

1 **Can climate models represent the precipitation**
2 **associated with extratropical cyclones?**

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7 **Abstract** Extratropical cyclones produce the majority of precipitation in many
8 regions of the extratropics. This study evaluates the ability of a climate model,
9 HiGEM, to reproduce the precipitation associated with extratropical cyclones.
10 The model is evaluated using the ERA-Interim reanalysis and GPCP dataset. The
11 analysis employs a cyclone centred compositing technique, evaluates composites
12 across a range of geographical areas and cyclone intensities and also investigates
13 the ability of the model to reproduce the climatological distribution of cyclone
14 associated precipitation across the Northern Hemisphere. Using this phenomena
15 centred approach provides an ability to identify the processes which are responsible
16 for climatological biases in the model. Composite precipitation intensities are found
17 to be comparable when all cyclones across the Northern Hemisphere are included.
18 When the cyclones are filtered by region or intensity, differences are found, in
19 particular, HiGEM produces too much precipitation in its most intense cyclones
20 relative to ERA-Interim and GPCP. Biases in the climatological distribution of
21 cyclone associated precipitation are also found, with biases around the storm track
22 regions associated with both the number of cyclones in HiGEM and also their
23 average precipitation intensity. These results have implications for the reliability
24 of future projections of extratropical precipitation from the model.

25 **Keywords** Precipitation · Extratropical cyclones · Climate models · HiGEM ·
26 Reanalysis · Remote sensing data

27 1 Introduction

28 Extratropical cyclones (hereinafter “ETCs”) play a key role in transporting en-
29 ergy and momentum polewards in the general circulation (?Kaspi and Schneider

30 2013) and have a major influence on the weather in the mid and high-latitudes.
31 Over two-thirds of the climatological precipitation in much of Europe and North
32 America is associated with ETCs and this figure can be as high as 90% in the
33 main stormtrack regions (Hawcroft et al 2012; Catto et al 2012). In addition, the
34 majority of large scale extreme precipitation events in the extratropics are asso-
35 ciated with the passage of ETCs (Pfahl and Wernli 2012; Catto and Pfahl 2013).
36 ETCs can have high socio-economic impacts from the winds, rain and associated
37 flooding they can bring (Ulbrich et al 2003; Pitt 2008; Sibley 2010; de Leeuw et al
38 2014). For example, in the summer of 2007, flooding associated with ETCs caused
39 major disruption in the UK and insurance claims of over £3bn (Pitt 2008; Pearson
40 et al 2014).

41 An ability to reproduce the current climate is a necessary condition of hav-
42 ing confidence in climate model projections. Assessing whether a climate model
43 adequately represents cyclone associated precipitation is important in terms of
44 quantifying the impact of any prospective changes in both mean and extreme cy-
45 clone associated precipitation in the future. In this paper, the ability of a climate
46 model, HiGEM, to represent the precipitation associated with ETCs is assessed.

47 The response of the storm tracks to climate change is driven by a number of
48 influences (see, for example, Held 1993; Woollings 2010) with the overall response
49 being modulated by the interplay of opposing controls, such as changes in hemi-
50 spheric temperature gradients (Lim and Simmonds 2009; Butler et al 2010; Harvey
51 et al 2014). In addition, any changes in the behaviour of ETCs themselves repre-
52 sents another such driver of the response of the storm tracks to climate change.
53 An ability to represent the mean behaviour of ETCs is an important component
54 of model evaluation in the extratropics. Models must also be able to reproduce the

55 magnitude and frequency of the most intensely precipitating ETCs and a realistic
56 spectrum of event intensity - from weakly to intensely precipitating ETCs - to
57 be considered reliable. This is particularly important since it is expected that the
58 precipitation intensity of the most severe ETCs will increase in a warmer climate
59 (Held 1993; Trenberth 1999) and that ETCs are often associated with high impact
60 precipitation events in the extratropics (Pfahl and Wernli 2012; Catto and Pfahl
61 2013).

62 Studies of precipitation in climate models often use statistical analysis to eval-
63 uate model performance (e.g. Kendon et al 2012; Cr  tat et al 2014; Pearson et al
64 2014; Roy et al 2014) and climate models have previously been shown to have
65 biases in both frequency and intensity of precipitation, even where the climato-
66 logical accumulations compare closely to observations (Stephens et al 2010). In
67 this paper, a process based approach is adopted by associating precipitation with
68 a phenomenon - extratropical cyclones. This allows the analysis to move beyond
69 a statistical evaluation of the precipitation climatology in the model to consider
70 questions relating to the behaviour of these precipitation producing phenomena,
71 for example, by linking precipitation biases to ETC frequency. This is particularly
72 important given it is not clear that ETCs will respond to a change in climate in the
73 same way as other precipitation producing phenomena, such as convective storms.

74 Cyclone tracking and compositing techniques are increasingly used in analyses
75 of ETCs (e.g. Field and Wood 2007; Catto et al 2010; Rudeva and Gulev 2011).
76 This study combines compositing with climatological analysis using techniques
77 developed in Hawcroft et al (2012) and further applied in Zappa et al (2014)
78 to provide a comprehensive evaluation of a climate model's ability to represent
79 precipitation associated with ETCs.

80 The focus of this study is on winter (December-February, DJF) precipitation
81 since this is the season where the majority of total annual precipitation falls in
82 many regions of the Northern Hemisphere extratropics and when the main storm-
83 tracks are at their most active. Anomalies in wintertime precipitation can also
84 play a role in contributing to the onset of summertime droughts and heatwaves
85 via deficits in soil moisture (e.g Ferranti and Viterbo 2006; Della-Marta et al 2007;
86 Vautard et al 2007; Wang et al 2011) such that an inability to represent the winter
87 precipitation climatology of the extratropics may have more far reaching effects in
88 climate model projections.

89 The paper is structured as follows. In Section 2 the High-Resolution Global En-
90 vironmental Model (HiGEM), ECMWF Interim Re-analysis (ERA-Interim) and
91 Global Precipitation Climatology Project (GPCP) remote sensing dataset are in-
92 troduced. The cyclone tracking algorithm is also discussed in addition to a sum-
93 mary of the technique applied to create and evaluate climatologies of ETC asso-
94 ciated precipitation. Section 3 evaluates composite precipitation associated with
95 ETCs in HiGEM. Section 4 considers the ability of HiGEM to reproduce the clima-
96 tological distribution of ETC associated precipitation. A summary and conclusions
97 are provided in Section 5.

98 **2 Data and Methods**

99 Many studies use reanalyses to evaluate the behaviour of climate models, with
100 reanalysis being used as a proxy for the real world (in the ETC literature exam-
101 ples include Bengtsson et al 2006, 2009; Catto et al 2010; Hodges et al 2011). At
102 the scale of ETCs, reanalyses may not be strongly constrained by observations

103 due to the location and nature of these phenomena, since many ETCs occur over
104 oceans and many of the key processes which govern their behaviour (such as la-
105 tent heat release) occur away from the surface. This introduces uncertainty in the
106 reanalysis product. Remotely sensed data may be employed to constrain the perfor-
107 mance of reanalyses and may also be employed to directly evaluate climate models.
108 This study therefore uses both reanalysis (ERA-Interim) and remote sensing data
109 (GPCP) to evaluate the HiGEM climate model.

110 2.1 ERAI

111 The ERA-Interim (ERA-Interim) reanalysis (Dee et al 2011; Simmons et al 2007) uses
112 a 4D-Var data assimilation system to incorporate observations over a 12-hour
113 analysis period, with forecasts commencing at 00:00UTC and 12:00UTC, and has
114 a spectral resolution of T255 (approximately 80km/0.7° in the mid-latitudes). The
115 ERAI model is based around the ECMWF's Integrated Forecast System (IFS)
116 cycle Cy31r2, which was used for operational forecasting at ECMWF from 12
117 December 2006 until 5 June 2007. ERAI has 60 model levels, with an atmospheric
118 top at 0.1 hPa. Precipitation is not an analysed field and in this paper is taken from
119 short-range forecast accumulations, discussed in section 2.1.1. Data is available for
120 the period of the GPCP data (see section 2.2) making ERAI particularly suitable
121 for this study. The climatological precipitation and total precipitation associated
122 with ETCs in the Northern Hemisphere have been shown to compare well to GPCP
123 by Hawcroft et al (2012).

124 *2.1.1 Spin-up in ERAI*

125 Given the requirement to have daily accumulations centred on 12:00UTC for com-
126 parison to GPCP, it would be possible to use either (1) a continuous 24-hour
127 accumulation from a single forecast for each day or (2) two 12 hour accumulations
128 from successive forecasts. During the first several hours of forecasts, the precipita-
129 tion field is affected by spin-up (see Källberg 2011). As such, the forecast periods
130 utilised in this study are accumulations from 12 to 24-hours from forecasts start-
131 ing at 12:00UTC the previous day and 00:00UTC on the day of interest. The
132 two forecast accumulations are combined to provide daily precipitation estimates.
133 The 12 to 24-hour forecast estimates have previously been found to compare well
134 to gridded rain gauge observations (Simmons et al 2010) and recent work indi-
135 cates that the lead time used in this paper offers the best estimates available from
136 ERAI given the daily accumulations required for this study (Hawcroft et al 2012;
137 de Leeuw et al 2014). A further evaluation, investigating any spin-up/adjustment
138 (as the model is initialised) or model drift (as the forecast increases in length
139 and the model is no longer closely constrained by observations) was performed for
140 this study, confirming the propriety of the 12-24 hour lead times. This is further
141 discussed in the Appendix to this paper.

142 The ERAI data used in this study is from DJF 1998/99-2007/08, providing a
143 decade of data which overlaps with the availability of GPCP. Analysis on a longer
144 period of data (from 1979 onwards) to assess uncertainty which may arise from
145 decadal variability did not materially affect the conclusions.

146 2.2 GPCP

147 The Global Precipitation Climatology Project one-degree-daily (GPCP) precip-
148 itation dataset (Huffman et al 2001, 2009; Adler et al 2003) is a $1^\circ \times 1^\circ$ gridded
149 dataset that combines multiple satellite estimates and rain gauge data to produce
150 daily accumulations centred on 12:00UTC. The satellite estimates are tuned using
151 monthly gauge observations. The GPCP data is available from December 1996 to
152 the present. The period DJF 1998/99-2007/08 is used here, which is the same as
153 the ERAI data.

154 GPCP has been evaluated against rain gauge observations, generally perform-
155 ing well (e.g. Nicholson et al 2003), though it has been shown that GPCP under-
156 estimates very high intensity events in the United States (McPhee and Margulis
157 2005) and India (Joshi et al 2013) and overestimates them at high-latitudes (Bolvin
158 et al 2009). It is not possible to systematically verify satellite derived estimates
159 over the oceans and other regions where gauge sampling is sparse (John et al 2009)
160 which increases uncertainty in the precipitation estimates over oceans.

161 There remains uncertainty in the precipitation estimates derived from both
162 satellite observations (Kummerow et al 2006; Field and Wood 2007; Stephens
163 et al 2010) and from reanalysis (Hou et al 2001). However, neither the GPCP or
164 ERAI datasets provide estimates of uncertainty for precipitation. As such, the use
165 of multiple datasets to evaluate HiGEM allows greater ability to assess uncertainty
166 with respect to the remotely sensed data and the reanalysis.

167 2.3 HiGEM

168 The model evaluated in this study is HiGEM1.2 (Shaffrey et al 2009), which
169 is based on the U.K. Met Office Hadley Centre Global Environmental Model
170 (HadGEM1). HiGEM is a higher resolution version of HadGEM1, in both at-
171 mosphere and ocean. The horizontal resolution is $0.83^\circ \times 1.25^\circ$ (N144) for the at-
172 mosphere, and $1/3^\circ \times 1/3^\circ$ globally for the ocean and sea ice. The atmosphere has 38
173 vertical levels with a model top at 39km. The atmospheric dynamics of HiGEM
174 use non-hydrostatic, fully compressible, deep-atmosphere equations and a semi-
175 Lagrangian advection scheme for all prognostic variables except density (Davies
176 et al 2005). Detailed description of the model formulation can be found in Shaf-
177 frey et al (2009); Johns et al (2006); Martin et al (2006); McLaren et al (2006)
178 and references therein. Precipitation is a diagnostic quantity in both the large-
179 scale precipitation and convection schemes with precipitation estimates produced
180 at the surface at each timestep. HiGEM has previously been shown to be capa-
181 ble of capturing the synoptic scale circulation features of composite ETCs when
182 compared to reanalysis (Catto et al 2010).

183 In this study, the precipitation from HiGEM is accumulated during a 24-hour
184 period centred on 12:00UTC in order to provide data comparable to GPCP (see
185 section 2.2). Data is available for 80 consecutive years in a control run forced with
186 late 20th-century radiative forcings. Data from the first 20 years of the integration
187 is thought to be affected by spin-up effects since this is the period it takes for
188 the net top of the atmosphere (TOA) radiation flux to stabilise (Shaffrey et al
189 2009). Analysis of decadal variability within the 80 year period indicates that the
190 precipitation associated with ETCs exhibits low variability - including during the

191 first 20 years (see Appendix). A decade of winter (DJF) seasons starting 30 years
192 into the model run is used in this study to provide a period of sufficient sampling
193 for which there is also a period of comparable length in the observations/renalysis
194 data for comparison.

195 2.4 Tracking and compositing methodology

196 The feature tracking algorithm used in this study (e.g. Hodges 1994, 1995, 1999,
197 and further described in Hoskins and Hodges 2002 and Bengtsson et al 2009),
198 has previously been applied in studies of ETCs (e.g. Hoskins and Hodges 2002;
199 Bengtsson et al 2006, 2007, 2009; Catto et al 2010; Hawcroft et al 2012). Northern
200 Hemisphere ETCs are identified as features exceeding $1 \times 10^{-5} \text{s}^{-1}$ in the 850 hPa
201 relative vorticity field, truncated to T42. Features identified poleward of 30N, with
202 a lifetime of at least 2 days and which travel at least 1000 km are retained as ETCs
203 and included in the analysis. The sensitivity of the results to these thresholds has
204 been assessed through investigating the impact of a relaxation of either the time
205 or distance criteria. Conclusions were insensitive to changing these thresholds.

206 Tracks are identified in 6-hourly fields in HiGEM and ERAI and are then
207 degraded to daily resolution with points at 12:00 UTC retained. Tracks of the
208 ETCs used for GPCP are identified in the analysed ERAI data, which represents
209 a best guess of the state of the atmosphere, and the precipitation fields are centred
210 on the analysed location at 12UTC. For ERAI, the ETCs are identified in the 12-
211 hour lead time forecast vorticity making their locations consistent with the forecast
212 precipitation accumulations. In HiGEM, the model is run in climate mode, so

213 precipitation and vorticity are simply extracted from the model fields and are
214 self-consistent.

215 The compositing methodology employed here has previously been applied in
216 studies of ETCs (e.g. Bengtsson et al 2007, 2009; Catto et al 2010; Dacre et al
217 2012; Dacre and Gray 2013). It involves several steps and is discussed in detail in
218 Catto et al (2010). To summarise the procedure, first the tracks to be composited
219 are identified and selected. The precipitation field is then extracted on a radial
220 grid centred on each of the identified cyclone points. A time within each track's
221 lifecycle is chosen for compositing, which in this study is the time of maximum
222 precipitation intensity based on the average precipitation within 5° of the ETC
223 centre. The precipitation, for each ETC at the relevant timestep, is then averaged
224 across all ETCs to create a composite. The ETCs are not rotated to their direction
225 of travel prior to compositing. This was not possible due to the technique employed
226 to extract ETCs within specified regions. The results for composites across the
227 whole Northern Hemisphere were not sensitive to using rotation. Sensitivity of the
228 results to the choice of a 5° radial cap for the identification and selection of ETCs to
229 be included in these composites was tested by increasing the size of this cap to 10°
230 and 15° , which would capture precipitation more distant from the storm centre,
231 such as that on an extended trailing cold front. The conclusions were insensitive
232 to changing the cap size. An analysis of the tracks identified using each radial
233 cap (not shown) shows that the tracks selected are largely identical irrespective of
234 the radius used. When producing composites, points with zero precipitation are
235 included in this study. The mean precipitation and intensity distributions would
236 differ if zero values were not included (see Rossow et al 2013). In this study, where

237 confidence intervals are expressed with respect to mean composite precipitation
238 rates, they have been calculated using bootstrapping.

239 It has previously been shown that the maxima of precipitation in ETCs typi-
240 cally occurs prior to the maximum dynamical intensity as the latent heat release
241 associated with the precipitation acts to intensify the storm (Bengtsson et al 2009;
242 Dacre et al 2014). Given the focus of this study is on precipitation, cyclones are
243 subset based on their precipitation intensity, rather than a dynamical field (e.g.
244 vorticity).

245 2.5 Precipitation climatologies methodology

246 The analysis of precipitation climatologies performed in section 3.2 is that devel-
247 oped in Hawcroft et al (2012) and further applied in Zappa et al (2014). Cyclones
248 are identified using the tracking technique described in section 2.4 at 12UTC on
249 each day. Precipitation within a 12° radial cap of an ETC centre is designated as
250 being associated with an ETC. The choice of this radius is justified in Hawcroft
251 et al (2012). The daily accumulated precipitation fields used in this part of the
252 study are created in the same way as for the composite analysis. At each grid
253 point, the precipitation produced within 12° of ETCs from all daily timesteps
254 is accumulated to provide a climatology of storm associated precipitation. This is
255 then compared to the total precipitation and the fraction of the total precipitation
256 associated with ETCs is further evaluated.

257 To assess the contribution of the most extreme storms to the climatology, ETCs
258 are subset by their maximum precipitation intensity (based on 5° areal average
259 precipitation around the ETC centre). Sensitivity of the climatologies to subsetting

260 the storms using a larger cap to assess intensity was tested and did not influence the
 261 conclusions. Using these filtered extreme storms, the same methodology is applied
 262 to create climatologies of precipitation solely associated with the most heavily
 263 precipitating ETCs. Using this technique, the ability of the model to produce a
 264 realistic spectrum of storms, from weakly to heavily precipitating, is evaluated.

265 A further decomposition of ETC associated precipitation is also undertaken,
 266 using the same methodology as Zappa et al (2014) which is similar to that em-
 267 ployed by Finnis et al (2007). Biases in the total storm associated precipitation
 268 climatology may be associated with errors in (1) the average ETC precipitation
 269 intensity, (2) the number of ETCs, or (3) a combination of the two. It is possible to
 270 separate these effects through considering the total Storm Associated Precipitation
 271 (SAP) at a gridpoint $P_{SAP}(x, y)$ to be a function of the total number of days when
 272 a gridpoint is within the radius of an ETC, $N(x, y)$, and the mean precipitation
 273 which falls at that gridpoint across these timesteps, $\mu(x, y)$, such that

$$P_{SAP} = N \cdot \mu, \quad (1)$$

274 N and μ can be calculated for HiGEM (N_H, μ_H), GPCP and ERAI (N_E, μ_E).
 275 The results for GPCP and ERAI are comparable, so for simplicity only ERAI is
 276 shown here. Using this approach, it is possible to decompose the extent to which
 277 biases (ΔP_{SAP}) in HiGEM are attributable to errors in N or μ as follows

$$\Delta P_{SAP} = N_H \cdot \mu_H - N_E \cdot \mu_E = (N_H - N_E) \cdot \mu_E + (\mu_H - \mu_E) \cdot N_E + (N_H - N_E) \cdot (\mu_H - \mu_E) \quad (2)$$

278 such that any biases in ETC associated precipitation can be attributed to errors
 279 in number, intensity or a cross—term associated with errors in both number and
 280 intensity.

281 **3 Cyclone associated precipitation**

282 3.1 Composite precipitation

283 In Figure 1 the track density for the datasets is shown for the 10 seasons analysed in
284 this study. The broad patterns of ETC activity in HiGEM are comparable to ERAI
285 (see also Catto et al 2011). The performance of HiGEM in this respect compares
286 favourably relative to the CMIP5 models (see Zappa et al 2013). Examining Figure
287 1 in further detail, it can be seen that in HiGEM there is a higher track density in
288 the central/western Pacific and lower density in the eastern Pacific when compared
289 to ERAI. Differences in the spatial distribution of ETCs are also observed in the
290 Atlantic.

291 *3.1.1 Northern Hemisphere composite precipitation*

292 In Figure 2 composites of precipitation from all ETCs (3662 in HiGEM and 3764
293 in ERAI/GPCP) are shown. In the innermost 5° of the composites, the precip-
294 itation averages vary from 6.98 to 7.67 mm day⁻¹. Maximum intensities (the
295 highest single grid point in each composite) are 10.38/10.52/10.63 mm day⁻¹ in
296 HiGEM/ERAI/GPCP, respectively, and are not statistically distinguishable (at
297 95% confidence levels). In Table 1, which shows the average precipitation asso-
298 ciated with composites of ETCs from the three datasets, ETCs are subset by
299 intensity. HiGEM produces relatively more intensely precipitating ETCs though
300 the mean precipitation values are generally not statistically different from one
301 of the two observational datasets. For example, for the 200 most intensely pre-
302 cipitating storms the 5° radially averaged precipitation is 25.33/24.31/24.66 mm

303 day^{-1} in HiGEM/ERA-Interim/GPCP, respectively, with 95% confidence intervals of
304 $\pm 0.55/0.57/0.75 \text{ mm day}^{-1}$.

305 *3.1.2 Regional composite precipitation*

306 Given the majority of the ETCs which are incorporated into Figure 2 are over
307 the ocean, it is instructive to construct composites from each dataset using storms
308 from both continental and oceanic regions.

309 In Figure 3 composites of precipitation in the most intensely precipitating 200
310 ETCs from four regions are shown. The location of the Pacific, Atlantic, European
311 and North American regions sampled in these composites are shown in Figure
312 1. The selection of 200 ETCs is justified on the basis that it provides sufficient
313 sampling to reduce noise but also samples fully developed ETCs in all regions - in
314 the continental regions, sampling a large number of ETCs requires the inclusion
315 of weakly precipitating systems which may not exhibit the typical structure and
316 behaviour of ETCs. Precipitation intensities in these composites for 5° radii are
317 provided in Table 2.

318 In Figure 3, in the Atlantic, the maximum precipitation intensity in HiGEM
319 exceeds 30 mm day^{-1} compared to maxima of 26 mm day^{-1} in GPCP and ERA-Interim.
320 The radial precipitation averages (Table 2) also reflect these intensity differences,
321 with 5° precipitation averages in HiGEM over 1 mm day^{-1} greater than in GPCP
322 and ERA-Interim (though this difference is only significant at a 95% level with respect to
323 ERA-Interim). In the Pacific composites, the precipitation maxima exceed $32/30/27 \text{ mm}$
324 day^{-1} in ERA-Interim/HiGEM/GPCP. The radial precipitation averages (Table 2) in the
325 Pacific are, however, closely comparable across the datasets.

326 For the Europe region, the magnitude of the individual (single pixel) precipita-
327 tion maxima are in better agreement than the oceanic composites across the three
328 datasets, with peak composite precipitation, all falling within a range of 12.5-15.0
329 mm day⁻¹. The spatial extent of the region of peak precipitation is more extensive
330 in GPCP leading to higher area averaged precipitation within the central 5° of the
331 composites (Table 2). In the North America region, the maximum precipitation
332 intensities in ERAI and GPCP are ~25mm day⁻¹ with a more intense maximum
333 of 31mm day⁻¹ in HiGEM.

334 The differences in precipitation rates across the regions can be better charac-
335 terised through an analysis of the 200 individual storms which contribute to each
336 composite. The storms are individually extracted and the precipitation around
337 each storm is gridded into a 14400 point array (360°x20° with 1x0.5° resolution).
338 Statistics are then derived from these 200 storms. In Figure 4 histograms of pre-
339 cipitation rates over all points in the 200 storms are shown. In these histograms,
340 the 95% confidence interval in each bin is less than 0.21% in all cases, such that
341 almost all bins are statistically separable across the datasets. Over 15% of points
342 are non-precipitating in GPCP in both the Atlantic and Pacific ETCs, with fewer
343 than 5% assigned as non-precipitating in both HiGEM and ERAI.

344 Analysing the points within 5° of each storm centre (not shown), where much
345 of the heaviest precipitation associated with the WCB occurs, the proportion of
346 gridpoints in GPCP with precipitation rates below 8mm day⁻¹ is much greater
347 than in ERAI and HiGEM (over 44% compared to less than 18% in both the At-
348 lantic and Pacific) with correspondingly fewer gridpoints with higher precipitation
349 rates. The differences between GPCP and ERAI/HiGEM in the Atlantic and Pa-

350 cific therefore appear to be associated with both the intensity of the most heavily
351 precipitating gridpoints and also the frequency of non-precipitating gridpoints.

352 For the Europe region, Figure 4 shows that in GPCP over twice as many
353 gridpoints have precipitation rates greater than 16mm day^{-1} compared to ERAI
354 and HiGEM. The number of gridpoints that are non-precipitating is much higher in
355 GPCP (over 22% compared to less than 8% in ERAI and HiGEM). The net result
356 of these competing effects is that composite precipitation in Europe is higher in
357 GPCP than in ERAI and HiGEM (see Figure 3 and Table 2). In the North America
358 region, the composite precipitation intensities in ERAI and GPCP in Figure 3 and
359 Table 2 are similar with more intense composite precipitation found in HiGEM.
360 In Figure 4 it can be seen that HiGEM produces a greater number of gridpoints
361 above 32mm day^{-1} than both ERAI and GPCP. As in other regions, the number
362 of non-precipitating gridpoints in GPCP is significantly greater than in ERAI and
363 HiGEM (over 23% compared to less than 12% and 8%, respectively).

364 In summary, though HiGEM generally compares well to both GPCP and ERAI
365 when mean composite precipitation rates are evaluated across all Northern Hemi-
366 sphere ETCs, differences occur as more intensely precipitating storms are analysed.
367 The statistical distribution of precipitation intensities within the ETCs show that
368 the mean precipitation rates may mask differences in intensity distribution.

369 3.2 Cyclone associated precipitation climatology

370 It has previously been shown in Hawcroft et al (2012) that estimates of the total
371 precipitation in the Northern Hemisphere produced by ETCs ('storm associated
372 precipitation') in ERAI and GPGP agree well. In Figure 5 the total precipita-

tion, total storm associated precipitation and percentage of the total precipitation contributed by ETCs is shown for HiGEM, ERAI and GPCP.

Figure 5(a-c) shows that HiGEM is able to reproduce the broad precipitation structure of the two major stormtracks. There are, however, biases in the location of the maxima in both stormtracks (i.e. located too close to the western boundaries of the Pacific and Atlantic) and an over-extension of the Atlantic stormtrack towards Iceland. The total precipitation within both the Atlantic and Pacific storm tracks reaches 7mm day^{-1} in DJF in GPCP/ERA1. In HiGEM, this peaks at 10mm day^{-1} in the Pacific and 9mm day^{-1} in the Atlantic. The high precipitation bias in the total precipitation in the storm track regions is also present in the storm associated precipitation climatology in HiGEM (Figure 5(d-f)). In the Pacific, the maximum storm associated precipitation reaches 8mm day^{-1} in HiGEM compared to $5\text{-}6\text{mm day}^{-1}$ in GPCP/ERA1. In the Atlantic, the maximum storm associated precipitation is in excess of 7mm day^{-1} in HiGEM and can again be contrasted with the $5\text{-}6\text{mm day}^{-1}$ maxima in GPCP/ERA1.

Figure 5(g-i) show the percentage of the total precipitation climatology which is contributed by ETCs, with ETCs contributing over 50% of total precipitation in much of the Northern Hemisphere. In some locations this contribution can exceed 90%. The percentage of total precipitation produced by HiGEM can generally be considered within the bounds of observational uncertainty in many regions given the differences observed between ERA1 and GPCP. However, around the Atlantic and Pacific stormtracks the spatial extent of the region where over 80% of total precipitation is contributed by ETCs is overestimated in HiGEM. Where the percentage figures in HiGEM agree with ERA1 and GPCP, but the total precipitation/storm associated precipitation is overestimated (such as in the storm tracks),

398 this implies that there may be some deficiencies in the representation of precipita-
399 tion in HiGEM - in the storm tracks, too much precipitation is being produced by
400 ETCs but too much precipitation is also produced when ETCs are not present.

401 *3.2.1 Decomposition of bias*

402 The number of ETCs in the Pacific/Atlantic stormtracks in HiGEM exhibits spa-
403 tial differences when compared to ERAI (see Figure 1). There are also differences
404 in the composite precipitation estimates across the regions (as shown in Figure 3).
405 The impact on the climatology of these differences in number and intensity can
406 be more fully decomposed to assess the contribution of errors in (1) storm num-
407 ber and (2) average storm precipitation intensity to the total storm associated
408 precipitation bias in HiGEM using the technique introduced in Section 2.5.

409 This analysis is shown in Figure 6 and the cross—term is generally small (Fig-
410 ure 6(e)). The regions with large bias in storm associated precipitation in HiGEM
411 (notably in the Pacific and Atlantic stormtracks and in the eastern Mediterranean)
412 are primarily associated with errors in the average intensity of ETCs (Figure 6(d)).
413 The positive precipitation bias in the central and western Pacific and north east
414 Atlantic is further enhanced by excessive ETC number (Figure 6(c)). In other
415 regions, such as the western Atlantic, an underestimate of storm number acts to
416 modulate and in some instances reverse high biases in average precipitation inten-
417 sity. In the central Atlantic, the significant underestimate in average intensity is
418 the dominant term. The spatial structure of these biases can, in part, be related
419 to SST errors in HiGEM (see Shaffrey et al 2009, Figure 3), such as a local cold
420 bias in SSTs situated in the central Atlantic which is spatially coincident with an
421 underestimate in precipitation. Keeley et al (2012) found this local precipitation

422 underestimate disappeared when the model was forced with observed SSTs. Across
423 the extratropics, the net effect of these two factors (number and intensity) is to
424 leave a complex pattern of over/underestimation of storm associated precipitation
425 in HiGEM.

426 *3.2.2 The contribution of heavily precipitating cyclones to the total storm*
427 *associated precipitation*

428 The differences in the storm associated precipitation climatology between HiGEM
429 and GPCP/ERA-Interim are related to both the spatial distribution of ETCs and differ-
430 ences associated with the average amount of precipitation produced by ETCs. If
431 the distribution of storm associated precipitation from heavily and lightly precip-
432 itating events differs (e.g. too much precipitation coming from a small number of
433 heavy events rather than a greater number of light events) this has implications
434 for the temporal distribution of precipitation at any given location, which is im-
435 portant for flooding, droughts and agriculture and also the plausibility of future
436 projections of any change in such events that might be derived from integrations
437 of HiGEM.

438 Figure 7 shows the contribution of ETCs to the total storm associated precipi-
439 tation climatology throughout their lifecycle as a function of each ETC's maximum
440 precipitation intensity. In HiGEM, the relative contribution of the most intense
441 storms is greater than in ERA-Interim/GPCP. For example, in HiGEM, the most in-
442 tense 10% of ETCs produce over 30% of the total storm associated precipitation
443 compared to less than 25% in both ERA-Interim and GPCP. As a result, substantially
444 less precipitation is produced by weaker ETCs in HiGEM. Greater differences are
445 seen between ERA-Interim and GPCP for weaker intensities, though the contribution of

446 weaker ETCs in HiGEM lies significantly outside the bounds of uncertainty be-
447 tween ERAI and GPCP. For the weakest 60% of ETCs, HiGEM/ERAI/GPCP
448 produce contributions of 21.1/30.8/26.2%, respectively. These biases again imply
449 that precipitation processes have some deficiencies in HiGEM.

450 **4 Summary and conclusions**

451 This study has investigated whether HiGEM is able to reproduce the precipita-
452 tion associated with ETCs using a tracking and compositing analysis. ETCs are
453 composited at the time of their most intense precipitation and the contribution of
454 ETCs across their whole lifecycle to total precipitation in the Northern Hemisphere
455 has been assessed. The output of the model has been evaluated against ERAI re-
456 analysis and GPCP remote sensing precipitation estimates. Given the importance
457 of precipitation associated with ETCs to the total precipitation climatology and
458 uncertainties about how ETCs will respond in a changing climate, evaluating the
459 ability of climate models to reproduce precipitation associated with ETCs assists
460 in establishing the likelihood that their projections of future precipitation change
461 are reliable.

462 This study has taken a process based approach to the evaluation of HiGEM
463 by identifying ETCs and evaluating processes around them. Such an approach
464 provides a platform to link biases in physical processes in the climate system with
465 the representation of a specific, identified phenomena and provides a different
466 perspective to a simply statistical evaluation of the model.

467 The key findings of this study as are follows

- 468 – Composites of precipitation associated with all Northern Hemisphere ETCs in
469 HiGEM compare well to ERAI and GPCP. See Figure 2.
- 470 – Differences in composite precipitation between HiGEM and ERAI/GPCP are
471 found when ETCs are selected by region. Differences in these composites are
472 also found between ERAI and GPCP. Within the composites, the statistical
473 distribution of precipitation rates is found to vary across the datasets. HiGEM
474 produces a greater frequency of very intense (over 64mm day^{-1}) precipitation
475 than both GPCP and ERAI. See Figures 3 and 4.
- 476 – HiGEM is able to reproduce the broad patterns of precipitation associated with
477 the Northern Hemisphere storm tracks. Localised biases are associated with
478 both the numbers of ETCs and the average precipitation intensity of ETCs,
479 though the patterns of these biases are spatially complex and of varying sign.
480 In the Pacific, HiGEM produces too many ETCs which typically produce too
481 much precipitation. In the Atlantic, a more complex pattern is observed, with
482 weaker precipitation intensity related to local cold SST biases. See Figure 6.
- 483 – HiGEM is found to produce a disproportionately high fraction of storm associ-
484 ated precipitation from the most intensely precipitating ETCs, with over 30%
485 of total storm associated precipitation coming from the most intense 10% of
486 ETCs compared to less than 25% in ERAI/GPCP, with a resultant underes-
487 timate of the fraction of precipitation produced by weaker ETCs. See Figure
488 7.

489 Over the ocean, the mean distribution of precipitation around composites of in-
490 tensely precipitating ETCs in GPCP and ERAI masks differences in the statistical
491 distribution of precipitation rates. This introduces uncertainty into the observa-

492 tional estimates which are being used to evaluate HiGEM. These results indicate
493 caution is required when validating model estimates of precipitation, particularly
494 intense precipitation, over the extratropical oceans.

495 Hawcroft et al (2012) have previously shown that the storm associated precip-
496 itation climatologies in GPCP and ERAI are comparable. In this study HiGEM is
497 shown to over estimate both the total precipitation and storm associated precipi-
498 tation (by up to 3mm day^{-1}) around the main stormtrack regions in the Atlantic
499 and Pacific. It has also been shown that intense ETCs produce too much of the to-
500 tal storm associated precipitation in HiGEM when compared to ERAI and GPCP.
501 Similar biases have been found when intense precipitation associated with fronts
502 has been evaluated in the ACCESS model, which is based on a similar model to
503 HiGEM (Catto et al 2013).

504 Given the importance of ETCs to the total precipitation climatology (Hawcroft
505 et al 2012) and the fact many large scale extreme precipitation events are asso-
506 ciated with ETCs (Pfahl and Wernli 2012; Catto and Pfahl 2013), these results
507 are important. The identified biases may have implications for the reliability of
508 any projections of the behaviour of ETCs, extreme extratropical precipitation
509 events or the frequency of precipitation derived from HiGEM using idealised fu-
510 ture scenarios. The techniques used in this study have been applied to evaluate the
511 CMIP5 dataset in the Mediterranean (Zappa et al 2014) and could be extended to
512 the whole Northern Hemisphere to understand whether the precipitation intensity
513 errors observed here are typical of GCMs.

514 The precipitation biases observed in HiGEM may be related to the large scale
515 dynamics of the model (including SST biases) and may also be influenced by a poor
516 representation of processes in ETCs, such as the location and magnitude of latent

517 heat release. Catto et al (2010) have shown that the large-scale features of ETCs
518 are well represented in HiGEM when compared to the ERA-40 reanalysis (Uppala
519 et al 2005) though the structure of the warm conveyor belt, where much precipita-
520 tion is produced and significant latent heat is released, is much deeper in HiGEM
521 (using relative humidity as a proxy for cloud) than ERA-40. Any biases in the
522 processes which produce precipitation around ETCs may have upscale dynamical
523 effects. The amount of precipitation produced by an individual cyclone is closely
524 related to the column integrated latent heat release since condensational heating
525 associated with precipitation is one of the primary diabatic processes which oc-
526 curs in ETCs (Joos and Wernli 2011). For example, Willison et al (2013) found
527 reducing latent heating in ETCs reduced the intensity of the Atlantic stormtrack
528 in a series of idealised experiments. The representation of latent heating around
529 ETCs and its relationship with the evolution and behaviour of ETCs in HiGEM
530 is the subject of ongoing investigation.

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535 **Appendix**

536 Decadal variability in HiGEM

537 The data used in this study is taken from a single decade of an 80 year integration of the
538 model forced with late 20th-century radiative forcings. Figure 8 shows the percentage of the
539 total precipitation contributed by ETCs in each of these decades. It can be seen that though
540 there are small variations in the locations of the highest precipitation accumulations, associated

541 with variability in the storm track locations, the biases in the model climatology relative to
542 the observations remain consistent across the decades.

543 Spin-up in ERAI

544 The ERAI reanalysis (Dee et al 2011; Simmons et al 2007) uses a 4D-Var data assimilation
545 system to incorporate observations over a 12-hour analysis period, with forecasts commencing
546 at 00:00UTC and 12:00UTC. Precipitation is not an analysed field and must therefore be
547 taken from short-range forecast accumulations. During the first several hours of the forecast
548 simulation, the precipitation field (and many other fluxes and tendencies) is affected by “spin-
549 up” as the model adjusts from the initialised fields, such that the estimates at the start of the
550 forecast period are less robust than at later lead times (see Kållberg 2011). Moving too far from
551 the start of the forecast also leads to degradation of the precipitation estimates. Given these
552 issues, a suitable window must be chosen for the accumulations to be used in this study. The
553 primary constraints on the selection of an appropriate period is the desire to use the GPCP
554 dataset in this work. The GPCP dataset provides daily total precipitation estimates from 00-
555 24UTC. Further, the ERAI forecasts are initialised every 12 hours so any accumulations must
556 be selected from continuous 12 or 24 hour periods in the forecast.

557 Given the requirement to have daily accumulations centred on 12:00UTC, it would be
558 possible to use either (1) a continuous 24-hour accumulation from a single forecast for each
559 day or (2) two 12 hour accumulations from successive forecasts. To assess this, evaluating
560 any spin-up/adjustment (as the model is initialised) or model drift (as the forecast increases
561 in length and the model is no longer closely constrained by observations) is required. The
562 adjustment/drift effect can be more readily demonstrated using shorter accumulation periods.
563 In this analysis, given the 12 hour or greater accumulation periods required for comparison to
564 GPCP, 0-12, 12-24 or 24-36 hours are likely candidate lead times for analysis. Longer forecasts
565 are likely to degrade the quality of the estimates as the forecast model relaxes into a state
566 which is less constrained by observations.

567 In Figure 9 composite precipitation taken from the 200 Atlantic storms in Figure 3 is
568 shown. The results for other regions are not materially different. The composites show accu-

569 mulated precipitation at variable lead times from 0-3, 12-15, 24-27 and 36-39 hours where the
570 accumulation is from each 3 hour window.

571 The storm position is centred on the analysed location at the time the precipitation fields
572 are extracted, since to sample the forecast location would be laborious and add little value
573 to the analysis. As such, there is some spatial offset in the location of the maxima in the
574 longer lead times. This is because ETCs tend to propagate too slowly in the forecast model,
575 giving the impression that the precipitation maxima move closer to the storm centre as lead
576 time increases (see Froude et al 2007a,b). It is clear that the 0-3 hour accumulation has lower
577 accumulated precipitation than the longer lead times. It is also apparent that the intensity of
578 the precipitation maxima steadily degrades with lead times beyond 12 hours.

579 This is further evident in the precipitation cross sections shown in Figure 10. Given the
580 location of the precipitation maximum changes due to the storm centring, the cross-sections are
581 shown for a number of locations, though the differences between the lead times remain clear.
582 As a result of the adjustment effect in the 0-3 hour period and the steady decay observed
583 in the precipitation maxima and structure in the 24 and 36 hour lead times, the forecast
584 periods utilised in this study for comparison to GPCP are accumulations from 12 to 24 hours
585 from forecasts starting at 12:00UTC the previous day and 00:00UTC on the day of interest, as
586 shown in Figure 11. The two forecast accumulations are combined to provide daily precipitation
587 estimates for comparison to GPCP. The 12 to 24-hour forecast estimates have previously been
588 found to compare well to gridded gauge data (Simmons et al 2010), with longer lead times
589 degrading the quality of the estimates (Kobold and Sušelj 2005). The results of de Leeuw et al
590 (2014) also indicate that this lead time offers the best estimates available from ERAI given
591 the daily accumulations required in this study.

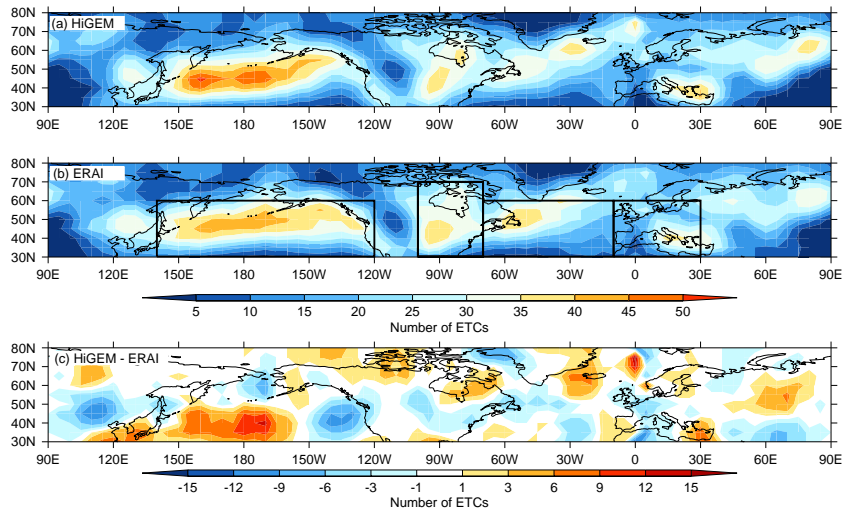


Fig. 1 Histogram of ETC track density in (a) HiGEM, (b) ERAI and (c) the difference between (a) and (b). Tracks from ERAI are used to identify ETCs in GPCP. The total number of ETCs per 5° across the 10 seasons used in this study is shown and the plots are smoothed over 3° to reduce noise. In the ERAI histogram, the Pacific, North American, Atlantic and European regions are shown which are used to subset the ETCs included in the composites in Figure 3 and statistics in Table 2.

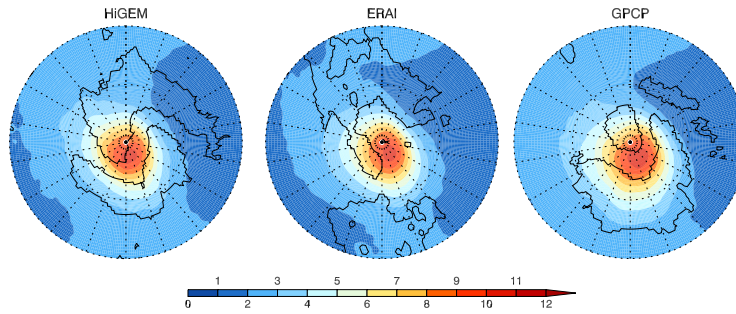


Fig. 2 Composite precipitation (mm day^{-1}) from all Northern Hemisphere ETCs in the HiGEM, ERAI and GPCP datasets for the 10 seasons used in this study. Composites have a 20° radius. The areas enclosed by black contours show where differences between the datasets are statistically significant at $\geq 95\%$. In the HiGEM composite, the 95% contour is shown with respect to GPCP. In the ERAI composite, the 95% contour is shown with respect to HiGEM. In the GPCP composite, the 95% contour is shown with respect to ERAI.

Northern Hemisphere ETCs					
	All	top 1000	top 500	top 200	top 100
HiGEM	7.67 (± 0.22)	16.75 (± 0.31)	20.60 (± 0.41)	25.33 (± 0.55)	28.33 (± 0.65)
ERA-Interim	7.54 (± 0.21)	16.43 (± 0.30)	20.05 (± 0.39)	24.31 (± 0.57)	26.91 (± 0.88)
GPCP	6.98 (± 0.21)	15.93 (± 0.33)	19.90 (± 0.47)	24.66 (± 0.75)	28.25 (± 1.08)

Table 1 Radially weighted precipitation averages for the 5° closest to the composite centres for all storms in the Northern Hemisphere (poleward of 30°N) with storms further sub-sampled by their maximum precipitation intensity showing, for example, the average precipitation in the 100 most intense storms (mm day^{-1}). Sampling of storms is based on the average precipitation in a 5° radius from the ETC centre at the time of maximum precipitation. Confidence intervals (at 95%) are shown in brackets.

Regional ETCs					
	All	Atlantic	Pacific	Europe	North America
HiGEM	25.33 (± 0.55)	19.02 (± 0.67)	21.46 (± 0.75)	9.03 (± 0.29)	16.26 (± 0.73)
ERA-Interim	24.31 (± 0.57)	17.51 (± 0.49)	21.68 (± 0.73)	9.13 (± 0.29)	14.92 (± 0.68)
GPCP	24.66 (± 0.75)	17.93 (± 0.67)	21.23 (± 0.90)	13.12 (± 0.49)	16.69 (± 0.92)

Table 2 Radially weighted precipitation averages for the 5° closest to the composite centres for the 200 most intensely precipitating ETCs in all of the Northern Hemisphere (poleward of 30°N) and in each region (mm day^{-1}). Sampling of storms is based on the average precipitation in a 5° radius from the ETC centre at the time of maximum precipitation within each region. Confidence intervals (at 95%) are shown in brackets. The regions are shown in Figure 1.

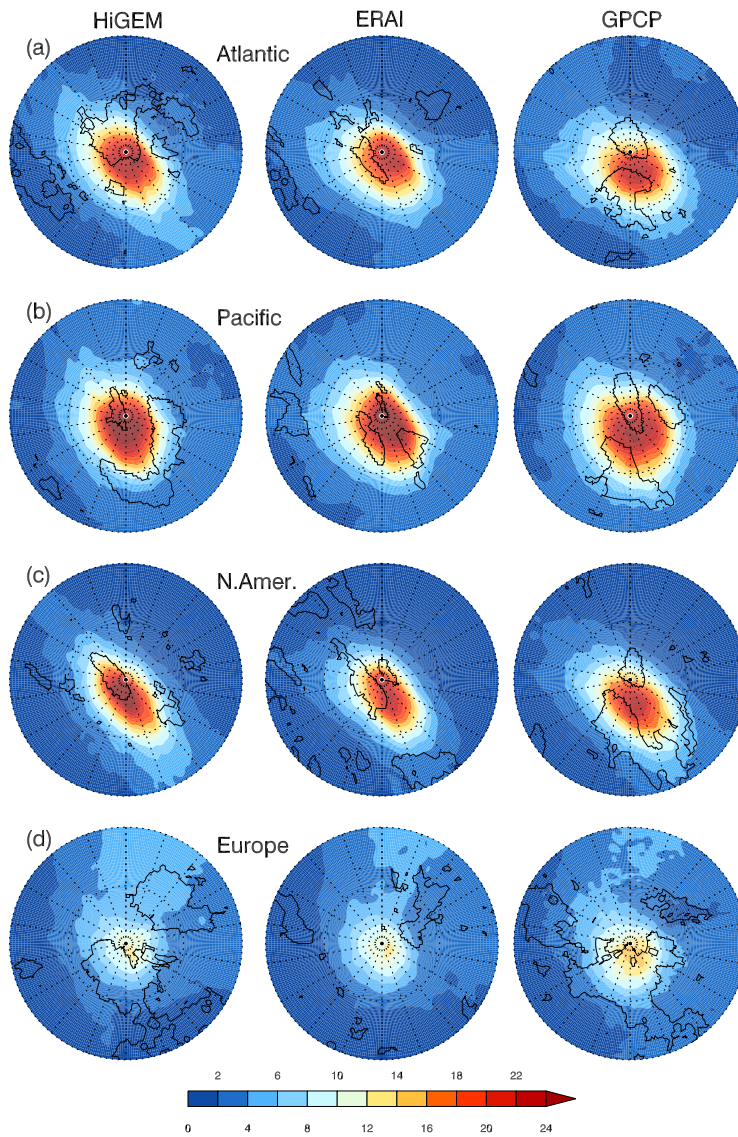


Fig. 3 Composite precipitation in HiGEM, ERAI and GPCP for the (a) Atlantic, (b) Pacific, (c) North America and (d) Europe regions from the most intensely precipitating 200 ETCs in each region. Figures are in mm day^{-1} . Composites have a 20° radius. The areas enclosed by black contours show where differences between the datasets are statistically significant at $\geq 95\%$. In the HiGEM composites, the 95% contour is shown with respect to GPCP. In the ERAI composites, the 95% contour is shown with respect to HiGEM. In the GPCP composites, the 95% contour is shown with respect to ERAI.

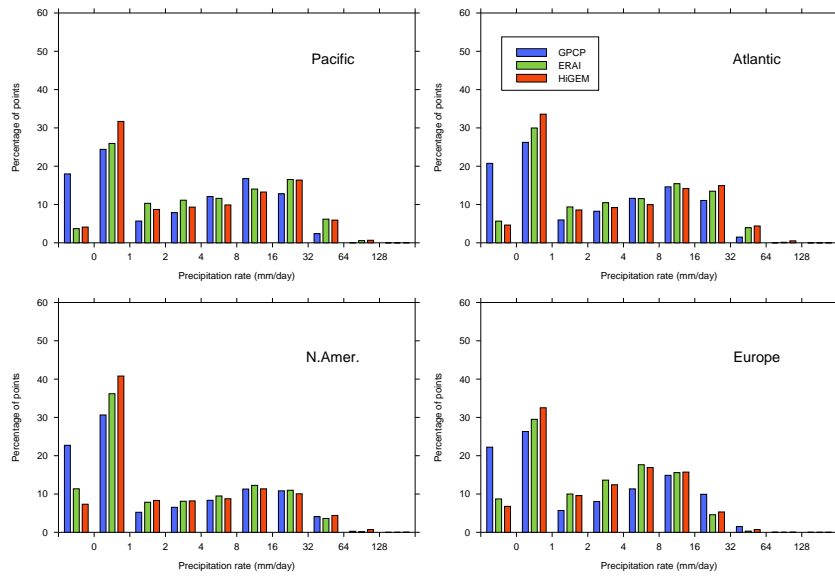


Fig. 4 Distributions of precipitation intensities across all pixels in all 200 storms for a 20° radial cap around the ETC centres for the four regions. The bin at the far left represents 0mm day^{-1} with the remaining bins between the values on the x-axis. Confidence intervals (at 95%) on all histogram bins are less than $\pm 0.21\%$ and are based on the standard error of the mean.

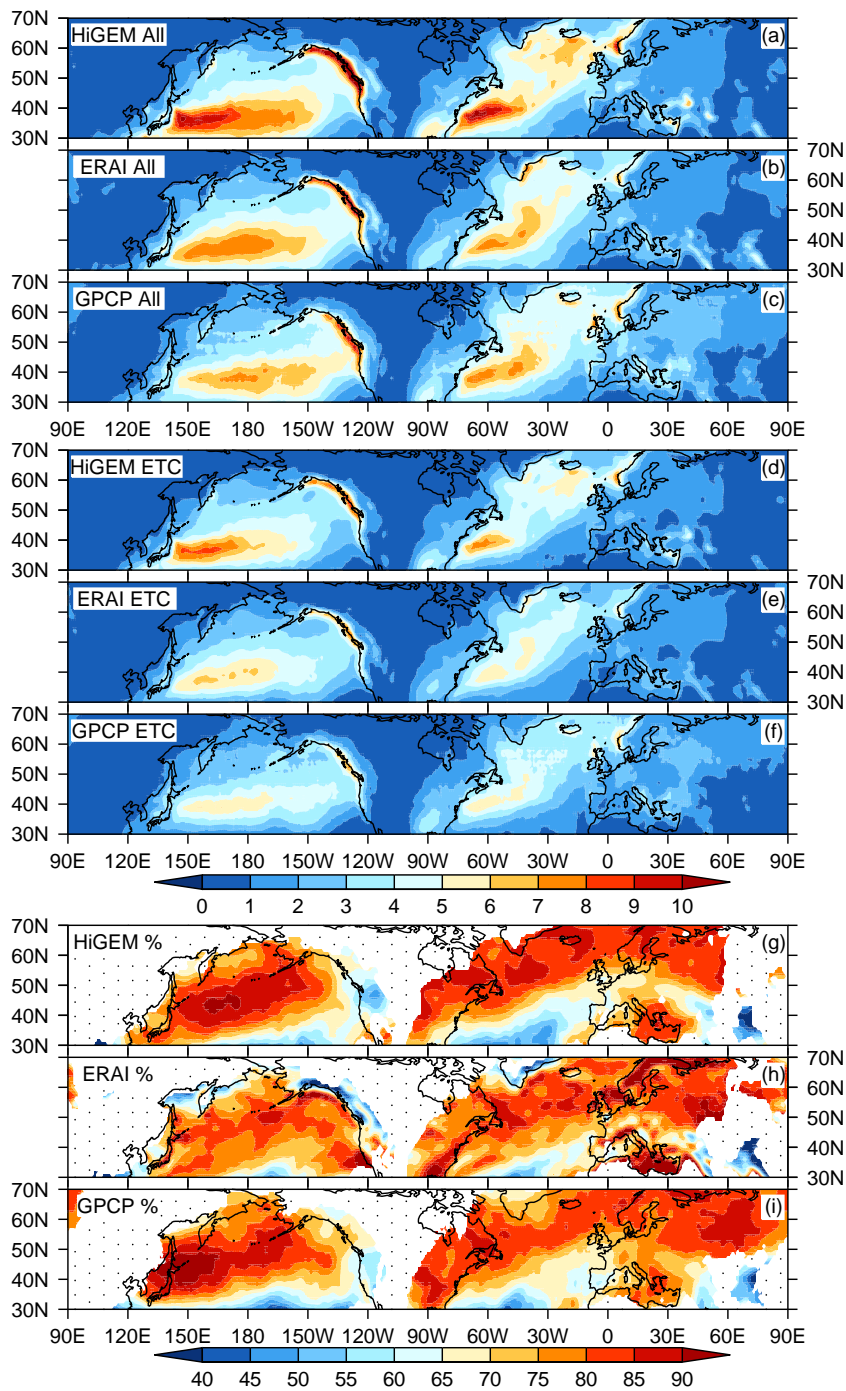


Fig. 5 Total precipitation (All, a-c), storm associated precipitation (ETC, d-f) and the percentage of the total precipitation contributed by ETCs (%) (g-i) in HiGEM, ERAI and GPCP. The masked and stippled areas in the percentage plots are where the total climatological precipitation is less than 1 mm day^{-1} . Figures are in mm day^{-1} for panels a-f and % for panels g-i.

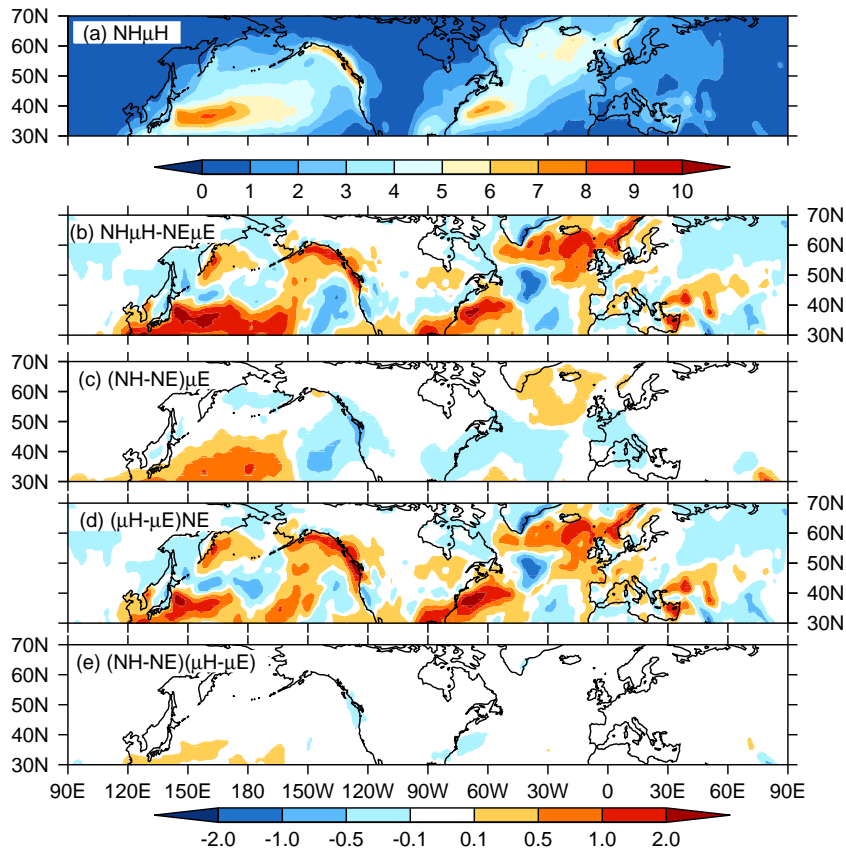


Fig. 6 Storm associated precipitation in (a) HiGEM ($\text{NH}\mu\text{H}$) and the differences in the storm associated precipitation climatology relative to (b) ERAI ($\text{NH}\mu\text{H}-\text{NE}\mu\text{E}$) associated with the differences in (c) the number of ETCs ($(\text{NH}-\text{NE})\mu\text{E}$), (d) the average precipitation intensity of ETCs ($(\mu\text{H}-\mu\text{E})\text{NE}$) and (e) the cross-term ($(\text{NH}-\text{NE})(\mu\text{H}-\mu\text{E})$). Figures are in mm day^{-1} and are smoothed over 3° to reduce noise. Terms are as in Equation 1.

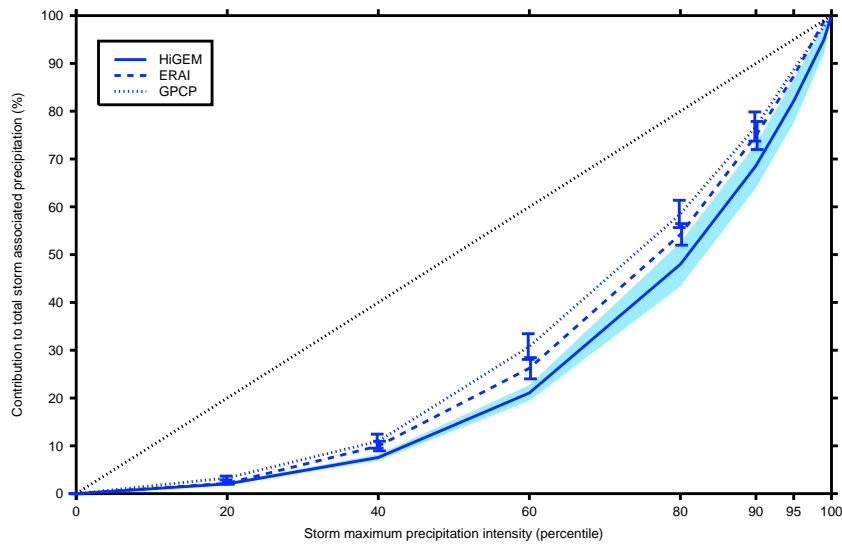


Fig. 7 Contribution to storm associated precipitation based on the maximum precipitation intensity of storms. Maximum intensity is derived from a 5° areal average around the storm centre at the time of peak precipitation. The precipitation associated with storms over their lifetime is then accumulated to derive the importance of storms - based on their maximum intensity - to the total climatological storm associated precipitation. Intensity values are percentiles of all storms in the study period with the contribution shown as a cumulative contribution of all storms below a given percentile threshold. The black dotted line demonstrates the relationship that would exist if all storms contributed equally and demonstrates the importance to the overall climatology of storms of different maximum precipitation intensity. Error bars show the standard deviation of interannual variability for GPCP and ERAI across the decade of data here. The shading shows the standard deviation for HiGEM.

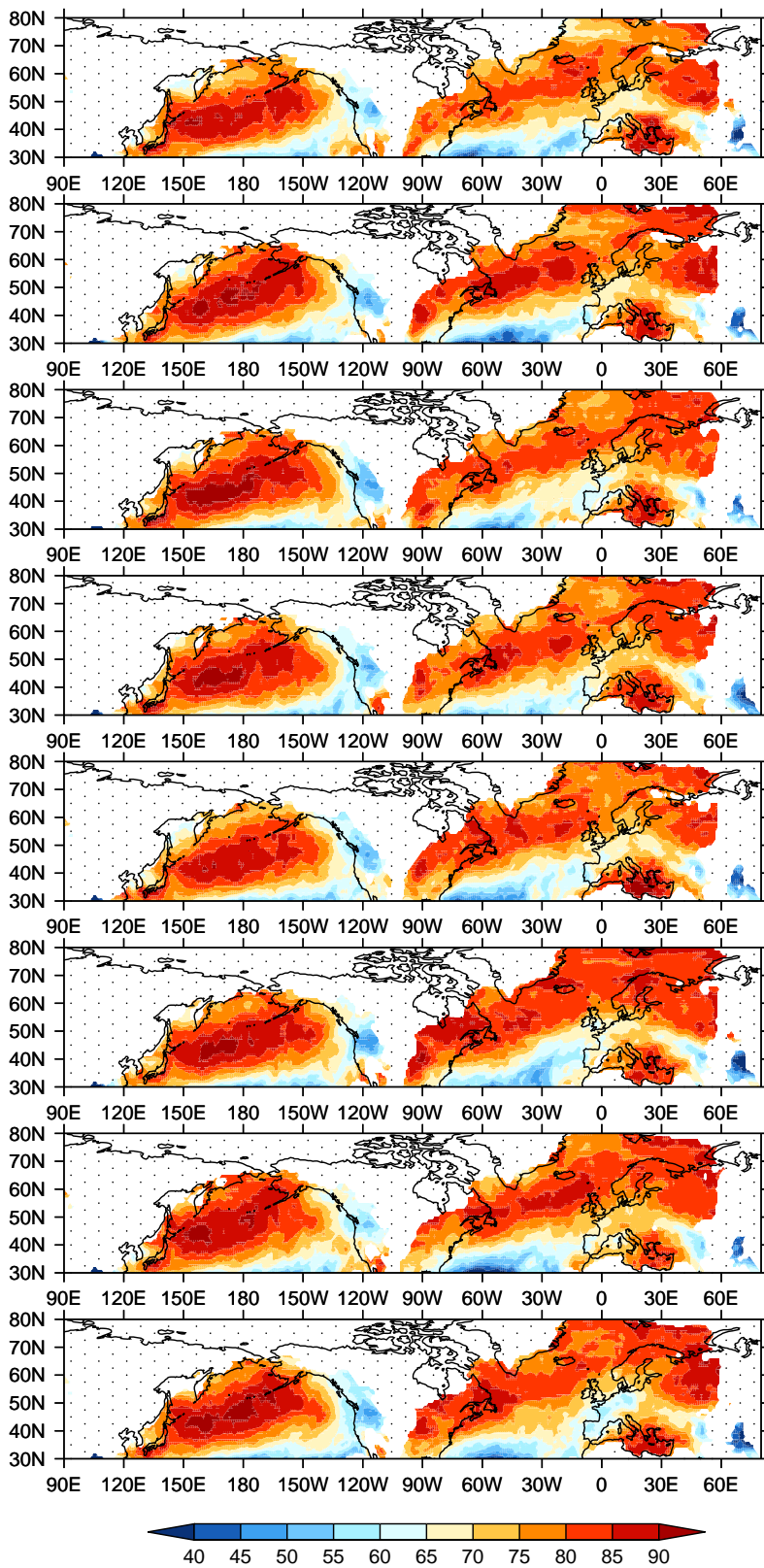


Fig. 8 Decadal variability in the percentage of the total precipitation contributed by ETCs (%) in HiGEM. Each panel represents a single decade from the model integration. The masked and stippled areas in the percentage plots are where the total precipitation for that decade is less than 1mm day^{-1} .

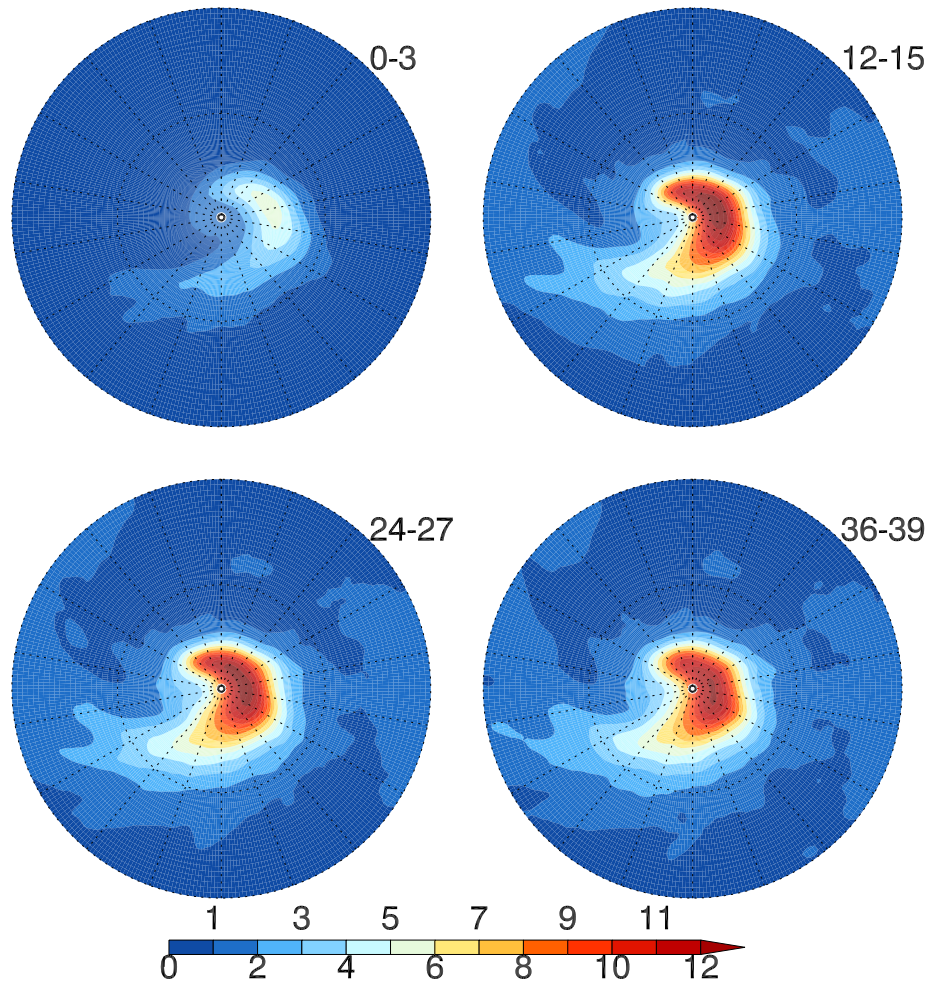


Fig. 9 The effect of spin-up on composite precipitation. The composites are taken from the 200 Atlantic storms shown in Figure 3. Accumulations are shown for leadtimes 0-3, 12-15, 24-27 and 36-39 hours. All figures are expressed in mm day^{-1} . Accumulations are from each 3-hour window.

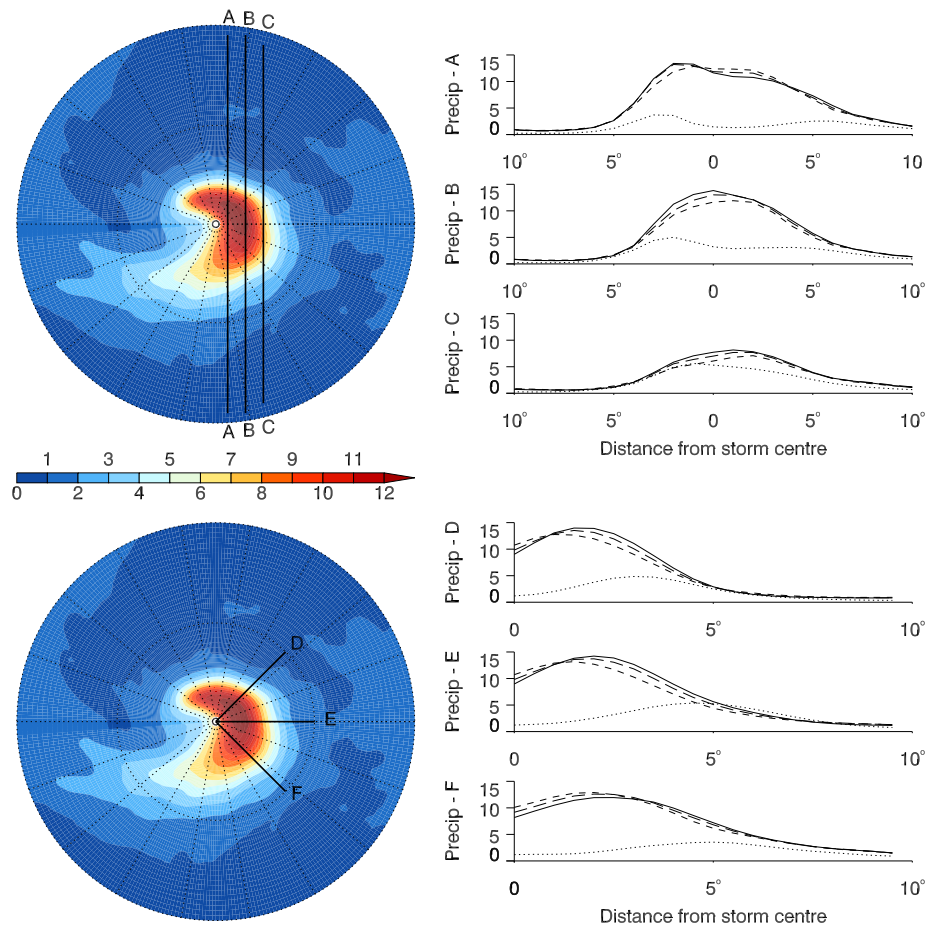


Fig. 10 Composite precipitation intensities. The left panels show a composite at 12-hour lead time, with the locations of the cross-sections (A-F) in the corresponding right hand panels overlaid. Lead times in the right hand panels are 0-3 (dotted line), 12-15 (solid), 24-27 (long dashes) and 36-29 hours (short dashes). All figures in mm day⁻¹. Accumulations are from each 3-hour window.

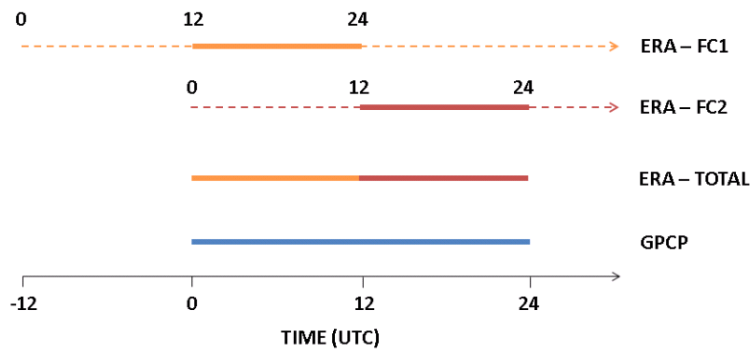


Fig. 11 ERAI precipitation accumulations used for the daily periods in this analysis. Precipitation is extracted from 12-24hours in two forecasts which are initialised at 12UTC on the previous day (FC1) and 00UTC on the day of interest (FC2). The two accumulations are then combined.

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