	AGU PUBLICATIONS
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2	GRL
3	Supporting Information for
4 5	Snow reconciles observed and simulated phase partitioning and doubles cloud feedback
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13 14 15 16	Contents of this file Text S1 to S5 Figures S1 to S11 Tables S1 to S3
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18 19 20 21 22 23 24 25 26 27 28 29 30 31 32	 the uncertainty estimates used for the CALIPSO-GOCCP observations in text S1, GISS-ModelE3 description in text S2, how the lidar simulator was modified to account for precipitation along with additional modifications to improve consistency with NASA-GISS ModelE3 in text S3, the two case studies used the main manuscript in text S4, how the simulated cloud feedbacks are computed in text S5, figures that further support our main findings in figures S1-S11, the averaged cloud feedbacks for different NASA-GISS ModelE3 configurations in table S1-S2 and the list of CMIP models used in this study as well as their ECS.

33 Supplementary Texts

34 Text S1:

35 To derive an observational uncertainty estimate for the SCF as a function of temperature 36 (liquid/[liquid+ice] cloud frequency), we use error estimates from a CALIPSO-GOCCP validation study against *in situ* aircraft measurements¹⁶ as well as the undefined-phase cloud 37 38 fraction. Cesana et al.(2016) show that the maximum disagreement fraction between CALIPSO-39 GOCCP and five *in situ* aircraft flights is ~ 20 % (their Table 3). We choose to apply this 40 maximum disagreement fraction of 20 % uniformly to the CALIPSO-GOCCP cloud phase ratio 41 although Cesana et al.¹⁶ showed that the ice clouds in high and cold clouds were rarely 42 misdiagnosed. In addition, we use the undefined-phase cloud fraction to derive a range of 43 possible SCF as a function of the temperature by considering the undefined-phase clouds as being 44 either all liquid or all ice. Finally, we assume that both uncertainty sources –from applying the 20 45 % disagreement fraction and from considering all undefined-phase clouds as being either liquid 46 or ice- are independent and add them in quadrature to derive the final uncertainty estimate. 47

48 Text S2:

49 In brief, GISS-ModelE3 uses a diagnostic determination of cloud fraction as a function of 50 grid-mean moisture and a condition-dependent sub-grid variance expressed as a threshold grid-51 mean relative humidity (RH) for cloud formation. The stratiform liquid and ice cloud fractions 52 are obtained using Smith (1990) and Wilson and Ballard (1999) probability density function 53 (PDF) schemes. The stratiform cloud microphysics treatment is based on a modified two-moment 54 microphysics scheme with prognostic precipitation (Gettelman and Morrison, 2015), in which 55 cloud water and ice, rain, and snow mixing ratios and number concentrations are prognostic 56 variables. Rain and snow both require other hydrometeors to already exist, unlike cloud droplets, 57 which form via aerosol activation, and cloud ice, which can form from aerosol and cloud droplet 58 freezing, homogeneously and heterogeneously. Typically, snow and rain hydrometeors are larger

59 and fall faster than cloud particles. Finally, the cumulus category realized for a given environment 60 is a function of dynamically determined entrainment and its cloud phase is based on a 61 temperature threshold. Compared to Cesana et al. (2019), the GISS-ModelE3 version used here 62 includes the following updates pertinent to our findings: depositional growth of stratiform snow, neglected in the original scheme¹², is treated; the Bergeron enhancement employed in the original 63 64 scheme¹², which transfers water directly from cloud droplets to cloud ice, is omitted and the 65 process instead only mediated through the vapor phase, as in nature; at supercooled temperatures, 66 heterogeneous ice nucleation occurs only in the immersion mode, using the temperature 67 dependence of Demott et al. (2010). Another update is that these GISS-ModelE3 simulations 68 have finer layering in the middle and upper troposphere, and a higher top at 0.002 hPa. The 69 primary structural difference between the Phys version and the Tun1-3 configurations is an 70 alternative formulation for convective entrainment. For the findings presented here, the impact of 71 the entrainment change is merely indirect, in that it coincidentally enables the overall 72 climatological skill requirement to be met using developers'-choice default values of uncertain 73 stratiform microphysical coefficients, rather than those determined by the objective approach for 74 Tun1-3.

75 Text S3:

76 We modified a few other elements of the lidar simulator to make it more consistent with 77 GISS-ModelE3. First, to be consistent with the definition of effective radius (Foot, 1988) we 78 modified the default bulk ice density from 500 to 917 kg/m³, which is used for all frozen 79 hydrometeors. This modification reduces and increases the lidar simulator cloud fraction at the 80 top and the bottom of the high clouds (not shown). Then, the ice particle shape in the lidar 81 calculation is set to nonspherical, which also increases the cloud fraction of ice clouds (not 82 shown). Finally, we slightly modified the discrimination line used to distinguish ice and liquid 83 cloud pixels in the CALIPSO-GOCCP and lidar simulator cloud phase diagnostic (Cesana and 84 Chepfer, 2013) to classify ice particles with a large total attenuated backscatter (ATB) that follow

the ice parameterized line but are located below the discrimination line (see supplementary Fig.
10a). These occurrences may be more frequent in GISS-ModelE3 than in the ESM used by
Cesana and Chepfer (2013) because GISS-ModelE3 has a higher vertical resolution and includes

88 contribution from snow.

89 Text S4:

90 The first case study was derived from observations during the Atmospheric Radiation 91 Measurement (ARM) West Antarctic Radiation Experiment (AWARE) (Silber et al., 2019). We 92 note that greater ice formation rates in GISS-ModelE3 Phys than estimated from observations 93 (Silber et al., 2020) correspond to less liquid water optical depth than observed, which we 94 obtained by changing the ice nucleation scale factor parameter from 0.1 to 8. This modification 95 allows us to probe the simulator capability to "see through" optically thinner liquid layers, which 96 are common over polar regions (Silber et al., 2020). The second case study corresponds to the 97 Small Particles in Cirrus (SPARTICUS) case (Muhlbauer et al., 2014), which represents an anvil 98 cirrus cloud system at midlatitudes over the Southern Great Plains (SGP). Note that we did not 99 change any model cloud parameters for the SPARTICUS case.

100 Text S5:

101 We quantify ESM cloud feedbacks (Fig. 4) using an International Satellite Cloud Climatology 102 Project (ISCCP)-derived radiative kernel method (Zelinka et al., 2016). The cloud feedback is 103 separated into contributions from low (at pressures ≥ 680 hPa, roughly 3 km) and non-low (at 104 pressures < 680 hPa) clouds and further decomposed into amount, altitude, optical depth, and 105 residual contributions (Supplementary Fig. 11 and Tables 1 and 2). The amount, altitude and 106 optical depth contributions quantify the feedback generated by changes in cloud fraction, altitude 107 and optical depth, respectively, while keeping the other two parameters constant in the cloud top 108 pressure and optical depth ISCCP bin space. The ISCCP-derived radiative kernel method and its 109 shortcomings are described in Zelinka et al. (2012b). The main shortcoming of this method comes

from the residual when decomposing the cloud feedback into amount, altitude and optical depth contributions. One must be careful when analyzing the different contributions if the residual is of the same order of magnitude.

113 Here we aim to characterize the atmospheric contributions to cloud feedbacks by prescribing 114 the SST in the control experiment, based on monthly observations, and by applying a uniform 115 warming of 4K in the perturbed experiment (Webb et al., 2017). While the atmospheric-only 116 cloud feedbacks (i.e., using prescribed SST perturbation) do not capture the effect of increased 117 CO_2 and SST-atmosphere coupling, they are representative of the global cloud feedbacks 118 determined from coupled atmosphere-ocean CO2-forced simulations (Ringer et al., 2014). The 119 cloud feedbacks are computed for the constrained configuration of the GISS-ModelE3, Phys (Fig. 120 4, Supplementary Table 1 and Fig. 11), but also for the three other configurations, Tun1-3 121 (Supplementary Table 2), to analyze the robustness of the feedbacks in a larger pool of models. 122 We note that the cloud fraction seen by the ISCCP simulator is consistent with the cloud fraction 123 seen by the radiation and the lidar simulator, meaning that when precipitation is neglected in the 124 radiation and the lidar simulator, its contribution to the ISCCP simulator is also neglected. 125 The CMIP5 and CMIP6 cloud feedback values are from Zelinka et al. (2020) and are 126 computed using different kernels than those used this study but produce very similar results 127 (Zelinka et al., 2012a). 128 The ECS values in Supplementary Table 3 are from Cesana and Del Genio (2021) and Zelinka 129 et al. (2020). For the CMIP5 and CMIP6 multimodel means (Fig. 4 and Supplementary Table 3), 130 all the results from each modeling center are first averaged, such that each modeling center 131 contributes one data point to the multimodel means to improve model independence. 132

133 Supplementary Figures

- 134
- 135 Figure S1: Total, ice, liquid and undefined-phase cloud profiles (from top to bottom) in the liquid-
- 136 topped mixed-phase cloud in the Antarctic case. The first column corresponds to the cloud water content
- 137 from the native GISS-ModelE3 while the second, third and fourth columns correspond to cloud fraction
- 138 from the lidar simulator outputs with and without precipitation and the difference, respectively.
- 139



141

Figure S2: Same as Figure S1 for the stratiform cirrus case over the southern great plains. Note that there

are no undefined-phase clouds in this case.



149 Figure S3: Zonal profiles (x axis, latitude, N; y axis, altitude, km) of the lidar simulator GISS-ModelE3

- 150 outputs without precipitation (a), the difference between with and without (b), the difference between with
- 151 large-scale frozen precipitation and without precipitation (c) and the difference between with large-scale
- rain and without precipitation (d). Note that no changes occur between panel b and c in the high levels and
- 153 that the color scale of panel d is smaller than that of panel c.
- 154



156 Figure S4: Zonal profiles (x axis, latitude, N; y axis, altitude, km) of CALIPSO-GOCCP observations

- 157 and the lidar simulator GISS-ModelE3 outputs with precipitation (top) and the difference between with and
- 158 without precipitation for the four different GISS-ModelE3 configurations: Phys and Tun1 to 3, from left to
- 159 right.
- 160



- 163 Figure S5: Zonal profiles (x axis, latitude, N; y axis, altitude, km) of CALIPSO-GOCCP observations
- 164 (top) and GISS-ModelE3 bias of the total, ice, liquid and undefined-phase cloud fractions for the four
- 165 different GISS-ModelE3 configurations with precipitation using the lidar simulator, from the second row to
- 166 the bottom row, Phys and Tun1 to 3.
- 167





- 171 Figure S6: Effect of the precipitation on the relation between temperature (y axis, °C) and frequency
- 172 supercooled condensate fraction (SCF, x axis). This figure emphasizes the variability of the relationship
- among the GISS-ModelE3 different configurations with (solid) and without (dotted) precipitation (the
- 174 specific names of each version are shown in the legend). The CALIPSO-GOCCP observation frequency
- 175 SCF is shown in black (2007-2016 Nighttime v2.9).



- 179 Figure S7: Zonal altitude (km, left) and temperature (°C, right) profiles of frequency SCF. The
- 180 CALIPSO-GOCCP observations are shown on the top row (2007-2016 Nighttime v2.9) while the lidar
- 181 simulator GISS-ModelE3 outputs with and without precipitation correspond to the middle and bottom
- 182 rows, respectively. The black and green dashed lines correspond to the 50 % liquid and ice iso contours of
- 183 the observations and the simulations, respectively.
- 184





Figure S8: Zonal mean of net, SW and LW cloud radiative effect at the top of the atmosphere. The

net, LW and SW CRE are represented in black, red and blue with (solid lines) and without (dotted lines) the

effect of large-scale precipitation for GISS-ModelE3 Phys. The area-weighted global averages are shown in

- the legend.





- 195 Figure S9: Schematic of the effect of making precipitation visible to the radiation scheme in GISS-
- 196 ModelE3. In response to global warming, ice crystals transition to water droplets globally. However,
- 197 depending on the region of the globe, cloud properties may respond differently to global warming. For
- example, in the tropics (left), the amount and optical depth of non-low clouds (at heights > 3 km) decrease,
- a process that is enhanced by making precipitation visible to radiation since cloud ice becomes scarcer and
- 200 produces less snow. As a result, both cloud ice and snow decrease, contributing to strengthen the SW
- 201 positive feedback (less SW radiation reflected back to space) and weaken the LW positive feedback (more
- 202 surface LW cooling). Over the Arctic (right), the cloud amount and optical depth increase while the snow
- amount decreases, for the reasons mentioned above. As a consequence, adding precipitation slightly offset
- 204 the increase in cloud amount and optical depth seen by radiation, thereby weakening the SW negative
- 205 feedback (less SW radiation reflected back to space) with negligible effect in the LW.



209 Figure 10: Phase diagram for the (a) SGP cirrus cloud case and Antarctica mixed-phase cloud case

210 using GISS-ModelE3. The color shading represents the number of cloudy pixels as a function of the

211 perpendicular attenuated total backscatter (ATBper, y-axis, km⁻¹ sr⁻¹) and the attenuated total backscatter

212 (ATBtot, x-axis, km⁻¹ sr⁻¹) as in Cesana and Chepfer (2013). The solid black line corresponds to the original

 $213 \qquad \text{discrimination line used in the lidar simulator while the dashed black line is the modified version used in}$

- 214 GISS-ModelE3 to account for ice paarticles with a large ATB signature, e.g., the pixels between the two
- black lines in the upper panel.







219 Figure S11: Effect of precipitation on cloud feedbacks (left to right) for different types of feedbacks

220 for GISS-ModelE3 Phys. The first row represents zonal means of standard net, LW and SW cloud

221 feedbacks (Wm⁻²K⁻¹; left to right) for all (black), non-low (blue) and low (red) clouds. The second, third

and fourth rows show further decomposition into total (black), altitude (purple), optical depth (orange) and

- 223 amount (green) contributions for all, non-low and low clouds, respectively. The simulations with and
- without large-scale frozen precipitation are represented by solid and dotted lines, respectively. Note that the
- corresponding area-weighted global averages are shown in Supplementary Table 1.



231 Supplementary Tables

232

233 Table S1: Effect of snow on cloud feedback. Global mean net, LW and SW total cloud feedbacks (Wm⁻

234 ²K⁻¹) and their non-low and low contributions further divided into altitude, amount and optical depth

235 components for GISS-ModelE3 (configuration Phys) using Zelinka et al. (Zelinka et al., 2016) kernels along

with amip and amip-p4K experiments. Note that the zonal means of the altitude, amount and optical depth

237 contributions for all, non-low and low clouds are shown in Figure S11. Differences that are smaller or equal

to the internal variability are shown in grey.

239

		Net			LW			SW		
		Ctrl	No_pcp	Δ	Ctrl	No_pcp	Δ	Ctrl	No_pcp	Δ
	total	0.26	0.14	0.12	0.44	0.47	-0.03	-0.19	-0.33	0.14
All	altitude	0.36	0.29	0.07	0.42	0.35	0.07	-0.06	-0.06	0
	amount	0.16	0.11	0.05	-0.15	-0.09	-0.06	0.31	0.19	0.12
	Optical depth	-0.26	-0.28	0.02	0.16	0.17	-0.01	-0.42	-0.44	0.02
Non	total	-0.14	-0.28	0.14	0.52	0.55	-0.03	-0.66	-0.83	0.17
low	altitude	0.2	0.12	0.08	0.21	0.13	0.08	-0.02	-0.01	-0.01
	amount	-0.08	-0.14	0.06	0.07	0.14	-0.07	-0.16	-0.28	0.12
	Optical depth	-0.25	-0.26	0.01	0.24	0.28	-0.04	-0.49	-0.54	0.05
Low	total	0.4	0.42	-0.02	-0.08	-0.08	0	0.48	0.5	-0.02
	altitude	0	0	0	0.01	0.01	0	0	0	0
	amount	0.39	0.41	-0.02	-0.08	-0.09	0.01	0.47	0.5	-0.03
	Optical depth	0.02	0.02	0	0	0	0	0.02	0.02	0

240

- **Table S2: Effect of snow on cloud feedback across all configurations**. Same as Table 1 but averaged
- 243 over the four GISS-ModelE3 configurations (Phys and Tun1-3). Note that, as in the GISS-ModelE3 phys
- 244 configuration used in the main manuscript, the total net cloud feedback roughly doubles when the
- 245 precipitation is seen by radiation.

		Net			LW			SW		
		Ctrl	No_pcp	Δ	Ctrl	No_pcp	Δ	Ctrl	No_pcp	Δ
	total	0.21	0.11	0.10	0.46	0.46	-0.01	-0.25	-0.35	0.10
All	altitude	0.34	0.27	0.06	0.40	0.33	0.07	-0.06	-0.06	-0.01
	amount	0.15	0.12	0.03	-0.14	-0.10	-0.03	0.28	0.22	0.06
	Optical depth	-0.28	-0.29	0.01	0.17	0.19	-0.02	-0.45	-0.48	0.03
	total	-0.18	-0.28	0.10	0.52	0.52	0.00	-0.70	-0.80	0.10
Non low	altitude	0.17	0.11	0.07	0.18	0.11	0.07	-0.01	-0.01	-0.01
	amount	-0.06	-0.07	0.02	0.06	0.09	-0.03	-0.12	-0.16	0.04
	Optical depth	-0.27	-0.28	0.01	0.30	0.36	-0.06	-0.57	-0.64	0.06
	total	0.38	0.39	-0.01	-0.06	-0.06	0.00	0.45	0.45	-0.01
Low	altitude	0.01	0.01	0.00	0.01	0.01	0.00	-0.01	-0.01	0.00
	amount	0.37	0.38	0.00	-0.07	-0.07	0.00	0.44	0.45	-0.01
	Optical depth	0.03	0.03	0.00	0.00	0.00	0.00	0.02	0.03	-0.01

250 Table S3: List of CMIP5 (left) and CMIP6 (right) models used in this study along with their

251 equilibrium climate sensitivities. The models marked with a star include the effect of large-scale

252 precipitation in their radiation schemes. The modeling center mean is shown on the rightmost column of

- each side.
- 254

CMIP5 Models	ECS (K)		CMIP6 Models	ECS (K)	
-	Model Mean	Center		Model Mean	Center Mean
ACESS1.0	3.85	3.69	ACCESS-CM2*	4.66	4.66 4.28
ACCESS1-3*	3.53		ACCESS-ESM1-5	3.89	3.89
BCC-CSM1-1-m	2.89	2.87	BCC-CSM2-MR	3.02	3.14
BCC-CSM1-1	2.84		BCC-ESM1	3.26	
BNU-ESM	4.04		CAMS-CSM1-0	2.29	2.29
CanESM2	3.70		CanESM5	5.64	5.64
CCSM4	2.94		CESM2*	5.15	4.95
CSIRO-Mk3-6-0*	4.09		CESM2-FV2*	5.16	
CNRM-CM5	3.25	<u> </u>	CESM2-WACCM*	4.68	
GFDL-ESM2G	2.43	2.95	CESM2-WACCM-FV2*	4.8	
GFDL-ESM2M	2.44		CNRM-CM6-1	4.9	4.67
GFDL-CM3	3.99		CNRM-CM6-1-HR	4.33	
GISS-E2-R	2.12	2.22	CNRM-ESM2-1	4.79	
GISS-E2-H	2.31		E3SM-1-0*	5.31	5.31
HadGEM2-ES*	4.58		EC-Earth3*	4.33	4.33
INMCM4	2.08		EC-Earth3-Veg*	4.33	
IPSL-CM5A-LR	4.13	3.62	GFDL-CM4	3.89	3.27
IPSL-CM5B-MR	4.11		GFDL-ESM4	2.65	
IPSL-CM5B-LR	2.61		GISS-E2-1-G	2.71	2.75
MIROC5	2.71	3.68	GISS-E2-1-H	3.12	
MIROCESM	4.64		GISS-E2-2-G	2.43	
MPI-ESM-MR	3.45	3.51	HadGEM3-GC31-LL*	5.55	5.45
MPI-ESM-P	3.46		HadGEM3-GC31-MM*	5.44	
MPI-ESM-LR	3.63		UKESM1-0-LL*	5.36	
MRI-CGCM3	2.61		INM-CM4-8	1.83	1.88
NorESM1-M	2.81	2.90	INM-CM5-0	1.92	
NorESM1-ME	2.98		IPSL-CM6A-LR	4.56	4.56
			MIROC-ES2L	2.66	2.63
Multimodel Mean	3.29		MIROC6	2.6	
Multimodel STD	0.69		MPI-ESM-1-2-HAM	2.95	2.99
Multimodel Mean precip*	4.07		MPI-ESM1-2-HR	2.98	
Multimodel STD precip*	0.53		MPI-ESM1-2-LR	3.03	

Multi	model Mean no LS precip	3.1	MRI-ESM2-0	3.13	3.13	
Multi	imodel STD no LS precip	0.53	NorCPM1	3.03	3.03	2.69
			NorESM2-LM*	2.56	2.53	
			NorESM2-MM*	2.49		
			SAM0-UNICON*	3.72	3.72	
				0.54		
			Multimodel Mean	3.76		
			Multimodel STD	1.16		
			Multimodel Mean precip*	4.42		
			Multimodel STD precip*	1.02		
			Multimodel Mean no LS precip	3.37		
			Multimodel STD no LS precip	1.05		
55						

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