



1 Insights of warm cloud biases in CAM5 and CAM6 from the single-column modeling

- 2 framework and ACE-ENA observations
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11 Abstract

12 There has been a growing concern that most climate models predict too frequent precipitation, 13 likely due to lack of reliable sub-grid variability and vertical variations of microphysical processes 14 in low-level warm clouds. In this study, the warm cloud physics parameterizations in the singe-15 column configurations of NCAR Community Atmospheric Model version 6 and 5 (SCAM6 and SCAM5, respectively) are evaluated using ground-based and airborne observations from the DOE 16 17 ARM Aerosol and Cloud Experiments in the Eastern North Atlantic (ACE-ENA) field campaign 18 near the Azores islands during 2017-2018. Eight-month SCM simulations show that both SCAM6 19 and SCAM5 can generally reproduce marine boundary-layer cloud structure, major macrophysical 20 properties, and their transition. The improvement of warm cloud properties from CAM5 to CAM6 21 physics can be found compared to the observations. Meanwhile, both physical schemes 22 underestimate cloud liquid water content, cloud droplet size, and rain liquid water content, but 23 overestimate surface rainfall. Modeled cloud condensation nuclei (CCN) concentrations are 24 comparable with aircraft observed ones in the summer but overestimated by a factor of two in 25 winter, largely due to the biases in the long-range transport of anthropogenic aerosols like sulfate. 26 We also test the newly recalibrated autoconversion and accretion parameterizations that account 27 for vertical variations of droplet size. Compared to the observations, more significant improvement 28 is found in SCAM5 than in SCAM6. This result is likely explained by the introduction of sub-grid 29 variations of cloud properties in CAM6 cloud microphysics, which further suppresses the scheme 30 sensitivity to individual warm rain microphysical parameters. The predicted cloud susceptibilities 31 to CCN perturbations in CAM6 are within a reasonable range, indicating significant progress since 32 CAM5 which produces too strong aerosol indirect effect. The present study emphasizes the 33 importance of understanding biases in cloud physics parameterizations by combining SCM with 34 in situ observations.





35 1. Motivation and Background

Marine boundary-layer (MBL) clouds are crucial for the global radiation budget, as they 36 37 efficiently regulate the solar radiation reaching the ocean surface and largely determine the climate 38 sensitivity (Dong et al., 2022; Sherwood et al., 2020). However, numerical simulations of MBL 39 clouds in global climate models (GCM) remain challenging, mainly due to the mismatch of the 40 spatial scales of MBL clouds (tens of meters) and GCM grids (~ 100 km). Therefore, empirical 41 parameterizations of subscale cloud properties and variabilities, for both microphysics and 42 macrophysics, play a critical role in predicting MBL clouds and precipitation in GCM (Wang et 43 al., 2013). Consequently, how to constrain and improve those cloud parameterizations using the 44 state-of-the-art observations become an important issue. One challenging aspect of the GCM cloud evaluation lies in the tight coupling between cloud physics and dynamics, as cloud microphysics 45 46 can feedback to dynamics and thermodynamics through heating profile alteration or radiation flux 47 interference (Wang et al., 2014, 2020).

48 To better probe the uncertainty source in the cloud physical parameterizations, a simplified 49 GCM configuration has been developed to separate cloud physics from large-scale dynamical and thermodynamical conditions. The so-called single column model (SCM) is ideal for utilizing in 50 51 situ observations from the field campaigns that are normally conducted intensively over the 52 targeted area (Zhao et al., 2021). The modeling framework adopted in this study, NCAR 53 Community Earth System Model (CESM), has a long history of providing such a modeling tool 54 along with the development of its comprehensive models (Liu et al., 2007; Gettleman et al., 2019). 55 With more added features and enhanced representations of cloud and aerosol in the cloud physical 56 parametrizations in CESM version 1 and 2, it is valuable to evaluate the single-column versions 57 of them using the recent field measurements.

58 The Eastern North Atlantic (ENA) is an ideal place around the world to study MBL clouds, 59 considering the prevailing MBL cloud occurrence, diverse mesoscale meteorological conditions (Jensen et al., 2021; Zheng et al., 2022a), and distinctive aerosol sources (Wang, J. et al., 2021). 60 61 A recent field campaign, the Aerosol and Cloud Experiments in the Eastern North Atlantic (ACE-ENA) provide ample ground-based and in situ aircraft observations of cloud micro- and 62 63 macrophysics, aerosol properties, as well as atmospheric states over a whole summer and winter 64 (Wang, J. et al. 2021; Wu et al., 2020). Recent WRF large-eddy simulations (LES) driven by the ERA5 reanalysis over the ENA well reproduce the general vertical variations of meteorological 65





66 factors and cloud cellular structure (Wang et al., 2020). Meanwhile, LES and observations exhibit 67 substantial discrepancies in the evolution of MBL clouds in two selected stratocumulus cases during the ACE-ENA field campaign, likely due to the biases in both warm cloud physical 68 69 parameterizations and large-scale forcing. Those issues motivate us to look for stronger 70 observational constraints in the single-column framework which minimizes the propagated errors from large-scale forcing. In this study, we use the ARM 3-hourly large-scale forcing of 71 72 atmospheric states specifically developed for the ACE-ENA Intensive Observation Periods (IOP) 73 to drive SCM.

74 The uncertainties of warm cloud physics in the atmospheric component of CESM1/2 have 75 been reported in many previous studies (e.g. Kay et al., 2016; Zhao et al., 2022), while most of 76 them focused on addressing the issues on the global scale. Leveraging the continuous radar 77 retrievals of MBL cloud and drizzle microphysical properties during ACE ENA, Dong et al. (2021) 78 modified the parameterizations of two key processes in warm cloud microphysics in CAM5, i.e., 79 autoconversion from cloud droplets to rain drops and accretion of cloud droplets by raindrops. 80 They showed that by applying this set of new parameterizations to CAM5 in global climate simulations, precipitation frequency is generally reduced but with enhanced intensity mainly in the 81 82 mid-latitude regions, alleviating the long-lasting issue in the climate models, e.g., "too frequent 83 and too light precipitation". Even the cloud radiative effect and top-of-atmosphere radiative flux 84 simulations can be improved consequently. Therefore, a remaining and outstanding question lies 85 in whether such a new scheme works well over the location where the radar observational 86 constraints come from originally. The single-column modeling framework enables us to examine 87 the effect of the modified microphysical scheme on the local scale.

88 2. Methodology

89 2.1 Single column version of Community Atmospheric Model

In this study, we use single-column configuration of Community Atmospheric Model version 6 (referred to as SCAM6 thereafter) in the Community Earth System Model (CEMS 2.1.1). NCAR CESM is a community GCM that has been widely used to study the climate change (Yeager et al., 2018), precipitation extremes (Wang et al., 2016), cloud processes (Wang et al., 2018), and aerosol-cloud-radiation-circulation feedbacks in the Earth system (Wang et al., 2015). The atmosphere component of CESM2 (CAM6) has been modified substantially with a range of enhancements and improvements for the representation of physical processes since its last version,





97 CAM5. In particular, the modifications on the aerosol and cloud parameterizations are extensive. 98 For example, a multivariate PDF-based third-order turbulence closure parameterization scheme, 99 Cloud Layers Unified By Binormals (CLUBB), is implemented to unify the representation of 100 boundary layer, shallow convection, and stratiform macrophysics in the model (Bogenschutz et al., 101 2013; Golaz and Larson, 2002). The two-moment cloud microphysical scheme is updated to its 102 version 2 (Gettelman and Morrison, 2015) by incorporating prognostic precipitation (rain and 103 snow), sub-stepping technique, and re-tuned autoconversion scheme which is critical for aerosol 104 indirect effect on cloud lifetime and precipitation (Malavelle et al., 2017). The strong coupling 105 between CLUBB and MG2 also facilitates cloud-aerosol-environment interactions. Deep 106 convection remains parameterized by the Zhang-McFarlane (1995) scheme and has been re-tuned 107 to increase the sensitivity to convective inhibition, which could potentially signify the impact of 108 absorbing aerosols within the planetary boundary layer (PBL). Parameterizations of homogeneous 109 ice nucleation and heterogeneous immersion nucleation in cirrus clouds (Liu and Penner, 2005) 110 explicitly consider the effects of sulfate and dust aerosol serving as ice nuclei on the cold clouds.

111 The aerosol module in CESM is updated from a three-mode to four-mode approach (MAM4) to better consider the aging processes of black carbon in the atmosphere (Liu et al., 2016; 112 113 Wang et al., 2018). Six types of aerosols with different hygroscopicity and optical properties are 114 considered in MAM3, including sulfate, black carbon (BC), primary organic matter (POM), 115 secondary organic aerosol (SOA), dust and sea salt. The aerosol module accounts for most of the 116 important processes associated with atmospheric aerosols, including emission, nucleation, 117 coagulation, condensational growth, gas and aqueous-phase chemistry, dry deposition, in-cloud 118 and below-cloud scavenging, re-production from evaporated cloud droplets and suppression, as 119 well as agricultural, deforestation, and peat fires (Li and Lawrence, 2017). To test the impacts of 120 cloud physical parameterization on the model fidelity, we also conduct the single-column 121 simulations using the CAM5 physics (SCAM5) under the same large-scale forcing data.

Because the ACE-ENA is a relatively new field campaign and does not have a pre-defined case in SCAM6, we create a new case in CAM6 based on a new set of large-scale data for this IOP. To cover the full IOP in our simulations, we run SCAM over 8 months from June 1, 2017, to Feb 1, 2018. The large-scale forcing over the ARM-ENA is developed from the constrained variational analysis (VARANAL, Xie et al., 2004; Tang et al., 2019). VARANAL is based on ERA5 reanalysis (Copernicus Climate Change Service, 2017) with the additional input of





observations from the ARM ENA site incorporated into the variational analysis, to represent the atmospheric states over a Global Climate Model (GCM) grid box. The original VARANAL data is produced specifically for the ACE-ENA IOP, with a temporal resolution of 3-hour and 45 vertical levels.

To minimize the biases in aerosol advection and dynamical forcing, aerosol and the temperature fields are nudged to their initial conditions on different timescales, varying from 10 days at the bottom of the model to 2 days at the top of the model (Gettelman et al., 2019). Also, to simulate the right seasonal variations of aerosol and temperature initial conditions, each of our model integration only lasts one month, and a new sequential run will follow with updated initial conditions. By doing so the seasonality of aerosols will follow that of climatology on the monthly basis.

139 2.2 ACE-ENA observations

140 Aircraft in situ observations during the ACE-ENA provide best available characterizations 141 of cloud and aerosol vertical distributions, with differentiation of aerosol types and hygroscopicity. 142 During the two IOPs, 39 flights were deployed to collect data for 39 days, 20 in the summer IOP, 19 in the winter IOP. Meanwhile, ground-based observations were conducted simultaneously and 143 144 consecutively. Based on the Ka-band ARM Zenith Radar (KAZR) measurements, cloud and rain 145 microphysical properties (cloud droplet effective radius, r_c ; cloud droplet number concentration, 146 N_c ; cloud liquid water content, *CLWC*; rain droplet mass median radius, $r_{m,r}$; rain droplet number 147 concentration, N_r ; and rain liquid water content, *RLWC*) over the ARM ENA site can be retrieved 148 (Wu et al. 2020). The cloud and drizzle microphysical retrievals were validated by the aircraft in-149 situ measurements from ACE-ENA field campaign, with the estimated median uncertainties of ~15% for r_c ; ~30% for $r_{m,r}$; and ~50% for N_r and RLWC. Note that the subscript "c" denotes 150 151 cloud and subscript "r" denotes rain. The model counterparts are extracted and compared with the 152 retrieval, except the $r_{m,r}$ which is not an output from the model. Following the method in Wu et al. 153 (2020) equation 2a, the $r_{m,r}$ can be calculated by:

154
$$r_{m,r} = \left(\frac{RLWC*3.67^4}{\rho_{W}*N_W*8\pi}\right)^{1/4}$$
(1)

155 where the ρ_w is water density, and the N_W is the normalized drizzle number concentration ($N_W = N_r/r_{m,r}$). Furthermore, the *CLWC* and *RLWC* are scaled by the cloud (rain) fraction within the 157 grid box to match the retrievals.





158 For the aircraft in-situ measurements, the Passive Cavity Aerosol Spectrometer (PCASP) 159 measured the aerosols with the size range from 0.1 μ m to 3.2 μ m (Goldberger, 2020), hence the accumulation mode aerosol number concentration (N_{Acc}) can be derived from the PCASP 0.1 μ m 160 to 1.0 μ m measurement. The CCN number concentration (N_{CCN}) is obtained by the CCN-200 161 162 particle counter on board the G-1 aircraft. The N_{CCN} is a measurement under the controlled 163 supersaturation of 0.35 % with a humidified particle size range from 0.75 to $10 \,\mu\text{m}$ (Uin and Mei, 164 2019). The PM1 aerosol chemical components mass concentrations are measured by the Aerodyne 165 High-Resolution Time-of-Flight Aerosol Mass Spectrometer (HR-ToF-AMS). The accuracy of each individual instrument can be found in the instrument handbooks available on the ARM 166 167 website. To make better comparisons, this study only selects the research flights with a 'L' shape 168 pattern center at the ARM-ENA site. The SCAM6 samples are selected within each time duration 169 of the aircraft cases. Note that the aircraft cases are selected up to end of Jan 2018 due to the end 170 of SCAM6 simulations. To ensure the apple-to-apple comparison between model and observations, the cloud and rain samples are selected following the same criteria: 1) $4 \mu m < r_c < 25 \mu m$; 2) 171 $CLWC > 0.01 \ gm^{-3}$; 3) $N_c > 1 \ cm^{-3}$; and 4) $RLWC > 1 \times 10^{-4} \ gm^{-3}$. The geopotential 172 173 height from the model output is extracted for each time step, hence the quantities at pressure level 174 can be converted to height level and compared with the observation results. Both model and 175 observation results are limited to below 3km.

176 3. Evaluation of SCAM6 using ACE-ENA observations

177 **3.1 Meteorological conditions**

178 To understand the cloud and drizzle property differences between simulations and 179 observations, we first evaluate the SCAM6 simulated meteorological conditions by the ARM Interpolated Sonde (INTERPSONDE) value-added product (VAP), which is an independent 180 181 dataset from the large-scale forcing data used to drive the SCM. As shown in Fig. 1, the simulated 182 air temperature (T_{air}) values are comparable to the observed ones with clear seasonal variations. 183 The statistics from the 8-month simulations shows that the differences in both mean and median 184 T_{air} agree within 1% to the observed ones, supporting the high fidelity of the model to reproduce 185 the temperature field. The situation of the moisture field is slightly different. Even though the 186 model captures the evolution of relative humidity (RH) throughout 8 months, both mean and 187 median RH have ~10% bias in the model. In particular, the biases become more severe when RH values fall into the high humidity regime. The RH frequency within the 90-100% range is about 188





two times higher in SCAM6 than Observation. A comparison of specific humidity (SH) shows that SCAM6 overpredicts SH by 11.8%, indicating that the RH bias stems from the absolute moisture bias, instead of temperature bias. It can be explained by the fact that temperature field is relaxed to the input as an additional constraint, while SH is predicted as a fully prognostic variable in SCM. We will examine the potential impact of moisture uncertainty in the large-scale forcing data on the cloud property simulation through sensitivity, and the results will be discussed below.

195 **3.2 Cloud properties**

196 We first compare CLWC and RLWC over time and altitude dimensions between SCAM6 197 simulations and ARM radar-lidar-MWR retrievals (Figure 2a-d). The simulated CLWC values in 198 both time and altitude are generally consistent with the ARM retrievals. More specifically, SCAM6 199 can capture those thick clouds in early November and middle December due to the prevalent 200 frontal systems during that time of the year. However, some high CLWC values are not reproduced 201 in the model. Similarly, the temporal evolution of simulated RLWC agrees with the retrievals as 202 demonstrated in Figure 2c-d, however, their magnitudes are much lower than the retrievals. The 203 relatively coarse vertical resolution near the PBL is discernable from the discretized cloud vertical 204 distribution in the model simulations (Fig. 2a, c). However, the vertical development of different 205 cloud types (stratus, stratocumulus, and cumulus) and their transitions are generally reproduced by 206 SCAM6. When cumulus occurs with cloud top height greater that 2000 m, the model can always 207 capture them. Despite good agreement on clout top height, SCAM6 overpredicts CLWC and 208 RLWC frequency near the surface (< 200 m) compared to the observations. The statistics of cloud 209 macrophysics in Fig. 3 supports the analyses above. Cloud-top heights show good agreement 210 between SCAM6 simulation and Observation, with 8-month mean values of 1561 m and 1425 m, 211 respectively (Fig. 3f). It corroborates the notion that SCAM6 can capture the cloud type transition 212 relatively well. However, due to the lower cloud-base height in SCAM6, cloud physical thickness 213 is overestimated in the model. Even with the above biases in cloud macrophysics, the modeled 214 cloud mass center (CMC) height (mean cloud layer heights weighted by CLWC) is comparable to 215 the observed one (Fig. 3h).

A further comparison of 8-month surface precipitation rate in Fig. 2e and 2f shows that SCAM6 can capture the heavy precipitation (>25 mm/day) under the large-scale forcing during the winter season (Oct. to Jan.). However, the "too-frequent-drizzle" issue persists throughout the 8-month simulations. The frequency of light precipitation (< 2 mm/day) is more than 80% which





220 is rather unrealistic compared to the observations. The mean surface precipitation in SCAM6 is 221 overestimated by 30% compared to the rain gauge measurements during the whole 8-month period. 222 The statistical comparisons of cloud and drizzle microphysical properties in Fig. 3a-d 223 reveal that CLWC is overestimated by about 30%. Consequently, r_c is slightly larger in the model, 224 and the bias becomes worse for those larger droplets (r_c greater than 10 micron). Too large CLWC 225 fosters fast cloud to warm rain conversion, but the simulated RLWC values are smaller than the 226 retrievals, leading to too frequent surface precipitation mainly in the drizzle form. Note that 227 retrieved RLWC from ground-based radar also bears with large uncertainty, as indicated by the 228 large error bar in Fig. 3c. Hence the real differences of RLWC between SCAM6 and Observation 229 remain hard to be quantified. Our analyses here include all 8-month simulation results and all types 230 of cloud during this time. In an additional analysis, we focus on the marine boundary layer (MBL) 231 stratiform cloud only but get quite similar cloud evaluation results. As shown in Fig. S1, then we 232 strengthen our selection criteria by only sampling consecutive cloud layers lasting more than 2 233 hours with the cloud top heights less than 3 km, the statistics of cloud micro- and macro- physical 234 properties do not differ significantly. It reflects the fact that over the ENA, MBL clouds are pre-235 dominated during those seasons. In observation of the specific humidity bias against the 236 observations (Fig. 1), additional SCAM6 sensitivity test is conducted by perturbing moisture 237 content and the associated advection with a scaling factor of 0.85. Results show that the 238 distributions of simulated SH and RH only slightly shift towards the lower tail with smaller mean 239 values, which cannot correct their biases. Notably, despite the minor changes in the simulated 240 cloud and drizzle microphysics, the cloud-top height and thickness and the CMC simulations 241 perform noticeably better than the control simulation (Fig. S2). It suggests that the moisture fields 242 in the large-scale forcing exert larger impacts on simulated cloud structure and macrophysics than 243 the microphysics. In other words, cloud microphysical properties are strongly regulated by the 244 parameterizations, and less sensitive to the external forcing.

Driven by the same large-scale forcing, SCAM5 simulated cloud properties are quite different from those by SCAM6. Instead of an overestimation in SCAM6, the SCAM5 simulated CLWC exhibits an underestimation. One possible reason is the change of formula for the saturation vapor pressure in the MG2 cloud microphysics scheme (Gettelman and Morrison, 2015). Previous single-column simulations for the MPACE case also show the larger LWC by MG2 than MG1 (Gettelman et al., 2015). The good agreement of the mean r_c in SCAM6 does not exist in the





251 SCAM5 simulations, and too many small cloud droplets (less than 6 micron) are present in 252 SCAM5, which are not found in either observation or SCAM6. RLWC in SCAM5 is still much 253 smaller than Observation, suffering the similar issue to SCAM6. Differing from SCAM6, SCAM5 254 overpredicts mean $r_{m,r}$ but underpredict mean r_c . The high bias in drizzle size but low bias in 255 drizzle amount in SCAM5 indicate that the sources of those biases can be different in the model. 256 The improvement of the cloud macrophysics from SCAM5 to SCAM6 is more evident than that 257 of microphysics. Too low cloud-base height and cloud-top height result in too thin cloud deck in 258 SCAM5. The cloud center mass is also systematically low in SCAM5. Overall speaking, the 259 updated cloud physics in CAM6 help improve many aspects of cloud simulations, but the drizzle 260 issues still linger on.

261 **3.3 Aerosols**

262 To probe the possible uncertainty sources for cloud droplet number concentration, vertical 263 profiles of aerosol and CCN number concentrations are compared between SCAM6 simulations 264 and aircraft in situ observations from 17 flights during the ACE-ENA field campaign (Fig. 5). SCAM6 generally gets seasonality right, i.e., aerosol and CCN number concentrations are high in 265 266 summer and low in winter. The model also agrees with observations on the magnitude of 267 accumulation-mode aerosol concentration (N_{ACC}) and CCN concentration (N_{CCN}) during the summer, which further leads to a reasonable comparison of N_C . The small bias of N_C generally 268 269 follows the performance of N_{CCN} , i.e., high bias near the bottom while low bias near the top. One 270 intruiguing phenomenon during the summertime is that N_{CCN} can be even higher than N_{ACC} , found 271 in both aircraft measurements and model simulations. The high N_{CCN} occurs within the MBL 272 (<1000 m) in SCAM6. In contrast, measured N_{CCN} in lower free troposphere (FT, 2000-2500 m) 273 is of the same magnitude with that within MBL, and FT N_{CCN} is higher than N_{ACC} in the 274 observations. A breakdown of aerosol number concentration budget in SCAM6 (Fig. S3) shows 275 that Aitken-model aerosols contribute to about 20% summertime and 45% wintertime total aerosol 276 numbers. In contrast, the coarse model aerosol number is only about 1% of the Aitken mode one. 277 Therefore, the large N_{CCN} within the MBL in SCAM6 should be attributed to the efficient Aitken-278 model aerosol activation near the cloud bottom in SCAM6. A further examination of aerosol 279 chemical composition in SCAM6 suggests that sulfate is the predominated aerosol species in the 280 Aitken model (Fig. S4). Understanding larger N_{CCN} than N_{ACC} in the lower FT in the observational 281 data is somewhat challenging, because coarse- and Aitken- mode aerosol number concentrations





was not measured during the IOP. However, previous study found that new particle formation 282 283 frequently occurs in the FT over the ENA, because of the sulfuric acids being elevated, especially 284 during summertime where the oceanic dimethyl sulfide (DMS) emissions are strong (Zawadowicz 285 et al., 2021). Previous back-trajectory analyses by Wang et al. (2020) suggest the long-range 286 transport of the fine-mode aerosols to the ENA site likely originates from the continental U.S. 287 Therefore, the oxidations of DMS, jointly with the long-range transported pollution, contribute to 288 the elevated Aitken-mode aerosol concentrations in the FT. Those Aitken-mode aerosols (e.g., 289 DMS oxides and diluted continental pollutants) are found to be substantial contributors to the CCN 290 budget (Wang et al., 2021). The FT aerosols and CCN can be further entrained down to the MBL, 291 consistent with what is shown in Fig. 5. Note that SCAM6 predicts the "top-heavy" Aitken model 292 aerosol concentration profile, but it does not lead to the larger N_{CCN} above the MBL. Hence, we 293 can only speculate that in the real atmosphere, there are significant Aitken mode aerosols that can 294 serve as CCN in the lower FT, but that is not the case in SCAM6. The above discussions reinforce 295 the notion that it is crucial to accurately simulate the long-range transport of aerosols over a remote 296 maritime region like ENA. And future investigation on how the aerosol activation processes are 297 being simulated in different model levels is warranted.

298 During the winter, N_{ACC} is comparable between model and observation, while N_{CCN} is 299 significantly overestimated from the surface to 2000 m altitude. Based on our analyses above for 300 the summer, we can infer that overestimated contribution from the Aitken mode to the CCN budget 301 also exists in winter. Moreover, it is non-negligible that the stronger convective activities due to 302 the frequent frontal passages during wintertime also likely result in the stronger activation of 303 Aitken mode aerosol. In contrast, the modeled N_c shows surprisingly good agreement with 304 observations, despite the overestimated N_{CCN} . One plausible reason is the canceling effect from 305 the overestimated droplet size in the model (Fig. 3b). Larger cloud droplets facilitate the 306 autoconversion and accretion processes, and in turn, efficiently deplete cloud droplets (Zheng et 307 al., 2022b), keeping the observed N_c at a comparable level with the model simulation.

308

4. Impacts of new observation-constrained warm rain parameterizations

To explore the possible sources of biases in simulated drizzle and LWC, we employ a retuned KK scheme (Dong et al., 2021, thereafter as D21-KK) that explicitly links the autoconversion and accretion rates with mass mean cloud droplet radius $(r_{m,c})$. The original KK2000 scheme is expressed as below:





314
$$R_{auto}(Z) = \left(\frac{\partial q_r}{\partial t}\right)_{auto} = A q_c^{a1}(Z) N_c^{a2}, \tag{1}$$

316
$$R_{accr}(Z) = \left(\frac{\partial q_r}{\partial t}\right)_{accr} = B\left(q_c(Z)q_r(Z)\right)^b,$$
(2)

where A = 1350, a1 = 2.47, and a2 = -1.79 in CAM5. CAM6 aims to reduce the autoconversion dependency on the N_c , so a2 and A are set as -1.1 and 13.5, respectively, with a2unchanged. In D21-KK, both autoconversion and accretion rates are further aware of the vertical variations of r_c , so the constant A and B are replaced as a function of r_c :

321
$$R'_{auto}(Z) = \frac{RLWC(Z)}{\int \rho_{air} P_r(Z) dt} R_{auto}(Z) = A'(Z) q_c^{2.47}(Z) N_c^{-1.79},$$
(3)

323
$$R'_{accr}(Z) = \frac{RLWC(Z)}{\int \rho_{air} P_r(Z) dt} R_{accr}(Z) = B'(Z) (q_c(Z)q_r(Z))^{1.15},$$
(4)

324 where A' and B' are further parameterized in CAM5 as:

325
$$A'(Z) = 121683exp\left(-0.528\,r_{m,c}(Z)\right) + 364,\tag{5}$$

326 and,

327
$$B'(Z) = 632exp\left(-24.5\frac{r_{m,c}(Z)}{r_{m,r}(Z)}\right) + 51.$$
 (6)

328 Dong et al. (2021) showed that this set of new parameterizations in CAM5 help alleviate 329 the long-lasting issue in the climate models, e.g., "too frequent and too light precipitation", on the 330 global scale. When we apply the same set of parameterizations in SCAM5 over the ENA (referred 331 to as SCAM5_{D21}), we find similar improvements on cloud and precipitation properties. As shown 332 in Fig. 6, CLWC in SCAM5_{D21} is elevated due to the less efficient autoconversion scheme, and the 333 simulated CLWC values agree better with the ARM retrievals compared with original SCAM5. r_c 334 is also enlarged in SCAM5_{D21}, becoming more consistent with retrievals. The mass median radius 335 of raindrops r_{mr} are reduced slightly, while there is no significant change in RLWC in SCAM5_{D21}. 336 Because of the improved cloud microphysical properties, cloud macrophysics also match up better 337 with observations. Cloud base height, cloud top height, and cloud mass center height (Fig. 6e-h) 338 are all improved to some extent in $SCAM5_{D21}$ simulations. These comparisons are encouraging, 339 indicating that the D21-KK new warm parameterizations in SCAM5 make significant 340 improvements on the simulated MBL cloud and drizzle properties.





341 Different from CAM5 microphysics, CAM6 starts to introduce sub-grid cloud variations 342 (Zhang et al., 2020) and re-tuned the parameters in the KK2000 scheme. One direct consequence 343 is that cloud LWC has been changed from underestimation to overestimation (Fig. 7a). Therefore, 344 an even slower autoconversion process with the new D21-KK scheme cannot further benefit the 345 warm rain processes in CAM6. As expected, SCAM6_{D21} does not exhibit improvement in 346 simulating both cloud microphysics and macrophysics (Fig. 7). Distinctive sensitivities to the same 347 microphysical parameter modification under different physics packages poses a challenge on 348 model improvement through only updating a certain set of parameterizations.

349 5. Assessing aerosol indirect effects under the single-column frameworks

350 Aerosol indirect effects, especially the second indirect effect concerning the liquid water 351 path change, was reported to be over-predicted in CAM5 when simulating the aerosol 352 perturbations, such as volcano eruptions, on the low clouds (Malavelle et al., 2017). Here we assess 353 the aerosol first and second indirect effects of CAM6 over the ENA under the single-column 354 framework. To perturb the CCN budget, we choose to modify the accumulation-mode aerosols in 355 their initial conditions. As the aerosol relaxation is on, such a perturbation is expected to constantly impact the aerosol field during the integrations. Considering the relatively low background aerosol 356 357 concentration, the change in aerosol direct effect on the clear-sky radiation fluxes can be ignored in this setup. Both aerosol number and mass concentrations in the accumulation mode are enlarged 358 359 by a factor of 2, the results are labeled as $S6_{pAero}$ and are compared with the original SCAM6 360 simulations (Fig. 8). With such an aerosol perturbation, N_{CCN} within MBL (< 1km) is increased 361 from 112.5 to 175.8 cm⁻³, corresponding to a 56% enhancement. Similarly, CCN in the lower FT 362 and upper MBL (1-3 km) increased by 61%. Aerosol first and second indirect effects are evident in SCAM6, as reduced r_c and increased LWC are both found in the perturbed experiment. We 363 further quantify the droplet size susceptibility and cloud water susceptibility with respect to MBL 364 CCN changes by $\frac{\partial ln(r_c)}{\partial ln(N_{CCN})}$ and $\frac{\partial ln(CLWC)}{\partial ln(N_{CCN})}$, respectively. The SCAM6 simulated droplet size 365 366 susceptibility is -0.2, close to the LES simulated range from -0.22 to -0.25 and the upper bound of the observed range over ENA (Wang et al., 2020; Zheng et al., 2022a). The SCAM6 simulated 367 368 cloud water susceptibility is +0.19 which also falls into the LES prediction (+0.18 to +0.30). Those 369 results suggest that the newly introduced sub-grid cloud variabilities in SCAM6 can account for 370 the aerosol indirect effects at a reasonable level. Mean surface precipitation amount shows very 371 small responses to CCN perturbation (less than 2%), because convective precipitation in early





372 winter dominates the study period while deep convective parameterization in SCAM6 is still 373 unlinked with cloud microphysics and unaware of CCN effects so far. Cloud top height (Z_T) shows 374 an increase with higher CCN concentration (Fig. 8f), likely due to the enhanced latent heat release 375 following the elevated condensational rate.

376 6. Conclusion and Discussion

377 The single-column versions of NCAR CAM5 and CAM6 are employed to simulate marine 378 boundary-layer cloud and aerosol properties over the eastern North Atlantic during the ACE-ENA 379 field campaign and to assess the uncertainty in cloud microphysical parameterizations. 3-hourly 380 large-scale forcing data are derived from the systematic measurements of atmospheric states 381 during the 8-month IOP. SCAM6 well reproduces the temperature field but overestimates specific 382 and relative humidity by about 10%, especially for those near-cloud grid points. Our moisture 383 adjustment simulation suggests that moisture variables in the large-scale forcing exert larger 384 impacts on simulated cloud structures than cloud microphysics. It further implies cloud 385 microphysical properties are strongly regulated by the parameterizations, and less sensitive to the 386 external forcing. Cloud frequency and transition between different types show good agreement 387 between SCM and observation. Cloud property simulations are generally improved from SCAM5 388 to SCAM6, in terms of droplet effective radius, cloud top height, and cloud thickness. However, 389 there are some common issues with warm precipitation in those two models, including too small 390 rainwater content and too frequent surface light precipitation. To probe the possible contributions 391 from the warm cloud parameterization to those drizzle biases, we implement the recalibrated 392 autoconversion and accretion processes in the KK scheme of SCAM5 and SCAM6 that explicitly 393 consider vertical variations of droplet size. This updated scheme tends to improve CLWC and r_c 394 in SCAM5 as well as $r_{m,r}$, but does not significantly alleviate the drizzle problem. The 395 improvement is absent in SCAM6, likely because sub-grid variations of cloud properties have been 396 introduced in CAM6 cloud microphysics (especially for the autoconversion parameterization), 397 suppressing the KK scheme sensitivity to other factors. Further study is warranted to test whether 398 the same warm rain precipitation sensitivity holds for different cases using SCM5/6.

Aerosol simulations in SCAM6 are evaluated against the aircraft measurements during the ACE-ENA. SCAM6 agrees with observations on the magnitude of concentration of accumulationmode aerosol, CCN, and cloud droplets during the summer, while N_{CCN} is significantly biased high from the surface to 2000 m in altitude during the winter. Aerosol budget analyses show that in





403	SCAM6, long-range transport provides too many Aitken-mode sulfates that entrain into the MBL			
404	and can grow to CCN-size particles consequently. We further quantify aerosol indirect effects by			
405	perturbing accumulation-mode aerosol concentrations in the model. SCAM6 predicted cloud water			
406	and droplet size susceptibilities line up with the classic CCN effects, i.e., reduced droplet size but			
407	enhanced liquid water content under the high CCN scenario. The magnitudes of the cloud water			
408	and droplet size susceptibilities are also close to the LES simulations conducted for the selected			
409	cases during the ACE-ENA.			
410	The present study provides new insight of model biases in aerosol and warm cloud			
411	simulations in the NCAR CAM models. Different from the previous evaluations of a full model			
412	run with potential large biases propagated from modeled large-scale conditions, the model biases			
413	discussed here, especially the drizzle property issue, should be adequately addressed in the future			
414	development of CAM. The existing progress of predicted cloud properties and aerosol effects is			
415	clearly demonstrated under the single-column framework in this study.			
416				
417	Code availability			
418	The code of CESM model used in this study is available at			
419	https://www.cesm.ucar.edu/models/cesm2/release_download.html.			
420				
421	Data availability			
422	All the CESM model simulation input and output used for this research can be downloaded from			
423	the website at http://web.gps.caltech.edu/~yzw/share/Wang-2023-SCM. The aircraft and ground-			
424	based measurements used in this study were obtained from the Atmospheric Radiation			
425	Measurement (ARM) Program sponsored by the U.S. Department of Energy (DOE) Office of			
426	Energy Research, Office of Health and Environmental Research, and Environmental Sciences			
427	Division. The data can be downloaded from http://www.archive.arm.gov/.			
428				
429	Competing interests			
430	Yuan Wang is a member of the editorial board of Atmospheric Chemistry and Physics.			
431				
432	Acknowledgement			

433 This study was primarily supported by the collaborative NSF grant (Award No. AGS-2031751,





- 434 2031750). We thank the instrument mentors of the instruments and the individuals collecting
- 435 measurements during the ACE-ENA field campaign. We also acknowledge high-performance
- 436 computing support from NCAR Cheyenne. All requests for materials in this paper should be
- 437 addressed to Yuan Wang (<u>yuanwang@purdue.edu</u>).





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572 **Table 1**. Single-column numerical experiment design.

573

Model Physics	Experiment Name	Experiment Description
	Ctrl	Default model setup and forcing data
CANK	D21	Using recalibrated warm rain parameterizations based on Dong et al. (2021)
САМб	pAero	Scale up aerosol number and mass concentrations in the accumulation mode by a factor of 2 in the initial condition
	ForcingQ_Adj	Adjust specific humidity state variable and related tendency terms by a factor of 0.85
CA115	Ctrl	Default model setup and forcing data
CAM5	D21	Using recalibrated warm rain parameterizations based on Dong et al. (2021)







575 Figures

Figure 1. Comparisons of meteorological conditions between SCAM6 simulations and ARM
 Interpolated Sonde (INTERPSONDE) soundings. Upper panels: Time series of air temperature

579 (left) and relative humidity (right) from SCAM6 (top) and ARM-ENA observations (bottom).

580 Lower panels: SCAM6 (red) simulated air temperature, relative humidity (RH), specific humidity

581 (SH) within 3 km, in comparison with the ARM-ENA observation (black).







Figure 2. Time series of the cloud liquid water contents (CLWC, top panels), rain liquid water
contents (RLWC, middle panels) and surface precipitation (bottom panels) from the SCAM6
simulations (left column) and the ARM-ENA retrievals and observations (right column).

586







587

Figure 3. Probability distribution functions (PDFs), mean, standard deviation, and median values of cloud and rain microphysics, and cloud macrophysics simulated from SCAM6 (red) and observed/retrieved from ground-based remote sensors (black). (a) Cloud liquid water content, CLWC; (b) Cloud droplet effective radius, r_c ; (c) Rain liquid water content, RLWC; (d) Rain droplet mass median radius, $r_{m,r}$; (e) Cloud base height, Z_B ; (f) Cloud top height, Z_T ; (g) Cloud thickness, Z_H and (h) Cloud mass center.







596 Figure 4. Same as Fig 3, except for SCAM5 (blue).

597







598

Figure 5. Vertical profiles of accumulation mode aerosol (N_{ACC}) (a, d); CCN concentration (N_{CCN}) at 0.35% supersaturation (b, e) during interstitial conditions, and Cloud droplet number concentration (N_C) at normalized height (c, f, 0 is cloud base, 1 is cloud top) for cloudy samples. For SCAM6 simulations (brown and purple) and aircraft in-situ measurement (black), during the Summer (top panels) and Winter (bottom panels) ACE-ENA IOPs. The shaded areas denote the standard deviation at each level. The SCAM6 simulations are selected within each time duration of the aircraft cases.









Figure 6. Comparisons of cloud and rain microphysics, and cloud macrophysics between observations (black), SCAM5 (blue) and SCAM5 with Dong2021 parameterization (*SCAM5*_{D21}, dark blue). (a) *CLWC*, (b) r_c , (c)*RLWC*, (d) $r_{m,d}$, (e) Z_B , (f) Z_T , (g) Z_{H_c} and (h) Cloud mass center.

Dots represent the mean values, and the bars from bottom to top represent 10%, 25%, 50%, 75%,

612 and 90% values, respectively.







614



616 (*SCAM*6_{*D*21}, pink).









619 Figure 8. Aerosol and cloud properties simulated from control (red) and aerosol-perturbing 620 experiments (pAero, orange) by SCAM6 and comparison to observations. The observed CCN at 621 0.35% SS are averaged from the selected aircraft measurements during the ACE-ENA.