

1                   **On the resolution-dependence of cloud fraction in**  
2                   **radiative-convective equilibrium**

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5                   **Key Points:**

- 6                   • Cloud-resolving simulations of radiative-convective equilibrium exhibit a marked in-  
7                   crease of anvil cloud fraction with resolution.  
8                   • This sensitivity is closely related to the resolution-dependence of evaporation and  
9                   precipitation efficiency  
10                  • The root of these sensitivities is the resolution-dependence of mixing between clear  
11                  and cloudy air

## Abstract

Tropical anvil clouds are an important player in Earth’s climate and climate sensitivity, but simulations of anvil clouds are uncertain. Here we pinpoint one source of uncertainty by demonstrating a marked increase of anvil cloud fraction with resolution in cloud-resolving simulations of radiative-convective equilibrium. This increase in cloud fraction can be traced back to the resolution dependence of horizontal mixing between clear and cloudy air. A mixing timescale is diagnosed for each simulation using the cloud fraction theory of *Seeley et al.* [2019] and is found to scale linearly with grid spacing, as expected from a simple scaling law. Thus mixing becomes more efficient with increasing resolution, generating more evaporation, decreased precipitation efficiency, greater mass flux, and hence greater detrainment and cloud fraction. The decrease in precipitation efficiency also yields a marked increase in relative humidity with resolution.

## 1 Introduction

Tropical anvil clouds exert considerable leverage over the Earth’s radiation budget, by reflecting sunlight as well as trapping thermal infrared radiation [e.g. *Hartmann et al.*, 2001]. Any change in anvil cloud area with warming is thus a potentially significant climate feedback [*Lindzen et al.*, 2001; *Mauritsen and Stevens*, 2015]. Indeed, this ‘tropical anvil cloud area feedback’ was recently assessed by *Sherwood et al.* [2020] to be  $-0.2 \pm 0.2 \text{ W/m}^2/\text{K}$ , a magnitude (and uncertainty) comparable to other cloud feedbacks, including low-cloud feedbacks.

While tropical anvil clouds and their area feedbacks are thus important players in the climate system, confidence in their simulation is low. Global climate models (GCMs) exhibit a significant spread in climatological anvil cloud fraction [*Cesana and Chepfer*, 2012; *Su et al.*, 2013], as well as an uncertain sign in anvil cloud area feedbacks [*Zelinka et al.*, 2016]. Even cloud resolving models (CRMs) exhibit an uncertain sign in anvil cloud area changes with warming, with some CRMs exhibiting a decrease [*Romps*, 2020; *Cronin and Wing*, 2017] and others exhibiting an increase [*Singh and O’Gorman*, 2015]. Similar ambiguities are found in global-scale, convection-permitting models [*Tsushima et al.*, 2014; *Narenpitak et al.*, 2017]. Such uncertainty led *Sherwood et al.* [2020] to base their assessment of the anvil cloud area feedback almost entirely on observations [*Williams and Pierrehumbert*, 2017]. This uncertainty in modeled anvil cloud area feedback is highlighted and reinforced by the results of the recent Radiative-Convective Equilibrium Model Intercomparison Project [RCEMIP, *Wing et al.*, 2020], which finds a strikingly large spread in both climatological anvil cloud fraction and anvil fraction changes with warming, across both convection-resolving and coarse-resolution simulations (see, e.g., their Fig. 15).

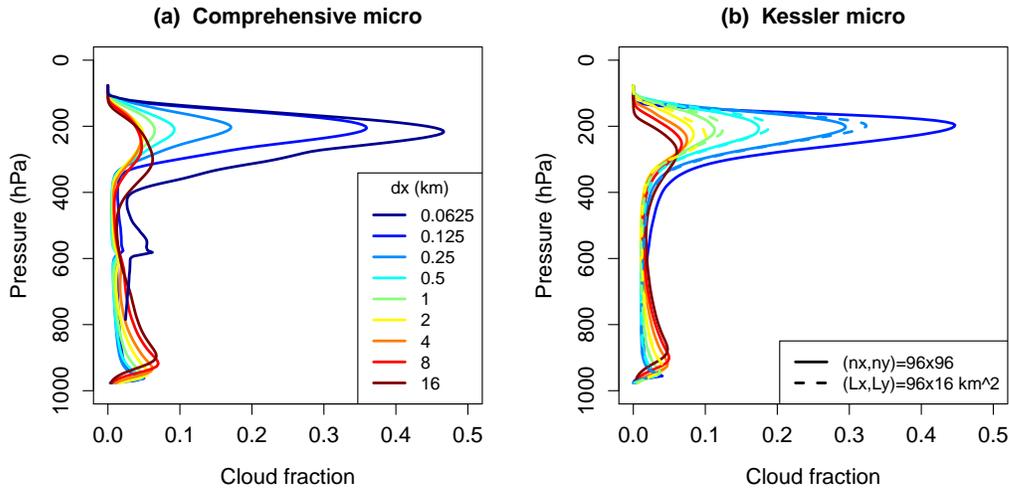
Given the importance of anvil cloud area to climate, as well as the aforementioned uncertainties in their simulation, a deeper study of the fundamental physics of anvil clouds seems warranted. Although divergence and detrainment have long been recognized as key determinants of anvil cloud fraction [*Hartmann and Larson*, 2002], the recently developed formalism of *Seeley et al.* [2019] (hereafter S19) emphasized the additional role of cloud lifetime in determining anvil cloud amount. While the lifetime of a cloudy parcel depends on a number of quantities, a key determinant in the S19 formalism is the characteristic timescale  $\kappa$  with which a volume of cloudy air mixes with an equal volume of clear air. This timescale influences a number of processes, including the rate of condensate evaporation, condensate dilution, and the spreading of anvil clouds.

The S19 formalism, and our physical picture of anvil cloud evolution in general, however, assumes that anvil clouds spread continuously after their detrainment from convective cores. But in simulations of cloud ensembles, such as cloud-resolving RCE, convective cores are typically only a few grid cells wide, even down to resolutions of  $O(100 \text{ m})$  [*Jeevanjee*, 2017]. Thus, we might expect the spreading of anvil clouds in such simulations to be grid-dependent. Indeed, if the turbulent horizontal wind speed which advects air between grid

63 cells is  $u_{\text{rms}}$ , then one expects the timescale  $\kappa$  (with which a cloudy grid cell completely  
 64 mixes with a neighboring clear grid cell) to scale with horizontal grid spacing  $dx$  as

$$\kappa \sim dx/u_{\text{rms}} . \tag{1}$$

65 If this is true, and given the varied and significant influences of  $\kappa$  on cloud fraction, we might  
 66 then also expect cloud fraction to depend on resolution. We confirm this in Fig. 1 by plotting  
 67 cloud fraction for a series of cloud-resolving radiative-convective equilibrium (RCE) sim-  
 68 ulations with  $dx$  varying from 0.0625 m to 16 km; details of these simulations are given in  
 69 Section 2. The left panel shows simulations with the six-class GFDL microphysics scheme  
 70 [Zhou *et al.*, 2019], while the right panel shows simulations with a Kessler-type warm-rain  
 71 microphysics scheme [Kessler, 1969, details below]. The solid lines show simulations on a  
 72 fixed grid, whereas dashed lines show simulations with a fixed domain size. A marked in-  
 73 crease of high cloud fraction with increasing resolution is evident, and is found in all sets of  
 74 simulations, suggesting that this result is robust. Similar results were also found with DAM  
 75 [Romps, 2008] (not shown).



76 **Figure 1. A striking dependence of cloud fraction on resolution** Time-mean cloud fraction profiles from  
 77 FV<sup>3</sup> RCE simulations with varying horizontal resolution (colors). Left panel shows simulations with com-  
 78 prehensive microphysics, while the right panel shows simulations with simplified Kessler microphysics. All  
 79 simulations are run on a 96 × 96 horizontal grid, except for those shown in dashed lines which were run on a  
 80 fixed domain of size 96 × 16 km<sup>2</sup>. Further simulation details are given in Section 2.

81 This resolution-dependence adds to the aforementioned uncertainties in anvil cloud  
 82 simulations, and casts further doubt on our ability to simulate anvil clouds with confidence.  
 83 Furthermore, this decrease in confidence may have unfortunate implications for machine-  
 84 learning applications in climate models, which sometimes use cloud-resolving simulations as  
 85 ‘ground-truth’ training data for AI algorithms [Rasp *et al.*, 2018; Brenowitz and Bretherton,  
 86 2018; Yuval and O’Gorman, 2020]. At the same time, however, a deeper understanding of  
 87 this resolution sensitivity may lead to a better understanding of our simulations and of anvil  
 88 cloud dynamics more generally, ideally pointing the way to more accurate simulations and  
 89 parameterizations.

90 The goal of this paper is to pursue such understanding. Key components of this pursuit  
 91 include not only the simulations shown in Fig. 1, but also the theoretical framework of S19,  
 92 as well as the process-level diagnostics required to utilize the theory. We begin in Section

2 by describing in detail our simulations and these process-level diagnostics. Section 3.1 then formulates a hypothesis for the resolution sensitivity seen in Fig. 1, followed by a brief exposition of the S19 theory in Sections 3.2 and 3.3. Section 4 provides supporting evidence for the hypothesis of Section 3.1. We summarize and conclude in Section 5.

## 2 Simulations

The atmospheric model used here is the non-hydrostatic version of GFDL’s FV<sup>3</sup> [Finite-Volume Cubed-Sphere Dynamical Core, *Harris and Lin, 2013; Lin, 2004*]. The simulations analyzed here are very similar, and in some instances the same as, those performed in *Jeevanjee [2017]* (hereafter J17). We give the salient features of our simulations below and refer the reader to J17 for further details, as well as plots and animations depicting the character of the convection in these simulations.

As in J17, a guiding principle in configuring the simulations is to avoid inessential complexity insofar as possible [*Jeevanjee et al., 2017*]. Thus, we run simple doubly-periodic radiative-convective equilibrium (RCE) simulations over a fixed sea surface temperature of 300 K, at resolutions spanning  $dx = 0.0625 - 16$  km by factors of two. Radiative cooling is non-interactive and is parameterized as a fit to the invariant divergence of radiative flux  $F$  found by *Jeevanjee and Romps [2018]*:

$$-\partial_T F = (0.25 \text{ W/m}^2/\text{K}^2) \cdot (T - T_{\text{tp}}) . \quad (2)$$

Here the temperature derivative is a vertical derivative,  $T_{\text{tp}} = 200$  K is the tropopause temperature, and the above cooling is applied between the surface and 125 hPa, above which temperatures are relaxed to  $T_{\text{tp}}$  over a timescale of 5 days (so the stratosphere is isothermal). The advantage of this non-interactive radiative cooling is that it is unaffected by the large changes in cloud fraction across our simulations, simplifying their analysis and interpretation. At the same time, cloud-radiation interactions are known to influence anvil and particularly anvil cirrus cloud development [e.g. *Hartmann et al., 2018*], so future work should investigate how such physics interacts with the mechanisms studied here.

No boundary layer or sub-grid turbulence schemes are used, though small amounts of vorticity and divergence damping are used to stabilize the model and reduce noise. The vertical discretization is Lagrangian [*Lin, 2004*] with 151 levels, and the horizontal grid has 96 points in both  $x$  and  $y$ , except for the runs shown in dashed lines in Fig. 1. The latter were more expensive, fixed-domain runs which due to computational constraints had a ‘bowling-alley’ domain of  $(L_x, L_y) = 96 \times 16 \text{ km}^2$  and were run over a smaller resolution range of  $dx=0.25 - 2$  km.

Again in the spirit of avoiding inessential complexity, and to enable use of the theory of *Seeley et al. [2019]*, microphysical transformations are performed with a warm-rain version of GFDL microphysics scheme [*Chen and Lin, 2013*] which models only water vapor  $q_v$ , cloud condensate  $q_c$ , and rain, with the only transformations being condensation/evaporation of condensate, re-évaporation of rain, and autoconversion of cloud condensate to rain as

$$\left. \frac{dq_c}{dt} \right|_{\text{auto}} = -q_c/t_{\text{aut}} \quad (3)$$

where the autoconversion timescale  $t_{\text{aut}} = 30$  minutes. The only exceptions are the simulations shown in Fig. 1a, which use the full complexity (six-class) GFDL microphysics scheme which includes ice processes [*Zhou et al., 2019*]. While Eq. (3) is extremely idealized, its use seems permissible since comprehensive microphysical processes do not seem essential for understanding how cloud fraction depends on resolution and mixing; indeed, this dependence is very similar for both our warm-rain and full complexity simulations (Fig. 1a).

To analyze convection in our simulations we partition the domain online at each time step into active, inactive, and environmental air. Active (updraft) air has  $q_c > q_{c0} \equiv 10^{-5}$

138 and vertical velocity  $w > w_0$ , where  $w_0$  is resolution-dependent (consistent with the findings  
 139 of J17) and varies between 0.25-1 m/s. Inactive air has  $q_c > q_{c0} = 10^{-5}$  and  $w < w_0$  and  
 140 should be thought of as detrained cloud. All other grid points are considered environmental.  
 141 Cloud fraction  $C$  is diagnosed as the fractional area at a given height occupied by active and  
 142 inactive air. We use this partitioning to conditionally average various quantities ( $w$ ,  $q_c$ , etc.)  
 143 over these subdomains. We also include microphysical diagnostics of evaporation  $e$ , auto-  
 144 conversion  $a$ , and condensation  $c$  (units  $\text{kg}/\text{m}^3/\text{sec}$ ), all of which can also be conditionally  
 145 averaged as above.

146 These primary diagnostics, while of interest in their own right, also allow us to derive  
 147 other diagnostics of interest. One such diagnostic is the convective mass flux  $M \equiv \rho w_{\text{up}} \sigma_{\text{up}}$   
 148 ( $\text{kg}/\text{m}^2/\text{sec}$ ) where  $\sigma_{\text{up}}$  is the fractional area occupied by active updraft air at a given height,  
 149 and the subscripts "up" and "in" will refer to quantities which are conditionally averaged over  
 150 active updrafts or inactive air, respectively. Another such diagnostic is the volumetric de-  
 151 trainment  $\delta M/\rho$  ( $1/\text{sec}$ ), where  $\delta$  is fractional gross detrainment ( $1/\text{m}$ ) and  $\rho$  is density.  
 152 This quantity can be interpreted as the fractional rate at which air at a given height becomes  
 153 cloudy, and is diagnosed (following *Seeley et al.* [2019]) by considering the cloud water bud-  
 154 get for inactive air, which has detrained condensate  $\delta M q_{c,\text{up}}$  as the sole source term (no con-  
 155 densation) and total evaporation and inactive autoconversion  $e + a_{\text{in}}$  as sinks. Assuming that  
 156 sources and sinks balance in steady-state then yields

$$\frac{\delta M}{\rho} = \frac{e + a_{\text{in}}}{\rho q_{c,\text{up}}} . \quad (4)$$

157 The right-hand side of this equation may be diagnosed from the simulations, yielding a method  
 158 for diagnosing  $\delta M/\rho$ . Since  $M$  and  $\rho$  can also be diagnosed independently, this also yields a  
 159 method for diagnosing the fractional detrainment  $\delta$ .

160 We initially spun up a  $dx = 1$  km simulation for 200 days, and then branched all other  
 161 runs off this run, running for at least 50 days to allow adjustment to different resolutions. All  
 162 quantities analyzed in this paper are averaged horizontally and over the last 5 days of simula-  
 163 tion.

### 164 3 Hypothesis and Theory

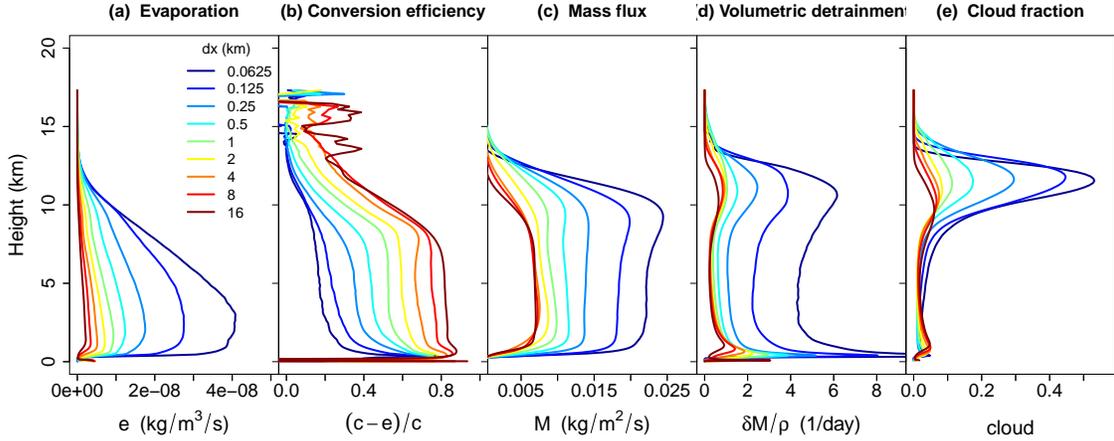
#### 165 3.1 Hypothesis for cloud fraction sensitivity

166 We now sketch a hypothetical explanation for the dramatic increase of cloud fraction  
 167 with resolution seen in Fig. 1. Later sections of the paper will buttress this initial explanation  
 168 with further evidence.

169 Equation (1) implies more effective mixing at higher resolutions, hence greater evapo-  
 170 ration. Greater evaporation suggests a decrease in the *conversion efficiency*  $(c - e)/c$  [*Lang-*  
 171 *hans et al.*, 2015; *Lutsko and Cronin*, 2018], which is the fraction of condensate which turns  
 172 to rain and is a vertically-resolved measure of precipitation efficiency. Since the non-interactive  
 173 radiative cooling (2) fixes the amount of latent heating which convection must provide, a de-  
 174 crease in conversion efficiency implies that the convective mass flux must increase. But if  
 175 mass fluxes go up, gross detrainment should too, leading to increased cloudiness. We sum-  
 176 marize this hypothesis as

$$\text{Increased evaporation} \longrightarrow \text{Decreased PE} \longrightarrow \text{Increased mass flux} \longrightarrow \text{Increased detrainment} \longrightarrow \text{Increased cloudiness} . \quad (5)$$

181 Figure 2 shows that qualitatively, the above quantities (diagnosed as outlined in the  
 182 previous section) behave as hypothesized. But confidence in the hypothesis (5) requires  
 183 *quantitative* confirmation of the proposed relationships, including the the basic scaling (1).  
 184 These tasks will be taken up in the next sections, and will be facilitated by the theory of *See-*  
 185 *ley et al.* [2019], which we describe next.



177 **Figure 2. Increasing evaporation with resolution leads to increased cloud fraction** These panels show  
 178 the quantities appearing in the hypothesis (5), as a function of both height and resolution  $dx$ . A qualita-  
 179 tive consistency between the simulations and the hypothesis (5) is evident. All quantities are diagnosed as  
 180 described in the main text.

### 186 3.2 Theory I: Cloud fraction as source times lifetime

187 To test the narrative in Eq. (5) we will employ the cloud-fraction theory of *Seeley et al.*  
 188 [2019], hereafter S19. The theory consists of two major components. The first is a decom-  
 189 position of cloud fraction  $C$  into a source times a lifetime, where the source is volumetric  
 190 detrainment  $\delta M/\rho$  and the lifetime  $\tau_{\text{cld}}$  represents the time it takes for a detrained, cloudy  
 191 parcel to cease being cloudy (i.e.  $q_c < q_{c0}$ ). Following S19 we write this as

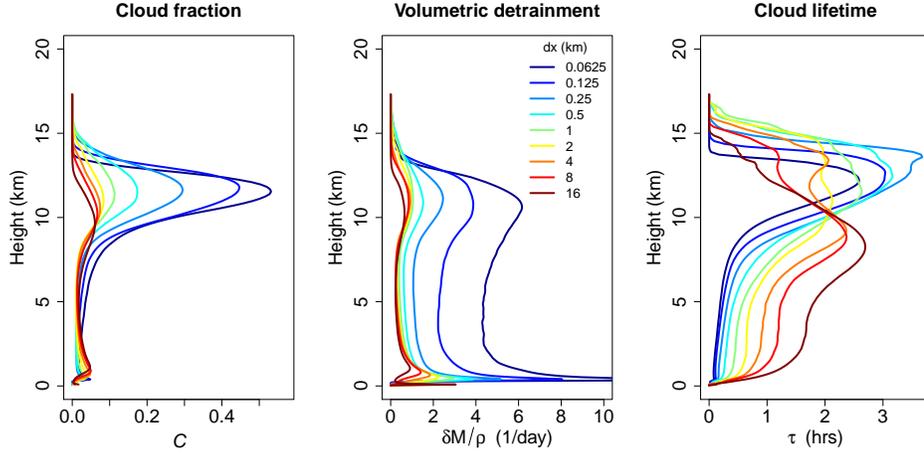
$$192 \quad C = \frac{\delta M}{\rho} \tau_{\text{cld}}. \quad (6)$$

193 Since  $C$  and  $\delta M/\rho$  are readily diagnosed as described above, one can then diagnose  $\tau_{\text{cld}}$  us-  
 194 ing (6); these quantities are plotted in Fig. 3. A few features are worth noticing. The first is  
 195 that in the mid-troposphere,  $\tau_{\text{cld}}$  decreases markedly with resolution, which as discussed be-  
 196 low is due to more efficient mixing and evaporation. In the upper troposphere, however,  $\tau_{\text{cld}}$   
 197 only varies by a factor of two or so, and does so non-monotonically with  $dx$ . Thus, changes  
 198 in  $\tau_{\text{cld}}$  are not driving the  $dx$ -dependence of upper-tropospheric cloud fraction. From Eq. (6)  
 199 we can then conclude that the increase of anvil cloud fraction with resolution must instead be  
 due to increases in volumetric detrainment  $\delta M/\rho$ , as hypothesized in (5).

### 204 3.3 Theory II: Analytical model for cloud lifetime

205 The second component of the theory is an analytical model for the cloud lifetime  $\tau_{\text{cld}}$ .  
 206 Though we found above that changes in  $\tau_{\text{cld}}$  at the anvil height do not directly drive anvil  
 207 cloud fraction changes, we will see below that the changes in  $\tau_{\text{cld}}$  in the mid-troposphere  
 208 reflect the changes in mixing which do end up driving anvil cloud changes (as per the hy-  
 209 pothesis (5)). In fact, combining the analytical model for  $\tau_{\text{cld}}$  with Eq. (6) will allow us to  
 210 diagnose mixing timescales  $\kappa$  for each of our simulations, allowing us to test Eq. (1) which is  
 211 a linchpin of our analysis.

212 The analytical model for  $\tau_{\text{cld}}$  begins with an ordinary differential equation for cloud  
 213 condensate  $q_c$  in a detrained parcel, assuming that evaporation and warm-rain autoconversion



200 **Figure 3. Cloud fraction changes are dominated by detrainment changes.** These panels show the quantities appearing in Eq. (6), as a function of height and resolution. Since  $\tau_{\text{cld}}$  at the anvil level does not exhibit  
 201 a strong trend with resolution, the strong trend in anvil cloud fraction with resolution is due to the trend in  
 202 volumetric detrainment  $\delta M/\rho$ .  
 203

214 on a fixed timescale  $t_{\text{aut}}$  are the only sinks of cloud water:

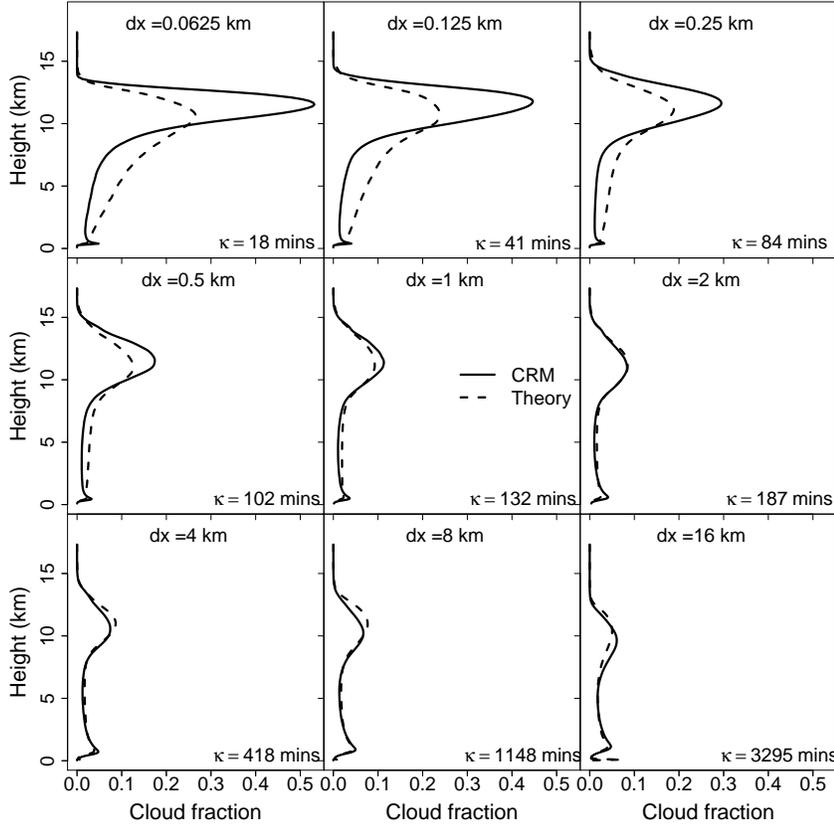
$$\frac{dq_c}{dt} = - \underbrace{\frac{1}{\kappa} \frac{1}{1+t/\kappa} [q_c + (1-RH)q_v^*]}_{\text{mixing}} - \underbrace{\frac{q_c}{t_{\text{aut}}}}_{\text{autoconversion}}. \quad (7)$$

215 The expression  $q_c + (1 - RH)q_v^*$  is the total water mass require to homogenize a unit mass of  
 216 clear air that is mixed into the inactive cloudy air, while  $1 + t/\kappa$  is the mass of the parcel at  
 217 time  $t$  relative to its initial (unit) mass, and  $1/\kappa$  is the mixing rate. For a complete derivation  
 218 of (7), see S19.

224 Equation (7) can be solved analytically, and an analytical formula for the lifetime  $\tau_{\text{cld}}$  at  
 225 which  $q_c < q_{c0}$  can be derived [Eqs. (A.2)]. This formula contains  $\kappa$  as an undetermined pa-  
 226 rameter, to be determined by optimization. We optimize  $\kappa$  by minimizing the RMSE between  
 227 the simulated cloud fraction and that given by Eq. (6), where  $\delta M/\rho$  is diagnosed directly  
 228 from the simulations but  $\tau_{\text{cld}}$  is given by Eq. (A.2). The results of this optimization for each  
 229 of our warm-rain (Kessler) simulations is shown in Fig. 4. One can see that for  $dx > 0.5$  km  
 230 or so, the S19 theory captures the simulated cloud fraction profiles reasonably well. For  
 231  $dx \lesssim 0.5$  km the fit degrades, likely due to our neglect of anvil cloud spreading (Appendix  
 232 A.2). What is of interest here, however, are the values for  $\kappa$  diagnosed from each of these fits,  
 233 which are noted in each panel in Fig. 4 and also shown in Fig. 5. Fig. 5 also shows a linear  
 234 fit of the form  $\kappa = dx/u_{\text{rms}}$ . This figure shows that the scaling (1) is indeed consistent with  
 235 our simulations and the S19 theory (which was used to diagnose  $\kappa$ ). Furthermore, the  $u_{\text{rms}}$   
 236 value derived from the linear fit is 0.1 m/s, roughly consistent with the variations in horizon-  
 237 tal velocity seen by inspection in our simulations.

#### 241 4 Evaporation, PE, and mass flux

242 The last section presented evidence that simulated mixing increases with resolution  
 243 following (1). But, how do we know that this mixing is behind the changes in evaporation  
 244 manifest in Fig. 2a? And how do we know that these evaporation changes indeed cause the  
 245 PE changes in Fig. 2b, and that these PE changes indeed driving the mass flux changes seen  
 246 in Fig. 2c? We turn to these questions now.



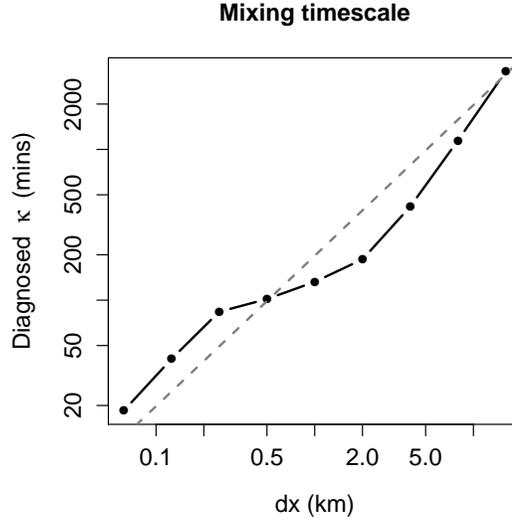
219 **Figure 4. The S19 theory approximates the simulated cloud fraction, and diagnoses a  $dx$ -dependent**  
 220  $\kappa$ . These panels show the simulated cloud fraction profile at a given resolution  $dx$  (solid lines), along with the  
 221 prediction from the S19 theory [dashed lines, Eqs. (A.2) and (6)]. The S19 theory approximates the simulated  
 222 cloud fraction profiles reasonably well for  $dx \gtrsim 0.5$  km. The S19 theory also yields, via optimization, a value  
 223 for  $\kappa$  at each  $dx$ , noted in the lower right of each panel.

247 To assess the influence of the mixing timescale  $\kappa$  on condensate evaporation, we note  
 248 that by Eq. (7) the evaporation rate in the neighborhood of an updraft grid cell (neglecting  
 249 inactive grid cells whose contribution in the mid and lower troposphere is small) should just  
 250 be  $\rho$  times the mixing term. Averaging over the domain and invoking (1) (evaluated at  $t = 0$   
 251 for simplicity) then yields

$$e = \frac{\rho u_{\text{rms}}}{dx} \sigma_{\text{up}} [q_{c,\text{up}} + (1 - \text{RH})q_v^*]. \quad (8)$$

252 We compare this estimate of evaporation to that diagnosed directly from our simulations in  
 253 Fig. 6. Here  $u_{\text{rms}}$  was chosen to optimize the accuracy of the estimate (8), and gives  $u_{\text{rms}} =$   
 254  $0.2$  m/s, similar to the previous value. The agreement in Fig. 6a,b is reasonable, suggesting  
 255 that Eq. (8) is indeed a good first-order description of the evaporation rate.

256 Equation (8) tells us that the evaporation rate  $e$  is proportional to  $dx$ , but also to the  
 257 fractional updraft area  $\sigma_{\text{up}}$  which also increases with resolution (since  $M \sim \sigma_{\text{up}}$ , cf. Fig. 2c).  
 258 To confirm the central role of the  $dx$ -dependence in (8), Fig. 6c shows the evaporation rate  $e$   
 259 normalized by the mass flux  $M$ , which can be interpreted as the rate at which  $q_{c,\text{up}}$  decreases  
 260 (due to evaporation) in a convecting parcel per unit height traveled. This quantity increases  
 261 markedly with resolution, confirming that the proportionality between  $e$  and  $dx$  in (8) is a  
 262 primary influence on evaporation rates.



238 **Figure 5. Diagnosed mixing timescale  $\kappa$  depends linearly on resolution** This figure shows the values of  
 239  $\kappa$  diagnosed as in Fig. 4, as a function of  $dx$  (black dots and lines). Also shown is a linear fit of the form (1)  
 240 with  $u_{\text{rms}} = 0.1$  m/s (gray line). The reasonable agreement supports the linear scaling (1).

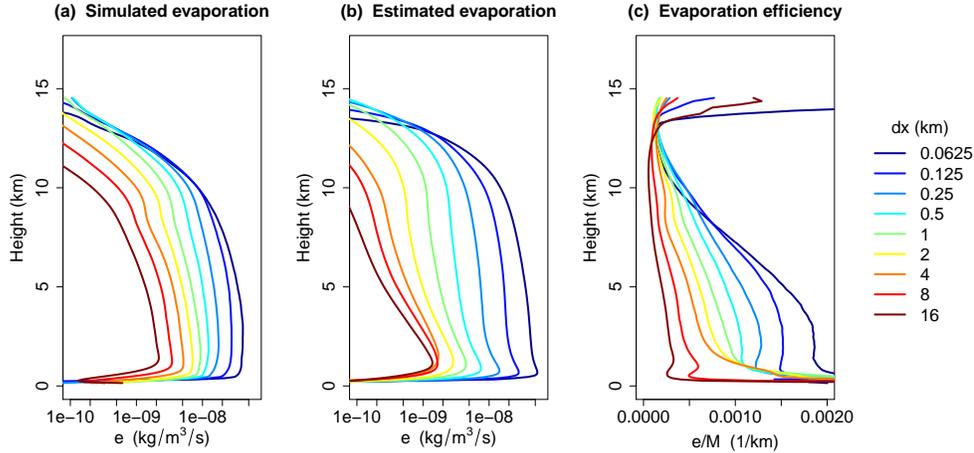
267 How do these marked increases in evaporation, even measured relative to mass flux  
 268  $M$ , relate to the actual increases in  $M$ ? The hypothesis (5) posits that this increase in mass  
 269 flux is due to a decrease in precipitation efficiency PE from enhanced mixing. To check this  
 270 connection, we calculate PE as precipitation  $P$  divided by vertically-integrated condensation,  
 271  $\text{PE} \equiv P / \int cdz$ , and also calculate a vertically-averaged  $\langle M \rangle$  over 2 and 10 km (the range  
 272 over which  $M$  in each simulation is roughly constant). From atmospheric energy balance, we  
 273 expect that the fixed column integrated radiative cooling  $Q = 120 \text{ W/m}^2$  should equal PE  
 274 times an estimated cloud base moisture flux of  $Lq_{v,\text{bl}}\langle M \rangle$ , where the boundary-layer humid-  
 275 ity  $q_{v,\text{bl}} = 0.017 \text{ kg/kg}$  is calculated as the time-mean lowest-level humidity averaged across  
 276 all the simulations. This implies that  $\langle M \rangle$  and PE should be related as

$$\langle M \rangle = \frac{Q}{Lq_{v,\text{bl}}} \frac{1}{\text{PE}}. \quad (9)$$

277 This relationship, along with  $\langle M \rangle$  and PE calculated from the simulations, are shown in Fig-  
 278 ure 7. This figure shows that PE indeed decreases markedly as resolution increases, and  
 279 that the corresponding increase in mass flux is indeed governed by the atmospheric energy  
 280 balance as encapsulated in Eq. (9). This provides quantitative confirmation of parts of the  
 281 mechanism proposed in Eq. (5), namely that more efficient evaporation reduces PE and  
 282 hence increases  $M$  as resolution increases.

283 It should be noted here that PE includes both the vertical integral of the conversion ef-  
 284 ficiency shown in Fig. 2, as well as the *sedimentation efficiency* which measures the ratio of  
 285 domain-integrated rain water production to surface rain rate [Langhans *et al.*, 2015; Lutsko  
 286 and Cronin, 2018]. The sedimentation efficiency can differ from unity due to re-evaporation  
 287 of rain, which is undiagnosed in our simulations. Future work will consider the sedimen-  
 288 tation efficiency of these simulations, and the extent to which these PE changes are due to  
 289 changes in conversion vs. sedimentation efficiency.

290 As an aside, we also note that the increase in evaporation and decrease in PE with res-  
 291 olution might also be expected to cause increases in relative humidity (RH). Indeed, such a  
 292 relationship was explicitly formulated in Romps [2014]. While such changes in RH are not



263 **Figure 6. Evaporation scales as  $1/dx$ , as captured by Eq. (8).** The vertically-resolved evaporation  $e$   
 264 diagnosed directly from our simulations (panel a) is well approximated by Eq. (8) (panel b). Normalizing  
 265 evaporation by the mass flux profiles  $M$  (panel c) confirms that the  $1/dx$  factor in Eq. (8) is influencing  
 266 evaporation rates. Note the logarithmic  $x$ -axis in panels a,b.

293 directly relevant to the changes in cloud fraction which are the focus of this paper, they are  
 294 straightforward to understand using the theory of *Romps* [2014] in conjunction with the diag-  
 295 nostics developed here. For completeness, this analysis is presented in Appendix B: .

## 301 5 Summary and Discussion

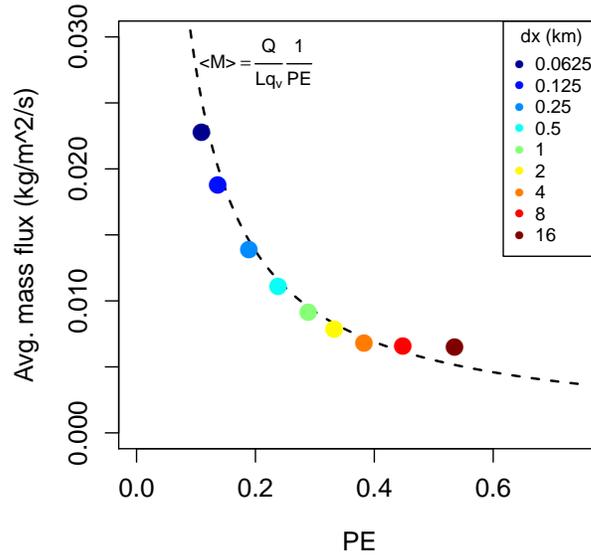
302 We summarize our main results as follows:

- 303 • Cloud-resolving simulations exhibit a marked increase of anvil cloud fraction with  
 304 resolution (Fig. 1).
- 305 • This sensitivity can be traced to the resolution-dependence of evaporation and hence  
 306 precipitation efficiency [Eq. (5), Figs. 2, 6, 7]
- 307 • The root of this sensitivity is that the mixing which causes evaporation scales linearly  
 308 with resolution [Eq. (1), Fig. 5]

309 A key ingredient in this analysis was the theory of S19, which allowed us to diagnose  
 310 values of the mixing timescale  $\kappa$  for each simulation and hence verify Eq. (1).

311 This work raises a number of questions and possible future research directions. Per-  
 312 haps most saliently, what are the implications of these results for more realistic simulations?  
 313 For regional or global simulations at  $O(1 - 10 \text{ km})$  resolution with explicit convection [e.g.  
 314 *Prein, 2015; Stevens et al., 2019*], does the scaling (1) still hold, with similar consequences  
 315 for precipitation efficiency? If so, what are the implications for rainfall rates at various spa-  
 316 tiotemporal scales? Note that for transient forecast simulations the atmospheric energy con-  
 317 straint may not be relevant, and so the knock-on effects of PE on mass flux and cloud fraction  
 318 may not occur, but the scalings (1) and (8) should hold at all timescales and still affect PE.

319 On climate timescales, *Zhao* [2014]; *Zhao et al.* [2016] found a close connection be-  
 320 tween gross precipitation efficiency and climate sensitivity for coarse-resolution models  
 321 with parameterized convection. Does the same hold true for global climate models with ex-  
 322 plicit convection, such as global CRMs [*Satoh et al., 2019; Stevens et al., 2019*] or super-  
 323 parameterized GCMs [*Khairoutdinov et al., 2005*]? And if so, do the relationships between



296 **Figure 7. Mass fluxes increase with decreasing PE, as dictated by energy balance.** This figure shows  
 297 vertically-averaged mass-flux  $\langle M \rangle$  plotted against precipitation efficiency PE, defined as precipitation divided  
 298 by vertically-integrated condensation, for our simulations at varying  $dx$  (colored points). Also shown is the  
 299 relationship (9), which is an expression of atmospheric energy balance (dashed line). A strong decrease of PE  
 300 with  $dx$  is evident, and the mass flux covaries according to (9).

324 resolution, PE, and cloud fraction found here also operate in such models? If so, then one  
 325 might expect a significant resolution dependence of PE, cloud fraction, and perhaps even cli-  
 326 mate sensitivity in such models, stemming from the simple scaling (1). As mentioned in the  
 327 introduction, such a resolution sensitivity of convection-resolving global models would also  
 328 complicate their use as benchmarks for machine learning.

329 Finally, it is worth commenting on why the resolution-dependence of cloudiness is  
 330 somewhat unique relative to other resolution sensitivities. In some sense, a resolution sensi-  
 331 tivity of cloudiness is not surprising because most aspects of atmospheric simulation, includ-  
 332 ing wind fields, thermodynamic variables, and moisture variables, are sensitive to resolution  
 333 to some degree. What is unique about cloud condensate, however – especially relative to  
 334 other tracers – is that its sources and sinks are largely given by saturation adjustment, which  
 335 is a threshold process and thus inherently nonlinear. This means that a change in mixing ef-  
 336 ficiency doesn't merely redistribute a conserved amount of condensate in space, as might be  
 337 the case for other tracers; because of saturation adjustment, mixing can actually dramatically  
 338 change how much condensate there *is*. Given the importance of clouds and precipitation to  
 339 both weather and climate simulations, further study of how resolution, numerics, and subgrid  
 340 mixing schemes affect cloud condensate in particular seems warranted.

## 341 **A: Further details of the cloud lifetime model**

### 342 **A.1 Derivation of cloud lifetime**

343 Equation (7) is a linear ordinary differential equation and can be solved by the usual  
 344 method of finding particular and homogenous solutions and taking their sum. Upon impos-

345 ing the initial condition that the initial  $q_c$  value for the detrained parcel is simply the updraft  
 346 value, i.e.  $q_c(t = 0) = q_{c,\text{up}}$ , one obtains (see also S19)

$$q_c(t) = \frac{1}{1 + t/\kappa} \left[ q_{c,\text{up}} e^{-t/t_{\text{aut}}} - \frac{t_{\text{aut}}}{\kappa} (1 - \text{RH}) q_v^* (1 - e^{-t/t_{\text{aut}}}) \right]. \quad (\text{A.1})$$

347 The factor of  $(1 + t/\kappa)$  is just the volume at time  $t$  relative to the parcel's initial volume, and  
 348 thus its appearance in the solution above represents the effect of dilution of condensate as  
 349 the parcel's volume grows. The first term in brackets represents the decay of  $q_c$  due to the  
 350 autoconversion sink, and the second term represents the effect of condensate evaporation into  
 351 entrained, subsaturated environmental air.

352 With the solution (A.1) in hand it is straightforward, if slightly tedious, to solve for the  
 353 time  $\tau_{\text{cld}}$  at which  $q_c = q_{c0}$ . Employing the Lambert  $W$  function (which satisfies by definition  
 354  $x = W(x)e^{W(x)}$ ) we have

$$\tau_{\text{cld}} = t_{\text{aut}} \left[ W(ae^b) - b \right] \quad (\text{A.2a})$$

where

$$a = \frac{\kappa}{t_{\text{aut}}} \frac{q_{c,\text{up}}}{q_{c0}} + \frac{(1 - \text{RH})q_v^*}{q_{c0}} \quad (\text{A.2b})$$

$$b = \frac{\kappa}{t_{\text{aut}}} + \frac{(1 - \text{RH})q_v^*}{q_{c0}} \quad (\text{A.2c})$$

355

## 356 **A.2 Accounting for anvil spread**

Multiplying  $\tau_{\text{cld}}$  derived above by the volumetric detrainment as in (6) gives a time-  
 mean cloud fraction, but assumes the cloud area stays fixed during its lifetime. Inspection  
 of coarse-resolution ( $dx \gtrsim 0.5$  km or so) simulations shows that this is a reasonable as-  
 sumption, but at higher resolutions the anvils begin to spread before disappearing, potentially  
 explaining the theory-CRM mismatch at high resolutions in Fig. 4. S19 incorporated anvil  
 spreading into their model by integrating the cloud area  $A(t) = A_0(1 + t/\kappa)$  over time to  
 obtain an *effective* cloud lifetime  $\tilde{\tau}_{\text{cld}}$ :

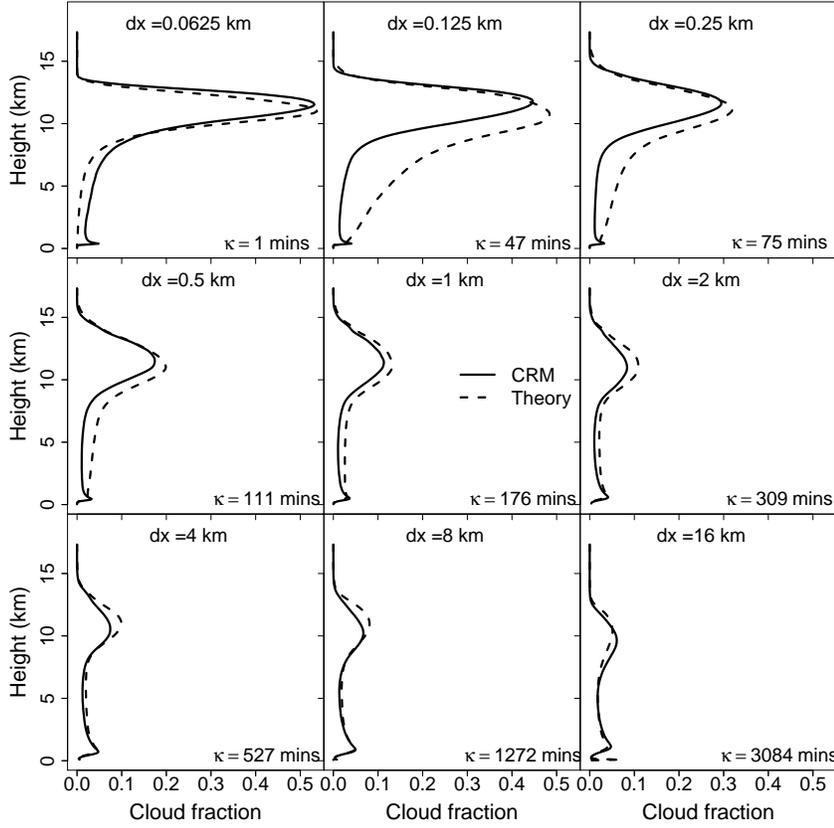
$$\int_0^{\tau_{\text{cld}}} A_0(1 + t/\kappa) dt = A_0 \left( \tau_{\text{cld}} + \frac{\tau_{\text{cld}}^2}{2\kappa} \right) \equiv A_0 \tilde{\tau}_{\text{cld}} \quad (\text{A.3a})$$

$$\text{where } \tilde{\tau}_{\text{cld}} = \tau_{\text{cld}} + \frac{\tau_{\text{cld}}^2}{2\kappa}. \quad (\text{A.3b})$$

357 One then obtains an alternative theory for cloud fraction by substituting  $\tilde{\tau}_{\text{cld}}$  for  $\tau_{\text{cld}}$  in Eq.  
 358 (6). The predictions from this modified theory are shown in Fig. A.1. At coarser resolutions  
 359 the modified cloud fraction profiles and associated  $\kappa$  values are quite similar to those in Fig.  
 360 A.1. This is expected since at coarse resolutions  $\kappa > \tau_{\text{cld}} \sim 150$  minutes (at the anvil level),  
 361 so the additional term  $\tau_{\text{cld}}^2/(2\kappa)$  in  $\tilde{\tau}_{\text{cld}}$  is not large compared to  $\tau_{\text{cld}}$ . At finer resolutions (e.g.  
 362  $dx = 0.125 - 0.25$  km), however, we have  $\kappa < \tau_{\text{cld}}$  and now the modified theory predicts  
 363 larger anvil cloud fractions for comparable  $\kappa$ , in better agreement with the CRM. The agree-  
 364 ment in the mid-troposphere is worse, however, likely because mid-tropospheric clouds at  
 365 fine resolution do not spread even though the upper-tropospheric anvils do. Finally, at 62.5 m  
 366 the modified cloud fraction profile in Fig. A.1 agrees quite well with the CRM, in contrast to  
 367 the mismatch in Fig. 4, but the diagnosed value  $\kappa = 1$  minute is inconsistent with the value  
 368 of 18 minutes found earlier in Figs. 4 and 5. The reasons for this are unclear.

## 373 **B: Implications for Relative Humidity**

The decreases in precipitation efficiency with resolution seen in the main text have im-  
 plications for the environmental RH in our simulations, which we explore in this Appendix.



369 **Figure A.1. Accounting for anvil spread improves predictions of anvil cloud fraction at high res-**  
 370 **olution, but degrades predictions of mid-tropospheric cloud fraction.** As in Fig. 4, but using  $\tilde{\tau}_{\text{cld}}$   
 371 from Eq. (A.3b) instead of  $\tau_{\text{cld}}$  in Eq. (6). Diagnosed  $\kappa$  values are similar to those in Fig. 4, except for  
 372 the  $dx = 0.0625$  km case.

Physically, one would expect that the increase in condensate evaporation per unit mass flux (Fig. 6c) would not only reduce PE, but would also lead to a moister environment and hence increased RH. These expectations may be quantified using the theory of *Romps* [2014] (hereafter R14), which provided expressions for RH both with and without evaporation, as encapsulated in the parameter  $\alpha \equiv e/c$ :

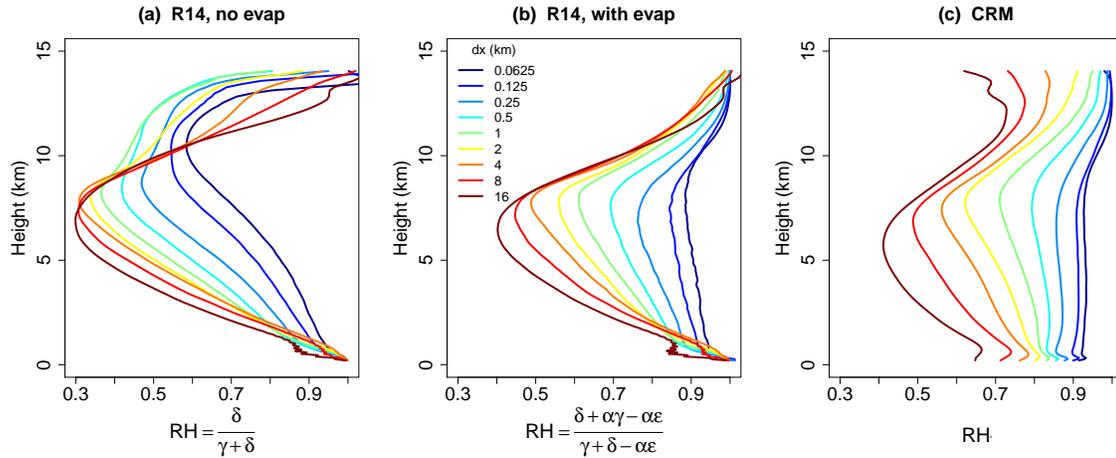
$$\text{RH} = \frac{\delta}{\gamma + \delta} \quad (\text{no evap}) \quad (\text{B.1a})$$

$$\text{RH} = \frac{\delta + \alpha\gamma - \alpha\epsilon}{\gamma + \delta - \alpha\epsilon} \quad (\text{with evap}). \quad (\text{B.1b})$$

374 Here  $\delta$  is the gross fractional detrainment diagnosed from Eq. (4),  $\gamma \equiv -d \ln q_v^*/dz$  is the  
 375 ‘water-vapor lapse rate’, and  $\epsilon$  is the gross fractional entrainment rate diagnosed from the  
 376 equation  $\frac{1}{M} \frac{dM}{dz} = \epsilon - \delta$ . Note that  $\alpha = e/c$  is also just 1 minus the conversion efficiency  
 377 shown in Fig. 2c, and also that (B.1b) reduces to (B.1a) if  $\alpha = 0$ . Equation (B.1a) expresses  
 378 RH in terms of the competing processes of convective moistening ( $\delta$ ) and subsidence drying  
 379 ( $\gamma$ ), while (B.1b) includes the additional effects of detrained condensate evaporation (R14).

380 Figure B.1 shows profiles of RH calculated from Eq. (B.1a), Eq. (B.1b), and as diag-  
 381 nosed directly from the simulations. The simulated profiles show that RH increases markedly  
 382 with horizontal resolution, with mid-tropospheric values ranging from 0.45 at  $dx = 16$  km

383 to 0.9 at  $dx = 62$  m. This RH increase is captured by Eq. (B.1b), but is much less consist-  
 384 tent with the RH profiles predicted by Eq. (B.1a). This suggests that the PE decreases seen in  
 385 Fig. 7 are largely driving the RH changes seen in Fig. B.1c, and that the latter are yet another  
 386 impact of increased evaporation resulting from more efficient mixing at higher resolution. A  
 387 caveat of these results is that rain re-evaporation should be included in the calculation of  $\alpha$   
 388 but is currently omitted; Future work will assess the effect of this omission.



389 **Figure B.1. Relative humidity increases markedly with resolution, driven largely by changes in PE**  
 390 These panels show RH profiles at varying resolutions as obtained (a) from Eq. (B.1a), (b) from Eq. (B.1b),  
 391 (c) directly from the simulations. The simulated RH increases dramatically with resolution (panel c), and this  
 392 increase is largely reproduced using Eq. (B.1b) which includes the effects of precipitation efficiency via the  
 393 parameter  $\alpha = e/c$  (panel b). Omitting PE effects by setting  $\alpha = 0$  yields a noticeably worse approximation to  
 394 the simulated RH profiles (panel a), suggesting that PE changes are a key driver in the resolution sensitivity of  
 395 RH seen here.

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