Var, 3D variational data assimilation;
 1180 TL255, triangular truncation 255, with linear grid (approximate horizontal grid spacing
 1181 in parentheses); L60 60 vertical levels; GSI, Grid-point Statistical Interpolation; IAU,
 1182 Incremental Analysis Update. Analysis grid is the grid on which the tracking is
 1183 performed.

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Category (CatP)	MSLP range	Official intensity using 1 min sustained wind speed (ms^{-1})
0	≥ 994	18-32
1	$980 \leq x < 994$	33-42
2	$965 \leq x < 980$	43-49
3	$945 \leq x < 965$	50-58
4	$920 \leq x < 945$	58-70
5	$860 \leq x < 920$	>70

1188 Table 5: The storm intensity categories (CatPx) as measured by mean sea level
 1189 pressure (MSLP) ranges as used in this work, together with the official Saffir-
 1190 Simpson 1 minute sustained wind speed classification.

1191

1192

Model/	Resol	Mean,std	%	%	%	%	%	%

mean freq	(nominal, km)	TRACK (<i>Tempest</i>)	TS	Cat1P	Cat2P	Cat3P	Cat4P	Cat5P
HadGEM 3-GC31	250	8.5, 2.7	84	12	3	0	0	0
		(1.9, 1.0)	64	28	8	0	0	0
	100	15.1, 4.6	72	21	5	2	0	0
		(9.8, 2.8)	60	31	7	2	0	0
	50	14.8, 3.3	57	24	13	6	0	0
		(16.0, 3.6)	50	28	16	5	0	0
EC-Earth	100	3.3, 2.2	84	12	3	2	0	0
		(0.7, 0.8)	77	16	9	0	0	0
	50	6.0, 3.2	81	6	6	7	0	0
		(2.3, 2.1)	65	14	10	11	0	0
CNRM- CERFAC S	250	14.7, 3.5	91	7	2	0	0	0
		(2.9, 2.0)	80	15	4	1	0	0
	50	15.0, 3.1	60	16	12	9	3	0
		(12.6, 3.4)	42	26	15	13	4	0
MPI	100	2.9, 2.7	92	3	2	2	1	0
		(0.6, 0.7)	86	14	0	0	0	0
	50	2.6, 1.6	85	5	3	7	0	0
		(0.7, 1.0)	87	8	4	0	0	0
CMCC	100	3.4, 1.8	75	13	11	1	0	0
		(NA)						
	25	9.4, 3.0	49	21	12	13	5	0
		(NA)						

ECMWF	50	7.9, 3.3	78	14	6	2	0	0
		<i>(4.3, 2.5)</i>	<i>68</i>	<i>21</i>	<i>8</i>	<i>3</i>	<i>1</i>	<i>0</i>
	25	10.0, 3.2	69	14	9	7	1	0
		<i>(7.4, 3.2)</i>	<i>57</i>	<i>19</i>	<i>15</i>	<i>8</i>	<i>1</i>	<i>0</i>
Reanalyses	ERA-I	8.7, 3.3	73	16	8	3	0	0
		<i>(5.2, 3.0)</i>	<i>66</i>	<i>24</i>	<i>10</i>	<i>1</i>	<i>0</i>	<i>0</i>
	CFSR	15.5, 4.3	85	10	4	1	0	0
		<i>(7.2, 3.5)</i>	<i>70</i>	<i>22</i>	<i>7</i>	<i>1</i>	<i>0</i>	<i>0</i>
	MERRA2	12.0, 4.9	69	16	13	2	0	0
		<i>(4.7, 2.0)</i>	<i>60</i>	<i>21</i>	<i>17</i>	<i>2</i>	<i>0</i>	<i>0</i>
	JRA55	13.6, 4.0	76	15	8	1	0	0
		<i>(6.0, 3.14)</i>	<i>60</i>	<i>25</i>	<i>14</i>	<i>1</i>	<i>0</i>	<i>0</i>
	ERA5	10.9, 4.1	63	15	12	9	1	0
		<i>(7.0, 3.5)</i>	<i>46</i>	<i>24</i>	<i>17</i>	<i>11</i>	<i>1</i>	<i>0</i>
Obs		11.3 (4.7)	43	23	10	9	10	3

1193 Table 6: Mean tropical cyclone frequency in the North Atlantic basin during May-
1194 November 1979-2014. Mean (std) indicates the mean frequency (standard deviation)
1195 of storms of all strengths, TS (tropical storm) and Cat 1P-5P show the percentage of
1196 this mean value that lies within these pressure-based categories. The mean and std
1197 are shown for both TRACK and TempestExtremes (in italics) respectively, where
1198 available.

1199

Model	Resol	Frequency corr (all, >= Cat1P)	ACE corr (all, >= Cat1P)	ACE corr (1950-2014)	ACE corr (ensemble mean)
HadGEM3-GC31	LM	0.48, 0.46	0.26, 0.26	0.23	0.54 (14)
	MM	0.68, 0.59	0.46, 0.45	0.35	0.68 (14)
	HM	0.32, 0.37	0.50, 0.48	0.29	0.56 (5)
ECMWF	LR	0.52, 0.46	0.42, 0.40	0.27	0.52 (3)
	HR	0.41 , 0.25	0.30, 0.26	0.34	0.50 (3)
EC-Earth	LR	0.33, 0.13	0.27, 0.23	0.24	0.44 (2)
	HR	0.34 , 0.26	0.28, 0.28	0.25	0.33 (3)
CNRM-CERFACS	LR	0.5, 0.4	0.49, 0.46	0.45	
	HR	0.26, 0.13	0.48, 0.45	0.35	
CMCC	LR	0.54, 0.45	0.31, 0.29	0.24	
	HR	0.51, 0.47	0.37, 0.35	0.30	
MPI-M	LR	0.33 , 0.12	0.34 , 0.31	0.26	
	HR	0.52, 0.43	0.38, 0.37	0.16	
Reanalyses	ERA-I	0.78, 0.73	0.86, 0.85		
	CFSR	0.32, 0.35	0.86, 0.85		
	MERRA2	0.78, 0.66	0.87, 0.85		
	ERA5	0.83, 0.72	0.91, 0.9		
	JRA55	0.68, 0.70	0.82, 0.82	0.82 (1957-2014)	

1200 Table 7: Correlations of Atlantic tropical cyclone interannual variability frequency and
1201 ACE₉₂₅ from TRACK against observations, during May-November 1979-2014.

1202 Correlations shown (a,b) are against observed all storms (tropical storm intensity and
1203 above), and against observed hurricanes only (\geq CatP1). Correlations of ensemble
1204 means are shown where available, with the ensemble size as indicated in brackets.
1205

Model/variante correlation	Nino3.4 ACE member 1 (ensemble mean)	AMO member 1 (ensemble mean)	AMM member 1 (ensemble mean)
HadGEM3-GC31			
LM	-0.3 (-0.55)	0.28 (0.37)	0.4 (0.56)
MM	-0.45 (-0.55)	0.29 (0.53)	0.38 (0.70)
HM	-0.25 (-0.41)	0.41 (0.41)	0.58 (0.62)
ECMWF			
LR	-0.26 (-0.46)	0.23 (0.34)	0.43 (0.56)
HR	-0.51 (-0.40)	0.22 (0.37)	0.27 (0.48)
EC-Earth			
LR	-0.18 (-0.28)	0.19 (0.32)	0.23 (0.43)
HR	-0.03 (-0.19)	0.35 (0.28)	0.35 (0.34)
CNRM			
LR	-0.22	0.27	0.31
HR	-0.27	0.15	0.34
CMCC			
LR	-0.15	0.10	0.26
HR	-0.41	0.41	0.42
MPI			
LR	-0.40	0.10	0.25
HR	-0.10	0.40	0.40

ERA1	-0.42	0.56	0.64
MERRA2	-0.41	0.63	0.74
CFSR	-0.49	0.45	0.58
JRA55	-0.44	0.39	0.55
ERA5	-0.42	0.56	0.65

1207 Table 8: Correlations of the Atlantic tropical cyclone interannual ACE₉₂₅ variability
1208 from TRACK for the North Atlantic (May-Nov, 1979-2014) with some potential drivers
1209 of that variability (Nino3.4 index, AMO, AMM) for each model-resolution. The
1210 ensemble mean correlations (where available) are shown in brackets, ensemble size
1211 as in Table 7.

1212

1213 **Figure caption list**

1214 Fig. 1: Tropical cyclone frequency (mean storms per year during May-November in
1215 Northern Hemisphere, and October-May for the Southern Hemisphere, 1979-2014)
1216 from models, reanalyses and observations, as diagnosed using the TRACK
1217 algorithm. The donut chart is divided into ocean basins, the totals in the centre are
1218 (NH, SH) mean storms per year. The thickness of the donut is scaled to the total NH
1219 TC observed frequency (i.e. donuts thicker than in panel r indicate more NH TCs
1220 while thinner indicate fewer NH TCs.).

1221 Fig. 2: As Fig. 1 but using the TempestExtremes algorithm. Note that the required
1222 diagnostics are not available for the CMCC-CM2-(V)HR models.

1223 Fig. 3: Model tropical cyclone track density (storm transits per month per 4 degree
1224 cap): for each pair of models, the bias for the higher resolution model, and the
1225 difference between higher and lower resolution models, are shown respectively,
1226 compared to observations (last plot). The period used is 1979-2014. Note the two
1227 reanalyses products (ERA-Interim, MERRA2).

1228 Fig. 4: (a), (b) Ensemble mean of the track density difference between pairs of high
1229 and low resolution models using TRACK and TempestExtremes respectively; (c), (d)
1230 Ensemble mean of the track density RMSE difference between pairs of high and low
1231 resolution models using TRACK and TempestExtremes respectively.

1232 Fig. 5: Scatter plot of the 10 m wind speed vs minimum MSLP of (a) North Atlantic,
1233 (b) North Western Pacific and (c) Eastern Pacific tropical cyclones at the peak of 925
1234 hPa wind speed. Each model is indicated (in pairs of lower and higher resolution,
1235 dashed and solid lines respectively), together with best-fit curves to all storms

1236 (indicated by symbols). Reanalyses from ERA-Interim MERRA2 and JRA55 (in
1237 gray), and observations, are also included.

1238 Fig. 6: Joint pdf of the normalised frequency of the MSLP and latitude at peak storm
1239 intensity from models, reanalyses and observations for all Northern Hemisphere
1240 tropical cyclones over 1979-2014.

1241 Fig. 7: Normalised probability density function of wind speeds at (a) 925 hPa (v_{max})
1242 and (b) 10 m, taken at the lifetime peak of the tropical cyclone intensity, for models,
1243 reanalyses and observations for Northern Hemisphere storms. Dashed lines show
1244 the low resolution models and solid lines are high resolution.

1245 Fig. 8: Composite storm structures from (a) lower and (b) higher resolution models,
1246 together with ERA-I, JRA55, CFSR and MERRA2 reanalyses, stratified by minimum
1247 surface pressure at peak storm intensity. Colour indicates the surface pressure, and
1248 contours the tangential velocity at 925 hPa. The dashed contour is 20 ms^{-1} and the
1249 solid contours are at $40, 60 \text{ ms}^{-1}$. The numbers on the right are the total number of
1250 tropical cyclones over the period, of which the percentage inset indicates how many
1251 occur for each category.

1252 Fig. 9: Mean seasonal cycle of tropical cyclone ACE and frequency in the North
1253 Atlantic for models and reanalyses (using TRACK) and observations. In each
1254 subplot, the gray bars represent the observed monthly mean ACE over the 1950-
1255 2014 period, with the solid lines representing the modelled ACE_{925} . The dashed lines
1256 show the TC frequency for observations (black) and models. The red line is the lower
1257 resolution and the blue line is the higher resolution for each model or reanalysis.

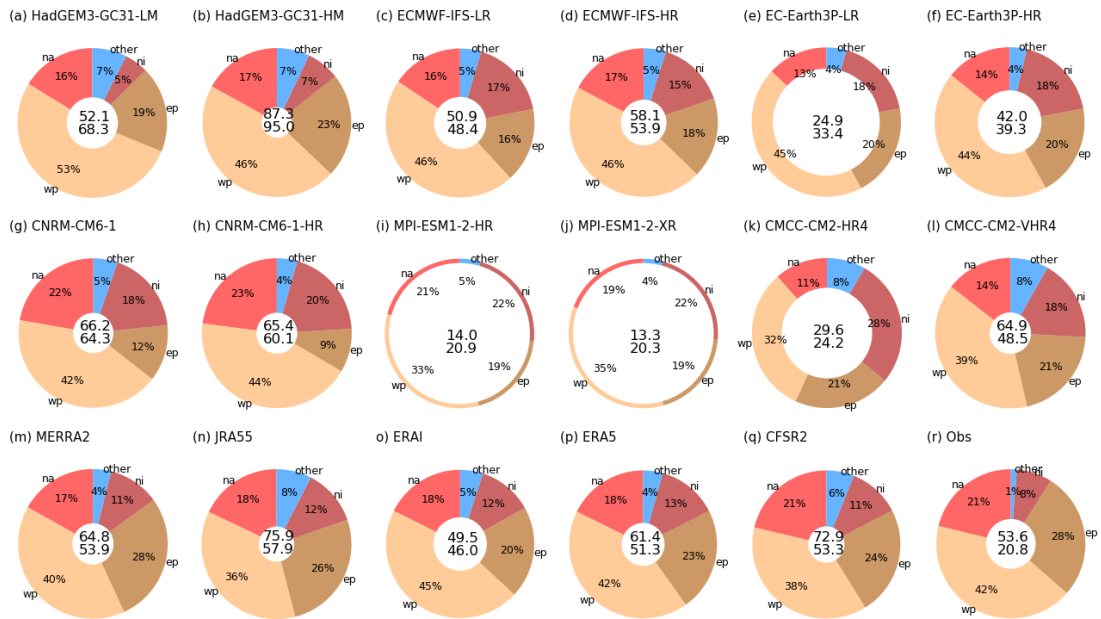
1258 Fig. 10: Correlation of model tropical cyclone frequency (left column) and ACE₉₂₅
1259 (right column) for the North Atlantic (NA), NW Pacific (WP) and NE Pacific (EP) over
1260 1979-2014 against observations for ensembles of HadGEM3-GC31 simulations (a
1261 total of 14 members at both MM (100 km) resolution and LM (250 km), and 5
1262 members at HM (50 km) resolution). For each combination of n ensemble members
1263 (x axis), a box and whiskers are plotted (the box showing the lower to upper quartile
1264 range, with a line at the median, while the whiskers show the range of the data). The
1265 mean correlations for each n ensemble member correlation are joined up by the line.
1266 The solid lines are for TRACK and the dashed lines for TempestExtremes. The solid
1267 and dashed black lines are approximations of the 95% and 99% confidence levels
1268 (assuming each of the 36 years are independent samples).

1269 Fig. 11: Correlation of TRACK ACE₉₂₅ from models and reanalyses for North Atlantic
1270 tropical cyclone variability against observed ACE as a function of time, using a
1271 moving 30 year period centred on the year shown. The dashed lines are for lower
1272 resolution, and solid lines for higher resolution models and reanalyses. The -ENS
1273 lines are for up to 3 member ensemble means from the available models.

1274 Fig. 12: Wind shear between 850 and 250 hPa for models and reanalyses. Mean
1275 over July-October 1980-2013. The dashed line shows 10 ms⁻¹, and the dotted line 20
1276 ms⁻¹.

1277 Fig. 13: (top) African Easterly Jet mean latitude in Aug-Sep for each model and
1278 reanalysis over 1980-2014; (middle) Mean number of African Easterly Waves over
1279 May-Oct for each model, counted at 15°W using the algorithm described in Bain et
1280 al. 2014; (bottom) AEW vorticity at 15°W using the algorithm described in Bain et al
1281 2014.

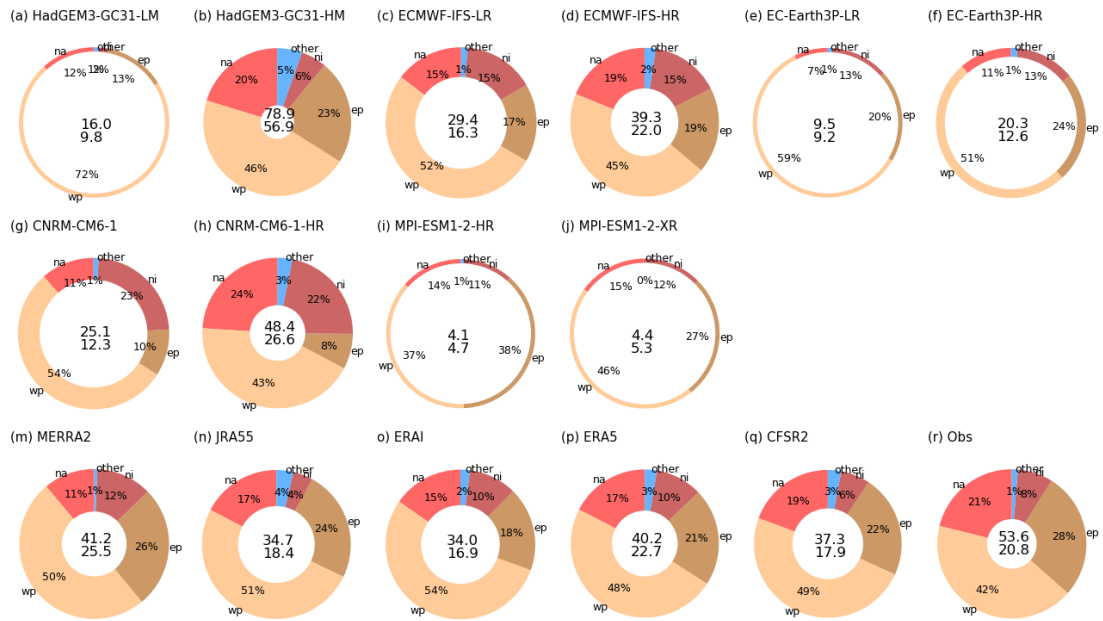
1282 **Figures**



1283

1284 Fig. 1: Northern Hemisphere tropical cyclone frequency (mean storms per year
 1285 during May-November, 1979-2014) from models, reanalyses and observations, as
 1286 diagnosed using the TRACK algorithm. The donut chart is divided into NH ocean
 1287 basins, the totals in the centre are (NH, SH) mean storms per year (Southern
 1288 Hemisphere uses October-May period). The thickness of the donut is scaled to the
 1289 total NH TC observed frequency (i.e. donuts thicker than in panel r indicate more NH
 1290 TCs while thinner indicate fewer NH TCs.).

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1293 Fig. 2: As Fig. 1 but using the TempestExtremes algorithm. Note that the required
 1294 diagnostics are not available for the CMCC-CM2-(V)HR models.

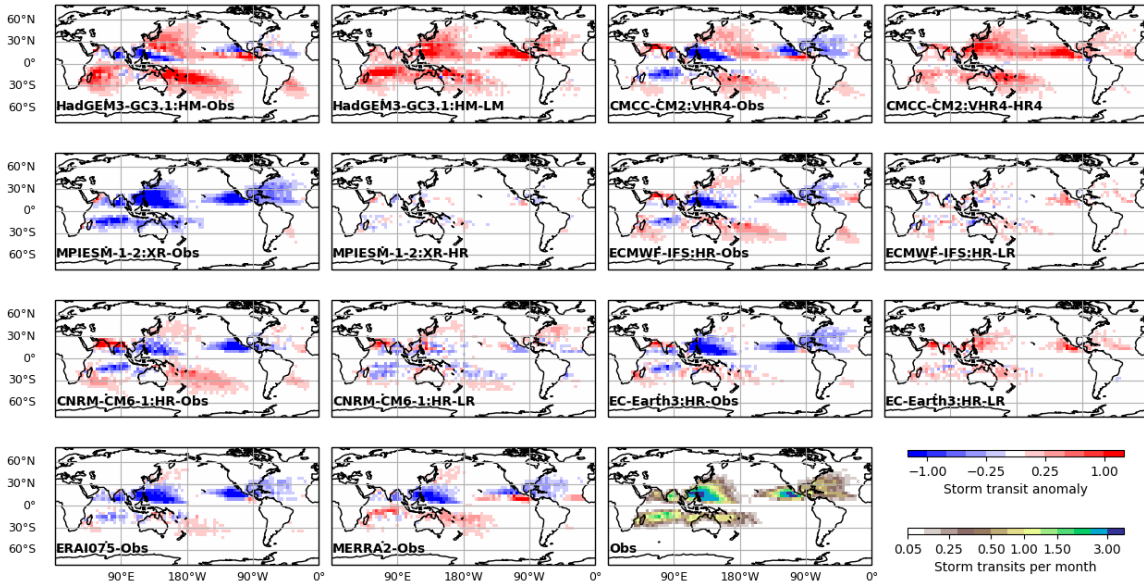
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1301 Fig. 3: Model tropical cyclone track density (storm transits per month per 4 degree
 1302 cap): for each pair of models, the bias for the higher resolution model, and the
 1303 difference between higher and lower resolution models, are shown respectively,
 1304 compared to observations (last plot). The period used is 1979-2014. Note the two
 1305 reanalyses products (ERA-Interim, MERRA2).

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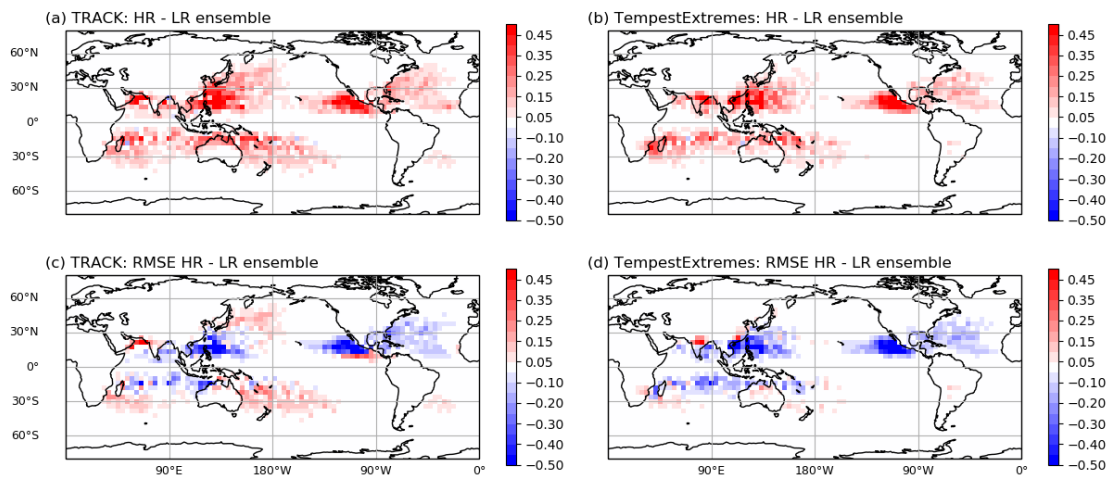
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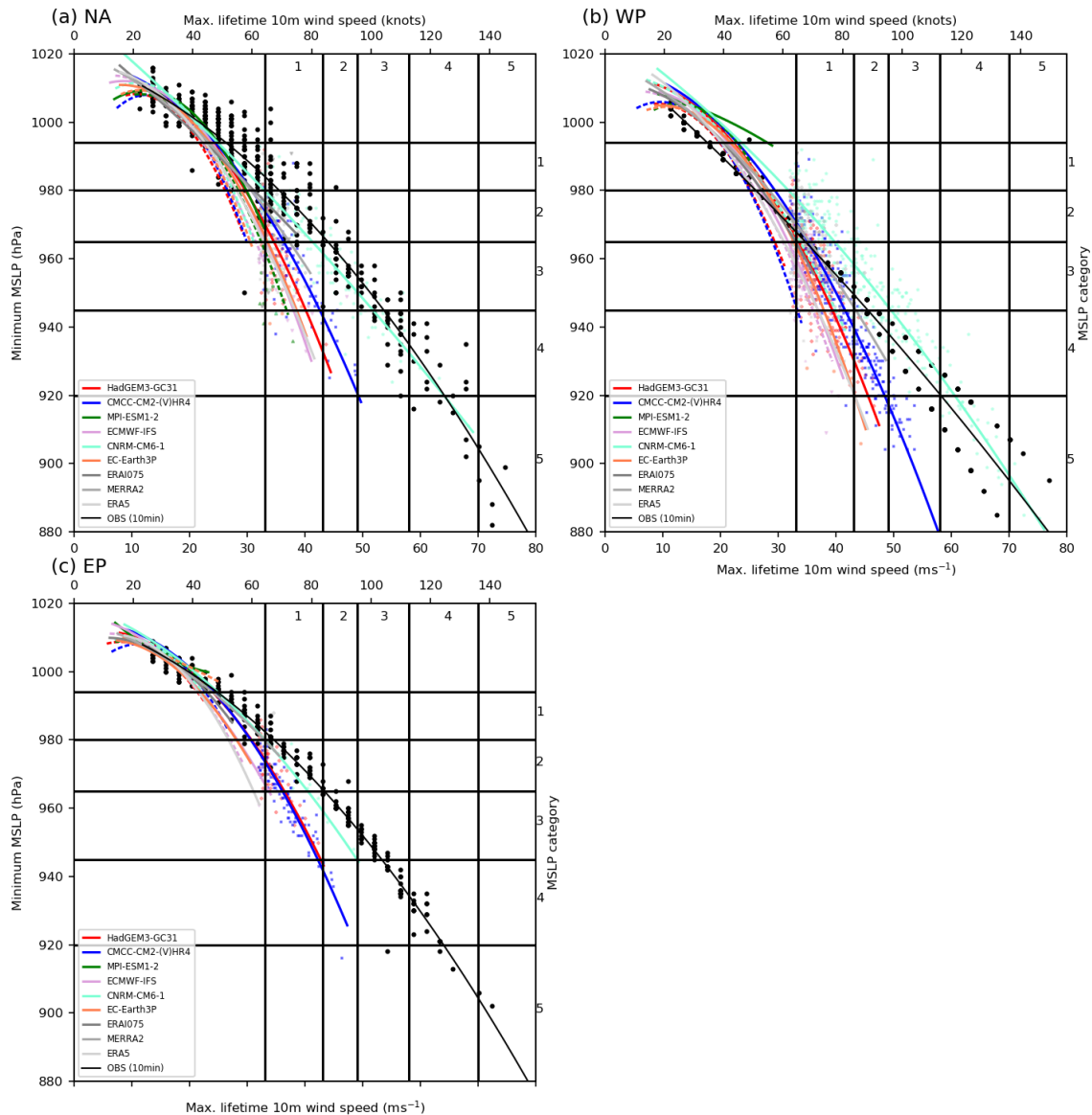
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1319 Fig. 4: (a), (b) Ensemble mean of the track density difference between pairs of high
1320 and low resolution models using TRACK and TempestExtremes respectively; (c), (d)
1321 Ensemble mean of the track density RMSE difference between pairs of high and low
1322 resolution models using TRACK and TempestExtremes respectively.

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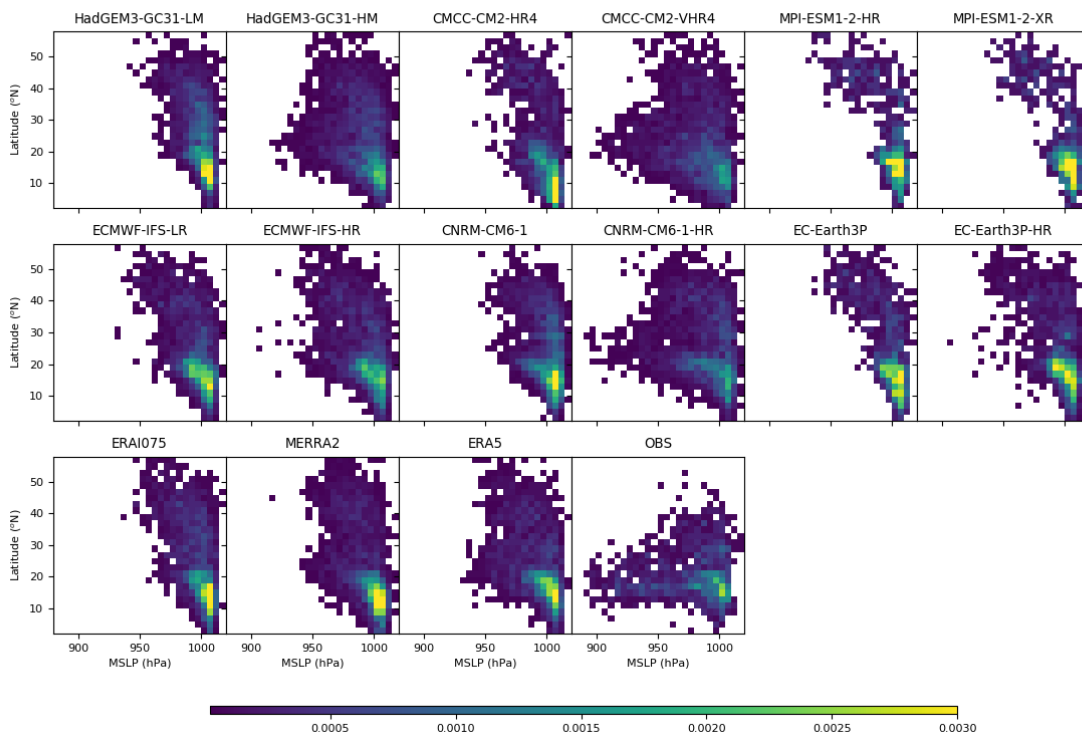
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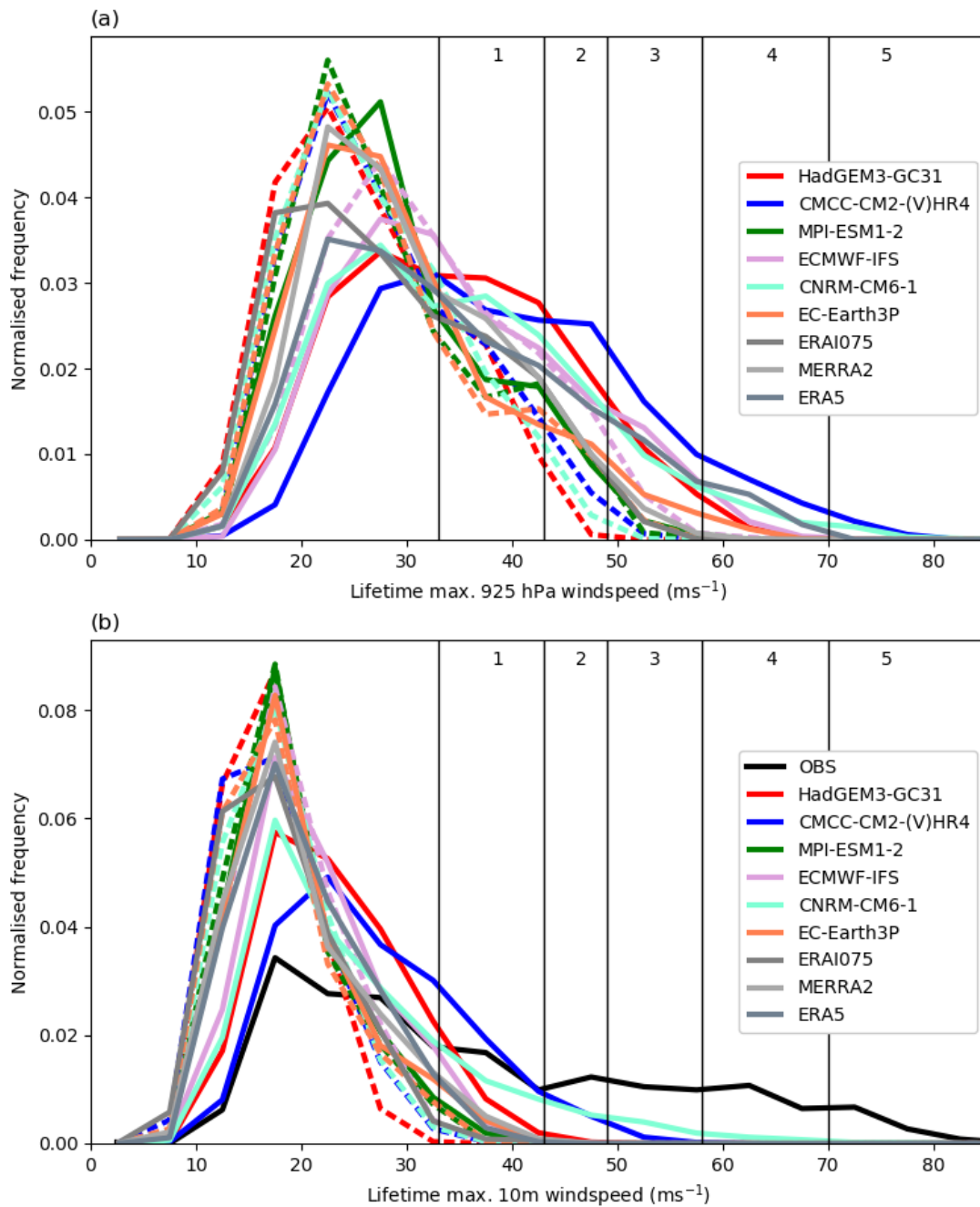
1327 Fig. 5: Scatter plot of the 10 m wind speed vs minimum MSLP of (a) North Atlantic,
 1328 (b) North Western Pacific and (c) Eastern Pacific tropical cyclones at the peak of 925
 1329 hPa wind speed. Each model is indicated (in pairs of lower and higher resolution,
 1330 dashed and solid lines respectively), together with best-fit curves to all storms
 1331 (indicated by symbols). Reanalyses from ERA-Interim, MERRA2 and ERA5 (in gray),
 1332 and observations, are also included. For clarify the model scatter points have not
 1333 been shown at the lower wind speeds.



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1335 Fig. 6: Joint pdf of the normalised frequency of the MSLP and latitude at peak storm
 1336 intensity from models, reanalyses and observations for all Northern Hemisphere
 1337 tropical cyclones over 1979-2014.

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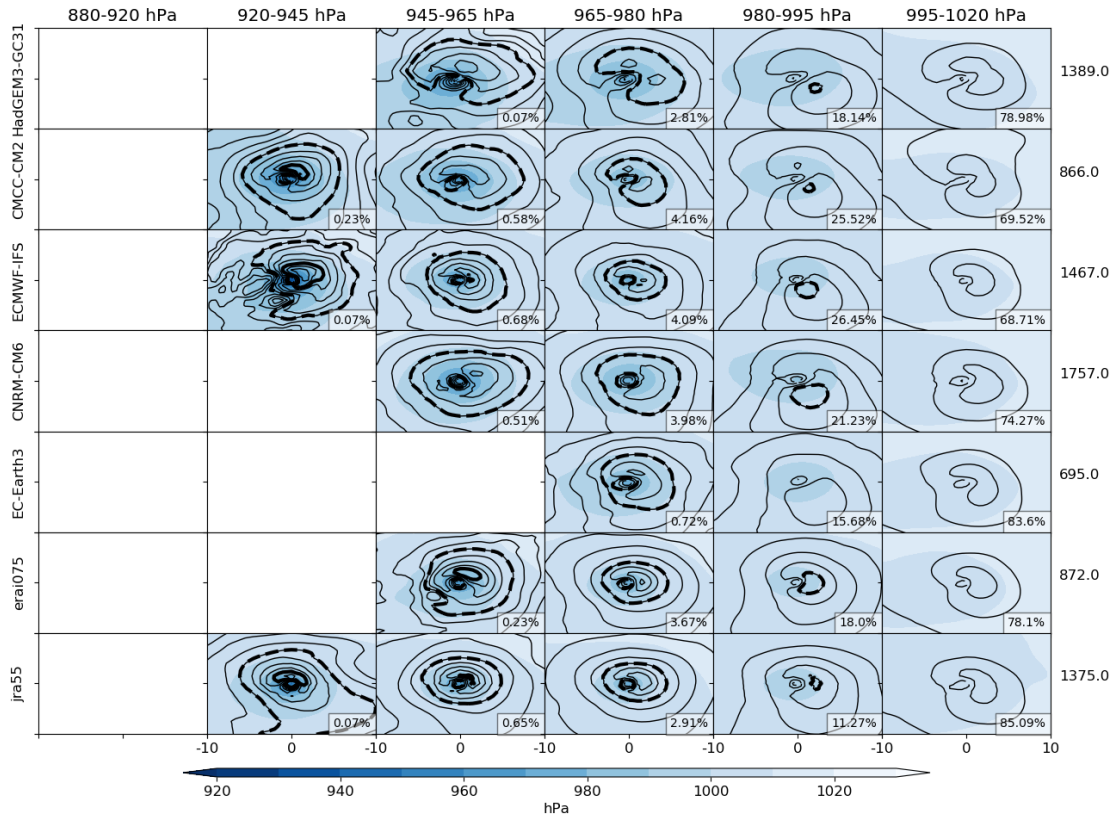
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1340 Fig. 7: Normalised probability density function of wind speeds at (a) 925 hPa (v_{max})
 1341 and (b) 10 m, taken at the lifetime peak of the tropical cyclone intensity, for models,
 1342 reanalyses and observations for Northern Hemisphere storms. Dashed lines show
 1343 the low resolution models and solid lines are high resolution.

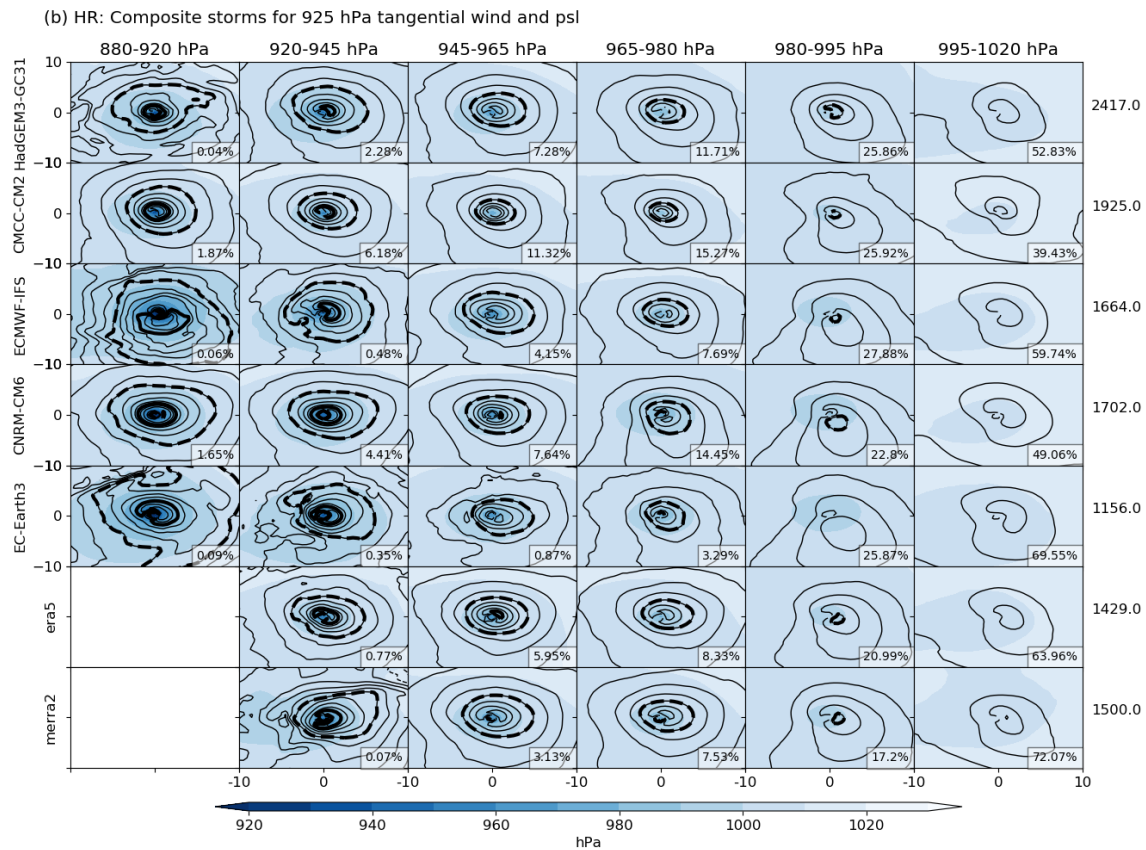
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(a) LR: Composite storms for 925 hPa tangential wind and psi

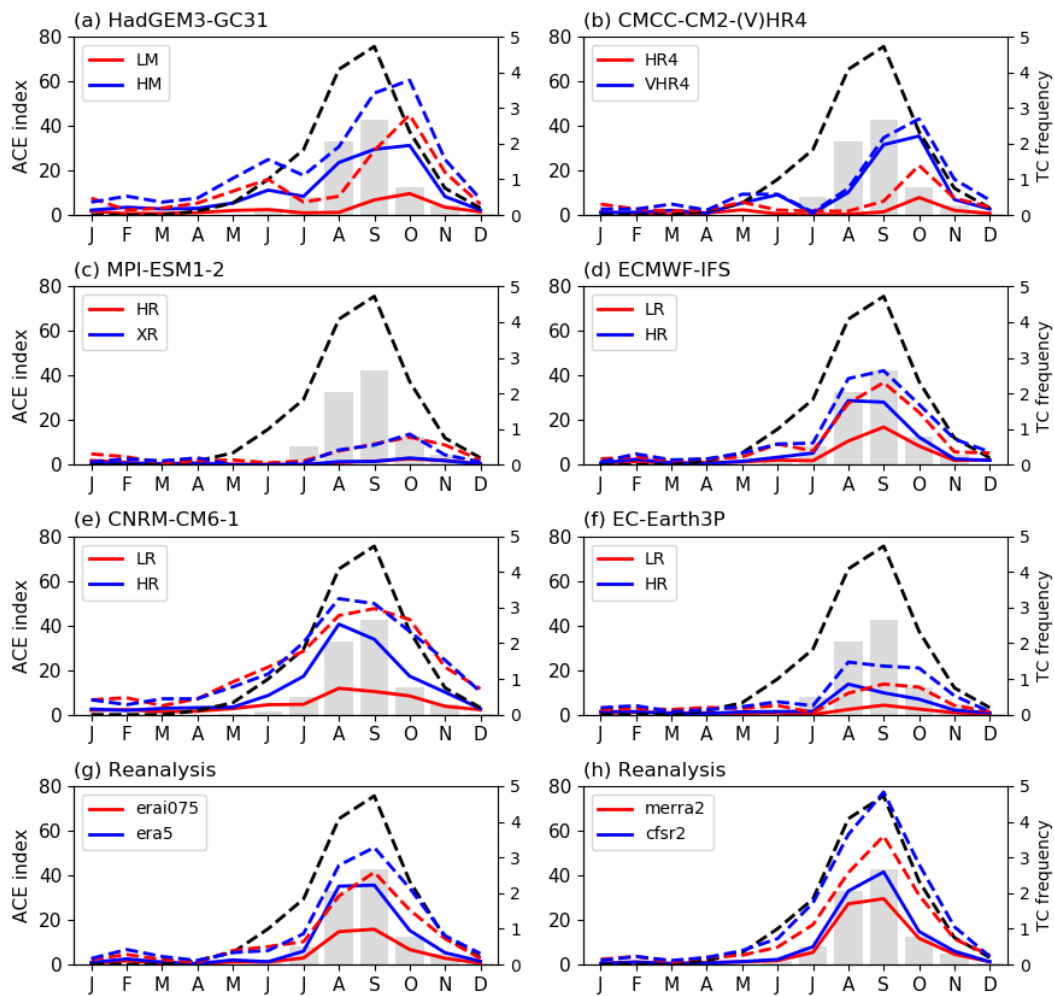


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1348 Fig. 8: Composite storm structures from (a) lower and (b) higher resolution models,
 1349 together with ERA-I, JRA55, CFSR and MERRA2 reanalyses, stratified by minimum
 1350 surface pressure at peak storm intensity. Colour indicates the surface pressure, and
 1351 contours the tangential velocity at 925 hPa. The dashed contour is 20 ms^{-1} and the
 1352 solid contours are at $40, 60 \text{ ms}^{-1}$. The numbers on the right are the total number of
 1353 tropical cyclones over the period, of which the percentage inset indicates how many
 1354 occur for each category.



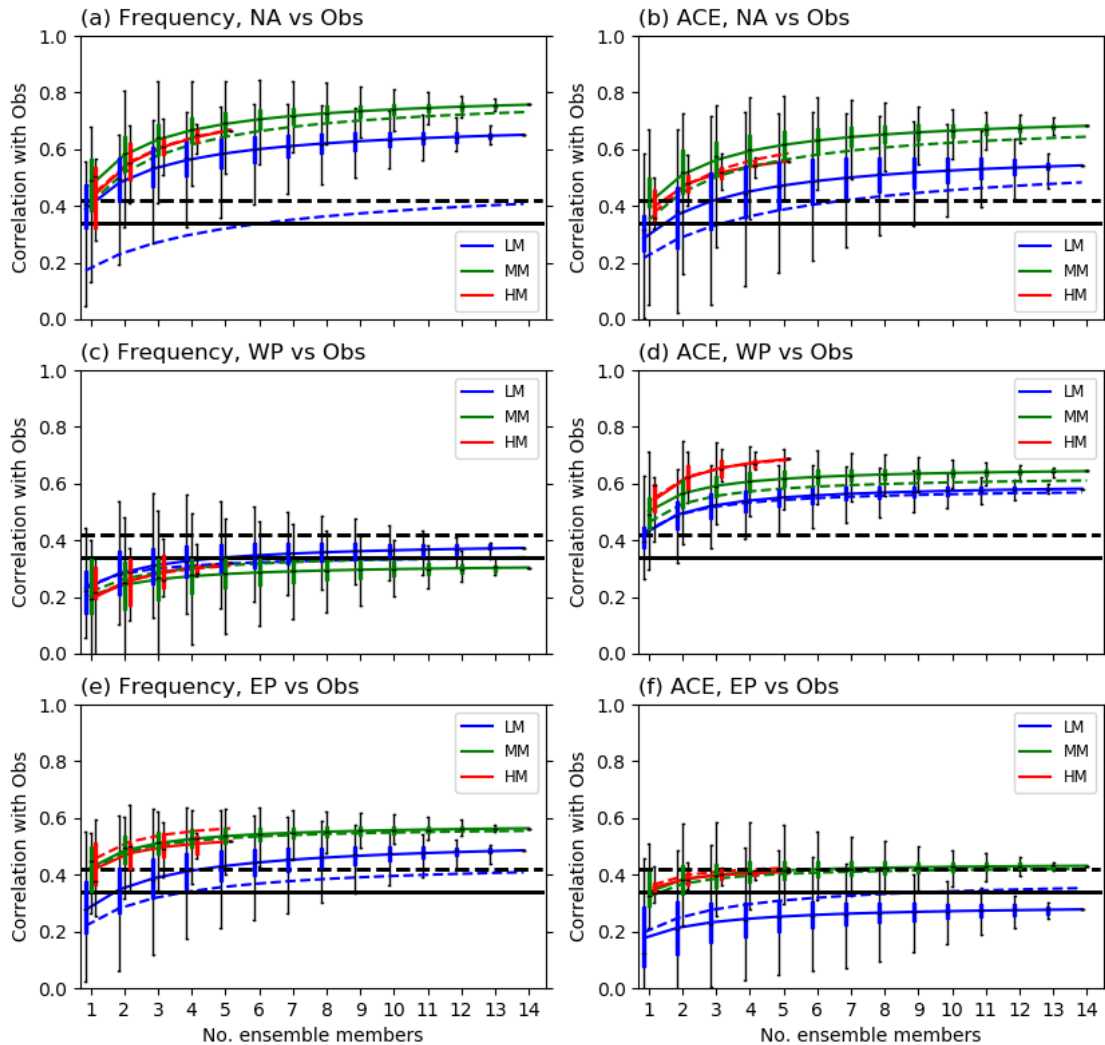
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1356 Fig. 9: Mean seasonal cycle of tropical cyclone ACE and frequency in the North
 1357 Atlantic for models and reanalyses (using TRACK) and observations. In each
 1358 subplot, the gray bars represent the observed monthly mean ACE over the 1979-
 1359 2014 period, with the solid lines representing the modelled ACE₉₂₅. The dashed lines
 1360 show the TC frequency for observations (black) and models. The red line is the lower
 1361 resolution and the blue line is the higher resolution for each model or reanalysis.

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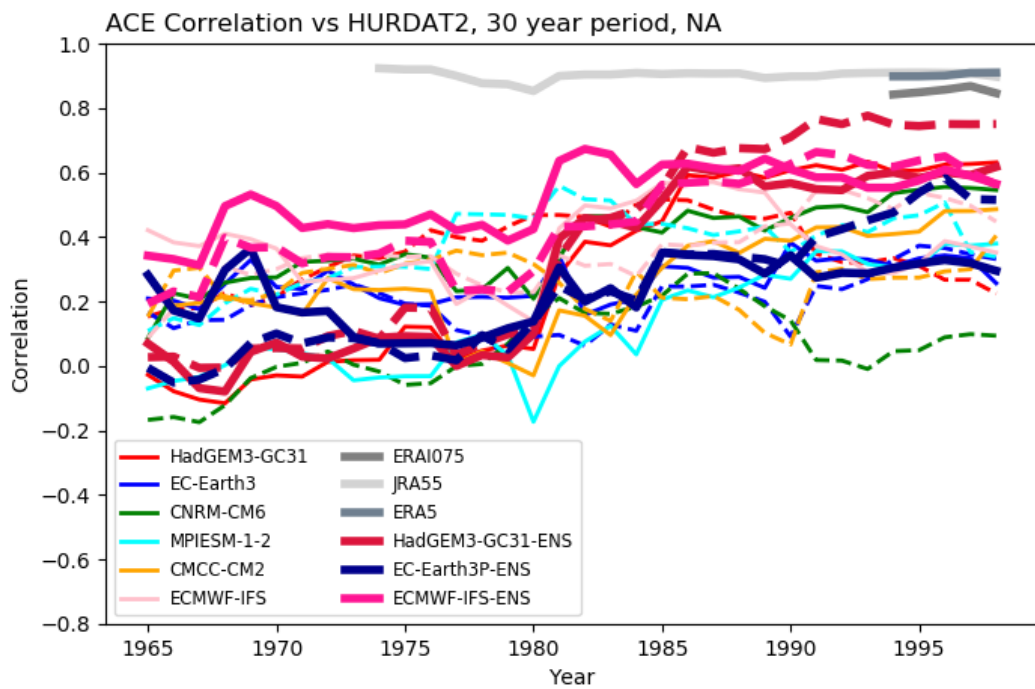
1366 Fig. 10: Correlation of model tropical cyclone frequency (left column) and ACE₉₂₅
1367 (right column) for the North Atlantic (NA), NW Pacific (WP) and NE Pacific (EP) over
1368 1979-2014 against observations for ensembles of HadGEM3-GC31 simulations (a
1369 total of 14 members at both MM (100 km) resolution and LM (250 km), and 5
1370 members at HM (50 km) resolution). For each combination of n ensemble members
1371 (x axis), a box and whiskers are plotted (the box showing the lower to upper quartile

1372 range, with a line at the median, while the whiskers show the range of the data). The
1373 mean correlations for each n ensemble member correlation are joined up by the line.
1374 The solid lines are for TRACK and the dashed lines for TempestExtremes. The solid
1375 and dashed black lines are approximations of the 95% and 99% confidence levels
1376 (assuming each of the 36 years are independent samples).

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1381 Fig. 11: Correlation of TRACK ACE₉₂₅ from models and reanalyses for North Atlantic
1382 tropical cyclone variability against Observed ACE as a function of time, using a
1383 moving 30 year period centred on the year shown. The dashed lines are for lower
1384 resolution, and solid lines for higher resolution models and reanalyses. The -ENS
1385 lines are for up to 3 member ensemble means from the available models.

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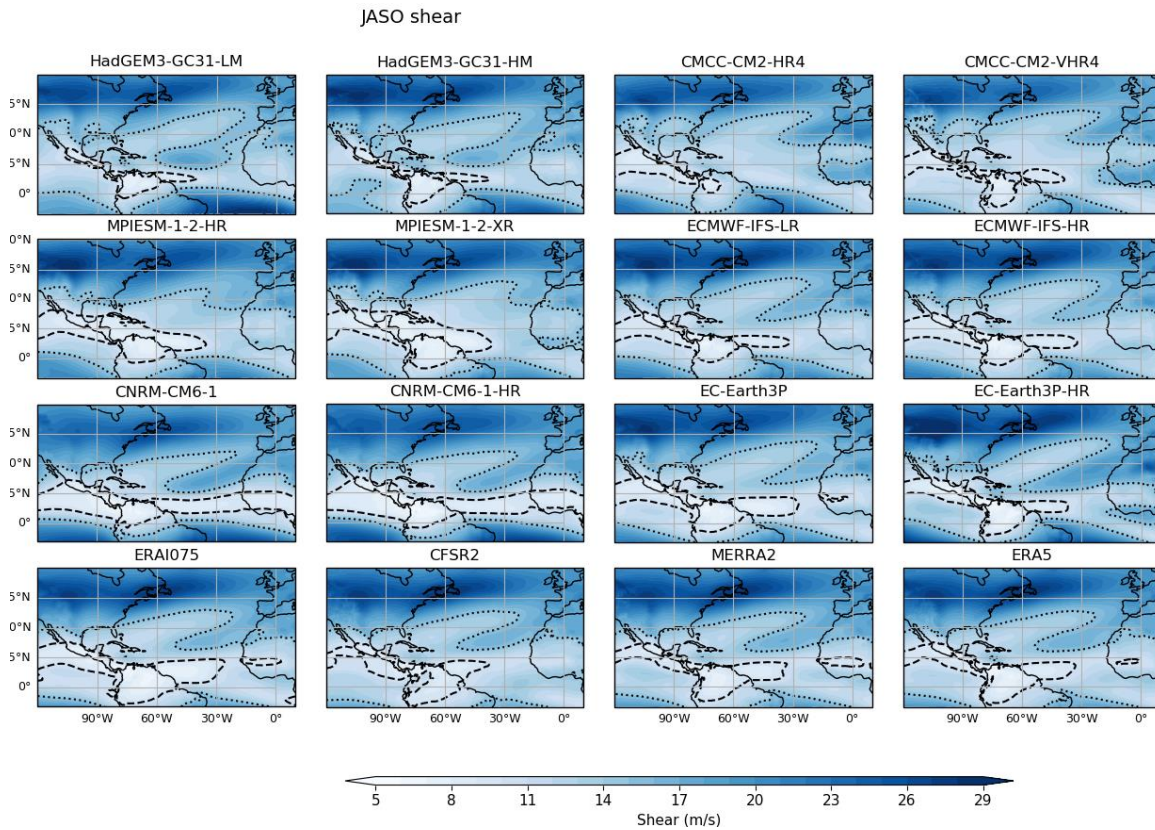
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1393 Fig. 12: Wind shear between 850 and 250 hPa for models and reanalyses. Mean
1394 over July-October 1980-2013. The dashed line shows 10 ms^{-1} , and the dotted line
1395 20 ms^{-1} .

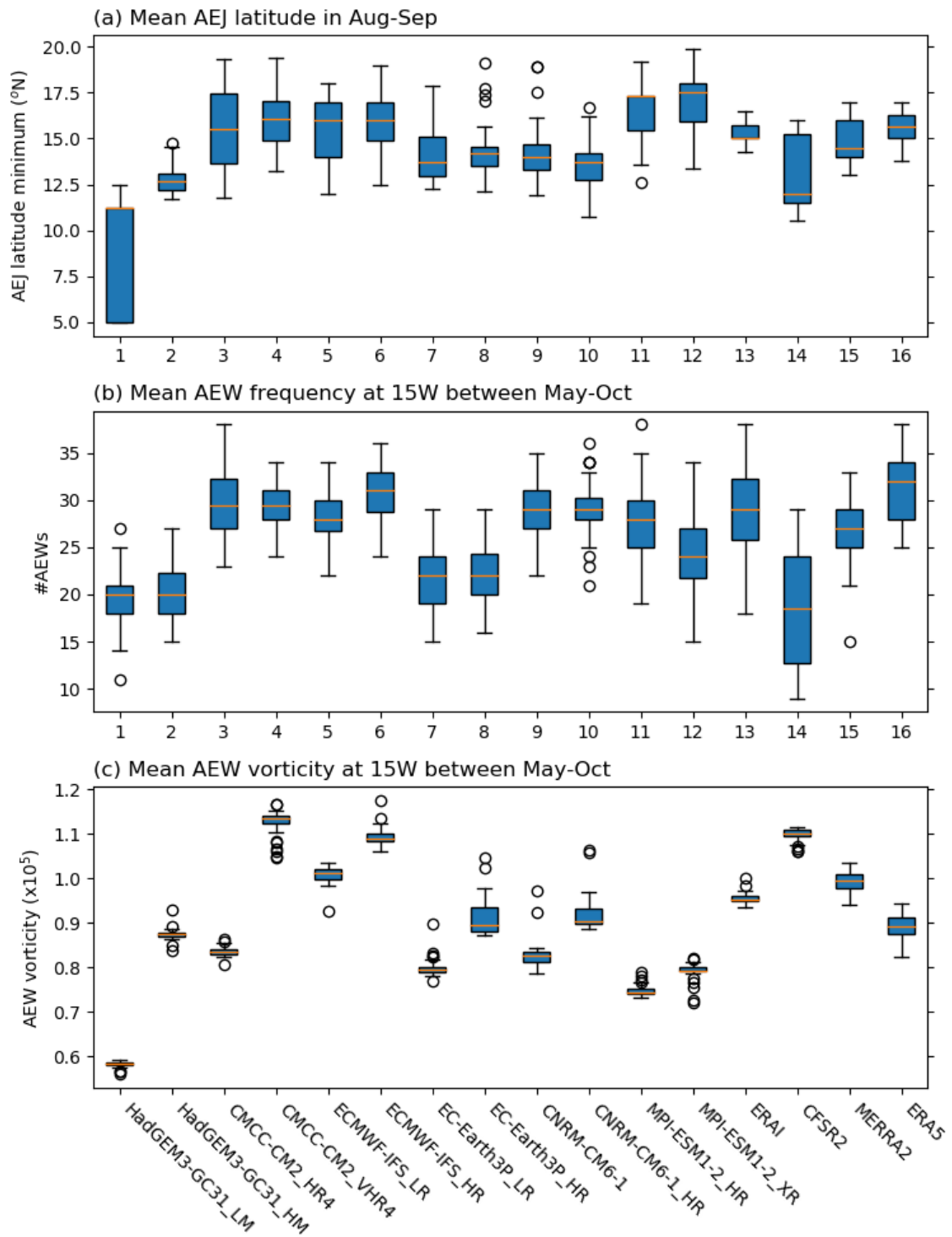
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1402 Fig. 13: (a) African Easterly Jet mean latitude in Aug-Sep for each model and
1403 reanalysis over 1980-2014; (b) Mean number of African Easterly Waves over May-
1404 Oct for each model, counted at 15°W using the algorithm described in Bain et al.
1405 2014; (c) AEW vorticity at 15°W using the algorithm described in Bain et al 2014.

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