

# Precipitation Efficiency and Climate Sensitivity (Invited Chapter for the AGU Geophysical Monograph Series “Clouds and Climate”)

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## Abstract

**Key Points:** \* The concept of precipitation efficiency is broad, and can be related to many proposed cloud feedback mechanisms  
\* Microphysical precipitation efficiency of tropical clouds likely increases with warming, but bulk precipitation efficiency and precipitation efficiency of midlatitude clouds could decrease \* The impacts of precipitation efficiency on clouds and feedbacks deserve further study and require better evaluation against observations A number of studies have demonstrated strong relationships between precipitation efficiency, particularly its changes under warming, and climate sensitivity. In this chapter, we review the evidence for these relationships, including how they depend on the definition of precipitation efficiency. We identify six mechanisms by which changes in precipitation efficiency may affect Earth’s net climate feedback, and also discuss evidence for an inverse relationship between present-day precipitation efficiency and climate sensitivity based on several perturbed physics ensembles. This inverse relationship hints at the possibility of developing emergent constraints on climate sensitivity using precipitation efficiency, though it is put in doubt by studies varying convective entrainment rates, which have found the opposite relationship. More work is required to refine our understanding of the mechanisms linking changes in precipitation efficiency to climate sensitivity and more observational data is needed to validate model results. In particular, the precipitation efficiency of mid-latitude clouds has been relatively understudied, but deserves more attention in light of the importance of extratropical cloud feedbacks for the high climate sensitivities of CMIP6 models.

# Precipitation Efficiency and Climate Sensitivity

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## Key Points:

- The concept of precipitation efficiency is broad, and can be related to many proposed cloud feedback mechanisms
- Microphysical precipitation efficiency of tropical clouds likely increases with warming, but bulk precipitation efficiency and precipitation efficiency of midlatitude clouds could decrease
- The impacts of precipitation efficiency on clouds and feedbacks deserve further study and require better evaluation against observations

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 19 ter, we review the evidence for these relationships, including how they depend on the def-  
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 31 high climate sensitivities of CMIP6 models.

32 **1 Introduction**

33 Clouds remain the largest source of uncertainty in Earth’s climate sensitivity. While  
 34 substantial progress has been made in recent years on constraining their response to warm-  
 35 ing, with a number of lines of evidence pointing to a positive cloud feedback<sup>1</sup> [Sherwood  
 36 et al., 2020], considerable uncertainty remains as to the cloud feedback’s magnitude. Un-  
 37 certainty in the net cloud feedback reflects the immense complexity of clouds: the vari-  
 38 ety of cloud types, the multi-scale turbulent interactions within clouds, the microphysics  
 39 of phase changes and water droplets, the interactions between clouds and large-scale cir-  
 40 culations, the difficulties of observing clouds, etc. Recent progress on many of these as-  
 41 pects of cloud physics is reviewed in other chapters of this monograph.

42 In this chapter, we focus on the relationship between the precipitation efficiency  
 43 of clouds and climate sensitivity. A number of studies have demonstrated strong rela-  
 44 tionships between climate sensitivity and either present-day precipitation efficiency or  
 45 the response of precipitation efficiency to warming<sup>2</sup>. In both cases, the link reflects the  
 46 variety of processes which determine precipitation efficiency, including the microphysics  
 47 within clouds, small-scale mixing between clouds and their environment, and the large-  
 48 scale organization of clouds and convecting systems. All of these contribute to the to-  
 49 tal cloud feedback, making precipitation efficiency a useful bulk metric for many uncer-  
 50 tain cloud processes. Constraining precipitation efficiency and its behavior under warm-  
 51 ing would not eliminate the uncertainty in climate sensitivity, but it would be an impor-  
 52 tant step.

53 We begin the chapter by reviewing the concept of precipitation efficiency, includ-  
 54 ing its various definitions, which in turn imply different relationships with climate sen-  
 55 sitivity. We then review the connections between the response of precipitation efficiency  
 56 to warming and climate sensitivity (section 3), including a discussion of the controver-  
 57 sial “Iris hypothesis”, followed by a discussion of the potential connections between present-

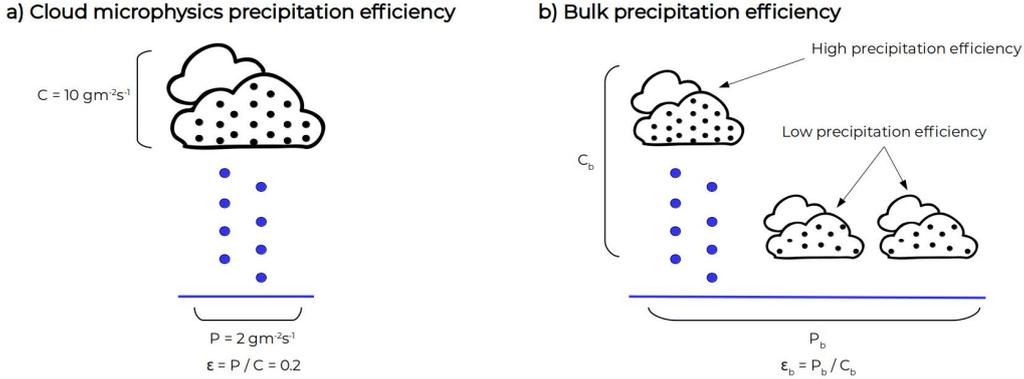
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<sup>1</sup> We define a positive climate feedback as a feedback which enhances greenhouse gas-induced warming, and vice-versa for a negative feedback.

<sup>2</sup> Note that these studies, reviewed below, have used various methods for evaluating climate sensitivity. For example, some studies used the Cess & Potter [1988] method for diagnosing climate sensitivity, while others performed coupled model simulations. But these ways of estimating climate sensitivity are well-correlated with each other, and with the net cloud feedback, so we will generally ignore the method used to evaluate climate sensitivity in the discussion.

58 day precipitation efficiency and climate sensitivity (section 4). Sections 3 and 4 are pri-  
 59 marily concerned with tropical clouds, so section 5 addresses the relationship between  
 60 the precipitation efficiency of extratropical clouds and climate sensitivity, before we end  
 61 with conclusions in section 6.

62 We do not attempt to summarize all of the existing literature on precipitation effi-  
 63 ciency; the reader is referred to Sui et al. [2020] for a recent overview. Instead, we fo-  
 64 cus more narrowly on work which has attempted to relate precipitation efficiency and  
 65 its changes to climate sensitivity. By necessity, this mostly limits our scope to modelling  
 66 papers, though we touch on observational work where appropriate.



**Figure 1.** a) Cloud microphysics precipitation efficiency is defined as precipitation  $P$  divided by the net condensation in a column  $C$ , calculated from microphysical tendencies (vapor condensation, vapor deposition, etc.) only. b) Bulk precipitation efficiency is the average of cloud microphysics precipitation efficiency across a collection of different cloud types, assuming steady-state and averaging over multiple convecting systems.

## 2 Defining Precipitation Efficiency

Precipitation efficiency can be simply defined as the ratio of surface precipitation to the rate at which cloud particles condense (see Figure 1):

$$\epsilon = P/C, \quad (1)$$

where  $P$  is surface precipitation in  $\text{kg m}^{-2} \text{ s}^{-1}$  and  $C$  is the rate of cloud condensation or, equivalently, the sink of atmospheric water vapor, also with units  $\text{kg m}^{-2} \text{ s}^{-1}$ .  $\epsilon$  is unitless, and can be thought of in a Lagrangian sense as the probability that water which condenses as a cloud droplet reaches the surface as precipitation at some point [Langhans et al., 2015].

The process of cloud condensate reaching the surface can be divided into two stages. First, the condensate must form (or accrete onto) droplets of precipitation—rain, snow or graupel. Next, the precipitation must fall through the atmosphere without re-evaporating. This picture leads to the decomposition of surface precipitation into the condensation rate  $C$  multiplied by a “conversion efficiency” and a “sedimentation efficiency” [Langhans et al., 2015; Lutsko & Cronin, 2018]:

$$P = C\alpha(1 - \beta), \quad (2)$$

where  $\alpha$  represents the efficiency with which cloud droplets are converted into precipitation, of which a fraction  $\beta$  is re-evaporated, so that  $1 - \beta$  is the sedimentation effi-

83      ciency. Precipitation efficiency can then be written as

$$\epsilon = \alpha(1 - \beta). \quad (3)$$

84      Idealized models of the tropical atmosphere often assume a conversion efficiency  $\alpha = 1$ ,  
 85      so that precipitation efficiency is set entirely by re-evaporation [e.g., Emanuel, 1987; Yano  
 86      & Emanuel, 1991], but simulations and observations both suggest that  $\alpha$  is substantially  
 87      less than 1.

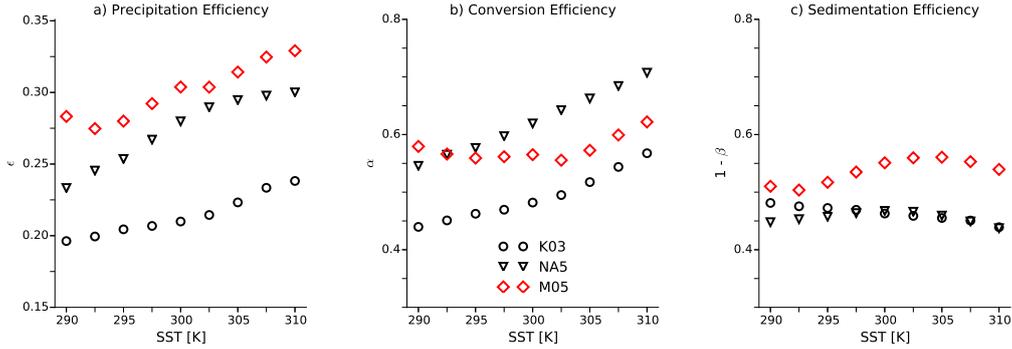
88      These simple definitions are difficult to apply in practice. One has to choose the  
 89      area and time interval over which precipitation efficiency is defined, and how to calcu-  
 90      late  $C$ . For example, when considering a limited domain,  $\epsilon$  can be affected by horizon-  
 91      tal advection of cloud condensate and precipitation into or out of the domain, changing  
 92      the value of  $\alpha$  and  $\beta$  for reasons not directly related to microphysics. Another question  
 93      concerns the re-evaporation or sublimation of cloud water, which can be difficult to dis-  
 94      tinguish from reduced cloud condensation. For simplicity, we follow Zhao [2014] in con-  
 95      ceptually separating out two paths for atmospheric water vapor which undergoes phase  
 96      changes: a rare/fast process in which water vapor condenses/deposits and precipitates  
 97      out quickly, and a frequent/slow process in which water vapor condenses/deposits and  
 98      forms clouds, that are eventually recycled back into the atmosphere through evapora-  
 99      tion and sublimation. Precipitation efficiency is then a measure of the efficiency of the  
 100      fast/rare process in the atmosphere’s hydrological cycle: if  $\epsilon = 0$  no precipitation falls  
 101      to the surface and if  $\epsilon = 1$  any cloud droplets which form fall out instantaneously.

102      As for the condensation  $C$ , Sui et al. [2007] distinguish between “cloud microphysics”  
 103      precipitation efficiency,  $\epsilon_{cm}$ , for which  $C$  is only calculated from microphysical tenden-  
 104      cies (vapor condensation, vapor deposition, etc.), versus “large-scale” precipitati-  
 105      on efficiency,  $\epsilon_{ls}$ , for which  $C$  is calculated as the sum of the large-scale horizontal convergence  
 106      of water vapor, surface evaporation and the change in local water vapor storage. The  
 107      latter definition represents the total water available for precipitation in a region, instead  
 108      of the water that condenses as cloud droplets only, and is similar to the early definitions  
 109      of precipitation efficiency in Emanuel [1987] and Yano & Emanuel [1991], as well as to  
 110      the “drying ratio (e.g., Eidhammer et al. [2018]), for which  $C$  is set equal to the hori-  
 111      zontal convergence of water vapor.

112      Because of our focus on climatological precipitation efficiency, we assume here that  
 113      all quantities are in steady-state, in contrast to Sui et al. [2007], and thus neglect changes  
 114      in vapor loading with time. Furthermore, while we otherwise follow the Sui et al. [2007]  
 115      definition of cloud microphysics precipitation efficiency  $\epsilon_{cm}$ , we define a “bulk” precipi-  
 116      tation efficiency  $\epsilon_b$ , rather than using  $\epsilon_{ls}$  for discussing precipitation efficiency at larger  
 117      scales.  $\epsilon_b$  is calculated solely from microphysical tendencies, instead of using the total  
 118      water budget, and integrates  $P$  and  $C$  over all clouds and updrafts in a given domain.  
 119      Thus  $\epsilon_b$  depends on the particular mix of cloud types in the domain, each having a dif-  
 120      ferent typical  $\epsilon_{cm}$ , and takes into account the higher precipitation efficiency of deep con-  
 121      vection versus the lower precipitation efficiency of shallow clouds (see Figure 1b; note  
 122      that because precipitation efficiency is a ratio  $\epsilon_b$  is not equal to the average of  $\epsilon_{cm}$  across  
 123      different cloud types).

### 124      3 Changes in Precipitation Efficiency and Climate Sensitivity

125      Here we discuss the physical basis for changes in precipitation efficiency to play a  
 126      role in climate sensitivity. There are two conditions for this. First, changes in global tem-  
 127      perature must lead to a systematic change in precipitation efficiency or some related mi-  
 128      crophysical process. Second, the microphysical change must affect cloud or water vapor  
 129      properties so as to alter the top-of-atmosphere energy budget. We discuss these two con-  
 130      ditions in sections 3.1 and 3.2 respectively.



**Figure 2.** a) Precipitation efficiency  $\epsilon$  as a function of SST for the three sets of small domain simulations in Lutsko & Cronin [2018] (their Figure 1). Black circles show results with the single-moment microphysics scheme and the parameter settings used by Khairoutdinov & Randall [2003]; black triangles show results with the NOSEDAALIQ5 parameter settings used by Lopez et al. [2009]; and red diamonds show results with the Morrison et al. [2005] microphysics scheme. b) Conversion efficiency  $\alpha$  as a function of SST for the same simulations. c) Sedimentation efficiency  $1 - \beta$  as a function of SST for the same simulations.

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### 3.1 Changes in cloud microphysics precipitation efficiency under warming

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Observational evidence and detailed modeling suggest that autoconversion of cloud droplets into rain becomes significant only when liquid water amount and/or droplet radii reach a critical threshold [Freud & Rosenfeld, 2012]. A liquid amount threshold is represented by the simple and very popular Kessler autoconversion scheme, where cloud condensate is converted into precipitation via an equation of the form:

$$\frac{\partial q_p}{\partial t} = \max [0, \eta(q_c - q_0)], \quad (4)$$

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where  $q_p$  is the mixing ratio of precipitation,  $\eta$  is a rate constant,  $q_c$  is the cloud condensate mixing ratio and  $q_0$  is a threshold cloud condensate mixing ratio. Thus denser clouds convert condensate into precipitation more efficiently and a minimum liquid mass is required for the process to occur at all. There is strong evidence that aerosol-induced reductions in droplet size can delay the onset of precipitation [e.g. Andreae et al., 2004; Rosenfeld, 2000], consistent with an increase in droplet collision efficiency when radii exceed 15-20 microns [Rosenfeld & Lensky, 1998]. Nevertheless, given an initial droplet number (i.e., with cloud condensation nucleus (CCN) number held fixed), the droplet radius and total liquid mass will grow jointly as a cloud rises and vapor condenses, such that either a minimum radius or mass requirement can produce the same behavior. Thus, a warmer climate with higher boundary-layer water-vapor concentrations (but no difference in CCN) will produce cloudy updrafts that attain required radii or condensed mass sooner, thereby plausibly increasing the precipitation efficiency, as first suggested by Lindzen et al. [2001, see below]. Whether this actually happens may however depend on factors such as cloud mixing and ice processes not considered in the above simple argument.

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Relatively few studies have directly examined the climate-dependence of tropical precipitation efficiency (studies of midlatitude clouds are covered in section 5). Observationally, precipitation efficiency is both difficult to measure and difficult to relate to the large-scale state of the atmosphere. Lau & Wu [2003] suggested that the precipitation efficiency of warm rain increases as the underlying SST increases, but required a microphysical parameterization to convert satellite data into precipitation efficiencies. Conversely, in an analysis of more than 10 years of high quality radar and sounding data from

160 the tropical Pacific, Narsey et al. [2019] found that  $\epsilon_{cm}$  is inversely related to surface tem-  
 161 perature and to convective available potential energy (which is expected to increase with  
 162 warming), though they noted that these relationships are modulated by co-varying fac-  
 163 tors such as relative humidity, which may limit the applicability of their findings to warmer  
 164 climates.

165 Idealized cloud-permitting simulations in small domains, with several different mi-  
 166 crophysics schemes, indicate that cloud microphysics precipitation efficiency should in-  
 167 crease with warming in the absence of major changes in circulation or convective mix-  
 168 ing [Lutsko & Cronin, 2018]. These increases are seen across a wide range of surface tem-  
 169 peratures (290K – 310K, see Figure 2) and are primarily driven by increases in the con-  
 170 densation efficiency  $\alpha$ , with the sedimentation efficiency  $1 - \beta$  generally showing small  
 171 decreases with warming. The increases in condensation efficiency reflect increases in cloud  
 172 condensate density of  $\sim 2\text{-}6\%/^{\circ}\text{C}$  of surface warming at almost all heights, consistent with  
 173 theoretical expectations for entraining plumes rising along a moist adiabat (Betts & Harsh-  
 174 vardhan [1987]; Lutsko & Cronin [2018])

175 In terms of the sedimentation efficiency, Lutsko & Cronin [2018] suggested that  $\beta$   
 176 scales as:

$$\beta \sim (1 - RH)h/w, \quad (5)$$

177 where  $RH$  is relative humidity,  $h$  is the average height at which precipitation forms and  
 178  $w$  is the average fall speed of the precipitation. Analysis of cloud-permitting simulations  
 179 demonstrated that warming-driven changes in sedimentation efficiency are primarily caused  
 180 by increases in the height at which clouds form, so that falling precipitation travels a greater  
 181 distance through the atmosphere and has a greater chance of being re-evaporated, in-  
 182 creasing  $\beta$  and decreasing  $\epsilon$ . However, these changes are small compared to the changes  
 183 in condensation efficiency  $\alpha$  for temperatures in the range 290K-310K (compare panels  
 184 b and c of Figure 2), so that increases in cloud density lead to increases in the precip-  
 185 itation efficiency of tropical clouds with warming.

186 A caveat to these results is phase changes. Clouds are increasingly composed of liq-  
 187 uid water droplets rather than cloud ice as the atmosphere warms. In turn, the precip-  
 188 itation in a column transitions from being primarily snow and/or graupel to primarily  
 189 rain. Ice clouds have a higher conversion efficiency than liquid water clouds, because larger  
 190 ice crystals grow more rapidly than liquid cloud droplets through collisions and collec-  
 191 tion of hydrometeors, but snow also re-evaporates much more readily than rain because  
 192 of its slower fall speeds. Hence a change from a predominantly-snow to a predominantly-  
 193 rain regime results in a decrease in conversion efficiency but an increase in sedimenta-  
 194 tion efficiency. For relatively warm surface temperatures (c. 290K), the increased sed-  
 195 imentation efficiency generally wins out in cloud-permitting simulations and precipita-  
 196 tion efficiency increases with warming [Lutsko & Cronin, 2018], though studies of mixed-  
 197 phase clouds at higher latitudes have found that the reduction in conversion efficiency  
 198 wins out at colder temperatures, leading to a reduction in precipitation efficiency with  
 199 warming (see section 5 for more).

200 These arguments ignore changes in convective aggregation, which can affect the ther-  
 201 modynamic environment in which precipitation forms as well as the bulk precipitation  
 202 efficiency (see below), but suggest that, with or without phase changes, the cloud-microphysics  
 203 precipitation efficiency of tropical clouds should be expected to increase with warming.  
 204 These arguments apply to the mean precipitation efficiency, rather than the precipita-  
 205 tion efficiency of extreme precipitation, but given our focus on the relationship with cloud  
 206 feedbacks, we speculate that mean precipitation efficiency is most relevant for the dis-  
 207 cussion (see Muller et al. [2011] and Singh & O’Gorman [2014] for more on the response  
 208 of extreme precipitation efficiency to warming).

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### 3.2 Precipitation efficiency-related feedbacks on climate

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We now consider various ideas for how climate-driven changes in precipitation efficiency could provide feedbacks on climate. Studies investigating this possibility have often been motivated by the Iris hypothesis. First proposed by Lindzen et al. [2001], the Iris hypothesis is a potential negative high cloud feedback, in which a reduction in cirrus cloudiness under warming leads to an increase in outgoing longwave radiation (OLR). The name comes from an analogy to the iris in the human eye, which contracts in the presence of bright light. Based on an analysis of observed changes in cloud cover coincident with higher surface temperatures in a region of the central Pacific, Lindzen et al. [2001] claimed a 22% reduction in cloud cover per degree warming, implying a strongly negative cloud feedback and a climate sensitivity of  $\sim 1^\circ\text{C}$ . However, these results were reported for localized regions, which typically involve confounding dynamical changes or atmospheric influences on the ocean [see Sherwood et al., 2010], and relationships can nearly disappear when averages are taken over the whole tropics [Williams & Pierrehumbert, 2017].

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One reason for the Iris hypothesis’ controversy is the lack of a clear description of what is contracting and why. Lindzen et al. [2001] suggested that increases in conversion efficiency cause decreases in anvil cloud area, but anvil clouds have only a weak net impact on the global energy budget, so a substantial net radiative effect presumably requires a more general contraction of cloudy conditions in favor of expanded clear sky, with implied reductions in other cloud types and/or relative humidity. This links to the concept of convective aggregation, whereby convection can spontaneously cluster into smaller regions; in idealized radiative convective equilibrium (RCE) models aggregation consistently leads to greater OLR [Wing et al., 2020]. Early studies suggested that such aggregation should increase at warmer surface temperatures in some global climate model (GCM) simulations [e.g., Bony, Stevens, et al., 2016] and in small-scale simulations, but due to radiative-dynamical mechanisms rather than anything involving precipitation efficiency [Wing & Emanuel, 2014]. Recent model intercomparisons are more ambiguous as to whether the process is climate-sensitive [Wing et al., 2020], but observational studies suggest that such contractions are generally associated with larger areas of low relative humidity and/or higher OLR [Bony, Semie, et al., 2016; Hohenegger & Jakob, 2020]. Thus, while the tropics appear capable of “Iris”-like fluctuations, it is not clear whether these will deliver a negative feedback on climate. For more discussion of convective aggregation see Chapter 8 in this collection.

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We also emphasize that any substantial Iris-like effect on climate sensitivity would likely have to come from the cloud field, rather than from reductions in relative humidity. While stronger convective clustering could lead to a reduction in re-evaporation and hence to a reduction in tropospheric relative humidity, theory and GCM experiments suggest that the sensitivity of tropospheric relative humidity to re-evaporation – to a change in  $\beta$  – is relatively weak (Sherwood & Meyer [2006]; Romps [2014]). Even in the case of a strong Iris effect, the changes in re-evaporation with warming are likely to be modest, and so are the changes in relative humidity.

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#### 3.2.1 Model investigations of changing the response of precipitation efficiency to warming

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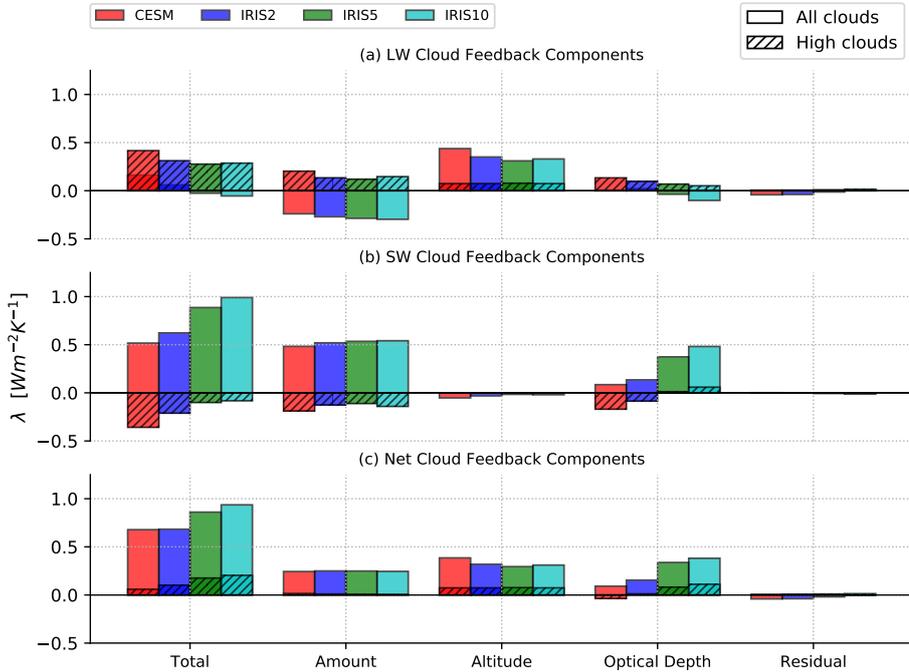
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Since the convective processes potentially responsible for an Iris-like effect are crudely represented in climate models, possible Iris effects on climate sensitivity have been explored by varying the response of  $\epsilon_{cm}$  with warming. In particular, Mauritsen & Stevens [2015] and R. L. Li et al. [2019] modified the autoconversion rate ( $\eta$ ) in ECHAM6 and in CESM, respectively, so that

$$\eta(T_s) = \eta_0(1 + I_e)^{T_s - T_0}, \quad (6)$$

258 where  $T_0$  is a reference temperature, set to  $25^\circ\text{C}$  in both studies,  $\eta_0$  is a reference au-  
 259 toconversion rate and  $I_e$  is a parameter which controls the strength of the Iris effect (larger  
 260  $I_e$  results in a higher  $\epsilon_{cm}$ ). Mauritsen & Stevens [2015] were originally motivated to add  
 261 this modification to ECHAM6 by their finding that most climate models underestimate  
 262 the increase in outgoing longwave radiation per  $^\circ\text{C}$  of tropical surface temperature warm-  
 263 ing on monthly time-scales, suggestive of a missing Iris-like effect.

264 Making the autoconversion rate temperature-dependent successfully increased the  
 265 OLR per degree warming, primarily through negative longwave cloud feedbacks – more  
 266 negative than any of the CMIP5 models analyzed by Mauritsen and Stevens, even for  
 267 the smallest value of  $I_e$  tested (0.2). But the inclusion of the temperature-dependent au-  
 268 toconversion also resulted in a more positive shortwave cloud feedback, leading to a par-  
 269 tial compensation of the longwave cloud feedback and modest reductions in ECHAM6’s  
 270 climate sensitivity, from  $2.8^\circ\text{C}$  to  $2.2^\circ\text{C}$ . Another factor compensating for the negative  
 271 longwave cloud feedback was a weakened lapse-rate feedback due to reduced warming  
 272 of the tropical upper troposphere.



**Figure 3.** Contributions to the global-mean cloud feedbacks in the Iris simulations of R. L. Li et al. [2019], separated into cloud-amount, cloud-altitude, and cloud-optical-depth components. Control CESM results are shown in red, results from simulation with  $I_e = 0.2$  are shown in blue, results from simulation with  $I_e = 0.5$  are shown in green and results from simulation with  $I_e = 1.0$  are shown in light blue. A separate decomposition is performed for high clouds ( $<440$  hPa), shown with hatched bars. Note that these high-cloud contributions are not additive with the low-cloud (i.e.,  $>440$  hPa, not shown) contributions to give back the all-cloud components (all pressure bins). Reproduced, with permission, from R. L. Li et al. [2019] (their Figure 9).

273 Mauritsen & Stevens [2015] noted that the positive shortwave cloud feedback over-  
 274 compensated for the negative longwave cloud feedback in unpublished experiments with

275 CESM, and this was confirmed by R. L. Li et al. [2019]. Using the same modifications  
 276 as Mauritsen and Stevens, Li et al found that CESM’s equilibrium climate sensitivity  
 277 increased from 3.79°C to 4.59°C as  $I_e$  was increased from 0 to 1. The sign of the sensi-  
 278 tivity change was robust across different cloud microphysics schemes, and was mostly  
 279 caused by increasingly large reductions in the optical depth of cirrus clouds, rather than  
 280 by changes in cloud amount, which were small (Figure 3). The reductions in cloud op-  
 281 tical depth were caused by thinning of anvil clouds as a stronger Iris feedback was im-  
 282 posed, though the cloud thinning was itself partially compensated by a negative cloud  
 283 phase feedback: the liquid water clouds which replace ice clouds in warmer climates are  
 284 longer-lived and more reflective, because they are made up of a large number of small  
 285 water droplets, rather than a relatively small number of large ice crystals. We return to  
 286 the negative cloud phase feedback in section 5.

287 Finally, in a study not directly motivated by the Iris hypothesis, Zhao et al. [2016]  
 288 found a strong relationship between cloud microphysics precipitation efficiency and cli-  
 289 mate sensitivity in their experiments with the GFDL-AM4 model. These experiments  
 290 involved modifying the scheme by which cumulus precipitation is formed to produce ei-  
 291 ther an increase in  $\epsilon_{cm}$ , a negligible change in  $\epsilon_{cm}$  or a decrease in  $\epsilon_{cm}$  with warming.  
 292 The configurations each produced good representations of the present-day climate, but  
 293 had very different climate sensitivities: the version in which  $\epsilon_{cm}$  increased had a high  
 294 climate sensitivity, the version in which  $\epsilon_{cm}$  stayed the same had a moderate climate sen-  
 295 sitivity and the version in which  $\epsilon_{cm}$  decreased had a low climate sensitivity. These dif-  
 296 ferences in climate sensitivity were caused mainly by cloud changes between 800 and 300hPa,  
 297 with the response of high clouds being weak in each configuration.

## 298 4 Present-Day Precipitation Efficiency and Climate Sensitivity

299 While changes in precipitation efficiency are likely responsible for the relationship  
 300 with climate sensitivity, studies with several different GCMs have shown strong links be-  
 301 tween present-day precipitation efficiency and climate sensitivity. These results demon-  
 302 strate that microphysical parameters related to precipitation efficiency can be used as  
 303 tuning parameters for controlling models’ climate sensitivity, and also imply correlations  
 304 between baseline  $\epsilon$  and  $\Delta\epsilon$ , which could allow observations of present-day precipitation  
 305 efficiency to be used to constrain its changes.

### 306 4.1 Mid- to high-clouds and microphysical mechanisms

307 The most focused study of the relationship between present-day precipitation ef-  
 308 ficiency and climate sensitivity is Zhao [2014] who, with the deliberate aim of altering  
 309 the model’s precipitation efficiency, varied two parameters in GFDL’s C48HIRAM model:  
 310 the warm-cloud autoconversion threshold  $q_0$ , and  $c_0$ , a parameter which controls the cu-  
 311 cumulus entrainment rate (parameterized as  $c_0/H$ ). Increasing  $q_0$  means that higher cloud  
 312 water densities are required to form precipitation, reducing the conversion efficiency and  
 313 thus decreasing the cloud microphysics precipitation efficiency. Large values of  $q_0$  also  
 314 decrease the vertical velocities of convective plumes by increasing condensate loading,  
 315 favoring shallow plumes, rather than the deep convective plumes in which the majority  
 316 of precipitation forms. Increasing  $c_0$  has a similar effect of decreasing plume vertical ve-  
 317 locities because of increases in lateral mixing and entrainment. In both cases, the bulk  
 318 precipitation efficiency decreases as the relative fraction of shallow plumes increases, and  
 319 the greater low-cloud fraction decreases the net cloud radiative effect (CRE).

320 The bulk precipitation efficiency consistently increased when the various model con-  
 321 figurations were subject to uniform SST warming, with the largest increases for the con-  
 322 figurations with the smallest base-state precipitation efficiencies (Figure 4). Zhao [2014]  
 323 explained this inverse relationship using a conceptual model of tropical convection in which  
 324 an ascending parcel rises through the atmosphere, exchanging air with the environment

325 such that the parcel conserves its total mass (although this picture is based on a par-  
 326 cel model, it should be thought of as representing the bulk tropical atmosphere). The  
 327 parcel is assumed to produce total cloud condensate  $q_c = aq_b$ , where  $q_b$  is the bound-  
 328 ary layer specific humidity and  $a$  is the fraction of  $q_b$  which condenses as the parcel as-  
 329 cends. Of this total condensate,  $aq_b - q_0$  reaches the surface as precipitation, where  $q_0$   
 330 is again a threshold specific humidity above which precipitation forms (note that the sed-  
 331 imentation efficiency is assumed to be 1, i.e.,  $\beta = 0$ ). The bulk precipitation efficiency  
 332 is then  $\epsilon_b = 1 - q_0/(aq_b)$  and the response of  $\epsilon_b$  to a small perturbation is

$$\Delta\epsilon_b = \frac{q_0}{aq_b} \left( \frac{\Delta a}{a} + \frac{\Delta q_b}{q_b} - \frac{\Delta q_0}{q_0} \right), \quad (7)$$

333 which can also be written as

$$\Delta\epsilon_b = (1 - \epsilon_b) \left( \frac{\Delta a}{a} + \frac{\Delta q_b}{q_b} - \frac{\Delta q_0}{q_0} \right). \quad (8)$$

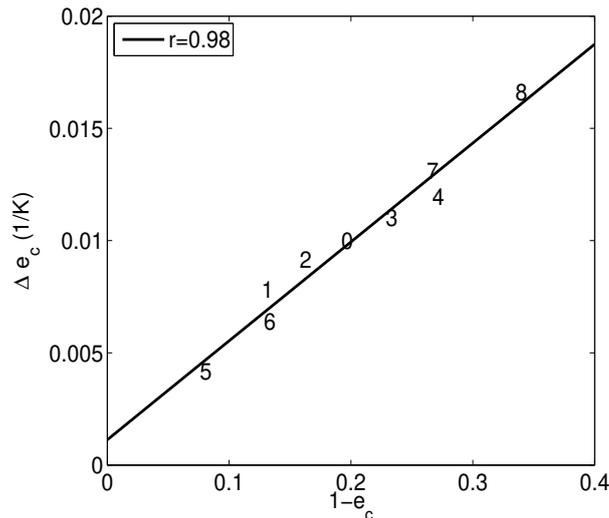
334 Zhao [2014] found that  $\Delta\epsilon_b$  was strongly correlated with  $1 - \epsilon_b$ , suggesting that  $\Delta a$  and  
 335  $\Delta q_b$  make small contributions to the variations in  $\Delta\epsilon_b$  across the model configurations  
 336 ( $q_0$  is unaffected by warming in this microphysics scheme)<sup>3</sup>, and providing the basis for  
 337 a possible connection between present-day precipitation efficiency and  $\Delta\epsilon_b$ .

338 Increases in bulk precipitation efficiency resulted in decreases in liquid and ice wa-  
 339 ter paths with warming in Zhao’s experiments, with low and mid-cloud fractions dimin-  
 340 ishing at faster rates than high cloud fractions because higher precipitation efficiencies  
 341 favor deep convection, rather than shallow plumes. Hence model configurations with larger  
 342  $\Delta\epsilon_b$  experienced larger reductions of low and mid-level clouds, which produced larger de-  
 343 creases in shortwave CRE and more positive cloud feedbacks. In this way, configurations  
 344 with smaller present-day precipitation efficiencies had higher climate sensitivities.

345 A potential inverse relationship between present-day precipitation efficiency and  
 346 climate sensitivity across different configurations of a single model is supported by sev-  
 347 eral other studies, though none were directly investigating precipitation efficiency. Tomassini  
 348 et al. [2015] found that increasing the autoconversion rate, which increases  $\epsilon_{cm}$  by in-  
 349 creasing  $\alpha$ , decreases the climate sensitivity of a coarse-resolution version of the MPI-  
 350 ESM GCM. Similarly, Mauritsen et al. [2012] found that doubling the autoconversion  
 351 rate in MPI-ESM-LR decreases the model’s climate sensitivity from 3.09K to 2.96K, while  
 352 Bender [2008] found that increasing the autoconversion rate by a factor of 5 decreases  
 353 CAM3.1’s climate sensitivity from 2.50 to 2.26K. These changes are modest, though both  
 354 sets of experiments involved other changes to the models.

355 Studies of the connection between the rate of entrainment for deep convection and  
 356 climate sensitivity have put the inverse relationship into question, however. Tomassini  
 357 et al. [2015], Mauritsen et al. [2012] and, earlier, Stainforth et al. [2005] found that in-  
 358 creasing the rate of entrainment in deep convective plumes led to large decreases in cli-  
 359 mate sensitivity. This is in contrast to the a priori expectation that higher entrainment  
 360 rates should produce lower precipitation efficiencies and higher climate sensitivities ac-  
 361 cording to the relationship between  $\epsilon$  and climate sensitivity established above. How-  
 362 ever, these studies did not report how  $\epsilon$  changed in their experiments. We also note that  
 363 varying the entrainment rate for deep convection is a different modification to Zhao’s ex-  
 364 periments, in which  $c_0$  governs the entrainment rate throughout the column as part of  
 365 a bulk plume representation of both shallow and deep convection. Nevertheless, the sur-  
 366 prising relationship between deep convective entrainment rates and climate sensitivity  
 367 indicates that while  $\Delta\epsilon$  is often correlated with present-day  $\epsilon$ , this is not always the case.

<sup>3</sup>The relationship between  $\Delta\epsilon_b$  and  $1 - \epsilon_b$  holds within different configurations of a single model, but does not necessarily hold when comparing across models. Differences in convective mixing schemes or in microphysics could cause large variations in  $\Delta a/a$ ,  $\Delta q_b/q_b$  and  $\Delta q_0/q_0$  across models.



**Figure 4.** Scatterplot of the change in precipitation efficiency with warming  $\Delta\epsilon$  versus the present-day precipitation efficiency (i.e.,  $1-\epsilon$ ) from the perturbed-physics ensemble in Zhao [2014] (their Figure 10). 0 denotes the control simulation while symbols 1-8 denote the perturbed-physics simulations. The line shows a linear regression with the correlation coefficient shown in the legend.

368 The mechanisms connecting deep entrainment rates and climate sensitivity have  
 369 not been investigated, except for Mauritsen et al. [2012], who suggested that the reductions  
 370 in climate sensitivity for higher deep entrainment rates are primarily caused by changes  
 371 in the rapid adjustments to CO<sub>2</sub> forcing, rather than by changes in temperature-dependent  
 372 feedbacks. In the absence of follow-up studies, further work is needed to verify this claim.

#### 373 4.2 Low clouds and convective mixing

374 A separate set of studies has proposed a connection between the strength of mixing  
 375 in shallow convection and climate sensitivity. Air lifted out of the boundary layer  
 376 can either continue ascending, rain out most of its water vapor and eventually return to  
 377 lower altitudes, or it can be detrained directly at lower altitudes and retain more of its  
 378 initial water vapor. The latter corresponds to a situation with stronger mixing between  
 379 the boundary layer and the lower troposphere, resulting in a smaller bulk precipitation  
 380 efficiency, less boundary-layer cloudiness and a greater net transport of moisture out of  
 381 the boundary layer for the same mean precipitation rate. Lower tropospheric mixing is  
 382 expected to strengthen in warmer climates, intensifying the dehydration of the bound-  
 383 ary layer and reducing low cloud cover, with the rate of increase in mixing thought to  
 384 be proportional to the initial mixing strength (Stevens [2007]; Rieck et al. [2012]; Zhang  
 385 et al. [2013]; Bretherton [2015]; Brient et al. [2016]; Vial et al. [2016]). Hence a model  
 386 with a lower initial bulk precipitation efficiency for shallow clouds should experience larger  
 387 low cloud reductions with warming and have a higher climate sensitivity – another in-  
 388 verse relationship between present-day precipitation efficiency and climate sensitivity.

389 In support of this argument, Sherwood et al. [2014] demonstrated that metrics for  
 390 the strength of lower tropospheric convective mixing could explain about half the vari-  
 391 ance in CMIP5 models' climate sensitivity, with mixing rates inferred from observations  
 392 implying a climate sensitivity greater than 3°C. They also confirmed that convective dry-  
 393 ing of the boundary layer increased with warming in models with stronger metrics of present-

394 day shallow mixing. However, modelling studies in which mixing into shallow convec-  
 395 tion is directly altered via the parametrized entrainment rate have found a seemingly dif-  
 396 ferent result: in Mauritsen & Roeckner [2020] a developmental version of ECHAM6 ex-  
 397 hibited a large decrease in climate sensitivity when the shallow convection entrainment  
 398 rate was increased by a factor of 10, while in an earlier study, MPI-ESM-LR’s climate  
 399 sensitivity declined from 3.09°C to 2.86°C when the shallow entrainment rate was in-  
 400 creased by a factor of 8/3 [Mauritsen et al., 2012].

401 These results are not necessarily inconsistent with Sherwood et al. [2014] as, for  
 402 example, increasing the entrainment rate of shallow convection could favor the develop-  
 403 ment of deep convection and thereby increase  $\epsilon_b$  for reasons unrelated to changes in shal-  
 404 low mixing. More direct tests of the shallow-mixing idea come from Zhao et al. [2016],  
 405 who found that the indices defined by Sherwood et al. [2014] were not well correlated  
 406 with climate sensitivity in their perturbed physics ensemble (PPE) simulations, and that  
 407 clouds above the boundary layer were more important for differences in cloud feedback  
 408 between the ensemble members (see section 3.2). Finally, Kamae et al. [2016] suggested  
 409 that the relationship between lower tropospheric mixing and climate sensitivity is model-  
 410 dependent, as strong correlations between the Sherwood metrics and climate sensitiv-  
 411 ity were seen in about half the PPEs in their larger multiphysics ensemble. However, PPE  
 412 ensemble members often exhibit unrealistic feedbacks [e.g. Joshi et al., 2010], reflecting  
 413 mean-state errors that are typically absent in CMIP-model runs because of model tun-  
 414 ing. Thus we feel these PPE results should be interpreted with caution, and that the shallow-  
 415 mixing mechanism described above cannot be definitely ruled out.

416 There are other factors that might alter the relationship between shallow mixing  
 417 and the low cloud feedback. For example, the effects of mixing near the top of the bound-  
 418 ary layer on low clouds can be modified by changes in latent heat fluxes and in radiative  
 419 cooling (Bretherton [2015]; Vial et al. [2016]; Schneider et al. [2019]). Enhanced de-  
 420 hydration of the boundary layer strengthens the surface latent heat flux, which damps  
 421 the reduction in low clouds. At the same time, low cloud reductions stabilize the lower  
 422 troposphere by decreasing the cloud-top radiative cooling, which in turn decreases the  
 423 surface latent heat flux and induces further low cloud reductions. The relative impor-  
 424 tance of low cloud mixing versus radiative cooling, and the resulting sign of the latent  
 425 heat flux response, depends on the convective parameterization [Vial et al., 2016]. A con-  
 426 vection scheme in which the surface latent heat flux is strongly coupled to low-cloud radi-  
 427 ative cooling will have a higher sensitivity of low-cloud fractions to convective mixing  
 428 parameters, and a stronger low cloud feedback in response to surface warming. But if  
 429 radiative cooling is less dominant the latent heat flux may increase with warming, weak-  
 430 ening the low cloud response and reducing the model’s climate sensitivity.

431 Thus a link between convective mixing and climate sensitivity (or between  $\epsilon_b$  for  
 432 low clouds and climate sensitivity) is plausible, but the modelling evidence is inconclu-  
 433 sive and the strength of the link is uncertain. The relationship between shallow entrain-  
 434 ment rates and climate sensitivity is evidently model-dependent, as is the relative im-  
 435 portance of entrainment rates versus other parameters in models’ convection and micro-  
 436 physics schemes. Klocke et al. [2011] found that the shallow entrainment rate was the  
 437 strongest control on climate sensitivity in their PPE and that the rate of autoconversion  
 438 had a negligible effect, while Tomassini et al. [2015] found that the autoconversion  
 439 rate exerted a strong control on climate sensitivity and the shallow entrainment rate had  
 440 a weak effect in their PPE. Putting these model results together, and given the complex  
 441 mechanisms which govern how shallow entrainment rates affect low cloud cover, the con-  
 442 cept of precipitation efficiency as defined here may not be the best way of framing the  
 443 link between shallow mixing and climate sensitivity.

## 444 5 Precipitation Efficiency of Extratropical Clouds

445 Investigations of the relationship between precipitation efficiency and climate sensi-  
 446 tivity have mostly focused on tropical clouds, which are often identified as the lead-  
 447 ing source of uncertainty in Earth’s climate sensitivity. Yet the high climate sensitivi-  
 448 ties of many of the newest CMIP6 models have been attributed to a reduction of strongly  
 449 negative extratropical cloud feedbacks compared to CMIP5, particularly over the South-  
 450 ern Ocean [Zelinka et al., 2020], suggesting that the precipitation efficiency of extratrop-  
 451 ical clouds merits more study. Moreover, while the connection between the precipitation  
 452 efficiency of extratropical clouds and climate sensitivity has not been investigated ex-  
 453 plicitly, an inverse relationship between the present-day  $\epsilon_{cm}$  of extratropical clouds and  
 454 climate sensitivity has been proposed, mediated by the cloud phase feedback mentioned  
 455 in section 3.2.

456 The cloud-microphysics precipitation efficiency of extratropical clouds is expected  
 457 to decrease with warming because of decreases in conversion efficiency associated with  
 458 the transition from mostly ice clouds to mostly liquid water clouds. The changes in con-  
 459 version efficiency win out over increases in sedimentation efficiency due to the transition  
 460 from snow to rain as the dominant form of precipitation (Kirshbaum & Smith [2008];  
 461 Storelvmo et al. [2015])<sup>4</sup>. Cloud phase changes also lead to a negative cloud optical depth  
 462 feedback as liquid clouds with higher optical depths replace ice clouds (see Chapter 4  
 463 in this collection), which may be a substantial effect: Mitchell et al. [1989] found that  
 464 the cloud phase feedback can alter a model’s climate sensitivity by a factor of two (see  
 465 also Z.-X. Li & Le Treut [1992]; Storelvmo et al. [2015]; McCoy et al. [2015]; Ceppi et  
 466 al. [2017]; Mauritsen & Roeckner [2020]). Hence models with higher initial ice cloud frac-  
 467 tions may experience larger reductions in precipitation efficiency driven by phase changes,  
 468 and stronger negative cloud optical depth feedbacks under warming. This suggests that  
 469 models with higher present-day extratropical precipitation efficiencies could have lower  
 470 climate sensitivities.

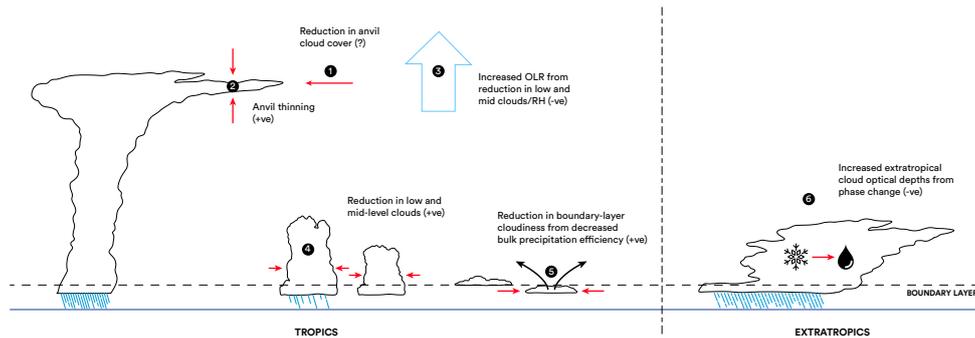
471 Zelinka et al. [2020] noted that one explanation for the weaker extratropical cloud  
 472 feedbacks in CMIP6 is the increased presence of mean-state supercooled liquid water in  
 473 mixed-phase clouds in many models. More supercooled water means smaller increases  
 474 in extratropical cloud optical depth and cloud lifetime compared to models which start  
 475 with more cloud ice initially. Although Zelinka et al did not calculate  $\epsilon$  for extratrop-  
 476 ical clouds explicitly, it is plausible that the high sensitivity CMIP6 models exhibit smaller  
 477 decreases in extratropical cloud microphysics precipitation efficiency with warming.

## 478 6 Concluding Remarks

479 The general notion of precipitation efficiency is broad, and it can be defined in sev-  
 480 eral different ways, each of which can be related to various cloud feedback mechanisms.  
 481 Moreover, the relationships between precipitation efficiency and cloud feedbacks are highly  
 482 model-dependent, and parameters which are important in one model may be less impor-  
 483 tant in another. This is perhaps best illustrated by the multiphysics, multiparameter en-  
 484 sembles of Kamae et al. [2016], in which some model configurations showed strong re-  
 485 lationships between lower tropospheric mixing metrics and climate sensitivity, while oth-

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<sup>4</sup> We hypothesize that changes in sedimentation efficiency likely become more important at warmer temperatures, when precipitation forms higher in the atmosphere and differences in fall speed lead to larger changes in re-evaporation. We also note that Eidhammer et al. [2018] found that the precipitation efficiency of orographic precipitation decreases with surface temperature in high resolution simulations of a region in the Colorado Rockies, and attributed this to decreases in vertical velocities. However, they defined precipitation efficiency as the drying ratio, which is different from our definitions based on microphysical properties.



**Figure 5.** Schematic illustration of the six mechanisms by which changes in precipitation efficiency can alter climate sensitivity, as well as the hypothesized signs of their effect on the net climate feedback.

486 ers did not. Similarly, Klocke et al. [2011], Zhao [2014] and Tomassini et al. [2015] all  
 487 demonstrated strong relationships between present-day precipitation efficiency and cli-  
 488 mate sensitivity, but used different parameter variations to establish these relationships.  
 489 This model-dependence reflects the fact that precipitation efficiency is a bulk metric for  
 490 the combined effects of the convective and microphysical processes it represents, and com-  
 491 paring the precipitation efficiencies of models can be deceptive if different processes control  
 492  $\epsilon$ .

493 Nevertheless, a few robust results do emerge from the literature. For example, there  
 494 is strong evidence that the cloud microphysics precipitation efficiency of tropical clouds  
 495 increases with warming, though bulk precipitation efficiency and the cloud microphysics  
 496 precipitation efficiency of extratropical clouds could decrease. After tracing the various  
 497 ways in which precipitation efficiency has been connected to climate sensitivity, we also  
 498 propose that there are six mechanisms by which changes in  $\epsilon$  could alter the planetary  
 499 radiative balance (see Figure 5):

- 500 1. Increased precipitation efficiency could lead to a reduction in anvil cloud cover.  
 501 This would increase OLR but also lower albedo, such that the sign of the net feed-  
 502 back is unclear.
- 503 2. Increased precipitation efficiency could cause thinning of cloud anvils, producing  
 504 a positive cloud optical depth feedback.
- 505 3. Increased convective organization could produce decreases in cloud cover gener-  
 506 ally, as well as decreases in relative humidity, such that OLR increases with warm-  
 507 ing. This could constitute a negative climate feedback, depending on the response  
 508 of shallow clouds outside the convective area.
- 509 4. Increased microphysical precipitation efficiency could lead to reductions in low and  
 510 mid-level cloud cover (independent of changes in convective organization), a posi-  
 511 tive feedback on warming.
- 512 5. Increased demand on boundary-layer moisture due to decreasing bulk precipita-  
 513 tion efficiency via shallow mixing could reduce boundary-layer cloudiness, produc-  
 514 ing a positive feedback.
- 515 6. Decreased mid-latitude precipitation efficiency could be associated with increased  
 516 extratropical cloud optical depths, a negative mid-latitude cloud feedback.

517 Mechanisms (1) and (3) correspond most closely to the original "Iris" idea of Lindzen  
 518 et al. [2001], but (1) is unlikely to produce a strong net radiative feedback while (3) ap-

519 pears to be more of a dynamical than a microphysical mechanism. Changes in anvil cloud  
 520 amount or tropospheric relative humidity driven by changes in precipitation efficiency  
 521 are unlikely to be capable of large changes to the planetary radiative balance, leaving  
 522 changes in other cloud-types as the source of changes in sensitivity. Mechanisms (2), (4),  
 523 (5) and (6) have all been reported in GCMs, and merit further investigation into how  
 524 they vary across models and to better understand the magnitude of their effects. For ex-  
 525 ample, evidence that increases in precipitation efficiency could result in thinning of cloud  
 526 anvils (mechanism (2)) comes from a single modelling study [R. L. Li et al., 2019]. Im-  
 527 proving understanding of the precipitation efficiency of extratropical clouds also seems  
 528 particularly urgent in light of the role of extratropical clouds in the high climate sensi-  
 529 tivities of CMIP6 models.

530 Another important question is clarifying whether there is a relationship between  
 531 present-day precipitation efficiency and climate sensitivity. A number of model pertur-  
 532 bation studies have found inverse relations between present-day precipitation efficiency  
 533 and climate sensitivity, with the possible exception of modeling studies varying shallow  
 534 and deep entrainment rates (though these have not actually documented how  $\epsilon$  changes  
 535 as parameters are varied). Such a relationship would presumably work through changes  
 536 in efficiency with warming following one or more of the six mechanisms listed above. A  
 537 robust relationship in models between present-day precipitation efficiency and climate  
 538 sensitivity would suggest the possibility of emergent constraints on climate sensitivity,  
 539 but the link between present-day  $\epsilon$  and  $\Delta\epsilon$  would need to be strengthened before pre-  
 540 cipitation efficiency could be used in this way, and measuring precipitation efficiency, par-  
 541 ticularly over large-scales and at the required accuracy, presents many challenges.

542 Despite the issues around model dependence, the various notions of precipitation  
 543 efficiency clearly play a central role in many types of likely cloud feedback. The concept  
 544 of precipitation efficiency is also a useful framework for connecting detailed process stud-  
 545 ies to emergent properties of climate models. This can be helpful in model development  
 546 and evaluation, while also suggesting new ways of engineering specific climates to explore  
 547 hypotheses and to investigate observational constraints. Thus we believe that further study  
 548 of the impacts of precipitation efficiency on clouds and feedbacks is called for, particu-  
 549 larly to refine our understanding of the mechanisms linking changes in precipitation ef-  
 550 ficiency to climate sensitivity and to provide more observational data with which to val-  
 551 idate model results.

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