



1 **Equilibrium climate sensitivity increases with aerosol concentration**
2 **due to changes in rain efficiency**

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34 **Abstract**

35 How Earth's climate reacts to anthropogenic forcing is one of the most burning
36 questions faced by today's scientific community. A leading source of uncertainty in
37 estimating this sensitivity is related to the response of clouds. Under the canonical
38 climate-change perspective of forcings and feedbacks, the effect of anthropogenic
39 aerosols on clouds is categorized under the forcing component, while the modifications
40 of the radiative properties of clouds due to climate change are considered in the
41 feedback component. Each of these components contributes the largest portion of
42 uncertainty to its relevant category and is largely studied separately from the other. In
43 this paper, using idealized cloud resolving, radiative-convective-equilibrium
44 simulations, with a slab ocean model, we show that aerosol-cloud interactions could
45 significantly affect cloud feedback. Specifically, we show that equilibrium climate
46 sensitivity increases under high aerosol concentration due to an increase in the
47 shortwave cloud feedback. The shortwave cloud feedback is enhanced under high
48 aerosol conditions due to a stronger increase in the precipitation efficiency with
49 warming, which can be explained by higher sensitivity of the droplet size and the cloud
50 water content to the CO₂ concentration rise. These results indicate a strong connection
51 between cloud feedback and aerosol-cloud interactions.

52

53 **1. Introduction**

54 Estimating Earth's equilibrium climate sensitivity (ECS), defined as the steady-state
55 global mean temperature increase for a doubling of CO₂, is considered as a first-order,
56 fundamental milestone on the way to understanding and predicting anthropogenic-
57 driven climate change (Sherwood et al., 2020). Decades of research have tried to
58 accurately quantify ECS, with only limited success. The most probable current ECS
59 estimates are in the range of 2.3–4.5K (Sherwood et al., 2020). The largest source of
60 uncertainty in estimating ECS is related to the response of clouds to the externally
61 forced warming and the feedback of these changes on the climate system (Sherwood et
62 al., 2020; Ceppi et al., 2017; Schneider et al., 2017). Clouds strongly modulate Earth's
63 radiation budget by reflecting the incoming shortwave radiation from the sun and by
64 absorbing and re-emitting the terrestrial longwave radiation (Loeb et al., 2018). Thus,
65 changes in the cloud macro-physical properties (such as coverage and vertical extent)
66 and micro-physical properties (such as liquid/ice partition or hydrometeors size) due to
67 anthropogenic-driven climate change could significantly alter the climate system's



68 response (Gettelman and Sherwood, 2016; Nuijens and Siebesma, 2019; Schneider et
69 al., 2017).

70 An important factor in determining cloud feedback magnitude is the sensitivity of the
71 Precipitation Efficiency (ϵ) (Lutsko et al., 2021; Li et al., 2022; Lutsko and Cronin,
72 2018). ϵ quantifies the fraction of condensed water in a cloud to reach the surface as
73 precipitation. Using idealized cloud resolving simulations, it was shown that ϵ is
74 expected to increase with temperature (Lutsko and Cronin, 2018). The increase in ϵ
75 with warming was shown to be mostly driven by an increase in the efficiency with
76 which cloud condensate is converted into precipitation, while changes in the
77 evaporation of falling precipitation was shown to play a smaller role (Lutsko and
78 Cronin, 2018).

79 An increase in ϵ with warming more efficiently depletes the water from the clouds, thus
80 affecting the radiation budget. On the one hand, increase in ϵ with warming was
81 suggested to reduce the anvil cloud coverage and hence increase the outgoing longwave
82 radiation (Lindzen et al., 2001; Mauritsen and Stevens, 2015), thus producing negative
83 feedback. On the other hand, however, it was recently shown that the longwave effect
84 of an ϵ increase is over-compensated for by changes in the shortwave flux (Li et al.,
85 2019), i.e., a large reduction in the cloud optical depth, driving a reduction in the
86 shortwave cooling effect of clouds, dominates the response.

87 The efficiency with which cloud condensate is converted into precipitation is closely
88 linked to the micro-physical properties of the clouds. The autoconversion of cloud
89 droplets into rain becomes significant when liquid water amount and/or droplet radii
90 reach a critical threshold (Freud and Rosenfeld, 2012). An important factor influencing
91 the droplet radii (and also the liquid water amount, to some degree) is the amount of
92 available cloud condensation nuclei (CCN). Generally, an increase in aerosol
93 concentration drives an increase in CCN concentration, which results in more numerous
94 and smaller droplets in the cloud (Twomey, 1974; Warner and Twomey, 1967). The
95 smaller droplets require longer time (or equivalently larger vertical distance) in the
96 clouds to grow by diffusion to the critical size enabling precipitation, thus delaying the
97 initial warm rain formation (Rosenfeld, 2000; Dagan et al., 2015b). Therefore, aerosols
98 could affect ϵ (Khain, 2009).

99 In addition to the effect on rain, aerosols could modify the radiative properties of clouds,
100 by modifying the droplet concentration and size distribution (Twomey, 1974) and by



101 affecting the clouds' macro-physical properties (Albrecht, 1989; Bellouin et al., 2019).
 102 These changes to the radiative properties of clouds result in radiative forcing that could
 103 affect the sea surface temperature [SST (Bellouin et al., 2019)]. Using cloud-resolving
 104 radiative-convective-equilibrium simulations with interactive SST, Khairoutdinov and
 105 Yang (2013) showed that the surface temperature decreases by 1.5K with each 10-fold
 106 increase in aerosol concentration, an effect quite comparable to a 2.1–2.3K SST
 107 warming obtained in a simulation with given (low) aerosol conditions but doubled CO₂
 108 concentration.

109 It has been suggested that cloud feedback and aerosol forcing are not independent of
 110 each other (Mülmenstädt and Feingold, 2018; Igel and van den Heever, 2021). In
 111 addition, the strong links between ϵ and cloud feedback and between ϵ and aerosol
 112 concentration merit a dedicated study on the potential mutual CO₂ and aerosol effect on
 113 clouds and thus also on ECS, which is the aim of the current study.

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116 2. Methods

117 Model description and experimental design

118 The model used herein is the System of Atmospheric Modeling [SAM - (Khairoutdinov
 119 and Randall, 2003)] version 6.11.7. Subgrid-scale fluxes are parameterized using
 120 Smagorinsky's eddy diffusivity model and gravity waves are damped at the top of the
 121 domain. The microphysics scheme used is Morrison et al. (2005) 2-moment bulk
 122 microphysics. The cloud droplet number concentration source assumes that the number
 123 of activated CCN depends on the super-saturation (S) according to a power-law: $CDNC$
 124 $= N_a S^k$, where N_a is the prescribed concentration of CCN active at 1 % supersaturation,
 125 and k is a constant (set in this study to 0.4 - a typical value for maritime conditions).
 126 Changes in N_a serve as a proxy for the change in aerosol concentration. Three levels of
 127 N_a are considered here, covering an extreme range of conditions – 20, 200 and 2000
 128 cm⁻³. While this wide range of conditions is unlikely to exist at any given geographical
 129 location, they are used here in order to cover the range of possible conditions at different
 130 locations and to maximize the effect for establishing better physical understanding. The
 131 activation of CCN at the cloud base is parameterized following Twomey (1959), using
 132 the vertical velocity and CCN spectrum parameters. The model computes cloud water
 133 and ice-crystal effective radius for the radiation; thus, the Twomey effect (Twomey,



134 1977) of both liquid and ice is considered. Direct interactions between aerosols and
 135 radiation are not considered here.

136 The simulations are conducted in a radiative-convective-equilibrium (RCE) mode and
 137 generally follow the RCEMIP (RCE model inter-comparison project (Wing et al.,
 138 2018)) small-domain instructions (but with interactive SST and changes in the CO₂ and
 139 aerosol concentration). The simulations were performed on a square, doubly periodic
 140 domain. In this case, we want to avoid the effect of convective self-aggregation on ϵ ;
 141 thus, the domain size is set to 96x96 km², which was shown to be small enough to
 142 prevent convective self-aggregation (Muller and Held, 2012; Lutsko and Cronin, 2018;
 143 Yanase et al., 2020). The horizontal grid spacing is set to 1km and 68 vertical levels are
 144 used, between 25m and 31km, with vertical grid spacing increasing from 50m near the
 145 surface to roughly 1km at the domain top. A time step of 10s is used, and radiative
 146 fluxes are calculated every 5 min using the CAM radiation scheme (Collins et al., 2006).
 147 The output resolution for all fields is 1h. The incoming solar radiation is fixed at 551.58
 148 Wm⁻² with a zenith angle of 42.05° (Wing et al., 2018), producing a net insolation close
 149 to the tropical-mean value. Convection is initialized with a small thermal noise added
 150 near the surface at the beginning of the simulation. The initial conditions for the
 151 simulations are as in Wing et al. (2018).

152 Greenhouse gases are varied for three different levels: pre-industrial level (280 PPM,
 153 1xCO₂), 2 times pre-industrial level (2xCO₂) and 4 times pre-industrial level (4xCO₂).
 154 As in the case of the aerosol concentrations, the large range of CO₂ conditions covered
 155 here are used to examine the clouds' sensitivity to greenhouse gas concentrations under
 156 a wide range of conditions. Nine different simulations, with all possible combinations
 157 of N_a and CO₂ concentrations, were conducted.

158 In all simulations, the SST is interactive and predicted by a slab ocean model (SOM).
 159 The SOM's mixed layer depth is set to 5m, which represented a compromise between a
 160 relatively deep layer (≥ 10 m), which reduces SST noise (Khairoutdinov and Yang,
 161 2013), and a relatively shallow layer ($\ll 1$ m), which requires a shorter computation time
 162 for equilibrium (Romps, 2020). As in Romps (2020), the SOM is cooled at a rate of 112
 163 Wm⁻² in order to ensure that the simulations with 1xCO₂ are kept at around the initial
 164 SST of 300K (Fig. 1). Each simulation was run for 1800 days, which is sufficient for
 165 reaching close to equilibrium (the surface energy imbalance is ≤ 0.1 Wm⁻² in all



simulations during the last 150 days). The last 150 days of each run are used for statistical sampling (gray shading in Fig. 1).

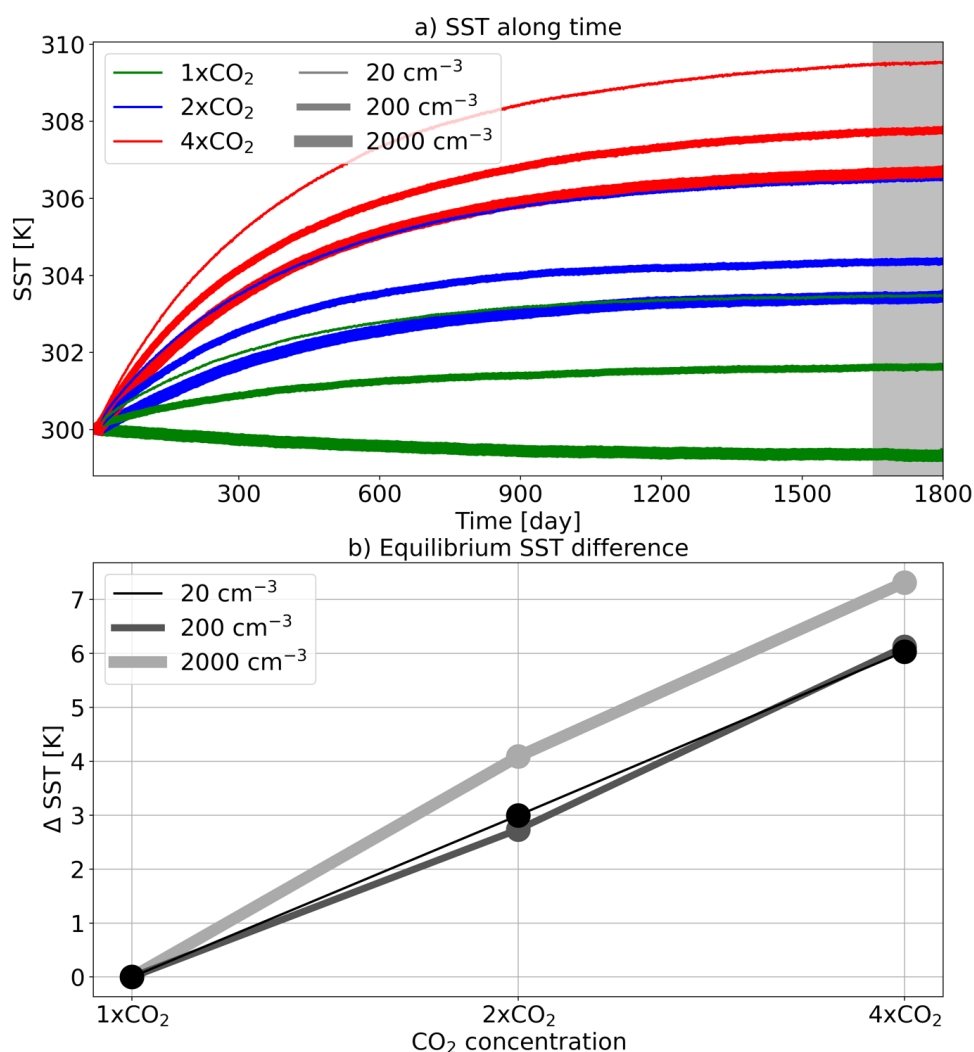


Figure 1. a) the sea surface temperature (SST) along time for the different simulations conducted under different aerosol and CO₂ concentrations. The gray shaded area is referred to as equilibrium conditions. b) Change in equilibrium SST due to a change in CO₂ concentration (compared to the 1xCO₂ case of each aerosol concentration), for the different aerosol concentrations (the different curves).



3. Results

Figure 1 presents the SST of the different simulations along time (panel a) and the change in the equilibrium SST with the CO₂ concentration for the different N_a cases (panel b). As expected, the equilibrium SST (gray shading in Fig. 1a) increases with the CO₂ concentration and decreases with N_a concentration. However, the rate of increase in equilibrium SST with CO₂ concentration increases under extremely high N_a concentrations (2000 cm⁻³), compared with the low and medium N_a concentrations (20 and 200 cm⁻³, respectively - Fig. 1b). Calculating the average ECS based on the three combinations available for each N_a condition [2xCO₂-1xCO₂, 4xCO₂-2xCO₂ and (4xCO₂-1xCO₂)/2], demonstrates that it increases with N_a from 3.0K at the lowest N_a to 3.7K at the highest N_a (i.e., a 23% increase – Table 1).

Table 1. Average equilibrium climate sensitivity (ECS), cloud-feedback parameter (λ_{cloud}), hydrological sensitivity (η), and change in precipitation efficiency ($\Delta\epsilon$) of the three combinations available for each N_a condition [2xCO₂-1xCO₂, 4xCO₂-2xCO₂ and 4xCO₂-1xCO₂]. For the calculation of the average ECS, the difference between 4xCO₂ and 1xCO₂ is divided by 2. The rest of the quantities are normalized by the SST change between the relevant simulations.

N_a [cm ⁻³]	ECS [K]	λ_{cloud} [W m ⁻² K ⁻¹]	η [% K ⁻¹]	$\Delta\epsilon$ [% K ⁻¹]
20	3.0	-0.45	3.8	1.2
200	3.1	-0.38	4.3	1.3
2000	3.7	-0.08	4.6	2.7

Figure 2 presents the time and domain mean vertical profiles of temperature and water vapor mixing ratio (q_v) in the different simulations (panels a and b) and their difference from the simulation with the lowest N_a and CO₂ concentrations (panels c and d). It demonstrates, as expected, that the vertical profile of air temperature is set by the surface temperature (increases with CO₂ concentrations and decreases with N_a) with an amplification of the change at the upper troposphere, as the profiles follow the moist adiabatic lapse-rate. It also shows that q_c increases with the temperature, as expected (Held and Soden, 2006).

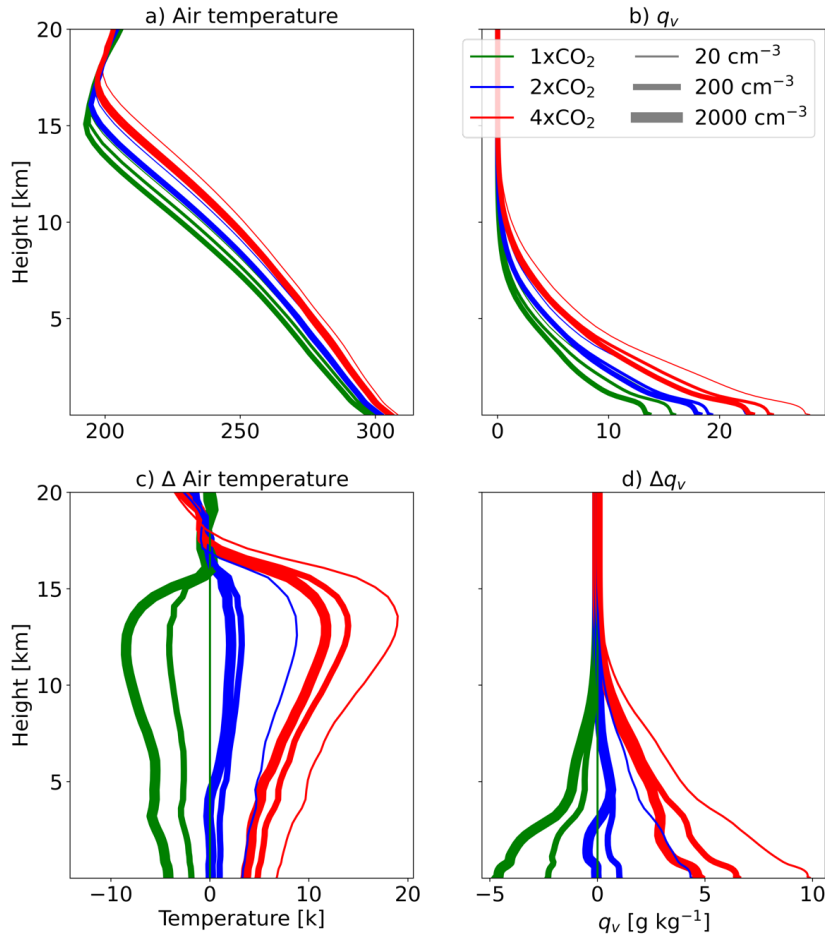


Figure 2. Time and domain mean vertical profiles of air temperature and water vapor mixing ratio (q_v) in the different simulations (a and b) and how they differ from the simulation with the lowest N_a and CO_2 concentrations (panels c and d).

In order to understand the increase in ECS with N_a , we next examine the top-of-atmosphere (TOA) energy budget. Figure 3 presents the change in the net shortwave and longwave TOA energy gain (R^{SW} and R^{LW} , respectively) with the CO_2 concentration for the different N_a conditions. In addition, Fig. 3 presents the change in the cloud radiative effect (CRE) with increasing the CO_2 concentration, where CRE is computed by subtracting the clear-sky from the all-sky TOA radiative fluxes ($R - R_{\text{clear-sky}}$), again for the shortwave and longwave separately (CRE^{SW} and CRE^{LW} ,



218 respectively). Figure 3a and b demonstrates that under equilibrium conditions R^{SW}
 219 increases, while R^{LW} decreases with the CO_2 concentration. However, the rate of change
 220 in both R^{SW} and R^{LW} is much faster under the high N_a conditions than under the low
 221 and medium N_a conditions. The trend in CRE^{SW} under the different N_a conditions (Fig.
 222 3c) resembles the trend in R^{SW} , suggesting that the clouds' response dominates the
 223 changes in the TOA shortwave fluxes. CRE^{LW} , on the other hand, decreases at a similar
 224 rate with CO_2 concentration for the different N_a conditions (Fig. 3d). Thus, the different
 225 decrease rates in R^{LW} with CO_2 concentration for the different N_a conditions (Fig. 3b)
 226 must be driven by clear-sky changes (specifically, the plank and the lapse-rate
 227 feedbacks – see Fig. 2 above).

228 In Table 1 above, we estimate the average cloud radiative feedback (λ_{cloud}) as the change
 229 in CRE with increasing surface temperature, i.e., $\lambda_{\text{cloud}} = d\text{CRE}/dT$, for the different N_a
 230 conditions. The table shows that λ_{cloud} becomes less negative with the increase in N_a ,
 231 leading to higher climate sensitivity. The differences in the values of λ_{cloud} between the
 232 different N_a conditions is mostly derived from the shortwave part of the spectrum (Fig.
 233 3).

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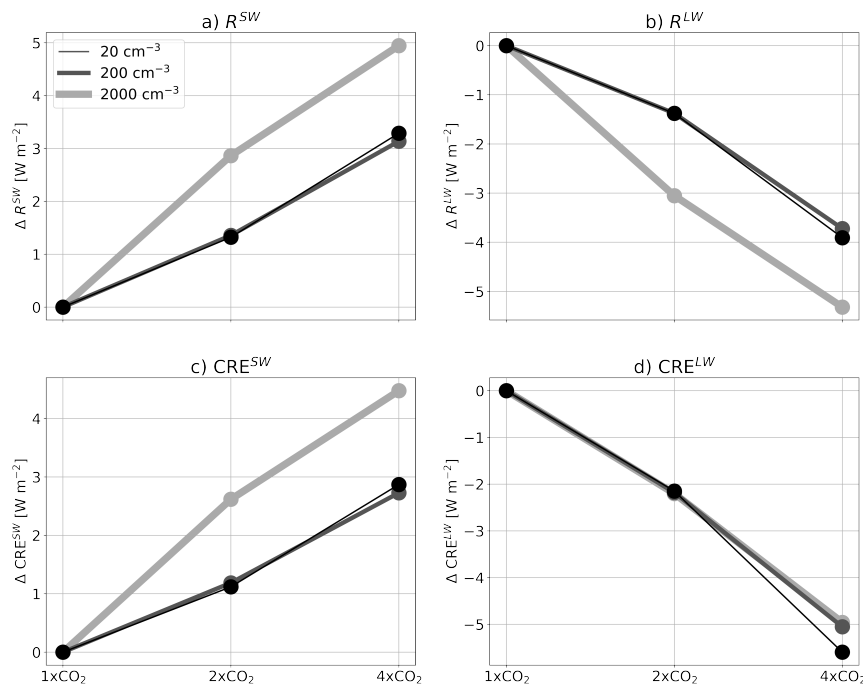


Figure 3. The change in the net top-of-atmosphere energy gain (R) in the shortwave (a) and in the longwave (b), and the change in the cloud radiative effect (CRE) in the shortwave (c) and in the longwave (d), due to a change in the CO_2 concentration (compared to the 1x CO_2 case of each aerosol concentration), for the different aerosol concentrations (the different curves).

Thus far, we have seen that the ECS increases with N_a (Fig. 1 and Table 1) and that this increase can be explained by changes in λ_{cloud} (Table 1) and specifically in CRE^{SW} (Fig. 3). To understand the changes in the cloud properties driving the changes in λ_{cloud} , and hence also in ECS, under the different N_a conditions, in Fig. 4 we present the change in cloud liquid water path (CWP), ice water path (IWP), rain water path (RWP) and cloud fraction (CF) with increasing CO_2 concentrations for the different N_a conditions. The figure shows that the CWP decreases with the CO_2 concentrations at a much faster rate (about 3 times faster) under the highest N_a conditions compared to the low and medium N_a conditions (Fig. 4a). The changes in the IWP, on the other hand, are about an order of magnitude smaller than the changes in CWP and are not consistent in sign for the different N_a conditions (Fig. 4b). The RWP increases with the CO_2 concentrations at a slightly faster rate (about 20% faster) under the highest N_a conditions compared to the



low and medium N_a conditions (however the response is non-monotonic with N_a - Fig. 4c). The CF decreases with the CO_2 concentrations, at a similar rate for the different N_a conditions (about 1.5% decrease in CF for each doubling of the CO_2 concentrations - Fig. 4d).

The faster decrease in CWP with CO_2 concentrations under high N_a conditions drives the faster increase in CRE^{SW} as the clouds become less opaque in the shortwave. We note that the difference in CRE^{SW} trend under different N_a conditions could not be explained by the minor differences in the CF trends. In addition, the small differences in the IWP between the different N_a conditions are consistent with the small differences in the CRE^{LW} seen above. The general increase in RWP with CO_2 concentrations is consistent with an increase in rain efficiency with warming (Lutsko and Cronin, 2018), as elaborated below.

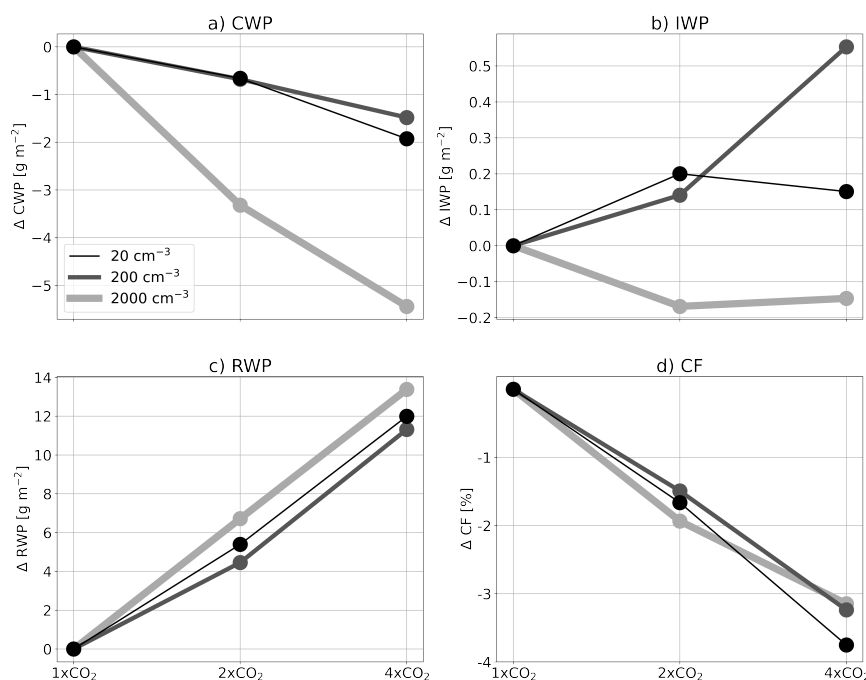
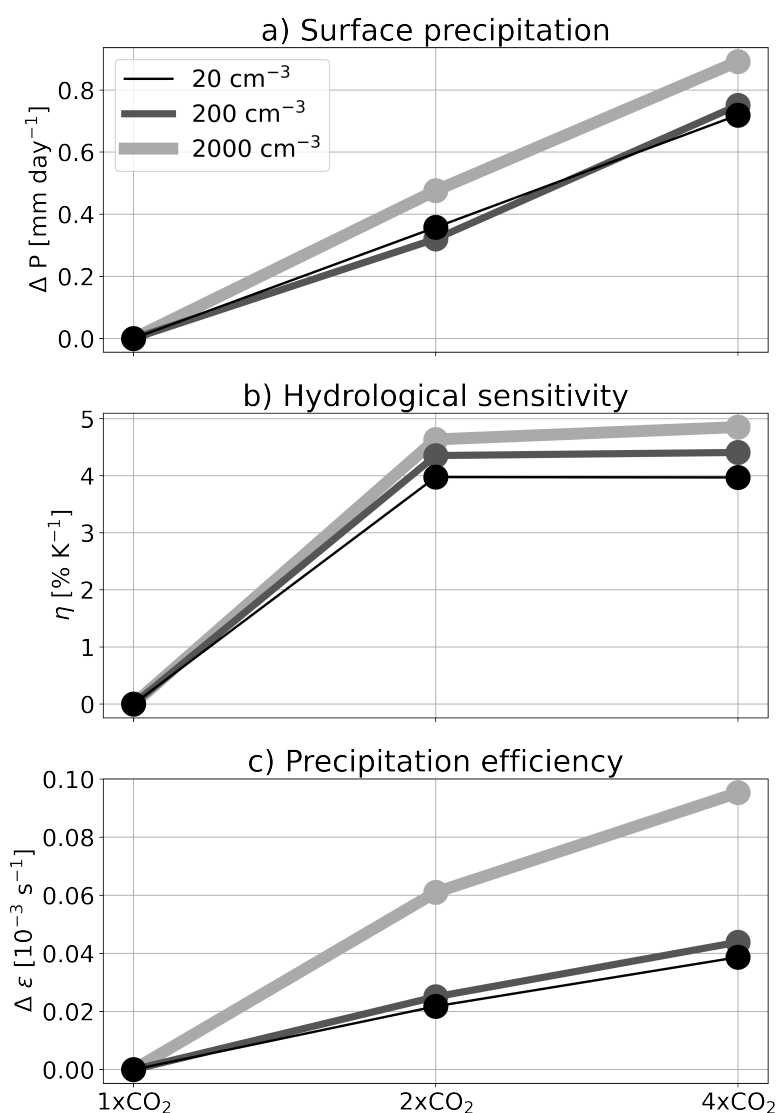


Figure 4. The change in: a) cloud liquid water path (CWP), b) ice water path (IWP), c) rain water path (RWP), and d) cloud fraction (CF) due to a change in the CO_2 concentration (compared to the 1x CO_2 case of each aerosol concentration), for the different aerosol concentrations (the different curves).



274 Figure 4 suggests that the largest difference in the cloud response to CO_2 under different
 275 N_a conditions is due to changes in CWP. The higher sensitivity of CWP to CO_2
 276 concentration under higher N_a conditions can explain the higher λ_{cloud} and thus also the
 277 larger ECS. Hence, the question arises: What causes the faster reduction in CWP with
 278 CO_2 concentration under high N_a conditions? A major sink for CWP is via precipitation.
 279 Hence, in Fig. 5 we present the change in the mean surface precipitation rate, the
 280 hydrological sensitivity (η - the rate of change in the surface precipitation per 1K
 281 increase in surface temperature) and the precipitation efficiency (ϵ - calculated
 282 following Li et al. (2022) as the ratio of surface precipitation-to-condensed water path,
 283 i.e., $\text{CWP} + \text{IWP} + \text{RWP}$). As expected, the surface precipitation increases with CO_2 (i.e.,
 284 η is positive) and so does ϵ (Lutsko and Cronin, 2018). This is true for all N_a conditions.
 285 However, the rates of increase in surface precipitation and ϵ with CO_2 concentration
 286 are higher under the highest N_a conditions (see also Table 1). We note that the larger
 287 rate of increase in surface precipitation under the highest N_a conditions is not solely due
 288 to the higher surface temperature increase, as η also increases with N_a .
 289 The much larger (more than double- Table 1) rate of increase in ϵ with the CO_2
 290 concentration under the highest N_a conditions depletes the cloud water more efficiently
 291 from the atmosphere, leading to a faster reduction in CWP with CO_2 concentration (Fig.
 292 4), which in turn leads to higher λ_{cloud} and ECS. The faster increase in RWP with CO_2
 293 concentration under the highest N_a conditions presented in Fig. 4c is consistent with
 294 this explanation.
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 299 **Figure 5. The change in: a) surface precipitation, b) hydrological sensitivity (η), and c)**
 300 **precipitation efficiency (ϵ) due to a change in the CO₂ concentration (compared to the**
 301 **1xCO₂ case of each aerosol concentration), for the different aerosol concentrations (the**
 302 **different curves).**

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 304 The last open question is why ϵ increases faster with CO₂ concentration under the
 305 highest N_a conditions. The increase in ϵ with warming was shown to be mostly driven
 306 by an increase in the efficiency with which cloud condensate is converted into

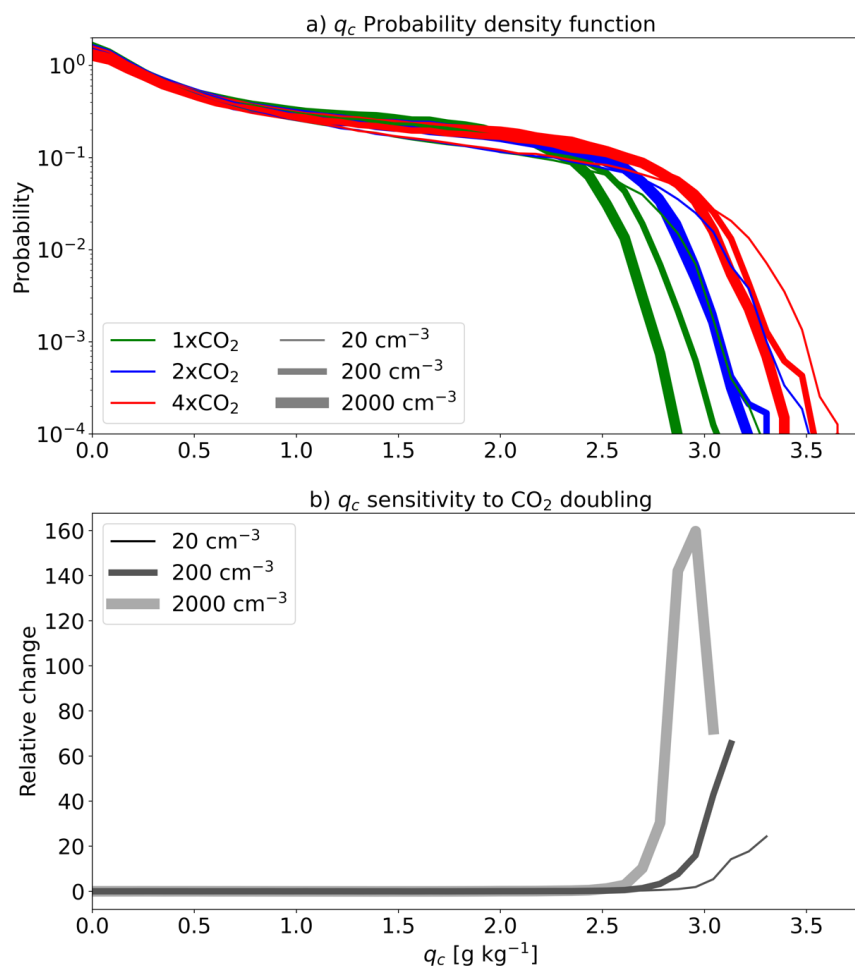


307 precipitation (Lutsko and Cronin, 2018). As was mentioned in the introduction, the
 308 conversion of cloud condensate into precipitation (or autoconversion of cloud droplets)
 309 becomes significant only when liquid water amount and/or droplet radii reach a critical
 310 threshold (Freud and Rosenfeld, 2012). To understand the faster ϵ increases with CO₂
 311 concentration under the highest N_a conditions, we present the histograms over the
 312 domain and time (during the last 150 days of the simulations based on 3D output in 1-
 313 hour resolution) of liquid cloud droplets mixing ratio (q_c – Fig. 6) and mean cloud
 314 droplet radii (\bar{r}_c – Fig. 7) around the height of the maximum in cloud droplet effective
 315 radii (1950m) and its mean sensitivity to doubling of CO₂ concentration for each N_a
 316 condition.

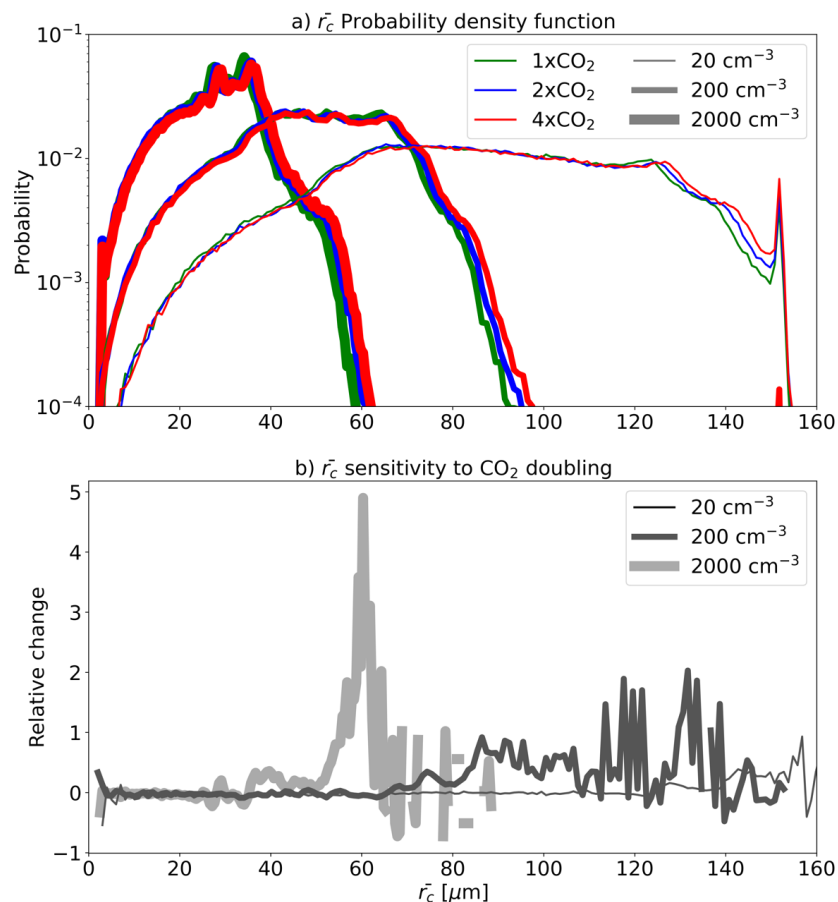
317 Figure 6 demonstrates that the cut-off of the q_c distribution (the mixing ratio for which
 318 the probability density function starts to decrease sharply) increases with the CO₂
 319 concentration and decreases with the aerosol concentration. However, the sensitivity of
 320 the relatively large q_c with CO₂ concentration is significantly larger under high aerosol
 321 concentrations compared to the lower aerosol concentrations (Fig. 6b). The larger
 322 relative increase in high q_c promotes the autoconversion process and hence enhances ϵ ,
 323 more under high aerosol concentrations than under low aerosol concentrations.

324 Figure 7 demonstrates, in line with expectations, that N_a has a strong effect on \bar{r}_c . In
 325 addition, it shows that under all N_a conditions, \bar{r}_c increases with the CO₂ concentration.
 326 This could be explained by the increase in the availability of water vapor (Fig. 2),
 327 which, for a given N_a conditions, enable larger diffusional growth of the droplets. Here
 328 again, the highest N_a conditions demonstrate the largest sensitivity of \bar{r}_c to CO₂
 329 concentration, especially at the right-hand side of the distribution (Fig. 7b). This could
 330 be explained by the fact that under these high N_a conditions, the cloud droplet growth
 331 is primarily limited by the availability of water vapor, as large number of droplets
 332 compete for the available water vapor (Koren et al., 2014; Dagan et al., 2015a; Reutter
 333 et al., 2009). Similarly to the q_c case, the larger relative increase in the relatively large
 334 droplets promotes the autoconversion process and hence enhances ϵ , more under high
 335 aerosol concentrations than under lower aerosol concentrations.

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 340 **Figure 6. Probability density functions (PDF) of the cloud droplet mixing ratio (q_c) for the**
 341 **different simulations (a), and the mean sensitivity of the q_c PDF to a doubling of the CO $_2$**
 342 **concentration based on the three combinations available for each N_a condition [2xCO $_2$ -**
 343 **1xCO $_2$, 4xCO $_2$ -2xCO $_2$ and (4xCO $_2$ -1xCO $_2$)/2] (b), calculated for the heights around which**
 344 **the cloud droplet effective radii reach a maximum (1950m) and using 3-D files output**
 345 **every hour of the last 150 days of the simulations. Note the logarithmic scales for the y-**
 346 **axes of a.**
 347



348
 349 **Figure 7.** Probability density functions (PDF) of cloud droplet mean radii (\bar{r}_c) for the
 350 different simulations (a), and the mean sensitivity of the \bar{r}_c PDF to a doubling of the CO₂
 351 concentration based on the three combinations available for each N_a condition [2xCO₂-
 352 1xCO₂, 4xCO₂-2xCO₂ and (4xCO₂-1xCO₂)/2] (b), calculated for the heights around which
 353 the cloud droplet effective radii reach a maximum (1950m) and using 3-D files output
 354 every hour of the last 150 days of the simulations. Note the logarithmic scales for the y-
 355 axes of a.

356

357 4. Summary and conclusions

358 The role of clouds in a climate-change is manifested by two pathways: (1) effects of
 359 anthropogenic aerosol on clouds, and (2) feedback that clouds exert on the changing
 360 climate. These two pathways are usually studied separately, and even by different



361 scientific communities. In this paper, we demonstrate that the two pathways are closely
362 linked to each other and should be examined concurrently.
363 Using long, idealized RCE simulations over a small domain with a slab ocean model,
364 we demonstrate that the ECS, i.e., the increase in surface temperature under equilibrium
365 conditions due to doubling of the CO₂ concentration, increases with the aerosol
366 concentration. The ECS increase is explained by a faster increase in precipitation
367 efficiency with warming under high aerosol concentrations, which more efficiently
368 depletes the water from the cloud and thus is manifested as an increase in the cloud
369 feedback parameter. The precipitation efficiency increases faster under high aerosol
370 concentration due to a higher sensitivity of the relatively high liquid water mixing ratios
371 and the relatively large mean droplet sizes to a CO₂ concentration increase.
372 The results presented here are based on idealized simulations over a small domain.
373 Under more realistic conditions, other processes, not included here, that could affect
374 the precipitation efficiency and hence the general trend will be introduced. In particular,
375 convective self-aggregation could be of interest as, while it is inhibited in the small
376 domain used here, it was shown to affect precipitation efficiency (Lutsko et al., 2021)
377 and to be affected by aerosols (Nishant et al., 2019). Other processes that should be
378 accounted for in future research include the presence of large-scale circulation and
379 direct aerosol radiative effects (Dagan et al., 2019; Dingley et al., 2021).
380 The results presented here suggest a strong connection between cloud feedback and
381 aerosol-cloud interactions. The regulation of aerosol emissions is known to be more
382 effective than the effort to reduce greenhouse gas emissions. This, together with the
383 short lifetime of aerosols in the atmosphere, has resulted in a reduction in the value of
384 the global mean aerosol effective radiative forcing in recent years (Quaas et al., 2022).
385 If the conclusions of this paper hold under higher levels of complexity (e.g., large-scale
386 circulation, convective self-aggregation, etc.) this might mean that the reduction in
387 global aerosol emissions could lead to a reduction in ECS, which could compensate, at
388 least partially, for the reduction in the negative forcing induced by aerosols (Quaas et
389 al., 2022; Bellouin et al., 2019), thus providing yet additional motivation for reducing
390 aerosol emissions globally.

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392 **Code availability**

393 SAM is publicly available at: <http://rossby.msrc.sunysb.edu/~marat/SAM.html>

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395 **Data availability**

396 The data presented in this study will become publicly available via zenodo prior to
 397 publication.

398

399 **Author contributions**

400 GD carried out the simulations and analyses presented and prepared the article.

401

402 **Competing interests**

403 The authors declare that they have no conflict of interest.

404

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