

On the resolution sensitivity in a GFDL global atmospheric model

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1 **On the resolution sensitivity of equatorial precipitation**
2 **in a GFDL global atmospheric model**

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7 **Key Points:**

- 8 • Aquaplanet simulations are performed in a global atmospheric general circulation
9 model at progressively finer resolution from 50km to 6km.
10 • The stronger resolved precipitation at finer resolution cannot be explained by changes
11 in the vertical velocity amplitudes.
12 • The simulated tropical precipitation becomes more organized at the planetary scale
13 in models with the finer resolution.

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Abstract

We performed a series of aquaplanet simulations at the horizontal resolution from 50km to 6km with identical parameterization settings using the Geophysical Fluid Dynamics Laboratory’s Atmosphere Model version 4 implemented with the two-moment Morrison-Gottelman cloud microphysics with prognostic precipitation (GFDL AM4-MG2). At the finer resolution, the global mean resolved-scale precipitation increases and that from cumulus parameterization decreases. The model also simulates less/thinner clouds over the low latitudes and more/thicker clouds over the high latitudes as the resolution increases. The precipitation over the deep tropics is investigated in detail. We find little resolution sensitivity in the daily mean precipitation extremes. Changes of the equatorial resolved precipitation with resolution cannot be fully explained by the resolution dependence in the vertical velocity amplitude. We report a robust sensitivity in the convective organization over the deep tropics to the model resolution. In simulations of finer resolution, the localized convection is suppressed, and the organized convective system associated with large-scale circulations becomes more prominent.

Plain Language Summary

Convection and precipitation events are important components of the climate system, but they are often too small to be directly resolved by a typical climate model. Increasing the resolution is therefore desirable but does not automatically solve all the model biases. Here, we seek a more physical understanding of how the simulated climate by a climate model is affected by its horizontal resolution. We systematically increased the horizontal resolution in a global atmospheric model from 50km to 6km. The difference between the high and low resolution simulations is not only evident in the small scales, but also evident in the large scales as well. In particular, our model with finer resolution simulates a closer relationship between convection events and large-scale circulation.

1 Introduction

The advance of the general circulation models (GCMs) is accompanied by increasing resolutions. It has recently become computationally feasible to simulate the global atmospheric general circulation at a horizontal resolution of a few kilometers for extensive periods of time. This is the so-called convective “gray-zone” resolution at which convection, especially the deep one, starts to be explicitly resolved (e.g., Shin & Hong, 2015; Jeevanjee, 2017; Gao et al., 2017). This new generation of models is referred to as global storm resolving models (GSRMs), global cloud resolving models (GCRMs), or global convection-permitting models in the literature. They generally show notable improvements compared to the current generation of GCMs with a typical resolution of $\sim 100\text{km}$, especially with regards to precipitation and convection (e.g., Stevens et al., 2019; Satoh et al., 2019; Caldwell et al., 2021). However, considerable inter-model spread and model biases still exist among these GSRMs (Stephan et al., 2019; Heim et al., 2021; Judt et al., 2021; Roh et al., 2021; Lang et al., 2021), and there is no consensus regarding when to turn off cumulus parameterization or how to make the cumulus parameterization scale-aware at the gray-zone resolution (e.g., Gao et al., 2017; Arnold et al., 2020; Satoh et al., 2019). Sorting out this chaos requires a physical understanding of the model’s sensitivity to resolution.

Several studies have investigated the resolution sensitivity in GCMs, most of which pushes the horizontal resolution up to 25km or 0.25° . A common feature of the resolution sensitivity found in these GCM simulations is that the resolved precipitation increases with model resolution while the parameterized precipitation decreases (e.g., Wehner et al., 2014; Herrington & Reed, 2017; Terai et al., 2018; Herrington & Reed, 2020). The stronger mean resolved precipitation at the finer resolution is often manifested in an intensification of the precipitation extremes, and the stronger extremes persist when the

precipitations are coarse-grained and sampled at daily frequency (Li et al., 2011; Wehner et al., 2014; O’Brien et al., 2016; Rios-Berrios et al., 2020). Studies have attributed the stronger mean resolved precipitation and stronger precipitation extremes to the stronger amplitude of vertical velocity at the finer scales (Li et al., 2011; Rauscher et al., 2016; Herrington & Reed, 2017, 2020). The reduced parameterized precipitation is in response to changes in the background state due to the resolved processes (Herrington & Reed, 2020).

While the increase of vertical velocity magnitude with horizontal resolution is commonly observed in various model simulations and well established in theory (Jeevanjee, 2017, and references therein), there are several factors that may potentially counteract its effect on the resolved precipitation. Precipitation is expected to increase with precipitable water (e.g., Bretherton et al., 2004; Ahmed & Schumacher, 2015; Terai et al., 2018), but many models simulate a decrease in precipitable water with resolution at least for the global average (Williamson et al., 1995; Herrington & Reed, 2017; Terai et al., 2018). Mean and extreme precipitation are also affected by precipitation efficiency. Reduced precipitation efficiency with finer resolution is reported in cloud resolving models (Lutsko & Cronin, 2018; Jeevanjee & Zhou, 2022). Studies also found the precipitation extremes to be strongly affected by the degree of convective aggregation and organization (Bao et al., 2017; Pendergrass, 2020, and references therein). Simulations from idealized cloud resolving models under the radiative-convective equilibrium typically show that coarser resolution is favored for self-aggregation (Muller & Held, 2012; Muller & Bony, 2015), indicating a potential resolution dependence of precipitation via changes of convective organization. However, it is worth noting that these cloud resolving models are generally at the resolution of sub-kilometer or finer, and the resolution sensitivity found in those models may not extend to the lower resolution regime.

In addition to precipitation, previous studies also reported resolution sensitivity in Hadley cell strength (Williamson et al., 1995), location of the eddy driven jet (Lu et al., 2015), and switching from single to double intertropical convergence zone (ITCZ; Yu et al., 2014; Benedict et al., 2017; Retsch et al., 2019). But these results appear to be more model dependent.

Here, we start with a state-of-art atmospheric GCM, and systematically increase the horizontal resolution from a typical GCM value to a GSRM one. We perform aquaplanet simulations using a non-hydrostatic dynamical core and document the model behavior as it approaches the convective gray-zone. At higher resolutions than previous GCM studies, we find that some of the previously reported resolution sensitivities no longer hold and new resolution sensitivity emerges in our simulations. In the following, section 2 describes the model and the simulation design, section 3 presents the results and a summary and discussion are given in section 4.

2 Model description and experiment setup

We performed aquaplanet simulations using an updated version of the Geophysical Fluid Dynamics Laboratory (GFDL) Atmosphere Model version 4 (AM4) referred to as AM4-MG2 (Guo et al., 2021). AM4-MG2 is built upon GFDL’s most recent atmospheric model AM4.0 (Zhao et al., 2018a, 2018b), replacing the original Rotstayn-Klein microphysical scheme (Rotstayn, 1997; Jakob & Klein, 2000; Donner et al., 2011) with the more sophisticated MG2 scheme (Gettelman & Morrison, 2015). This two-moment bulk cloud microphysics scheme with prognostic precipitation improves simulations of coastal stratocumulus. AM4-MG2 also implements a new mineral dust and temperature-dependent ice nucleation scheme (Fan et al., 2019). Same as AM4.0, AM4-MG2 utilizes the GFDL finite-volume cubed-sphere dynamical core (FV3, Harris, Zhou, Chen, & Chen, 2020), a double-plume convection scheme (Zhao et al., 2018b), the Tiedtke scheme for cloud amount (Tiedtke, 1993), and the Lock scheme for planetary boundary layer (Lock

115 et al., 2000). Detailed configuration of AM4-MG2 and its performance are documented
 116 in Guo et al. (2021).

117 Different from the simulations presented by Zhao et al. (2018a) or Guo et al. (2021),
 118 we use the nonhydrostatic solver described by Harris, Chen, et al. (2020) instead of a
 119 hydrostatic one. Hydrostatic approximation starts to break down at the scale of a few
 120 kilometers and leads to large errors for sub-kilometer resolutions (Jeevanjee, 2017). While
 121 solutions from a hydrostatic solver may not differ much from those from a nonhydrostatic
 122 one for most of the resolutions considered here, we use the nonhydrostatic solver for all
 123 resolutions for consistency.

124 The model is run in aquaplanet configuration by prescribing a zonally symmetric
 125 sea surface temperature profile (“Control” in Neale & Hoskins, 2000), which is invari-
 126 ant in time. The aquaplanet simulations are widely used for evaluating the performance
 127 of the atmospheric models (e.g., Neale & Hoskins, 2000; Blackburn et al., 2013; Medeiros
 128 et al., 2015; Merlis & Held, 2019). Aquaplanet simulations using AM4.0 have been used
 129 to study tropical cyclones (G. Zhang et al., 2021) and have contributed to the Cloud Feed-
 130 back Model Intercomparison Project (CFMIP) (Silvers et al., 2018). By using an ide-
 131 alized lower boundary, the aquaplanet simulations are simpler and therefore easier to un-
 132 derstand than the more realistic simulations while preserving the general behavior of the
 133 more realistic models, especially for tropical phenomena such as the ITCZ, tropical cy-
 134 clones and convectively coupled equatorial waves. But we note that the aquaplanet set-
 135 tings ignore any resolution sensitivity arising from resolving topography and surface con-
 136 ditions.

137 This is different from the simulations proposed in the DYnamics of the Atmospheric
 138 general circulation Modeled On Non-hydrostatic Domains (DYAMOND) project and its
 139 successor DYAMOND2, which intends to compare GSRMs developed around the world
 140 under the real world settings with each other and against observations (Stevens et al.,
 141 2019). In particular, the GFDL System for High-resolution prediction on Earth-to-Local
 142 Domains (SHiELD, Zhou et al., 2019; Harris, Zhou, Lin, et al., 2020) is a participant of
 143 the DYAMOND project. SHiELD has been configured to run at different resolutions and
 144 its performance at a globally uniform 3km grid (X-SHiELD configuration) has been re-
 145 ported by F. Zhang et al. (2019) and Harris et al. (2023). The AM4-MG2 model used
 146 here shares the same dynamical core as SHiELD, but the physics packages in the two
 147 models are generally disparate. We hope that our idealized aquaplanet simulations at
 148 similar resolutions may help to understand the simulations by SHiELD and to interpret
 149 the inter-model differences and model biases seen in DYAMOND simulations (Heim et
 150 al., 2021; Judt et al., 2021; Roh et al., 2021; Lang et al., 2021).

151 We perform a series of simulations with varying horizontal resolutions. AM4 model
 152 grid has cubed-sphere topology and its horizontal resolution is denoted by the number
 153 of grid boxes along the side of each cubed face such that a resolution of Cn signifies $n \times$
 154 n grid boxes per cubed face. Simulations are done at the resolutions of C192, C384, C768
 155 and C1536, corresponding to a nominal resolution of about 50km, 25km, 13km, and 6km,
 156 respectively. As listed in Table 1, both physical and dynamical time steps are reduced
 157 to accommodate the increased resolution. Note that the radiation time step is different
 158 from physical time step in this model, which does not change with resolution (3 hours
 159 for longwave and 1 hour for shortwave). The vertical resolution are kept identical for all
 160 these simulations. The model consists of 33 model levels with a model top at 1 hPa (see
 161 Open Research for specification). We use the fourth order divergence and vorticity damp-
 162 ing with the same non-dimensional damping coefficients for all simulations here, which
 163 effectively yield weaker damping for higher resolution runs. A more detailed description
 164 regarding the diffusion settings can be found in the appendix. All the tuning paramet-
 165 ers (including those used in cumulus parameterization) are kept identical for all the sim-
 166 ulations considered here. The detailed configuration of each simulation is included in the
 167 Open Research section. We use the same parameters as Guo et al. (2021) for their his-

Table 1. Experiment setting

Experiment	Δx (km)	Δt phy (s)	Δt dyn (s)
C192	50	1200	75
C384	25	600	28.6
C768	13	300	16.7
C1536	6	200	8.3

168 torical AMIP simulations at the resolution of C96(100km). For a fair comparison, the
 169 outputs from all experiments are remapped to the same $0.5^\circ \times 0.5^\circ$ grid. The spatial
 170 remapping is done conservatively using fregrid (<https://github.com/NOAA-GFDL/FRE-NCtools>). We use the coarse-grained data to evaluate the climatology, and evaluate vari-
 171 ability using both coarse-grained and raw data.
 172

173 The model is set to be on the perpetual equinox and run for one year. The first
 174 three months are considered as spin-up and discarded. Greenhouse gases concentrations
 175 are set to constant values (CO_2 : 348 ppmv, CH_4 : 1.65 ppmv, N_2O : 0.306 ppmv, $CFC-11$:
 176 264.325 ppbv, $CFC-12$: 536 pptv, $CFC-113$: 82.765 pptv, $HCFC-22$: 13.455
 177 pptv), and the solar constant is 1365 W/m^2 . Aerosol emissions are set to the year 1860
 178 level based on the CMIP6 forcing data (Eyring et al., 2016). Aerosol emissions include
 179 a seasonal cycle. We note that the simulated precipitation shows strong hemispherical
 180 symmetry and weak seasonal dependence despite the asymmetric and time-varying aerosol
 181 emissions.

182 3 Results

183 3.1 Climatology

184 We start by calculating a few globally integrated indices representing the basic hy-
 185 drological, radiative and dynamical climatology simulated in these experiments. Table
 186 2 lists the global mean total precipitation rate (PREC_tot), precipitation at the resolved
 187 scale (PREC_res), precipitation from the deep plume in the cumulus parameterization
 188 (PREC_deep) and precipitation from the shallow plume (PREC_shallow). The global mean
 189 resolved precipitation increases with resolution. The parameterized precipitation, on the
 190 other hand, decreases with resolution, which mostly comes from the deep plume. This
 191 divergent response to resolution changes between the resolved and parameterized pre-
 192 cipitation is consistent with previous studies (e.g., Wehner et al., 2014; Herrington & Reed,
 193 2017; Terai et al., 2018; Herrington & Reed, 2020). Changes in the total precipitation
 194 with resolution is in general small and insignificant, but statistically significant reduc-
 195 tion is found at the highest resolutions considered (from C768 to C1536), which hints
 196 at a regime shift.

197 The latitudinal distribution of the precipitation is plotted in Fig. 1. The param-
 198 eterized precipitation from the deep plume shows consistent reduction with resolution
 199 at all latitudes, while changes in the shallow plume are less coherent across latitudes and
 200 generally weak. The latitudinal structure of the resolved precipitation changes is more
 201 complex. The resolved precipitation climatology shows a strong peak at the equator and
 202 a secondary peak centered around 40° . As the resolution increases, the mid-latitude peak
 203 becomes wider but little changes in the peak amplitude. The equatorial precipitation peak,
 204 on the other hand, responds to model resolution variations mainly via its amplitude but
 205 not the width. The equatorial resolved precipitation increases with resolution from C192
 206 to C768, but decreases slightly from C768 to C1536. The total precipitation from both
 207 resolved and parameterized processes shows a similar two-peak structure as the resolved
 208 precipitation, but its variations across resolution is generally subtle.

Given these changes in precipitation as resolution varies, other components in the hydrological cycle are expected to vary with resolution as well. Herrington and Reed (2017) reported a drying atmosphere with resolution in terms of total precipitable water and cloud fraction. We see a similar reduction in the global mean precipitable water (measured by water vapor path WVP) and cloud fraction with resolution (Table 2). We further examined the clouds simulated in these experiments by evaluating the cloud liquid and ice water path (LWP, IWP) as well as the cloud radiative effect (CRE). Most liquid water resides in the low cloud and exerts its radiative effects in the shortwave bands, while ice water mostly resides in the high clouds and has stronger effects in the longwave bands. As shown in Fig. 1, finer resolution runs show less cloud water and weaker CRE over regions equatorward of $\sim 35^\circ$, but more cloud water and stronger CRE on the poleward side. This compensation between the lower and higher latitudes is more substantial for the ice phase and the longwave CRE, which show appreciable resolution dependence locally (Figs. 1e, h) but trivial changes in the global mean (Table 2). The LWP and shortwave CRE, on the other hand, is dominated by changes over the subtropics. A reduction of 12 W/m^2 in the global mean shortwave CRE is seen from C192 to C1536. Table 2 also list the global mean outgoing longwave radiation (OLR) and upward shortwave radiation at the top of the atmosphere (SWUP TOA). Changes in these all-sky radiative flux are largely driven by changes in clouds, whereas the variation in the global mean clear-sky radiative flux across resolutions does not exceed 0.5 W/m^2 (not shown).

We also evaluate the general circulation simulated in these simulations. Following Lu et al. (2015), we diagnose the intensity of the extratropical eddy-driven jet by the maximum zonal mean zonal wind speed at 250 hPa ($U_{\text{max}250}$) and the location of the jet by the latitude of where the maximum zonal mean zonal wind occurs at 850 hPa ($\phi_{\text{umax}850}$). Lu et al. (2015) reported that the extratropical jet tends to be weaker but more poleward as the resolution increases, but converges for resolutions finer than 50km. Here, we find no monotonic relationship between the jet intensity or location with the resolution, which are all at or finer than 50km. The Hadley cell is diagnosed using the zonal mean mass flux stream function at 500 hPa following Lu et al. (2007). We find that neither the intensity nor the width of the Hadley cell shows any strong or robust sensitivity to the resolution changes considered here.

In short, we find a similar resolution dependence in the globally averaged precipitation and other hydrometeors as reported in earlier GCM studies, that is, an increase in the resolved precipitation with resolution and a decrease in the parameterized precipitation, total precipitable water and cloud fraction. However, we find that changes in these hydrometeors are not uniform across latitudes and several cloud-related variables show opposite sensitivity between low and high latitudes. In addition, we note that our model simulates a larger cloud fraction and a smaller global mean precipitation than earlier aquaplanet simulations (Williamson et al., 2012, 2013), which may not only arise from differences in model resolution but also from differences in model physics. We defer discussions on such inter-model difference in climatology to a future study. In the following subsections, we will provide a thorough investigation on the resolution dependence of the equatorial precipitation.

3.2 Precipitation intensity distribution in the deep tropics

In this subsection, we focus on the resolved precipitation in the deep tropics. This is the region where the strongest precipitation and deepest convection occur. Results of this subsection are based on one month of data (the 6th month) and are insensitive to the choice of the month. We analyze data on the lat-lon grid between 5.5°N and 5.5°S . For data on the native model grid, we analyze a swath of grids centered at the equator, that is 24×768 grids in C192, 48×1536 grids in C384, 96×3072 grids in C768 and 192×6144 grids in C1536. These grids roughly correspond to a latitude band between 5.56N - 5.56S covering all longitudes. Note that the area of each native model grid and

Table 2. Summary of mean climate diagnostics. Bold font indicates the difference against its immediate lower resolution counterpart is statistically significant, based on the Student’s t test of monthly data at 95% confidence level. Orange color indicates a positive difference and blue color indicates a negative difference. The statistics are evaluated using monthly mean data. See text for the definitions of the variables.

	C192	C384	C768	C1536
PREC_tot (mm/day)	2.56	2.59	2.58	2.52
PREC_res (mm/day)	1.81	2.00	2.20	2.22
PREC_deep (mm/day)	0.42	0.26	0.07	0.02
PREC_shallow (mm/day)	0.33	0.33	0.32	0.28
OLR (W/m^2)	211.73	212.64	213.63	212.55
SWUP TOA (W/m^2)	115.86	114.12	108.74	103.44
Longwave CRE (W/m^2)	43.66	43.12	42.29	43.07
Shortwave CRE (W/m^2)	-79.74	-78.15	-73.00	-67.80
WVP (kg/m^2)	20.76	20.45	20.07	20.02
LWP (g/m^2)	72.08	69.92	65.59	59.97
IWP (g/m^2)	63.52	63.04	61.12	61.44
cloud fraction (%)	80.49	79.1	76.09	73.89
Umax250 (m/s)	47.96	44.96	47.41	48.33
$\phi_{umax850}$	39.49°	41.94°	41.97°	42.55°
Hadley cell strength ($10^{11} kg/s$)	1.58	1.64	1.64	1.59
Hadley cell edge	27.06°	27.79°	27.88°	27.75°

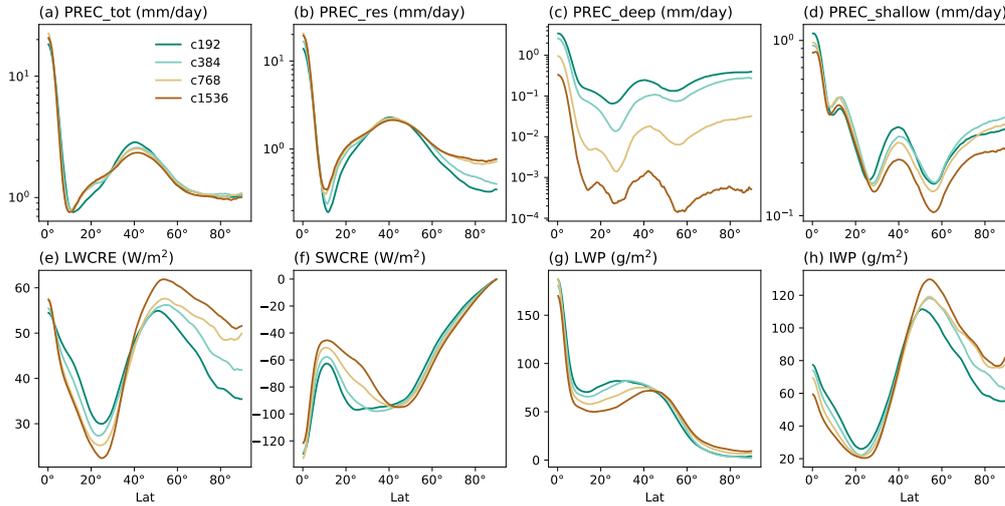


Figure 1. Zonal mean hemispherically-averaged climatology of (a) total precipitation, (b) precipitation at the resolved scale, (c) precipitation from the parameterized deep convection, (d) precipitation from the parameterized shallow convection, (e) longwave cloud radiative effect, (f) shortwave cloud radiative effect, (g) cloud liquid water path, and (h) cloud ice water path.

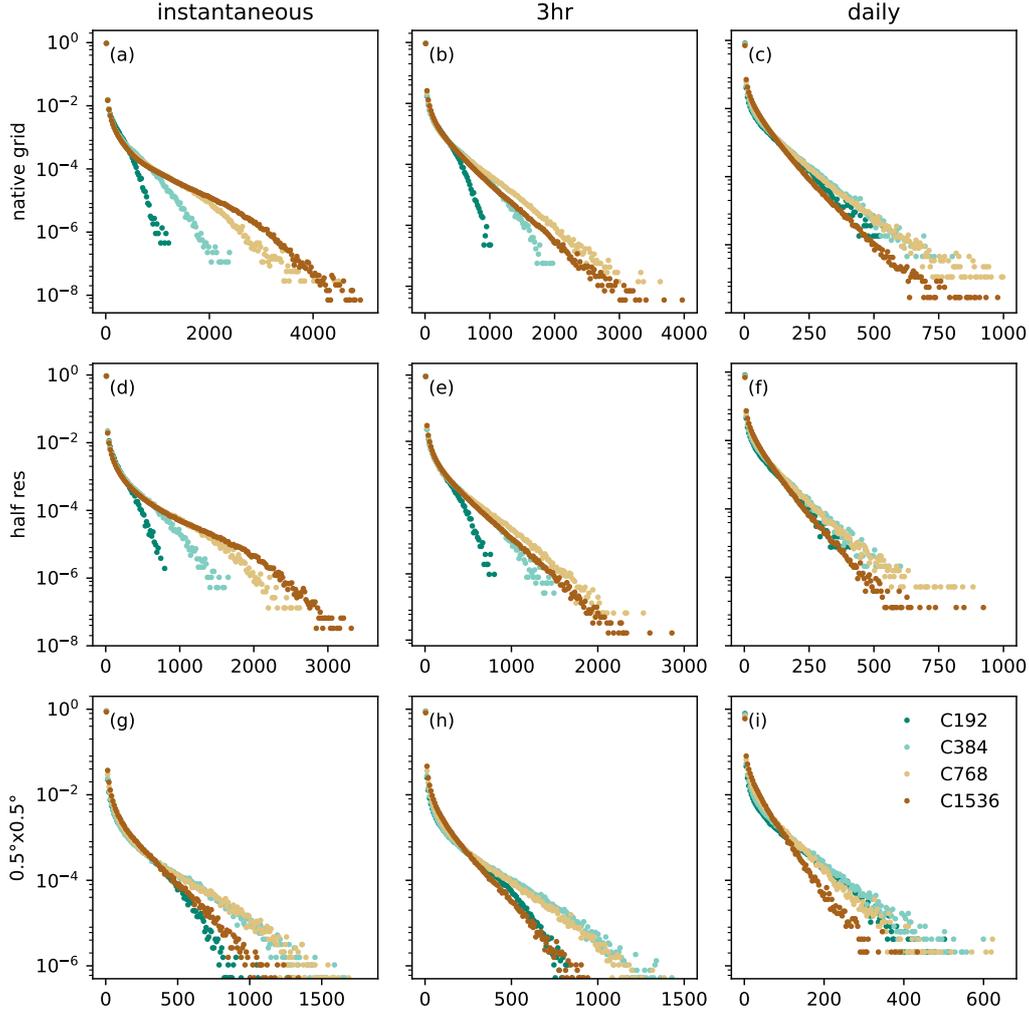


Figure 2. Normalized distribution of resolved precipitation intensity calculated from (a) instantaneous data at the native model grid, (b) 3 hourly averaged data at the native model grid, (c) daily averaged data at the native model grid). (d-f) As in (a-c) except that precipitation conservatively remapped to $1^\circ \times 1^\circ$ for C192, $0.5^\circ \times 0.5^\circ$ for C384, $0.25^\circ \times 0.25^\circ$ for C768 and $0.125^\circ \times 0.125^\circ$ for C1536. (g-i) As in (a-c) except that precipitation is conservatively remapped to $0.5^\circ \times 0.5^\circ$ grid. Precipitation is in units of mm/day. All histograms are in unit of 1.

261 lat-lon grid varies with location, but we treat them equally when calculating distribu-
 262 tion.

263 We first calculate the probability distribution of the resolved precipitation intensi-
 264 ty and explore how it is affected by spatial and temporal sampling. We considered three
 265 temporal samplings: instantaneously every 6 hours, 3 hour mean, and daily mean; as well
 266 as three spatial samplings: at native model grid, remapped to a lat-lon grid that is roughly
 267 half of the model grid resolution, and remapped to $0.5^\circ \times 0.5^\circ$ lat-lon grid. The time
 268 averaging is done for all time step and is equivalent to the accumulated precipitation.
 269 The spatial remapping employs a conservative algorithm (available in Open Research).
 270 As shown in Fig. 2, the intensity of the extreme precipitation is sensitive to the sampling
 271 method. We see a stronger extreme in the finer resolution simulations for instantaneously

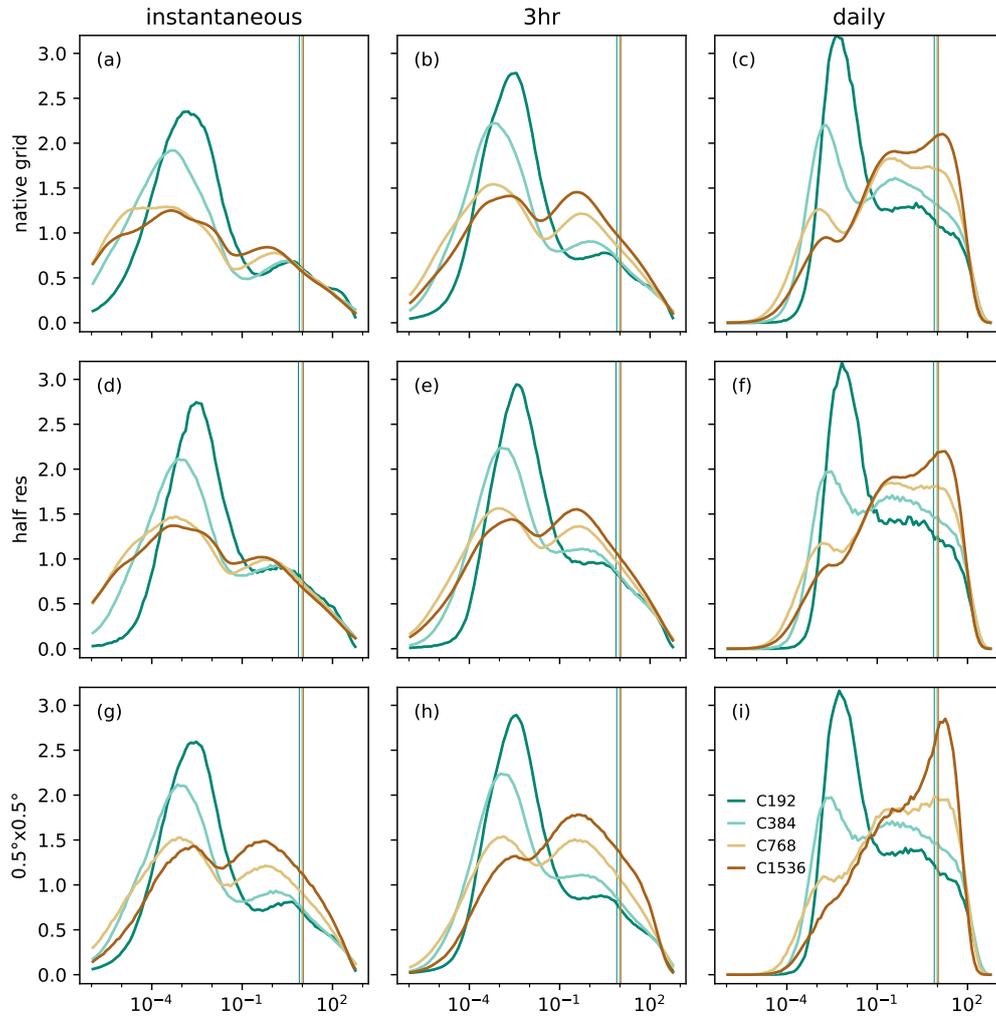


Figure 3. As in Fig. 2 but the histograms are calculated over 100 bins spaced evenly on log scale between 10^{-6} - $10^{2.8}$ mm/day. The thin vertical lines marked the averaged values from all samples. All histograms are in units of %.

272 precipitation at the native model grid (Fig. 2a), which is consistent with earlier stud-
 273 ies (Herrington & Reed, 2020). However, such resolution dependence does not hold for
 274 instantaneous precipitation remapped to the $0.5^\circ \times 0.5^\circ$ grid (Fig. 2g). Similarly, av-
 275 eraging in time also distorts the resolution dependence in the extreme precipitation. For
 276 3 hourly averaged resolved precipitation, similar distribution is found among C384, C768
 277 and C1536 runs, whereas C192 shows a shorter tail than other (Fig. 2b). All four sim-
 278 ulations show similar intensity for extremes in the daily averaged precipitation (Fig. 2c).
 279 When coarse-graining is done in both space and time, it is C1536, the highest resolution
 280 run, that shows the weakest extreme (Fig. 2i). Unlike earlier studies reporting that the
 281 stronger extremes in finer resolution simulation persist with coarse-graining and daily
 282 averaging (Li et al., 2011; Wehner et al., 2014; O’Brien et al., 2016; Rios-Berrios et al.,
 283 2020), we find an absence and even a reversal of the resolution dependence in the daily
 284 precipitation extremes.

285 To illustrate changes in the resolved precipitation at weaker intensity, we calculate
 286 the probability distribution over log-scaled bins. We find that the distributions in the
 287 high resolution runs are sensitive to the temporal and spatial averaging. For C768 and
 288 C1536 simulations, the instantaneous resolved precipitation at the native model grid shows
 289 a relatively flat distribution across all bins (Fig. 3a). Both remapping to the $0.5^\circ \times 0.5^\circ$
 290 grid (Fig. 3g) and daily averaging (Fig. 3c) lead to a narrower distribution and a higher
 291 mode value. Applying both spatial coarse-graining and daily averaging results in a dis-
 292 tinct single peak located near the mean values (Fig. 3j). On the other hand, the spa-
 293 tial and temporal averaging has less effect on the low resolution simulations. The dis-
 294 tribution function of C192 shows similar structure for the different sampling strategies
 295 considered here, that is a strong peak centered between 10^{-3} and 10^{-2} mm/day and a
 296 much muted secondary peak centered between 1 and 10 mm/day. As a result, the tem-
 297 porally and spatially coarse-grained resolved precipitation shows a robust resolution de-
 298 pendence that the finer resolution simulations produce more precipitation stronger than
 299 0.1mm/day and less weaker precipitation.

300 Our simulations clearly show that the intensity distribution of the resolved precip-
 301 itation depends on the sampling and the higher resolution simulations show a stronger
 302 sensitivity to the sampling method. Both the conservative spatial remapping and tem-
 303 poral averaging considered here effectively take an average of the samples within a sub-
 304 set. If the variation within each subset is comparable to the variation among all sam-
 305 ples, then averaging of a subset yields a value similar to the all-sample mean, and the
 306 resulting distribution of the re-sampled data will be a delta function centered at the all-
 307 sample mean value. On the other hand, If the variation within the subset is small, the
 308 re-sampled data would have a similar distribution to the raw data. Here, a $0.5^\circ \times 0.5^\circ$
 309 grid roughly corresponds to 1 C192 model grid, but 64 C1536 model grids. Naturally,
 310 there is stronger variance within each $0.5^\circ \times 0.5^\circ$ subset for the C1536 run than the C192
 311 run. Correspondingly, the spatial remapping of the C1536 data leads to a large reduc-
 312 tion of the extreme (Fig. 2 a vs g) and narrowing of the distribution (Fig. 3 a vs g), while
 313 the same remapping has little impacts on the C192 data. What is less expected is that
 314 the finer resolution runs shows a stronger sensitivity to the temporal averaging as well,
 315 which implies a resolution dependence in the temporal variance. To measure the sub-
 316 daily variance, we calculate the correlation between the daily mean precipitation and the
 317 instantaneous at the first time step of each day. The correlation is calculated over all days
 318 and all native model grid points considered here. A strong correlation of 0.71 is found
 319 for C192, indicating sampling the data instantaneously would not differ too much from
 320 the daily average. This correlation decreases monotonically with resolution, coming to
 321 0.57 for C384, 0.44 for C768, and 0.36 for C1536, confirming that stronger sub-daily vari-
 322 ance is simulated in models of finer resolution. While a smaller time step is used in the
 323 finer resolution runs, the physical time step in all simulations are much smaller than the
 324 time averaging length (1 day). We therefore suspect that the more time steps per day
 325 in the high resolution runs are not the main reason for the stronger sub-daily variance.

Table 3. Statistics of the deep tropical precipitation, gross upward mass flux (M_{up}) and gross upward moisture flux (Q flux) evaluated using the instantaneous variables at the native model grids over the region 5.56°N-5.56°S for the 6th month. The precipitation area is defined as the fraction of grids where non-zero precipitation occurs. The ascent area is defined as the fraction of grids where the vertical velocity is larger than 0.

		C192	C384	C768	C1536
mean precip (mm/day)	total	11.25	12.11	12.06	11.60
	resolved	7.87	9.59	10.64	10.63
	deep	2.49	1.71	0.58	0.22
	shallow	0.89	0.81	0.83	0.75
precip area (%)	total	99.66	99.21	98.53	98.27
	resolved	99.53	98.83	97.87	97.72
	deep	49.51	40.39	13.36	4.25
	shallow	51.82	55.19	55.47	50.72
848.8 hPa	ascent area (%)	59.96	55.67	51.12	49.79
	M_{up} ($\times 0.01$ kg/m ² /s)	1.57	1.99	2.69	3.54
	Q flux ($\times 10^{-4}$ kg/m ² /s)	2.12	2.68	3.56	4.66
532.5 hPa	ascent area (%)	45.06	45.79	46.71	47.18
	M_{up} ($\times 0.01$ kg/m ² /s)	1.21	1.52	1.89	2.41
	Q flux ($\times 10^{-4}$ kg/m ² /s)	0.68	0.82	0.96	1.19

326 Instead, the intrinsic time scale of the precipitation variance changes with model reso-
 327 lution. In other words, resolving the high frequency variance is not limited by the model’s
 328 time step but by the grid size since the high frequency variance are often of small spa-
 329 tial scales.

330 For completeness, we also calculate the distribution of the total precipitation and
 331 the parameterized precipitation from the deep and shallow plumes shown in Fig. 4. For
 332 simplicity, we only show the distribution using the instantaneous data at the native model
 333 grid and daily averaged coarse-grained data. At the native model grid, the deep plume
 334 precipitation intensity shows a similar mode across resolutions, but the fraction of model
 335 grids with non-zero deep plume precipitation drastically reduced (Fig. 4h). As listed in
 336 Table 3, the deep plume precipitation area decreases from 49.5% in C192 to 4.2% in C1536.
 337 The distribution of the shallow plume precipitation generally shows little sensitivity to
 338 varying resolution, except that C192 shows a slightly wider range than others. The ex-
 339 tremes of the combined precipitation from both resolved and parameterized processes
 340 largely come from the resolved precipitation and thus show a similar sensitivity to res-
 341 olution (Figs. 4a vs 2a, 4d vs 2i).

342 3.3 Relationship between the resolved precipitation and vertical veloc- 343 ity

344 Previous studies have attributed the resolution dependence in the resolved precip-
 345 itation to changes in the vertical velocity amplitude (Rauscher et al., 2016; Herrington
 346 & Reed, 2017, 2020). The strongest vertical velocity intensifies at finer resolutions, which
 347 produces a stronger gross upward moisture flux at the cloud base. The resolved precip-
 348 itation is found to be proportional to the gross upward moisture flux (Rauscher et al.,
 349 2016; O’Brien et al., 2016; Herrington & Reed, 2020). Therefore, an intensification of
 350 the strongest precipitation is expected following the intensification of the strongest as-
 351 cent. Herrington and Reed (2020) further showed that the enhancement of the mean re-
 352 solved precipitation in simulations of higher resolution mainly comes from precipitation
 353 of the strongest intensity that is co-located with the strongest upward motion.

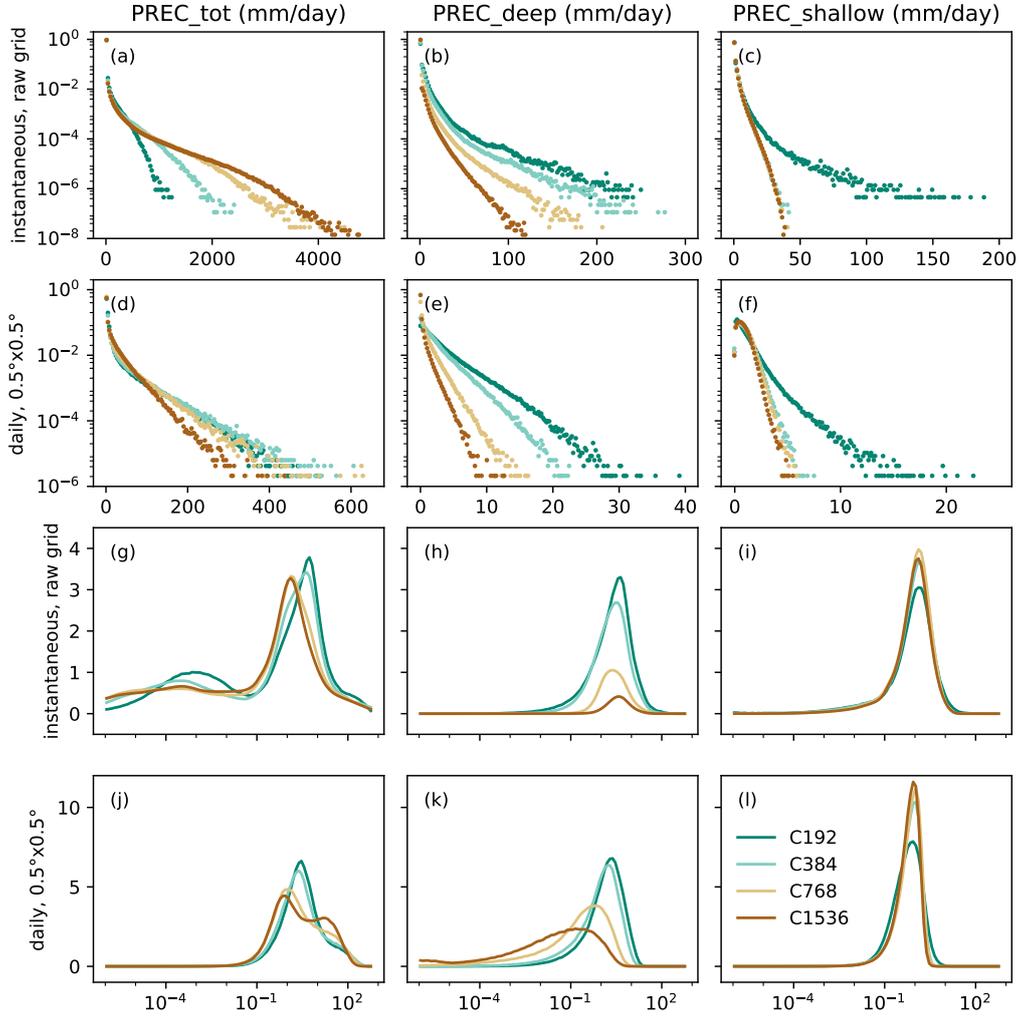


Figure 4. Normalized distribution of (a, d, g, j) total precipitation intensity, (b, e, h, k) parameterized precipitation from the deep plume, and (c, f, i, l) parameterized precipitation from the shallow plume. (a-c) Distribution is calculated using instantaneous data at the native model grid over 200 bins spaced evenly on linear scale. (d-f) As in (a-c) but using daily averaged data conservatively remapped to $0.5^\circ \times 0.5^\circ$ grid. (g-i) Distribution is calculated using instantaneous data at the native model grid over 100 bins spaced evenly on log scale. (j-l) As in (g-i) but using daily averaged data conservatively remapped to $0.5^\circ \times 0.5^\circ$ grid.

354 We verify this argument in our simulations over the deep tropics. Table 3 lists the
 355 gross upward mass flux, the gross upward moisture flux along with the areal averaged
 356 precipitation. These quantities are calculated from the instantaneous fields sampled at
 357 the native model grid. Consistent with earlier studies (Herrington & Reed, 2017, 2020),
 358 stronger gross upward mass flux and stronger gross upward moisture flux are found at
 359 the cloud base level as well as at mid-troposphere in simulations of finer resolution. Each
 360 resolution doubling leads to roughly 30% increase in the upward mass flux at 848.8 hPa,
 361 and roughly 25 % increases at 532.5 hPa. This stronger upward mass flux does not come
 362 from changes in the ascent area but is driven by the stronger intensity of the vertical ve-
 363 locity. The gross upward moisture flux generally scales with the mass flux, confirming
 364 that changes in the moist flux is driven by the vertical velocity. The resolved precipi-
 365 tation, on the other hand, does not scale with the upward mass flux or the moisture flux.
 366 It increases by 22% when the resolution doubles from C192, but only 11% for the sec-
 367 ond resolution doubling, and decreases slightly for the third resolution doubling. Such
 368 disproportion between resolved precipitation and vertical velocity is also seen in the ex-
 369 treme and mode values as evident in Fig. 5a vs Fig. 2a and Fig. 5b vs Fig. 3a.

370 To probe into the relationship between the vertical velocity and the resolved precipi-
 371 tation, we sort the data points according to the vertical velocity and calculate the
 372 fraction of data points and the mean resolved precipitation in each bin, denoted as f_i
 373 and P_i , respectively. The temporal and areal averaged precipitation over the deep tropics
 374 can be written as the sum over bins: $P = \sum_i f_i P_i$. We further calculate $f_i \langle P_i \rangle$ and
 375 $\langle f_i \rangle P_i$, where $\langle \rangle$ indicates the average among the 4 experiments. Comparing $f_i P_i$ against
 376 $f_i \langle P_i \rangle$ and $\langle f_i \rangle P_i$ answers the question whether changes in the precipitation are driven
 377 by changes in the vertical velocity intensity. Similar decomposition is carried out by Terai
 378 et al. (2018) and Herrington and Reed (2020). As shown in Fig. 6a, the resolution de-
 379 pendence of precipitation is contributed by both strong and weak ascent bins. Changes
 380 in the strong ascent bins mainly comes from a larger fraction of grid points in those bins
 381 with strong ascent, but the mean precipitation in those bins changes little with resolu-
 382 tion. This is consistent with the aforementioned mechanism and the results shown by
 383 Herrington and Reed (2020). Change in the weak ascent bins, on the other hand, mainly
 384 comes from a weaker mean precipitation intensity in those bins rather than changes in
 385 f_i . Changes in f_i alone lead to a $\sim 30\%$ increase of the deep tropical mean precipitation
 386 from each resolution doubling (Fig. 6c), which is consistent with changes in the gross
 387 upward mass flux and the gross upward moisture flux listed in Table 3. This is compen-
 388 sated by changes in P_i over weak ascent bins, and the actual resolved precipitation re-
 389 sponse to resolution is much more muted, especially for simulations at finer resolutions.

390 Similar calculations are done for the daily averaged coarse-grained data. Note that
 391 the daily averaged coarse-grained vertical velocity is different from the averaged upward
 392 motion. The discrepancy between the two is small for the extreme strong ascent but large
 393 for mean weak ascent. As shown in Fig. 6d, varying resolution mainly affects precipi-
 394 tation in bins with weak vertical velocity but not in bins with strong ascent. The larger
 395 contribution to precipitation under the weak vertical velocity condition in higher reso-
 396 lution simulations is brought by the stronger precipitation intensity sampled at the same
 397 vertical velocity. On the other hand, the fraction of data points in each vertical veloc-
 398 ity bin is similar among simulations except for C1536, which shows larger fraction in weak
 399 velocity bins and smaller fraction in strong velocity bins (Fig. 6f). This precipitation de-
 400 composition using the coarse-grained data is consistent with results by Terai et al. (2018),
 401 who reported that the resolution dependence in the resolved precipitation mainly comes
 402 from changes in the precipitation irrespective to vertical velocity. This breakdown based
 403 on the daily averaged coarse-grained data highlights the precipitation changes over weak
 404 ascent regions, which cannot be explained by the resolution dependence in the vertical
 405 velocity amplitude.

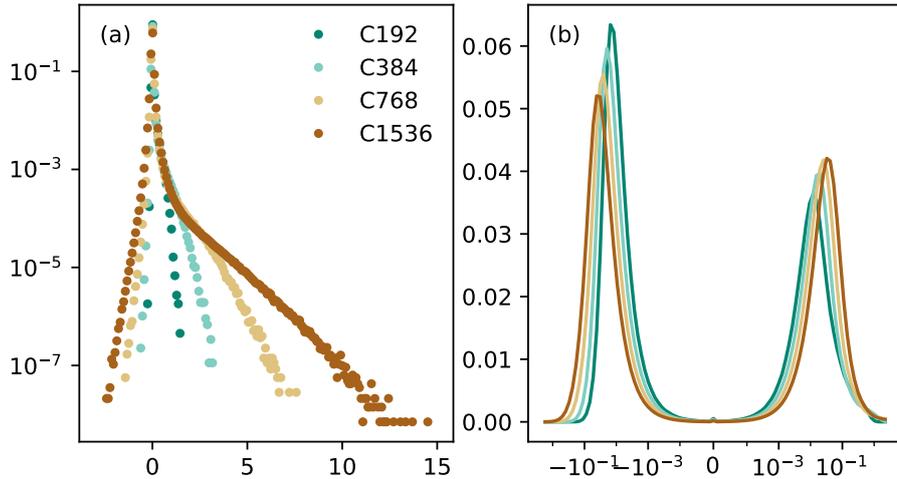


Figure 5. Normalized distribution of vertical velocity at 532 hPa sampled instantaneously every 6 hours at the native model grid (a) over 200 bins spaced evenly on linear scale between -3 and 15 m/s in units of 1, (b) over 50 bins spaced evenly on log scale between $-10^{0.4}$ and -10^{-4} m/s and 50 bins between 10^{-4} and $10^{0.4}$ m/s in units of %.

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3.4 Precipitation organization in the deep tropics

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We examine the organization of precipitation and its associated circulation in the deep tropics. We use daily averaged data coarse-grained to the $0.5^\circ \times 0.5^\circ$ grid over the entire 9 months after spin-up. The precipitation is further averaged over 5°N and 5°S . As will be shown below, the dominant variance after these temporal and spatial averaging is mostly Kelvin wave.

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Figure 7 shows the Hovmöller plot for precipitation averaged over 5°N - 5°S . In all experiments, the eastward propagating Kelvin waves is manifested in the parallel stripes of strong precipitation in the Hovmöller plots. The dominance of the Kelvin waves is confirmed in the space-time spectra of precipitation and OLR shown in Fig. 8. The eastward propagating Kelvin waves are readily seen in both resolved and parameterized precipitation. The phase speed of the Kelvin wave indicated by the slope of the precipitation stripes are similar among different experiments and precipitation components. In the C192 experiment, the resolved precipitation shows localized extreme intensity, and the precipitation stripe is frequently interrupted. These popcorn-like pockets are greatly suppressed as the resolution increases, and the precipitation stripes become smoother and more continuous (Fig. 7e-h). The smoother precipitation stripes at the finer resolution are also seen in the precipitation from the parameterized deep plume (Figs. 7i-l) and shallow plume (Figs. 7m-p). The suppression of the popcorn pockets and the more continuous precipitation indicate a stronger role of the large-scale circulation.

This transition from the localized popcorn convection to the more organized convection is evident in the one-point correlation maps against the equatorial precipitation. The correlation is calculated as:

$$r(\theta, \Delta\phi) = \frac{[(x(t, \theta, \phi + \Delta\phi) - [x])(y(t, \phi) - [y])]}{\sqrt{[(x - [x])^2]} \sqrt{[(y - [y])^2]}}$$

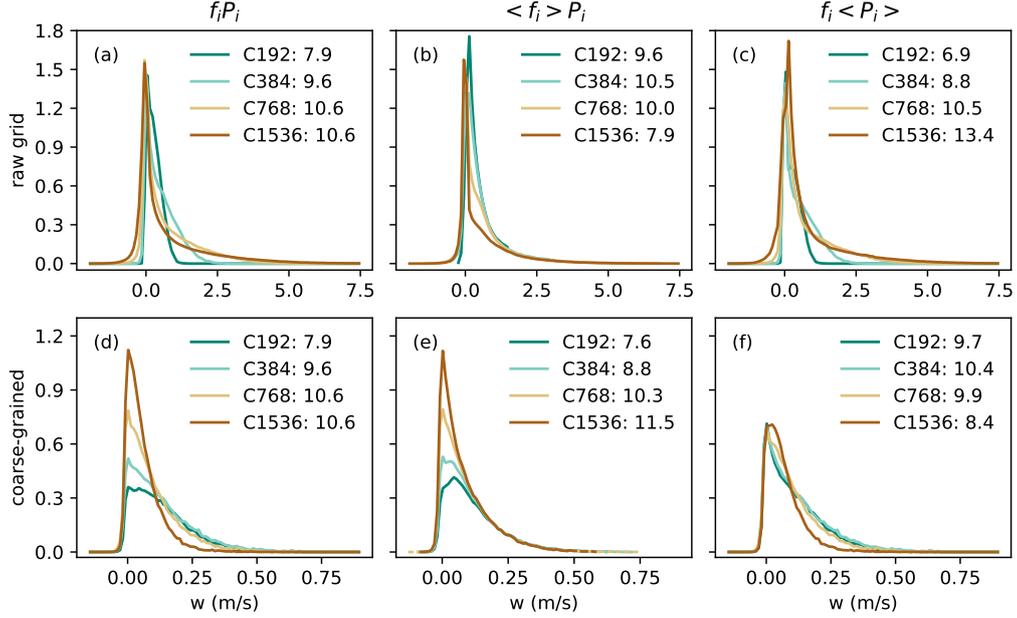


Figure 6. (a) Resolved precipitation amount binned with respect to the vertical velocity at 532 hPa evaluated using the instantaneous data at the raw model grid. It is calculated as the product of the mean precipitation intensity in each bin P_i and the fraction of data points in each bin f_i . The sum of $f_i P_i$ from each experiment is listed in the legend, corresponding to the monthly mean areal mean resolved precipitation intensity in units of mm/day. The vertical velocity is divided into 100 bins linearly ranging from -2 m/s to 7.5 m/s. (b) As (a), but assuming a common fractional distribution among vertical velocity bins $\langle f_i \rangle$ for all experiments. (c) As (a), but assuming a common mean precipitation intensity in each vertical velocity bin $\langle P_i \rangle$ for all experiments. (d)-(f) As (a)-(c) except for using the daily mean coarse-grained data and the vertical velocity is divided into 100 bins linearly ranging from -0.15 m/s to 0.9 m/s.

426 where x is the variable, y is the equatorial precipitation averaged over 5°N - 5°S , t is time,
 427 θ is latitude, ϕ is the reference longitude, $\Delta\phi$ is the longitudinal distance from the ref-
 428 erence, and $[]$ indicates a zonal mean over all longitudes and time mean over the entire
 429 9 months after spin-up.

430 Since the variance of this precipitation index is dominated by strong intensities,
 431 the one-point correlation maps show how precipitation is organized around a local pre-
 432 cipitation maximum, which often results from a deep convection core. Note that the rel-
 433 ative distance in longitude is equivalent to the relative sequence in time here given that
 434 the eastward moving Kelvin wave is the dominant variance. Features found to the east
 435 of the deep convection core (relative longitude > 0) occur prior the deep convection, and
 436 vice versa.

437 In the C192 experiment, high correlation is found at the same location where the
 438 precipitation index is defined, but near-zero correlation is found anywhere else. This is
 439 consistent with the localized popcorn convection seen in Figs. 7a, 7e, 7i, 7m. As the res-
 440 olution increases, correlations start to emerge outside the location where the precipita-
 441 tion index is defined. The longitudinal scale of the correlation patterns becomes wider
 442 and the non-local correlations becomes stronger. These non-local correlations indicate
 443 modulations from the large-scale circulation associated with the deep convection. At the
 444 resolution of C1536, the correlation maps of the total (Fig. 9d) and the resolved precip-
 445 itation (Fig. 9h) show a Gill-type response to the deep convection (Gill, 1980): positive
 446 correlation is found over a tongue extending to the east of the deep convection core and
 447 a pair of patches centered off-equator to the west. Negative correlations are found along
 448 the equator, corresponding to the descending branch of the Gill-type circulation anomaly.
 449 The precipitation from the parameterized deep and shallow plumes both show a pattern
 450 of zonal wave number 1. For the deep plume (Fig. 9l), stronger parameterized precip-
 451 itation is found to the west or after the deep convection core. Contrarily, the shallow plume
 452 produces stronger precipitation to the east or prior of the deep convection core (Fig. 9p).

453 To examine the organization in the circulation associated with the precipitation,
 454 we calculate similar one-point correlation maps between the precipitation index and var-
 455 ious variables. As shown in Figs. 11 and 10, all these one-point correlation maps show
 456 stronger non-local correlations as the model resolution increases. A longitudinal expan-
 457 sion is evident as resolution increase from C192 to C384, though further expansions are
 458 more subtle for higher resolutions. These common features among all variables indicate
 459 a robust sensitivity in the organization state of the equatorial convection to the model
 460 resolution. In particular, we see a closer relationship between the large-scale circulation
 461 and the deep convection core at finer resolution, which provides more favorable condi-
 462 tions for convection organization.

463 A common structure seen in all convective coupled equatorial waves is the shallow
 464 convection occurring prior the deep convection and the stratiform clouds and precipi-
 465 tation trailing the deep convection, which distinguish them from the isolated unorganized
 466 convection (Kiladis et al., 2009, and references therein). This shallow-to-deep-to-stratiform
 467 transition is associated with a slantwise circulation as well as vertical displacement of
 468 convective and radiative heating, which all contribute to the maintenance and propaga-
 469 tion of convective waves. Similar shallow-to-deep-to-stratiform transition is also impor-
 470 tant for the mesoscale convective systems (MCSs) (e.g., Houze, 2004; Moncrieff, 2010).
 471 Properly simulating this shallow-to-deep-to-stratiform transition is therefore crucial for
 472 simulating these equatorial waves and the organized convective system in general (e.g.,
 473 Frierson et al., 2011; Seo et al., 2012). Such transition is clearly manifested in vertical
 474 velocity (Figs. 10a-b), cloud fraction (Figs. 10e-h), relative humidity (Figs. 10i-l) and
 475 moist static energy (MSE; Figs. 10m-p). We see that on the east side of the deep con-
 476 vection core, the lower troposphere is moist and of high MSE, upward motion is largely
 477 confined within the lower troposphere and clouds are forming below ~ 750 hPa, all of which
 478 indicate shallow convection. On the west side of the deep convection core, MSE and hu-

479 midity are higher over the upper troposphere than the lower troposphere, and upward
 480 motion and clouds are found over the upper troposphere, signaling the stratiform phase.
 481 The parameterized convection also contribute to the shallow-to-deep-to-stratiform tran-
 482 sition as indicated by the convective mass flux from the deep plume (Figs. 10q-t) and
 483 the shallow plume (Figs. 10u-x). The parameterized shallow plume varies inversely with
 484 the convective inhibition (CIN) in our model, which is tightly linked to the low level hu-
 485 midity. Thus, the high low-level relative humidity prior the deep convection indicates
 486 a low CIN and a stronger shallow plume from the parameterization. In the deep plume
 487 parameterization, the fractional lateral mixing rate decreases with the free troposphere
 488 column relative humidity. Higher free troposphere relative humidity is found at the deep
 489 convection core and over the stratiform region, which reduces lateral mixing there and
 490 promotes a stronger deep plume.

491 We further show the one-point correlation on the latitude-longitude plane in Fig.
 492 11. The low surface pressure anomalies to the east of precipitation and high anomalies
 493 to the west (Figs. 11e-h) are consistent with the theoretical prediction for the equato-
 494 rial Kelvin waves (Matsuno, 1966). OLR anomalies (Figs. 11a-d) largely reflect the clouds
 495 anomalies associated with convective system: low OLR anomalies come from the strat-
 496 iform anvil clouds and high OLR anomalies are found over the region where there is lit-
 497 tle high clouds. The column-integrated MSE anomalies (Figs. 11i-l) are dominated by
 498 moisture anomalies over the lower troposphere, showing high MSE anomalies prior pre-
 499 cipitation at the equator. Similar to the one-point correlations shown above, all three
 500 variables show a clear longitudinal expansion with resolution. On the other hand, the
 501 latitudinal scales of these precipitation-associated anomalies do not vary much with res-
 502 olution.

503 All the variables shown in Figs. 9, 10 and 11 manifest a robust resolution depen-
 504 dence in the convective organization. The shallow-to-deep-to-stratiform transition is barely
 505 discernible in the C192 run but expands to a much wider system in longitudes at the finer
 506 resolutions, and the non-local effects of the convection becomes stronger as the resolu-
 507 tion increases. Whether the convection is dominated by the organized system or the un-
 508 organized popcorn would lead to different relationship between precipitation and the lo-
 509 cal vertical velocity. For a localized convection, strong ascent is always co-located with
 510 strong precipitation. For a convective system, strong precipitation and strong ascent are
 511 found at the deep convection core, but precipitation also forms over the shallow convec-
 512 tion and stratiform region, which is less controlled by the local vertical velocity. As the
 513 model resolution increases, the convective system becomes stronger, and more moder-
 514 ate precipitation forms over the shallow and stratiform region, which might explain the
 515 precipitation changes irrespective of vertical velocity seen in Fig. 6e.

516 Note that the zonal wavenumber-1 structures apparent in these one-point corre-
 517 lation maps are not contradictory to spectra analysis showing power over a range of zonal
 518 wavenumbers (Fig. 8). This is because precipitation does not vary along longitude as
 519 a sinusoidal wave but more as individual solitons. Fourier transform of a single soliton
 520 project powers on a range of zonal wavenumbers. It is also worth noting that the stronger
 521 organization at finer resolution is not only contributed by the resolved processes but by
 522 the parameterized ones as well, despite the fact that the cumulus parameterization here
 523 is not directly “scale-aware”. These resolution dependence in the parameterized convec-
 524 tion reflects the modulation of the large-scale circulation to the parameterized convec-
 525 tion via the mean states, mostly the relative humidity.

526 4 Summary and discussion

527 We performed a series of aquaplanet simulations using the GFDL AM4-MG2 model
 528 with horizontal resolution ranging from 50km to 6km. As the resolution increases, the
 529 globally averaged precipitation at the resolved scale intensifies while the precipitation

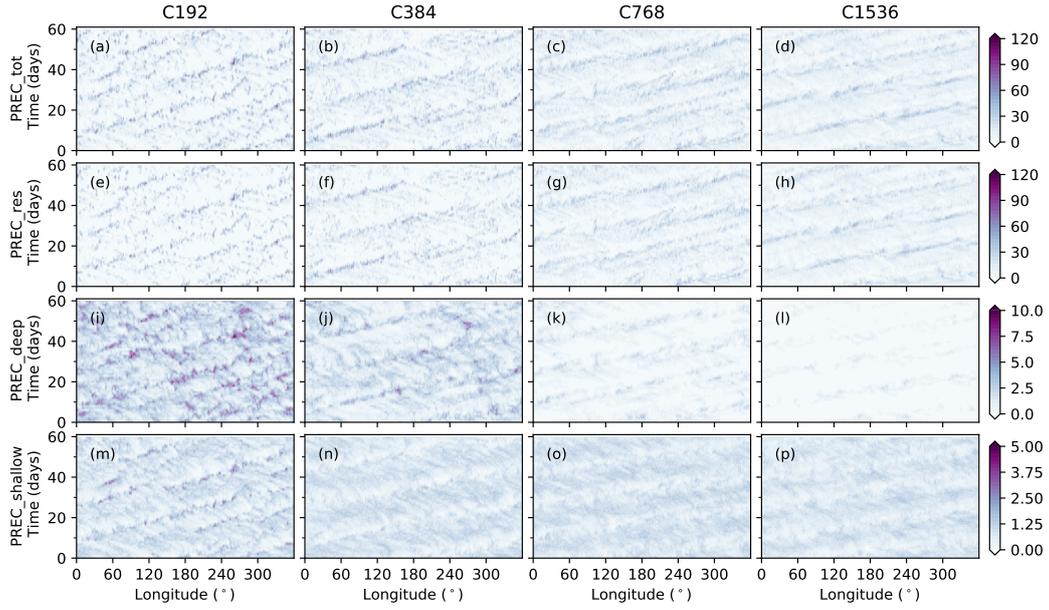


Figure 7. Hovmöller plot of daily mean precipitation averaged over 5°N - 5°S over the 6th and 7th months for (a-d) total precipitation, (e-h) resolved precipitation, (i-l) parameterized deep plume precipitation, and (m-p) parameterized shallow plume precipitation. (a, e, i, m) show results for C192, (b, f, j, n) for C384, (c, g, k, o) for C768, and (d, h, l, p) for C1536. Precipitation is in units of mm/day.

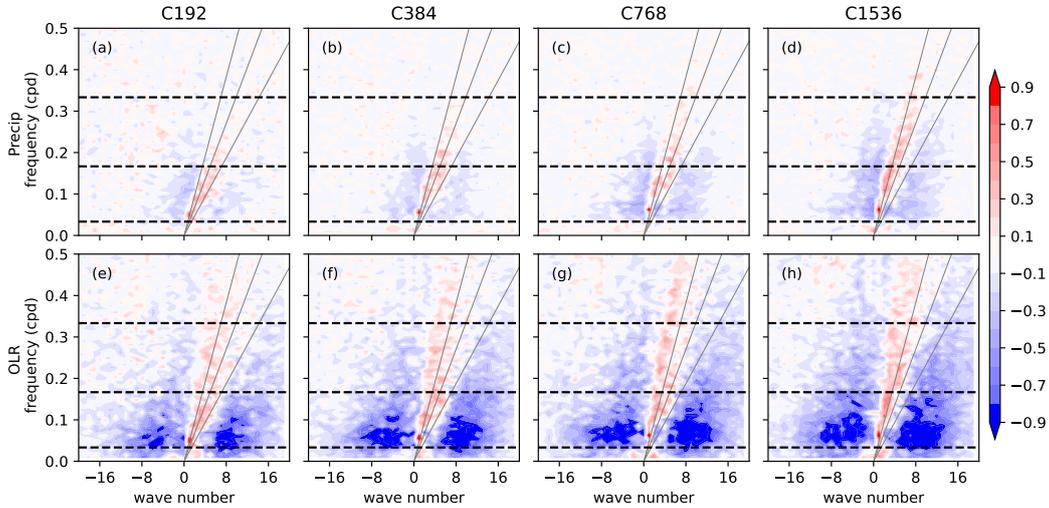


Figure 8. The 10 base logarithm of the ratio between the symmetric component and the background spectra in (a-d) total precipitation, and (e-h) OLR following Wheeler and Kiladis (1999). The spectra is calculated using the daily mean coarse-grained data over 15°N - 15°S over the entire 9 months. The gray lines indicate the theoretical dispersion relationship for Kelvin waves corresponding to equivalent depths of 12, 25, and 50 m. The black dashed lines mark the period of 3, 6 and 30 days. (a, e) show results for C192, (b, f) for C384, (c, g) for C768 and (d, h) for C1536.

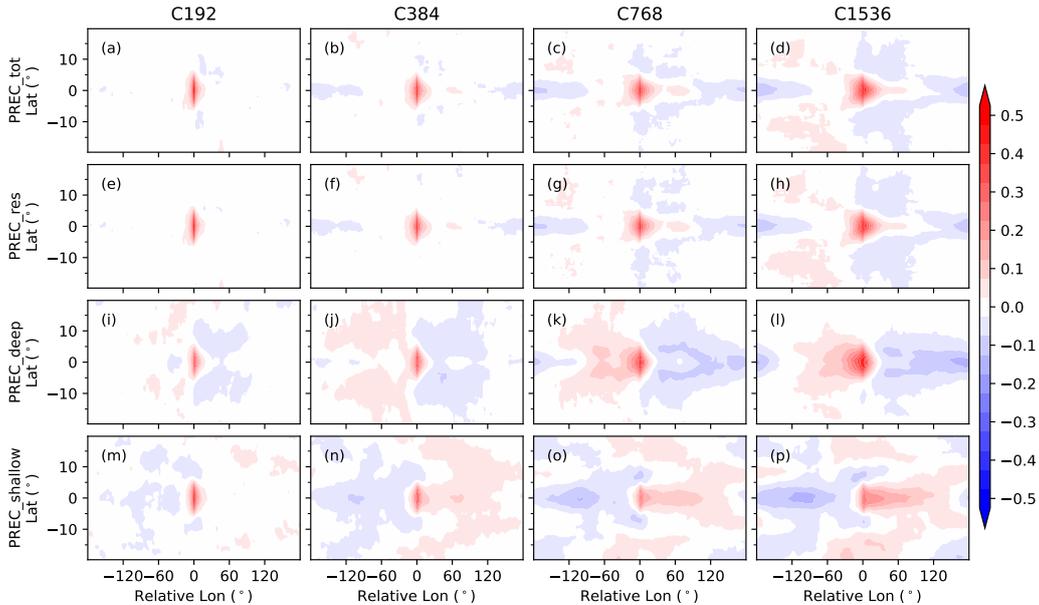


Figure 9. Correlation against the total precipitation averaged over 5°N - 5°S at a reference longitude for (a-d) total precipitation, (e-h) precipitation at the resolved scale, (i-l) precipitation from the parameterized deep plume, and (m-p) precipitation from the parameterized shallow plume. (a, e, i, m) show results for C192, (b, f, j, n) for C384, (c, g, k, o) for C768, and (d, h, l, p) for C1536.

530 produced by the cumulus parameterization weakens. This is consistent with earlier stud-
 531 ies using models of resolutions coarser than 25km (e.g., Wehner et al., 2014; Herrington
 532 & Reed, 2017; Terai et al., 2018; Herrington & Reed, 2020). The resolved precipitation
 533 seems to approach convergence for resolutions finer than 13km in our simulations, es-
 534 pecially over the deep tropics. The precipitation from the parameterized deep plume de-
 535 creases by an order as the resolution increases from 50km to 6km, while variations in the
 536 shallow plume across resolution are generally weak. More and/or thicker clouds are sim-
 537 ulated at the finer resolution over high latitudes, and less and/or thinner clouds are found
 538 over low latitudes.

539 Studies have attributed the enhancement of the mean resolved precipitation with
 540 resolution to the intensification of the extreme precipitation, which is linked to the in-
 541 tensification of the strongest ascent (Rauscher et al., 2016; O’Brien et al., 2016; Herring-
 542 ton & Reed, 2017, 2020). Our simulations at higher resolution suggest that the resolu-
 543 tion dependence in the resolved precipitation cannot be fully explained by the intensi-
 544 fication of the strongest ascent. Changes in the precipitation with resolution occurs not
 545 only over the extreme intensity range but also over weak and moderate intensity range
 546 and outside of the strongest ascent region. Intensification of the extreme precipitation
 547 with resolution is only seen in instantaneous samples but not in the daily averaged one.
 548 We report a robust resolution sensitivity in the convective organization state in our model,
 549 which has not been reported in previous GCM studies. A stronger correlation is found
 550 between the local precipitation event and the large-scale circulation in simulations at finer
 551 resolution. As the large-scale convective system takes over, the localized popcorn con-
 552 vection is suppressed, moderate precipitation is enhanced, but the extreme precipitation
 553 is less affected.

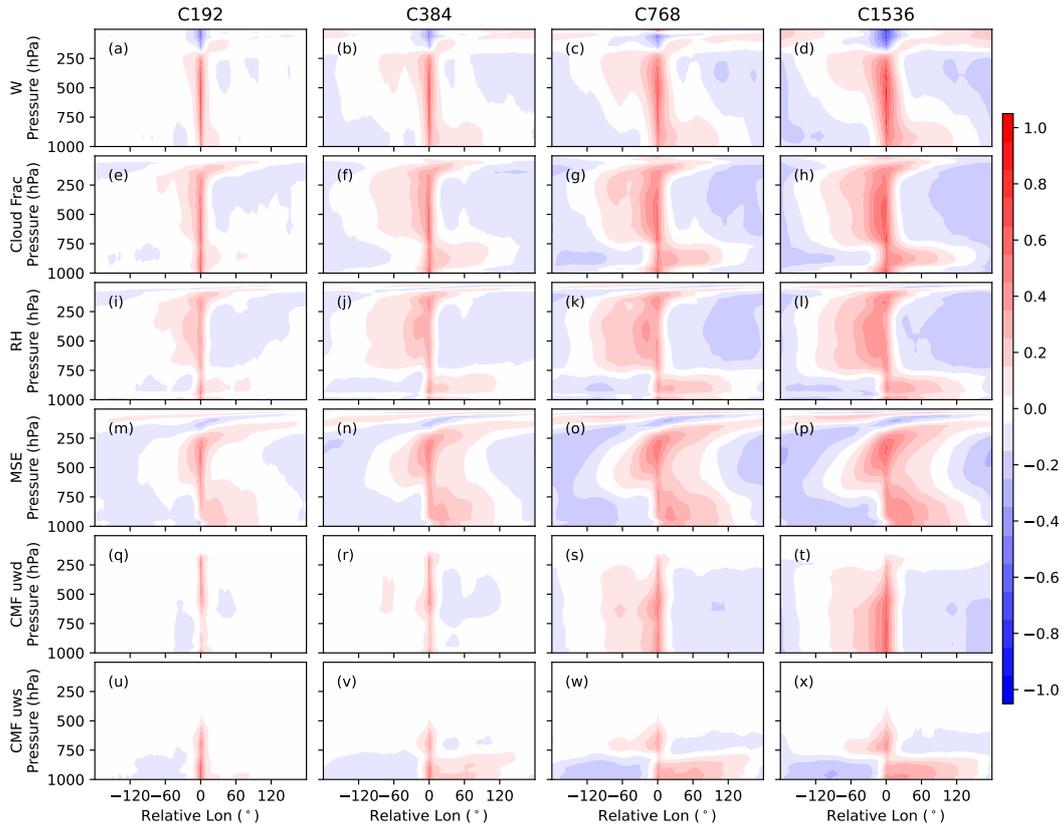


Figure 10. As Fig. 9, except for (a-d) vertical velocity, (e-h) cloud fraction, (i-l) relative humidity, (m-p) moist static energy, (q-t) convective mass flux from the parameterized deep plume, and (u-x) convective mass flux from the parameterized shallow plume. All variables are averaged over 5°N - 5°S .

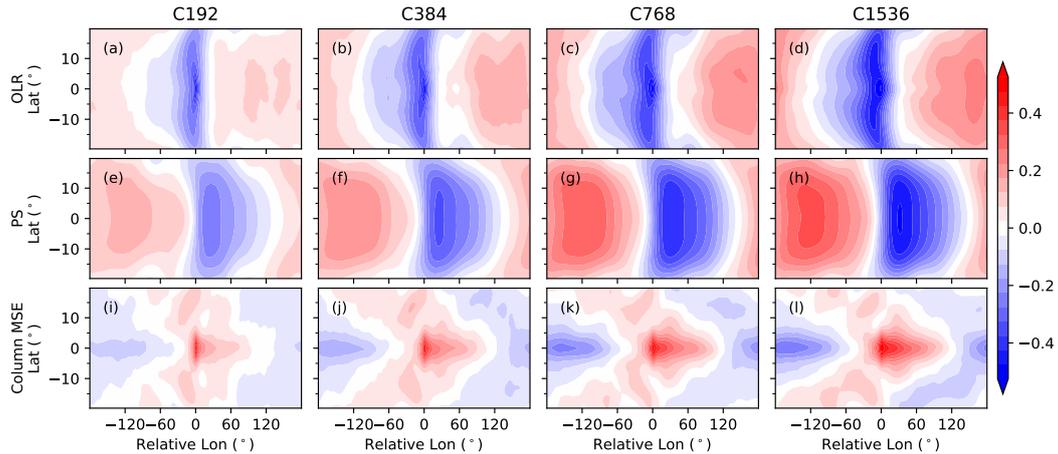


Figure 11. As Fig. 9, except for (a-d) OLR, (e-h) surface pressure, (i-l) column integrated moist static energy.

554 We show that the precipitation extremes and intensity distribution simulated in
 555 the higher resolution model is strongly affected by whether precipitation has been spa-
 556 tially coarse-grained and/or averaged over time, whereas the lower resolution models show
 557 less sensitivity to the re-sampling. This explains why earlier GCM studies at the reso-
 558 lution lower than 25km reported similar resolution dependence in extreme precipitation
 559 regardless of whether data is sampled at native model grid or coarse-grained, instanta-
 560 neously or daily averaged (e.g., Li et al., 2011; Wehner et al., 2014; O’Brien et al., 2016;
 561 Rios-Berrios et al., 2020; Herrington & Reed, 2020). On the other hand, recent model
 562 studies at higher resolutions reported distinction between extremes in instantaneous and
 563 daily precipitation (Bao & Sherwood, 2018; Bao & Windmiller, 2021; O’Gorman et al.,
 564 2021).

565 Besides model resolution, the precipitation extremes and convective organization
 566 are also sensitive to the diffusive damping setting in the dynamical core. Anber et al.
 567 (2018) evaluated the sensitivity in convection organization and precipitation extremes
 568 to the damping settings in a radiative-convective equilibrium (RCE) configuration based
 569 on the same FV3 dynamical core used here. They found a weaker damping setting (ei-
 570 ther by using a higher order damping or a weaker damping coefficient) leads to weaker
 571 extremes in the 6-hourly averaged precipitation. As discussed in the appendix, the dy-
 572 namical core setting in our simulations may be too diffusive for the finer resolution runs.
 573 If higher order damping and/or weaker damping coefficients to be used in the finer res-
 574 olution runs, we expect the daily precipitation extremes to reduce even more in the finer
 575 resolution runs, leading to a further departure from the estimation based on vertical ve-
 576 locity. On the other hand, the simulations by Anber et al. (2018) are limited to a small
 577 domain of 32km x 32km so that convective organization on the larger scales are ignored.
 578 The sensitivity to diffusion settings found in their model may not hold in a global sim-
 579 ulation. Given the complex coupling across different scales, how artificial diffusion af-
 580 fects convection in a global model may be counter-intuitive as discussed by Zhao et al.
 581 (2012).

582 This work highlights the complexity to understand the global simulations at the
 583 convective gray zone resolution, where the underlying physics may be different from the
 584 conventional GCMs or the cloud-resolving models and the Large Eddy Simulations (LES)
 585 of limited domain. Since it remains challenging to run the global simulation at a reso-
 586 lution fully resolving convection and clouds in the foreseeable future, more investigations
 587 are called for to understand the resolution dependence and the interaction between the
 588 parameterized and resolved convection at the convective gray zone resolution.

589 **Appendix A Diffusion Settings**

590 Numerical diffusion is an indispensable component of the dynamical core, repre-
 591 senting the viscous dissipation of kinetic energy cascading towards molecular scales by
 592 the unresolved turbulent eddies. This is achieved implicitly from the advection opera-
 593 tor as well as explicitly by adding artificial damping. Choices of these diffusion settings
 594 would certainly affect the characteristics of the simulated circulation. A detailed doc-
 595 umentation of the numerical diffusion settings in the FV3 dynamical core as well as guide-
 596 lines for choosing these diffusion settings can be found in Harris et al. (2021, Chapter
 597 8). Here, we provide a short summary of the diffusion settings used in our simulations.

We use a monotonic operator for advection in our simulations, which is more dif-
 fusive than the unlimited or positive-definite operators. More specifically, we use the third-
 order piecewise-parabolic method with the “fast monotonicity constraint” of S.-J. Lin
 (2004) for tracers. Horizontal advection of momentum, vorticity, potential temperature
 and mass uses the quasi-monotone constraint proposed by Huynh (1997), which is sig-
 nificantly less diffusive than the one used for tracers. For the explicit damping, we use
 separate damping on the divergent and rotational components of the flow. The diver-

gence damping is applied to horizontal winds as following:

$$\mathbf{v}^{n+1} = \mathbf{v}^n + \dots + (-1)^N \nu_D \frac{\delta_x(\nabla^{2N} D)}{\Delta \mathbf{x}}$$

598 where \mathbf{v} is the vector of horizontal wind, n is the time index, δ_x is a centered-difference
 599 operator, D is the divergence of horizontal winds, $\Delta \mathbf{x}$ is the horizontal grid length, and
 600 ν_D is the damping coefficient. ν_D is calculated in the model as $(d_{2N} \Delta A_{min})^{N+1}$, in which
 601 ΔA_{min} is the global minimum grid-cell area and d_{2N} is a specified non-dimensional con-
 602 stant. Such formulation is equivalent to a ∇^{2N+2} form of hyper diffusion for the diver-
 603 gence field (i.e., $(2N+2)$ -th order damping), and $\nu_D/\Delta t$ is equivalent to the dimensional
 604 hyperviscosity coefficient (Δt is the dynamical time step). We use $N = 1$ and $d_{2N} =$
 605 0.15 for all our simulations, that is a 4th order damping with hyperviscosity coefficient
 606 of $6.32 \times 10^{14} m^4 s^{-1}$ for C192, $1.03 \times 10^{14} m^4 s^{-1}$ for C384, $1.10 \times 10^{13} m^4 s^{-1}$ for C768
 607 and $1.38 \times 10^{12} m^4 s^{-1}$ for C1536. Vorticity damping is of the same order as the diver-
 608 gence damping, and the vorticity damping coefficient ν_v is calculated in a similar fash-
 609 ion to ν_D , that is $\nu_v = (d_v \Delta A_{min})^{N+1}$. We use $d_v = 0.02$ for all our simulations, which
 610 corresponds to a dimensional damping coefficient of $1.12 \times 10^{13} m^4 s^{-1}$ for C192, $1.84 \times$
 611 $10^{12} m^4 s^{-1}$ for C384, $1.96 \times 10^{11} m^4 s^{-1}$ for C768 and $2.45 \times 10^{10} m^4 s^{-1}$ for C1536.

612 As discussed in Harris et al. (2021, Chapter 8), the choices of the diffusion settings
 613 should be chosen for desirable simulation features rather than objectively determined.
 614 A model with high resolution typically employs a less diffusive advection operator and
 615 a higher-order artificial damping scheme that is more scale selective, whereas a conven-
 616 tional climate model often employs a more diffusive advection operator and a lower-order
 617 damping scheme to improve the large-scale circulation features. But this is not always
 618 the case. The diffusion setting used in this study follows the setting used in the C192
 619 AM4 climate simulations runs (Zhao, 2020), which choose a lower order divergence damp-
 620 ing than in the lower resolution ones (4th order in C192 vs 6th order in C96) to improve
 621 simulations of tropical cyclones. We note that the diffusion settings here may not be the
 622 optimal choice for high resolution runs. As shown in Fig. A1, the $k^{-5/3}$ slope in the hor-
 623 izontal kinetic energy spectra is barely resolved even in our high resolution simulations,
 624 suggesting that our model setting is too diffusive to fully resolve the mesoscale energy
 625 cascade. Takahashi et al. (2016) argue that the dimensional damping coefficients of a 4th
 626 order damping should scale with $\Delta x^{3.22}$ to properly resolve the mesoscale kinetic energy,
 627 which leads to a decrease by an order of magnitude in the damping coefficient for each
 628 resolution doubling. Our explicit dimensional divergence and vorticity damping coeffi-
 629 cients do decrease as resolution increases but not as much as the scaling proposed by Takahashi
 630 et al. (2016), which may partly explain the early departure from the $k^{-5/3}$ slope in our
 631 simulations. However, one should note that the strength of the diffusion is not solely de-
 632 termined by the damping coefficients. Choices of the advection operator and the order
 633 of the damping also affect how diffusive the model is, and their effects are usually im-
 634 plicit, nonlinear and not straightforward to quantify. For example, a much better resolved
 635 $k^{-5/3}$ slope is seen in simulations by the FV3 dynamical core with a less diffusive ad-
 636 vection operator (“virtually-inviscid” scheme vs monotonic scheme), a higher order di-
 637 vergence damping (8th vs 4th) and a similar non-dimensional damping coefficient (e.g.,
 638 S.-J. Lin et al., 2018).

639 Open Research

640 The source code of the AM4-MG2 nonhydrostatic aquaplanet model and config-
 641 urations of the simulations presented in this manuscript is available at: [doi.org/10.5281/](https://doi.org/10.5281/zenodo.7476908)
 642 [zenodo.7476908](https://doi.org/10.5281/zenodo.7476908) (Robinson et al., 2022). The specification of the model’s vertical co-
 643 ordinate, analysis scripts and model outputs used in the manuscript are available at: [doi](https://doi.org/10.5281/zenodo.7537434)
 644 [.org/10.5281/zenodo.7537434](https://doi.org/10.5281/zenodo.7537434) (P. Lin et al., 2023). The spatial remapping is done us-
 645 ing fregrid, which is part of the FRE-NCtools, available at: [https://github.com/NOAA-](https://github.com/NOAA-GFDL/FRE-NCtools)
 646 [GFDL/FRE-NCtools](https://github.com/NOAA-GFDL/FRE-NCtools) (GFDL modeling systems group, 2022).

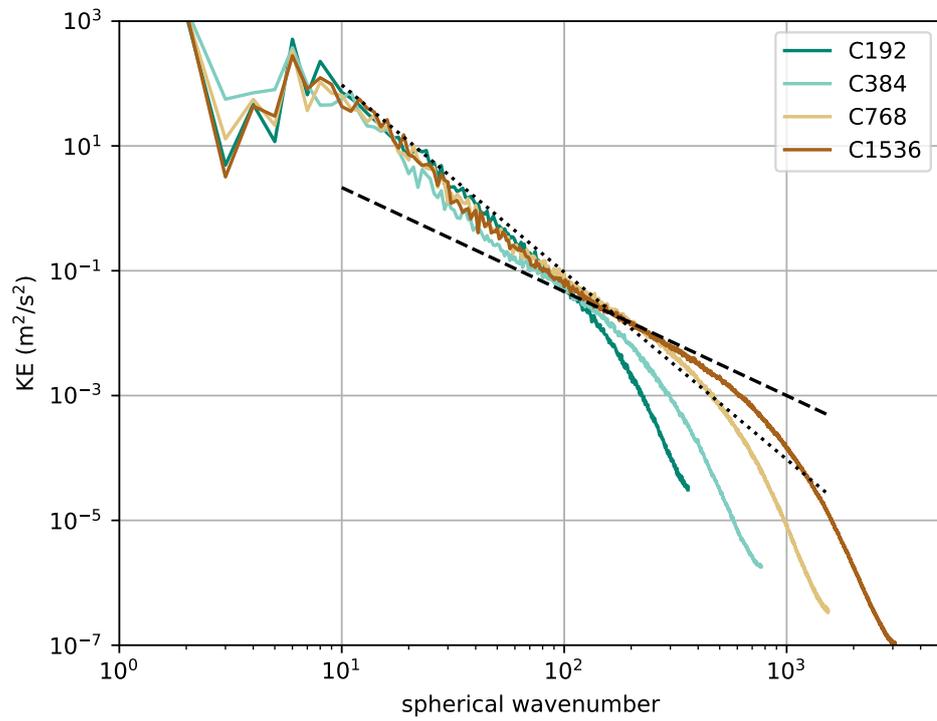


Figure A1. Kinetic energy spectra at 221 hPa. The dotted line indicates the k^{-3} slope and the dashed line indicates the $k^{-5/3}$ slope.

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References

- Ahmed, F., & Schumacher, C. (2015). Convective and stratiform components of the precipitation-moisture relationship. *Geophys. Res. Lett.*, *42*, 10453-10462. doi: 10.1002/2015GL066957
- Anber, U. M., Jeevanjee, N., Harris, L. M., & Held, I. M. (2018). Sensitivity of radiative-convective equilibrium to divergence damping in GFDL-FV3-based cloud-resolving model simulations. *J. Adv. Model. Earth Sy.*, *10*, 1528-1536. doi: 10.1029/2017MS001225
- Arnold, N. P., Putman, W. M., & Freitas, S. R. (2020). Impact of resolution and parameterized convection on the diurnal cycle of precipitation in a global nonhydrostatic model. *J. Meteorol. Soc. Jpn.*, *98*, 1279-1304. doi: 10.2151/jmsj.2020-066
- Bao, J., & Sherwood, S. C. (2018). The role of convective self-aggregation in extreme instantaneous versus daily precipitation. *J. Adv. Model. Earth Sy.*, *11*, 19-33. doi: 10.1002/2018MS001503
- Bao, J., Sherwood, S. C., Colin, M., & Dixit, V. (2017). The robust relationship between extreme precipitation and convective organization in idealized numerical modeling simulations. *J. Adv. Model. Earth Sy.*, *9*, 2291-2303. doi: 10.1002/2017MS001125
- Bao, J., & Windmiller, J. M. (2021). Impact of microphysics on tropical precipitation extremes in a global storm-resolving model. *Geophys. Res. Lett.*, *48*. doi: 10.1029/2021GL094206
- Benedict, J. J., Medeiros, B., Clement, A. C., & Pendegrass, A. G. (2017). Sensitivities of the hydrological cycle to model physics, grid resolution and ocean type in the aquaplanet Community Atmosphere Model. *J. Adv. Model. Earth Sy.*, *9*, 1307-1324. doi: 10.1002/2016MS000891
- Blackburn, M., Williamson, D. L., Nakajima, K., Ohfuchi, W., Takahashi, Y. O., Hayashi, Y.-Y., ... Stratton, R. (2013). The aqua-planet experiment (APE): control SST simulations. *J. Meteorol. Soc. Jpn.*, *91A*, 17-56. doi: 10.2151/jmsj.2013-A02
- Bretherton, C. S., Peters, M. E., & Back, L. E. (2004). Relationships between water vapor path and precipitation over the tropical oceans. *J. Clim.*, *17*, 1517-1528. doi: 10.1175/1520-0442(2004)017<1517:RBWVPA>2.0.CO;2
- Caldwell, P. M., Terai, C. R., Hillman, B., Keen, N. D., Bogenschutz, P., Lin, W., ... Zender, C. S. (2021). Convection-permitting simulations with the E3SM global atmosphere model. *J. Adv. Model. Earth Sy.*, *13*. doi: 10.1029/2021MS002544
- Donner, L. J., Wyman, B., Hemler, R. S., Horowitz, L. W., Ming, Y., Zhao, M., ... coauthors (2011). The dynamical core, physical parameterizations, and basic simulation characteristics of the atmospheric component AM3 of the GFDL Global Coupled Model CM3. *J. Clim.*, *24*, 3484-3519.
- Eyring, V., Bondy, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., &

- 700 Taylor, K. E. (2016). Overview of the Coupled Model Intercomparison Project
701 phase 6 (cmip6) experimental design and organization. *Geosci. Model Dev.*, *9*,
702 1937-1958. doi: 10.5194/gmd-9-1937-2016
- 703 Fan, S., Ginoux, P., Seman, C. J., Silvers, L. G., & Zhao, M. (2019). Toward im-
704 proved cloud-phase simulation with a mineral dust and temperature-dependent
705 parameterization for ice nucleation in mixed-phase clouds. *J. Atmos. Sci.*, *76*,
706 3655-3667. doi: 10.1175/JAS-D-18-0287.1
- 707 Frierson, D. M. W., Kim, D., Kang, I.-S., Lee, M.-I., & Lin, J. (2011). Structure of
708 AGCM-simulated convectively coupled Kelvin waves and sensitivity to convec-
709 tive parameterization. *J. Atmos. Sci.*, *68*, 26-45. doi: 10.1175/2010JAS3356.1
- 710 Gao, Y., Leung, L. R., Zhao, C., & Hagos, S. (2017). Sensitivity of U.S. sum-
711 mer precipitation to model resolution and convective parameterizations
712 across gray zone resolutions. *J. Geophys. Res.*, *122*, 2714-2733. doi:
713 10.1002/2016JD025896
- 714 Gettelman, A., & Morrison, H. (2015). Advanced two-moment bulk microphysics
715 for global models: Part I: off-line tests and comparison with other schemes. *J.*
716 *Clim.*, *28*, 1268-1287. doi: 10.1175/JCLI-D-14-00102.1
- 717 GFDL modeling systems group. (2022). *Fre-nctools (release 2022.02)* [software].
718 GFDL. Retrieved from <https://github.com/NOAA-GFDL/FRE-NCTools>
- 719 Gill, A. E. (1980). Some simple solutions for heat-induced tropical circulation. *Q. J.*
720 *Roy. Meteorol. Soc.*, *106*, 447-462. doi: 10.1002/qj.49710644905
- 721 Guo, H., Ming, Y., Fan, S., Zhou, L., Harris, L., & Zhao, M. (2021). Two-moment
722 bulk cloud microphysics with prognostic precipitation in GFDL's Atmospheric
723 Model AM4.0: Configuration and performance. *J. Adv. Model. Earth Sy.*, *13*.
724 doi: 10.1029/2020MS002453
- 725 Harris, L., Chen, X., Putman, W., Zhou, L., & Chen, J.-H. (2021). *A scientific*
726 *description of the GFDL finite-volume cubed-sphere dynamical core* (NOAA
727 Technical Memorandum OAR GFDL No. 2021-001). doi: 10.25923/6nhs-5897
- 728 Harris, L., Chen, X., Zhou, L., & Chen, J.-H. (2020). *The nonhydrostatic solver*
729 *of the GFDL finite-volume cubed-sphere dynamical core* (NOAA Techni-
730 cal Memorandum OAR GFDL No. 2020-003). NOAA OAR GFDL. doi:
731 10.25923/9wdt-4895
- 732 Harris, L., Zhou, L., Chen, X., & Chen, J.-H. (2020). *The GFDL finite-volume*
733 *cubed-sphere dynamical core* (NOAA Technical Memorandum No. 2020-001).
734 NOAA OAR GFDL. doi: 10.25923/7h88-c534
- 735 Harris, L., Zhou, L., Kaltenbaugh, A., Clark, S. K., Cheng, K.-Y., & Bretherton,
736 C. S. (2023). A global survey of rotating convective updrafts in the GFDL
737 X-SHiELD 2021 global storm resolving model. *J. Geophys. Res.*, *128*. doi:
738 10.1029/2022JD037823
- 739 Harris, L., Zhou, L., Lin, S.-J., Chen, J.-H., Chen, X., Gao, K., et al. (2020). GFDL
740 SHIELD: a unified system for weather-to-seasonal prediction. *J. Adv. Model.*
741 *Earth Sy.*, *12*. doi: 10.1029/2020MS002223
- 742 Heim, C., Hentgen, L., Ban, N., & Schär, C. (2021). Inter-model variability in
743 convection-resolving simulations of subtropical marine low clouds. *J. Meteorol.*
744 *Soc. Jpn.*, *99*, 1271-1295. doi: 10.2151/jmsj.2021-062
- 745 Herrington, A. R., & Reed, K. A. (2017). An explanation for the sensitivity of the
746 mean state of the Community Atmosphere Model to horizontal resolution on
747 aquaplanets. *J. Clim.*, *30*, 4781-4797. doi: 10.1175/JCLI-D-16-0069.1
- 748 Herrington, A. R., & Reed, K. A. (2020). On resolution sensitivity in the Commu-
749 nity Atmosphere Model. *Q. J. Roy. Meteorol. Soc.*, *146*, 3789-3807. doi: 10
750 .1002/qj.3873
- 751 Houze, R. A. (2004). Mesoscale convective systems. *Rev. Geophys.*, *42*. doi: 10
752 .1029/2004RG000150
- 753 Huynh, H. T. (1997). Schemes and constraints for advection. In P. Kutler, J. Flores,
754 & J.-J. Chattot (Eds.), *Fifteenth international conference on numerical*

- 755 *methods in fluid dynamics* (p. 498-503). Berlin, Heidelberg: Springer Berlin
 756 Heidelberg. doi: 10.1007/BFb0107151
- 757 Jakob, C., & Klein, S. A. (2000). A parameterization of the effects of cloud and
 758 precipitation overlap for use in general-circulation models. *Q. J. Roy. Meteorol.*
 759 *Soc.*, *126*, 2525-2544. doi: 10.1002/qj.49712656809
- 760 Jeevanjee, N. (2017). Vertical velocity in the gray zone. *J. Adv. Model. Earth Sy.*, *9*,
 761 2304-2316. doi: 10.1002/2017MS001059
- 762 Jeevanjee, N., & Zhou, L. (2022). On the resolution-dependence of anvil cloud frac-
 763 tion and precipitation efficiency in radiative-convective equilibrium. *J. Adv.*
 764 *Model. Earth Sy.*, *14*. doi: 10.1029/2021MS002759
- 765 Judt, F., Klocke, D., Rios-Berrios, R., Vanniere, B., Ziemer, F., Auger, L., ... Zhou,
 766 L. (2021). Tropical cyclones in global storm-resolving models. *J. Meteorol.*
 767 *Soc. Jpn.*, *99*, 576-602. doi: 10.2151/jmsj.2021-029
- 768 Kiladis, G. N., Wheeler, M. C., an K. H. Straub, P. T. H., & Roundy, P. E. (2009).
 769 Convectively coupled equatorial waves. *Rev. Geophys.*, *47*, 2008RG000266.
- 770 Lang, T., Naumann, A. K., Stevens, B., & Buehler, S. A. (2021). Tropical free-
 771 tropospheric humidity differences and their effect on the clear-sky radiation
 772 budget in global storm-resolving models. *J. Adv. Model. Earth Sy.*, *13*. doi:
 773 10.1029/2021MS002514
- 774 Li, F., Collins, W. D., Wehner, M. F., Williamson, D. L., Olson, J. G., & Algieri, C.
 775 (2011). Impact of horizontal resolution on simulation of precipitation extremes
 776 in an aqua-planet version of Community Atmospheric Model (CAM3). *Tellus*
 777 *A*, *63*, 884-892. doi: 10.1111/j.1600-0870.2011.00544.x
- 778 Lin, P., Ming, Y., & Robinson, T. (2023). *Dataset supporting "on the resolu-*
 779 *tion sensitivity of equatorial precipitation in a gfdl global atmospheric model"*
 780 *(version 2)* [dataset]. Zenodo. Retrieved from [https://doi.org/10.5281/](https://doi.org/10.5281/zenodo.7537434)
 781 [zenodo.7537434](https://doi.org/10.5281/zenodo.7537434) doi: doi.org/10.5281/zenodo.7537434
- 782 Lin, S.-J. (2004). A "vertically Lagrangian" finite-volume dynamical core for global
 783 models. *Mon. Wea. Rev.*, *132*, 2293-2307.
- 784 Lin, S.-J., Zhou, L., Chen, J.-H., Harris, L., Chen, X., & Rees, S. (2018). Evaluation
 785 of the FV3-powered next generation unified prediction system for medium-
 786 range weather prediction. In *Eighth conference on transition of research to*
 787 *operations*. Austin, Texas. Retrieved from [https://ams.confex.com/ams/](https://ams.confex.com/ams/98Annual/meetingapp.cgi/Paper/335242)
 788 [98Annual/meetingapp.cgi/Paper/335242](https://ams.confex.com/ams/98Annual/meetingapp.cgi/Paper/335242)
- 789 Lock, A. P., Brown, A. R., Bush, M. R., Martin, G. M., & Smith, R. N. B. (2000).
 790 A new boundary layer mixing scheme. Part I: scheme description and single-
 791 column model tests. *Mon. Wea. Rev.*, *128*, 3187-3199.
- 792 Lu, J., Chen, G., Leung, L. R., Burrows, D. A., Yang, Q., Sakaguchi, K., & Hagos,
 793 S. (2015). Toward the dynamical convergence on the jet stream in aquaplanet
 794 AGCMs. *J. Clim.*, *28*, 6763-6782. doi: 10.1175/JCLI-D-14-00761.1
- 795 Lu, J., Vecchi, G. A., & Reichler, T. (2007). Expansion of the Hadley cell under
 796 global warming. *Geophys. Res. Lett.*, *34*. doi: 10.1029/2006GL028443
- 797 Lutsko, N. J., & Cronin, T. W. (2018). Increase in precipitation with surface
 798 warming in radiative-convective equilibrium. *J. Adv. Model. Earth Sy.*, *10*,
 799 2992-3010. doi: 10.1029/2018MS001482
- 800 Matsuno, T. (1966). Quasi-geostrophic motions in the equatorial area. *J. Meteorol.*
 801 *Soc. Jpn.*, *44*, 25-43.
- 802 Medeiros, B., Stevens, S., & Bony, S. (2015). Using aquaplanets to understand the
 803 robust response of comprehensive climate models to forcing. *Clim. Dyn.*, *44*,
 804 1957-1977. doi: 10.1007/s00382-014-2138-0
- 805 Merlis, T. M., & Held, I. M. (2019). Aquaplanet simulations of tropical cyclones.
 806 *Curr. Clim. Change Rep.*, *5*, 185-195. doi: 10.1007/s40641-019-00133-y
- 807 Moncrieff, M. W. (2010). The multiscale organization of moist convection and the
 808 intersection of weather and climate. In D.-Z. Sun & F. Bryan (Eds.), *Climate*
 809 *dynamics: Why does climate vary?* (Vol. 189, p. 3-26). Amer. Geophys. Union.

- 810 doi: 10.1029/2008GM000838
- 811 Muller, C. J., & Bony, S. (2015). What favors convective aggregation and why?
- 812 *Geophys. Res. Lett.*, *42*, 5626-5634. doi: 10.1002/2015GL064260
- 813 Muller, C. J., & Held, I. M. (2012). Detailed investigation of the self-aggregation of
- 814 convection in cloud-resolving simulations. *J. Atmos. Sci.*, *69*, 2551-2565. doi:
- 815 10.1175/JAS-D-11-0257.1
- 816 Neale, R., & Hoskins, B. J. (2000). A standard test for AGCMs including their
- 817 physical parameterizations: I: the proposal. *Atmos. Sci. Lett.*, *1*, 101-107. doi:
- 818 10.1006/asle.2000.0022
- 819 O'Brien, T. A., Collins, W. D., Kashinath, K., Rübél, O., Byna, S., Gu, J., ...
- 820 Ullrich, P. A. (2016). Resolution dependence of precipitation statistical fi-
- 821 delity in hindcast simulations. *J. Adv. Model. Earth Sy.*, *8*, 976-990. doi:
- 822 10.1002/2016MS000671
- 823 O'Gorman, P. A., Li, Z., Boos, W. R., & Yuval, J. (2021). Response of extreme
- 824 precipitation to uniform surface warming in quasi-global aquaplanet sim-
- 825 ulations at high resolution. *Phil. Trans. R. Soc. A.*, *379*, 20190543. doi:
- 826 10.1098/rsta.2019.0543
- 827 Pendergrass, A. G. (2020). Changing degree of convective organization as a mech-
- 828 anism for dynamic changes in extreme precipitation. *Curr. Clim. Change Rep.*,
- 829 *6*, 47-54. doi: 10.1007/s40641-020-00157-9
- 830 Rauscher, S. A., O'Brien, T. A., Piani, C., Coppola, E., Giorgi, F., Collins, W. D.,
- 831 & Lawston, P. M. (2016). A multimodel intercomparison of resolution effects
- 832 on precipitation: simulations and theory. *Clim. Dyn.*, *47*, 2205-2218. doi:
- 833 10.1007/s00382-015-2959-5
- 834 Retsch, M. H., Mauritsen, T., & Hohenegger, C. (2019). Climate change feedbacks
- 835 in aquaplanet experiments with explicit and parameterized convection for hori-
- 836 zontal resolutions of 2525 up to 5km. *J. Adv. Model. Earth Sy.*, *11*, 2070-2088.
- 837 doi: 10.1029/2019MS001677
- 838 Rios-Berrios, R., Medeiros, B., & Bryan, G. H. (2020). Mean climate and trop-
- 839 ical rainfall variability in aquaplanet simulations using the Model for Pre-
- 840 diction Across Scales-Atmosphere. *J. Adv. Model. Earth Sy.*, *12*. doi:
- 841 10.1029/2020MS002102
- 842 Robinson, T., Radhakrishnan, A., & Underwood, S. (2022). *NOAA-GFDL/AM4:*
- 843 *Non-hydrostatic aquaplanet MG (version highres_aquaplanet_2022)* [software].
- 844 Zenodo. Retrieved from <https://doi.org/10.5281/zenodo.7476908> doi:
- 845 10.5281/zenodo.7476908
- 846 Roh, W., Satoh, M., & Hohenegger, C. (2021). Intercomparison of cloud properties
- 847 in DYAMOND simulations over the Atlantic Ocean. *J. Meteorol. Soc. Jpn.*,
- 848 *99*, 1439-1451. doi: 10.2151/jmsj.2021-070
- 849 Rotstayn, L. D. (1997). A physically based scheme for the treatment of stratiform
- 850 clouds and precipitation in large-scale models. I: description and evaluation of
- 851 the microphysical processes. *Q. J. Roy. Meteorol. Soc.*, *123*, 1227-1282. doi:
- 852 10.1002/qj.49712354106
- 853 Satoh, M., Stevens, B., Judt, F., Khairoutdinov, M., Lin, S.-J., Putman, W. M., &
- 854 Düben, P. (2019). Global cloud-resolving models. *Curr. Clim. Change Rep.*, *5*,
- 855 172-184. doi: 10.1007/s40641-019-00131-0
- 856 Seo, K.-H., Choi, J.-H., & Han, S.-D. (2012). Factors for the simulation of convect-
- 857 ively coupled Kelvin waves. *J. Clim.*, *25*, 3495-3514. doi: 10.1175/JCLI-D-11
- 858 -00060.1
- 859 Shin, H. H., & Hong, S. (2015). Representation of the subgrid-scale turbulent trans-
- 860 port in convective boundary layers at gray-zone resolutions. *Mon. Wea. Rev.*,
- 861 *143*, 250-271. doi: 10.1175/MWR-D-14-00116.1
- 862 Silvers, L., Blanton, C., McHugh, C., John, J. G., Radhakrishnan, A., Rand, K.,
- 863 ... Zhao, M. (2018). *NOAA-GFDL GFDL-CM4 model output prepared*
- 864 *for CMIP6 CFMIP aqua-control*. Earth System Grid Federation. doi:

- 10.22033/ESGF/CMIP6.8512
- Stephan, C. C., Strube, C., Klocke, D., Ern, M., Hoffmann, L., Preusse, P.,
& Schmidt, H. (2019). Intercomparison of gravity waves in global
convection-permitting models. *J. Atmos. Sci.*, *76*, 2739-2759. doi:
10.1175/JAS-D-19-0040.1
- Stevens, B., Satoh, M., Auger, L., Biercamp, J., Bretherton, C. S., Chen, X., ...
Zhou, L. (2019). DYAMOND: the DYnamics of the Atmospheric general cir-
culation Modeled On Non-hydrostatic domains. *Prog. Earth Planet Sci.*, *6*, 61.
doi: 10.1186/s40645-019-0304-z
- Takahashi, Y. O., Hamilton, K., & Ohfuchi, W. (2016). Explicit global simulation of
the mesoscale spectrum of atmospheric motions. *Geophys. Res. Lett.*, *33*. doi:
10.1029/2006GL026429
- Terai, C. R., Caldwell, P. M., Klein, S. A., Tang, Q., & Branstetter, M. L. (2018).
The atmospheric hydrological cycle in the ACME v0.3 model. *Clim. Dyn.*, *50*,
3251-3279. doi: 10.1007/s00382-017-3803-x
- Tiedtke, M. (1993). Representation of clouds in large-scale models. *Mon. Wea. Rev.*,
121, 3040-3061. doi: 10.1175/1520-0493(1993)121<3040:ROCILS>2.0.CO;2
- Wehner, M. F., Reed, K. A., Li, F., Prabhat, Bacmeister, J., Chen, C.-T., ...
Jablonowski, C. (2014). The effect of horizontal resolution on simulation
quality in the Community Atmospheric Model, CAM5.1. *J. Adv. Model. Earth
Sy.*, *6*, 980-997. doi: 10.1002/2013MS000276
- Wheeler, M., & Kiladis, G. N. (1999). Convectively coupled equatorial waves: analy-
sis of clouds and temperature in the wavenumber-frequency domain. *J. Atmos.
Sci.*, *56*, 374-399.
- Williamson, D. L., Blackburn, M., Hoskins, B. J., Nakajima, K., Ohfuchi, W., Taka-
hashi, Y. O., ... Stratton, R. (2012). *The APE atlas* (NCAR Technical note
Nos. TN-484+STR). NCAR. doi: 10.5065/D6FF3QBR
- Williamson, D. L., Blackburn, M., Nakajima, K., Ohfuchi, W., Takahashi, Y. O.,
Hayashi, Y.-Y., ... Stratton, R. (2013). The Aqua-Planet Experiment (ape):
response to changed meridional SST profile. *J. Meteorol. Soc. Jpn.*, *91A*,
57-89. doi: 10.2151/jmsj.2013-A03
- Williamson, D. L., Kiehl, J. T., & Hack, J. J. (1995). Climate sensitivity of the
NCAR community climate model (CCM2) to horizontal resolution. *Clim.
Dyn.*, *11*, 377-397. doi: 10.1007/s003820050082
- Yu, H.-Y., Bao, Q., Zhou, L.-J., Wang, X.-C., & Liu, Y.-M. (2014). Sensitivity of
precipitation in aqua-planet experiments with an AGCM. *Atmos. Ocean. Lett.*,
7, 1-6. doi: 10.3878/j.issn.1674-2834.13.0033
- Zhang, F., Sun, Y. Q., Magnusson, L., Buizza, R., Lin, S., Chen, J., & Emanuel, K.
(2019). What is the predictability limit of midlatitude weather? *J. Atmos.
Sci.*, *76*, 1077-1091. doi: 10.1175/JAS-D-18-0269.1
- Zhang, G., Silvers, L. G., Zhao, M., & Knutson, T. R. (2021). Idealized aquaplanet
simulations of tropical cyclone activity: significance of temperature gradients,
Hadley circulations, and zonal asymmetry. *J. Atmos. Sci.*, *78*, 877-902. doi:
10.1175/JAS-D-20-0079.1
- Zhao, M. (2020). Simulations of atmospheric rivers, their variability, and response to
global warming using GFDL's new high-resolution general circulation model.
J. Clim., *33*, 10287-10303. doi: 10.1175/JCLI-D-20-0241.1
- Zhao, M., Golaz, J.-C., Held, I. M., Guo, H., Balaji, V., Benson, R., ... others
(2018a). The GFDL global atmosphere and land model AM4.0/LM4.0: 1.
simulation characteristics with prescribed SSTs. *J. Adv. Model. Earth Sy.*, *10*,
691-734. doi: 10.1002/2017MS001208
- Zhao, M., Golaz, J.-C., Held, I. M., Guo, H., Balaji, V., Benson, R., ... others
(2018b). The GFDL global atmosphere and land model AM4.0/LM4.0: 2.
model description, sensitivity studies, and tuning strategies. *J. Adv. Model.
Earth Sy.*, *10*, 735-769. doi: 10.1002/2017MS001209

- 920 Zhao, M., Held, I. M., & Lin, S.-J. (2012). Some counterintuitive dependencies of
921 tropical cyclone frequency on parameters in a GCM. *J. Atmos. Sci.*, *69*, 2272-
922 2283. doi: 10.1175/JAS-D-11-0238.1
- 923 Zhou, L., Lin, S., Chen, J., Harris, L. M., Chen, X., & Rees, S. L. (2019). Toward
924 convective-scale prediction within the next generation global prediction system.
925 *Bull. Am. Meteor. Soc.*, *100*, 1225-1243. doi: 10.1175/BAMS-D-17-0246.1