Antarctic Sea Ice Area in CMIP6

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18 Key Points:

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19	• CMIP6-mean Antarctic sea ice area is close to observations but inter-model spread
20	remains substantial.
21	• We find modest improvements in the simulation of sea ice area and concentration
22	compared to CMIP5.
23	• Most CMIP6 models simulate sea ice losses and stronger-than-observed GMST

trends over 1979-2018.

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25 Abstract

Fully-coupled climate models have long shown a wide range of Antarctic sea ice states 26 and evolution over the satellite era. Here, we present a high-level evaluation of Antarc-27 tic sea ice in 40 models from the most recent phase of the Coupled Model Intercompar-28 ison Project (CMIP6). Many models capture key characteristics of the mean seasonal 29 cycle of sea ice area (SIA), but some simulate implausible historical mean states com-30 pared to satellite observations, leading to large inter-model spread. Summer SIA is con-31 sistently biased low across the ensemble. Compared to the previous model generation 32 (CMIP5), the inter-model spread in winter and summer SIA has reduced and the regional 33 distribution of sea ice concentration has improved. Over 1979-2018, many models sim-34 ulate strong negative trends in SIA concurrently with stronger-than-observed trends in 35 global mean surface temperature (GMST). By the end of the 21st century, models project 36 clear differences in sea ice between forcing scenarios. 37

³⁸ Plain Language Summary

Coupled climate models are complex computer programs that simulate the inter-39 action of the atmosphere, ocean, land surface and cryosphere. An important feature of 40 the Southern Ocean is its sea ice cover, which typically expands in winter to cover an 41 area comparable to that of Russia. Climate models have shown very different amounts 42 of Antarctic sea ice coverage and very different trajectories of sea ice change in response 43 to expected greenhouse gas emissions. This year, new coupled climate models released 44 under the Coupled Model Intercomparison Project (CMIP6) will form the basis of the 45 next IPCC assessment report. Here, we compare output from those models to satellite 46 observations of the areal coverage of sea ice. As a whole, the models successfully cap-47 ture some elements of the observed seasonal cycle of sea ice, but under-estimate the sum-48 mer minimum sea ice area. Compared to results from the previous model generation (CMIP5), 49 the range across models has reduced and the location of sea ice agrees better with ob-50 servations. Models project sea ice loss over the 21st century in all scenarios, but confi-51 dence in the rate of loss is limited as most models show stronger global warming trends 52 than observed over the recent historical period. 53

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54 1 Introduction

Antarctic sea ice area increases sixfold across the austral autumn and winter months 55 in one of the largest seasonal area changes of any surface type on Earth. At the inter-56 face between ocean and atmosphere, the sea ice cover determines fluxes of heat, mass 57 and momentum between these two fluids. Its presence also influences surface albedo, oceanic 58 circulation (Pellichero et al., 2018) and the vulnerability of ice sheets to open ocean forc-59 ing (Massom et al., 2018). While Arctic sea ice has clearly decreased over the now-40-60 year multichannel passive-microwave satellite record, the areal extent of Antarctic sea 61 ice shows a small positive trend over 1979-2018 (Parkinson, 2019). The increase between 62 2000 and 2014 was several times larger than the increase between 1979 and 1999 (Meehl 63 et al., 2019), but was followed by sudden decreases in recent years, such that the 2017 64 and 2018 yearly averages were the lowest for the whole 1979-2018 record (Parkinson, 2019). 65 A variety of mechanisms have been proposed for the increase (J. Zhang, 2007; P. R. Hol-66 land & Kwok, 2012; Haumann et al., 2014; Ferreira et al., 2015; Purich et al., 2016; Ar-67 mour et al., 2016; Pauling et al., 2017) and the decrease (Meehl et al., 2019; Schlosser 68 et al., 2018; Stuecker et al., 2017; Wang et al., 2019), but neither is well-understood. 69 Global coupled climate models can aid our understanding of such climate system 70 variability and provide projections of future climate change. By providing a common model 71 experiment protocol, the Coupled Model Intercomparison Project (CMIP) permits eval-72 uation of climate models developed by 40 or so modelling groups worldwide. As sea ice 73 responds to changes in the atmosphere and ocean, it is often used as a climate diagnos-74 tic. Yet despite advances in climate modelling capabilities over recent decades, simula-75 tion of Antarctic sea ice has remained a fundamental problem for state-of-the-art climate 76 models (Turner et al., 2013; Zunz et al., 2013; Shu et al., 2015; Rosenblum & Eisenman, 77 2017; Roach et al., 2018; Holmes et al., 2019). The Intergovernmental Panel on Climate 78 Change (IPCC) Fifth Assessment Report (AR5) concluded that there is 'low confidence' 79 in climate model projections for Antarctic sea ice due to "the wide inter-model spread 80 and the inability of almost all of the available models to reproduce the mean annual cy-81 cle, interannual variability and overall increase of the Antarctic sea ice areal coverage 82 observed during the satellite era" (Collins et al., 2013). Similarly, the recent IPCC Spe-83 cial Report on the Oceans and Cryosphere in a Changing Climate found 'low confidence' 84 in model ability to explain changes in observed Antarctic sea ice cover (Meredith et al., 85

86 2019).

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Here we present an initial, high-level evaluation of Antarctic sea ice simulated by models in the sixth phase of the Coupled Model Intercomparison Project (CMIP6, Eyring et al., 2016). We focus on the areal coverage of sea ice, as this quantity can be readily obtained from satellite microwave passive radiometers. We examine the historical mean, inter-annual variability and trends in sea ice areal coverage, and leave investigation of the processes driving any particular biases to future studies.

93 2 Methods

The Sea Ice Model Intercomparison Project (SIMIP, Notz et al., 2016) coordinated 94 an evaluation of Arctic sea ice in CMIP6 and established a number of community best 95 practices (SIMIP Community, 2019). In this study, to aid comparison with Arctic re-96 sults, we adopt similar approaches and diagnostics. Following SIMIP Community (2019), 97 rather than sea ice extent, we principally consider sea ice area (SIA), computed by mul-98 tiplying sea ice concentration (SIC) with individual grid-cell areas and then summing 99 over the Southern Hemisphere. Here we also include consideration of SIC in the Sup-100 plementary Material and for calculation of the integrated ice area error (IIAE). The IIAE, 101 adapted from the extent-based integrated ice-edge error metric (IIEE, Goessling et al., 102 2016), describes the area of sea ice on which models and observations disagree (Roach 103 et al., 2018). It is the sum of SIA overestimated (O) and underestimated (U), 104

$$IIAE = O + U, \tag{1}$$

105 with

$$O = \int_{A} \max(c_m - c_o, 0) \delta A \tag{2}$$

106 and

$$U = \int_{A} \max(c_o - c_m, 0)\delta A, \tag{3}$$

where A is the area of interest, c_m is the simulated SIC for each model and c_o is the observed SIC on a common grid. For this computation, we interpolate all data to a regular 1 degree grid, following Roach et al. (2018).

SIA from satellite observations is calculated from daily data on native grids and then averaged for each month. To sample uncertainty in retrieval algorithms (Ivanova et al., 2014), we use three observational records of SIC: OSI SAF (Lavergne et al., 2019), NASA-Team (Cavalieri et al., 1997) and Bootstrap (Comiso et al., 1997). Differences between the three observational products are greatest at the Southern Hemisphere winter maximum and the observational spread in the Antarctic is greater than in the Arctic (Fig. 1),
with the lowest year-round SIA coming from the NASA-Team product. To sample uncertainty in observational products for global mean surface temperatures, we use the mean
of four—Berkeley (Rohde et al., 2013), NOAA globaltemp v5.0.0 (Vose et al., 2012), GISTEMPv4 (GISTEMP Team, 2019; Lenssen et al., 2019) and HadCRUT4.6.0.0 (Morice
et al., 2012)—following SIMIP Community (2019).

We use the period 1979-2014 in Sec. 3.1-3.2 to take advantage of the higher num-121 ber of CMIP6 models available from the historical experiments that end in 2014, result-122 ing in 40 CMIP6 models for comparison to 19 CMIP3 models and 38 CMIP5 models (Ta-123 ble S1-2). Due to the recent variability in observed Antarctic sea ice, in Subsec. 3.3 we 124 consider trends over 1979-2018, extending the historical experiments with the Scenar-125 ioMIP experiments (O'Neill et al., 2016) where available. For this we use the SSP2-4.5 126 experiments, resulting in 28 CMIP6 models for Sec. 3.3, as these have the largest num-127 ber of participating models, and scenarios are almost identical until 2020 (Riahi et al., 128 2017). 129

So as not to give extra weight to models providing multiple ensemble members, and 130 for consistency with both SIMIP Community (2019) and the sea-ice analysis in IPCC 131 AR5 (TS.SM.7.2, Stocker et al., 2013), we generally consider the first ensemble mem-132 ber for each ensemble. We refer to the 'CMIPx r1-ensemble' as having one ensemble mem-133 ber from each contributing model, and refer to individual ensembles as being the con-134 tributions from each CMIP model. All available members from individual ensembles are 135 used only to calculate internal variability in mean sea ice area in Subsec. 3.1 and to show 136 internal variability in sea ice area trends in Subsec. 3.3. Models are weighted equally al-137 though they may share components, a statistical limitation common to CMIP studies. 138 Similarly, individual model ensembles are treated equally here, although methods of en-139 semble generation vary (c.f. Golaz et al., 2019; Danabasoglu et al., 2020). We do not 140 demarcate individual models and observations in the main body of this paper; additional 141 figures showing key metrics for individual models are included in the Supplementary Ma-142 terial. 143

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144 **3 Results**

145

3.1 Mean state (1979-2014)

Fig. 1a shows the 1979-2014 mean seasonal cycle in Antarctic SIA from the CMIP6-146 r1 ensemble. The multi-model mean is lower than the three observational products all 147 year, with the difference from the lowest observational product ranging between 0.4 mil-148 lion km² in December and 1.4 million km² in May. Two models show a very clear low 149 bias year round, having a lower SIA in winter than many models in summer. There is 150 substantial inter-model spread in Antarctic SIA across the ensemble. Relative to the multi-151 model mean values, the inter-model standard deviation in Antarctic SIA is more than 152 twice that in the Arctic in corresponding months, and is particularly large in austral sum-153 mer. In spite of the inter-model variance in mean SIA values, all models but one cap-154 ture the asymmetry in the timing of the Antarctic SIA seasonal cycle, with five months 155 retreat and seven months growth, when considering monthly data in the 1979-2014 mean. 156

To evaluate CMIP6 simulations in September and February, the typical maximum 157 and minimum months of the seasonal cycle, we consider both the CMIP6 r1-ensemble 158 as a whole (Fig. 2a-b) and agreement of individual models (Fig. S1a-b). Estimates of in-159 ternal variability vary by model and we cannot judge which is most realistic, so rather 160 than aggregating them in Fig. 2a-b, we show all estimates individually in Fig. S1a-b. The 161 three observational products fall within the interquartile range of the CMIP6 r1-ensemble 162 in September, indicating some consistency between the ensemble and observations (Fig. 2a). 163 In February, the entire interquartile range is below the observations: a consistent under-164 estimation of summer SIA (Fig. 2b). These conclusions hold when accounting for inter-165 nal variability (Fig. S1a-b). As in SIMIP Community (2019), we describe individual mod-166 els as being consistent with observations if the 1979-2014 mean plus or minus our esti-167 mate of internal variability falls within the observed range. Internal variability is esti-168 mated as two standard deviations across individual model ensembles with three or more 169 ensemble members and correcting for small sample size, following SIMIP Community (2019), 170 or two standard deviations of the corresponding pre-industrial experiment in other cases. 171 Where both calculations are possible, estimates are generally similar (Fig. S1a-b). Us-172 ing whichever is the larger estimate, 26 of the 40 CMIP6 models are consistent with ob-173 servations in September and 16 out of 40 in February (Fig. S1a-b). Models may achieve 174 consistency with observations by overestimating simulated Antarctic SIA variability, see 175 Sec. 3.2. 176

Next, we consider Antarctic SIA simulated in CMIP6 relative to two previous gen-177 erations (Fig. 2a-b). Comparisons between generations are unlikely be affected by in-178 ternal variability, as the probability of choosing an ensemble member that is biased in 179 any particular direction for all models in a generation is low. Besides the 40 CMIP6 mod-180 els and three observational products, Fig. 2a-b show the 1979-2014 mean September and 181 February SIA for the 19 CMIP3 models and 38 CMIP5 models. The inter-model spread 182 is large compared to the SIA values, especially in February, and especially for CMIP5, 183 with two CMIP5 models having more than three times the February SIA in observations. 184 Inter-model spread is lower in CMIP6 than CMIP3 and CMIP5 in February and com-185 parable to CMIP3 in September, despite CMIP6 having twice as many models. Multi-186 model r1-ensemble February mean and median values are below observations for all three 187 model generations, but are lowest for CMIP6, indicating that the low bias in summer 188 sea ice has worsened compared to previous CMIP generations. 189

The regional distribution of Antarctic sea ice is highly variable across CMIP5 (M. M. Hol-190 land et al., 2017; Roach et al., 2018). Compared to figures from those papers, the spa-191 tial distribution of SIC generally appears more uniform and more similar to observations 192 in CMIP6 (Fig. S2-S3). Several CMIP6 models retain compact summer ice cover (Fig. S3), 193 an aspect that was particularly poorly simulated in CMIP5 (Roach et al., 2018). In Fig. 2e-194 f, we quantify the spatial distribution of sea ice in February and September using the 195 integrated ice area error (IIAE) over 1979-2014. We show the IIAE relative to the Boot-196 strap product only; results are similar for the two other observational products. Errors 197 are high relative to the mean SIA values in those months, particularly in February, where 198 in CMIP6 the model-mean IIAE is $1.6 \text{ million } \text{km}^2$ and the model-mean SIA is 1.4 million199 lion km². In both February and September, the multi-model mean and median IIAE are 200 slightly lower in CMIP6 than CMIP5. The model inter-quartile range in IIAE is sim-201 ilar in CMIP6 and CMIP5, but CMIP6 has fewer outliers with a very high IIAE. 202

Sea ice thickness is a high-level diagnostic of energy fluxes associated with atmospheric radiation bias, ocean stratification, and heat and mass transport. We show the climatology of sea ice volume per unit grid cell area (SIVOL), sometimes referred to as 'equivalent thickness, across the CMIP6 r1-ensemble in September and February in Fig. S4-5. The cross-model standard deviation approaches 1 m around the Antarctic Peninsula, where models show the highest SIVOL values. At least a quarter of models show large areas where SIVOL is lower than 0.5 m in September (Fig. S4) despite having high SIC

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(Fig. S2). Regrettably, the lack of climatological sea ice thickness observations preclude
model evaluation.

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3.2 Inter-annual variability (1979-2014)

Assessments of CMIP5 models concluded that models strongly over-estimated the 213 inter-annual variance of Antarctic sea ice extent (Collins et al., 2013; Zunz et al., 2013). 214 Over 1979-2014, observational-mean standard deviations in detrended Antarctic SIA are 215 0.34 million km² in September and 0.26 million km² in February. Considering individ-216 ual (detrended) CMIP6-r1 models over 1979-2014, in February, they are more or less di-217 vided equally between having higher and lower inter-annual variability than observations 218 (Fig. S1c). In September, most individual models have higher variability than observa-219 tions, in some cases exceeding observations by a factor of four (Fig. S1d). 220

This aspect is mostly unchanged in CMIP6 from CMIP5 and CMIP3. All three model 221 generations have higher variability than the observations in September and overlap the 222 observations in February (Fig. 2c-d). Thus, as a whole, models continue to over-estimate 223 inter-annual variability at the winter maximum but appear consistent with observations 224 in terms of variability at the summer minimum over 1979-2014. However, given that the 225 models underestimate summer sea ice area, variability as a fraction of the mean is gen-226 erally higher in models than observations in February. This result holds over 1979-2018 227 despite the increase in observed variability over this longer time period (not shown). 228

229

3.3 Recent historical trends (1979-2018)

The signal of observed change in Antarctic SIA and concentration over 1979-2018 230 is weak (Yuan et al., 2017; Handcock & Raphael, 2019; Maksym, 2019). SIA trend mag-231 nitudes over 1979-2018 are approximately half their 1979-2014 values and vary with ob-232 servational product by a factor of two (Fig. 3a-b). Assuming a 2-tailed t-test and using 233 the 95 % confidence level as a rough indicator of statistical significance, observed 1979-234 2018 SIA trends are significant only during winter months (Fig. S6). A small dipole pat-235 tern of increases and decreases in SIC remains in February, but few significant trends 236 are observed in September (Fig. S7-8). 237

Fig. 3a-b show the observed SIA trends compared to trends in all possible 40-year segments of the pre-industrial control runs. A wide range of trends occur in the absence of greenhouse gas and aerosol forcing. This large variability may be unrealistic, given the overestimation of interannual variability (Subsec. 3.2). As with CMIP5 (e.g. Polvani
& Smith, 2013), observed SIA trends lie well within this range. The more appropriate
model-observations comparison is with simulations including anthropogenic forcings similar to those observed, as shown for 1979-2018 (historical simulations extended with SSP24.5) in Fig. 3c-d. In this case, CMIP6 sea ice trends are only marginally consistent with
observed SIA trends. The values and significance of SIA trends (Fig. S6) and regions of
sea ice loss (Fig. S7-S8) vary substantially across the CMIP6 r1-ensemble.

To help explain the modelled trends, Fig. 3e shows the linear trend in annual-mean 248 SIA as a function of the annual-mean trend in global mean surface temperature (GMST) 249 over 1979-2018. In contrast to the Arctic (e.g., Gregory et al., 2002; Winton, 2011; Mahlstein 250 & Knutti, 2012), in the Antarctic, the observed correlation between SIA and GMST is 251 weak, while CMIP6 models generally simulate a strong anti-correlation but with sub-252 stantial across-ensemble variance (Fig. 3e). This could suggest modelled SIA is too de-253 pendent on GMST, but equally it is possible that the observed correlation would be neg-254 ative and stronger in a world with stronger GMST trends and corresponding sea ice loss. 255 From Fig. 3e, models with strong negative trends in SIA also have positive GMST trends 256 much greater than observations—in some cases nearly twice the observations. This sug-257 gests that at least some of the mismatch with observations may relate to model climate 258 sensitivity, rather than processes specific to the polar regions. 259

260

3.4 21st Century Projections

Finally, we consider SIA time series from 1950 to 2100 (Fig. 4), noting that pro-261 jections should be treated with caution given the model biases discussed above. Fig. 4a-262 b show the multi-model means from the historical and midrange emissions scenarios for 263 the CMIP3, CMIP5 and CMIP6 r1-ensembles (SRESA1b, RCP4.5 and SSP2-4.5 respec-264 tively), as this is the scenario with the largest number of model experiments. The rate 265 of change in SIA in February and September is similar across the three generations, but 266 with a slightly higher rate of decline in September in CMIP6 towards the end of the cen-267 tury. CMIP6 has the lowest multi-model mean SIA and, in February, the smallest stan-268 dard deviation across the multi-model ensemble. 269

Fig. 4c-d show CMIP6 SIA for the historical and three forcing scenarios: SSP1-2.6, SSP2-4.5 and SSP5-8.5. The scenario multi-model means agree until around 2040 in February and September, reflecting the close agreement of the scenarios in the initial decades

(Riahi et al., 2017) and possibly the dominant role of ozone forcing in the first half of 273 the 21st century (Barnes et al., 2014), which is similar across scenarios (Dhomse et al., 274 2018). Differences between scenario multi-model means are much smaller than inter-model 275 differences within each scenario, reflecting substantial model uncertainty. By the end of 276 the 21st century, there is clear divergence between scenarios in both February and Septem-277 ber SIA. In February, the 2090-2099 SSP1-2.6 multi-model mean is 29 % lower than the 278 1979-2014 historical multi-model mean, compared to a loss of over 90 % in SSP5-8.5. In 279 September, the losses relative to 1979-2014 are approximately 15 % and 50 % in scenar-280 ios SSP1-2.6 and SSP5-8.5 respectively. 281

²⁸² 4 Conclusions

In this study, we evaluated sea ice simulated by models from the sixth phase of the 283 Coupled Model Intercomparison Project (CMIP6) using the now-forty-year observational 284 record of the areal coverage of sea ice. Sea ice thickness varies across the multi-model 285 ensemble but cannot be evaluated due to the lack of long-term observational references. 286 We have not explored the reasons behind changes in sea ice compared to CMIP5, which 287 may include changes to ocean vertical mixing schemes, multi-phase cloud parametriza-288 tions, ozone forcing and increased spatial resolution, including improved bathymetry. Nor 289 have we explored the causes for continued sea ice biases in CMIP6. These may include 290 cloud effects (Zelinka et al., 2020; Kay et al., 2016), spatial resolution that does not per-291 mit eddies, which are understood to be highly important for representation of Southern 292 Ocean dynamics (Hallberg & Gnanadesikan, 2006; Poulsen et al., 2018; Rackow et al., 293 2019), and the lack of coupled ice sheet interactions, which have relevance for the en-294 tire Antarctic climate system (Bronselaer et al., 2018; Golledge et al., 2019; Pauling et 295 al., 2017). We anticipate that future studies will investigate these aspects. 296

Our analysis suggests a smaller discrepancy between models and observations than 297 previously identified due to the extended observational record. Now with four additional 298 years of satellite data, the observed trend in SIA has weakened and the regional signals 299 are less clear over 1979-2018 than 1979-2014. This suggests that natural variability played 300 a major role in the observed trend, as discussed previously (Meehl et al., 2016; L. Zhang 301 et al., 2019), and that inability of models to reproduce a positive trend should not be 302 used as a criterion to exclude them from projections. Models with the most negative trends 303 in SIA are those with large trends in GMST over 1979-2018, in some cases reflecting high 304

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climate sensitivity (Zelinka et al., 2020). This suggests that the disagreement with observations in historical sea ice trends is related more to climate forcing than sea ice physics.
Using the full model ensemble in future emissions scenarios, model uncertainty in SIA
dominates over scenario uncertainty, but multi-model means clearly diverge for the different scenarios by the end of the 21st century.

Considering SIA and concentration, we find some modest improvements in simu-310 lated Antarctic sea ice from the 40 models available compared to previous CMIP phases. 311 Compared to CMIP5, the regional distribution of sea ice has slightly improved and the 312 inter-model spread in mean sea ice quantities has decreased. CMIP6 models show con-313 sistency with observations at the winter maximum in September and a greater number 314 of models retain high-concentration summer sea ice cover than CMIP5. However, they 315 broadly under-estimate the summer minimum SIA, more so than CMIP5. Inter-annual 316 variability of sea ice is still generally larger than that observed over the historical period, 317 and many individual models still simulate implausible mean SIA, resulting in a large inter-318 model spread substantially larger than that in the Arctic. While these issues remain, over-319 all, results suggest that we should have moderately higher confidence in simulation of 320 Antarctic climate in CMIP6 than previous generations. 321



Figure 1. 1979-2014 mean seasonal cycle in SIA for the CMIP6 r1-ensemble (faint green lines), the CMIP6 multi-model mean (thick green dashed line) and three observational products (black lines) in (a) the Antarctic and (b) the Arctic.



Figure 2. 1979-2014 SIA seasonal cycle statistics for the Antarctic, where boxplots contain one data point per CMIP model in the r1-ensemble. Boxes extend from the lower to upper quartile values of the data with a line at the median and a cross ('X') at the mean. Whiskers show 1.5 times the interquartile range, and data outside this range are considered outliers and shown circles. The number of models included is noted in brackets. (a) shows the September mean, (b) the February mean, (c) the September standard deviation of detrended time series, and (d) the February standard deviation of detrended time series (SD), for CMIP3, CMIP5, CMIP6 and the three observational products (marked with +). (e-f) show the integrated ice area error (IIAE) from CMIP5 and CMIP6 models in (e) February and (f) September for the 1979-2014 mean, relative to the Bootstrap observations.



Figure 3. (a-b) Histograms of trends in Antarctic SIA in all possible 40-year segments of CMIP6 pre-industrial control runs, calculated from a least-squares linear regression and regardless of statistical significance in (a) September and (b) February. Vertical lines show trends in three observational products for (black long-dashed, -) 1979-2018 and (grey short-dashed, :) 1979-2014. (c-d) As (a-b) but for CMIP6 historical (forced) experiments over 1979-2018, using all available members from individual ensembles. (e) The linear trend in annual-mean Antarctic SIA over 1979-2018 versus the linear trend in global mean surface temperature over 1979-2018 for (circles) CMIP6 models, including all available ensemble members as individual points, and (squares) observations. The shading indicates the value of the Pearson correlation coefficient between annually-varying SIA and GMST. SIA trends that are not statistically significant at the 95 % level are hatched. Note that one model (not hatched) lies beneath the observations.



Figure 4. Antarctic SIA time series from 1950 to 2100 in February (b,d) and September (a,c). Upper plots (a,b) show the r1-ensemble-means for historical simulations and mid-range forcing scenarios: SRESA1B for CMIP3 (blue), RCP45 for CMIP5 (red) and SSP245 for CMIP6 (green). The mean plus or minus one standard deviation across the multi-model ensemble is shown as faint lines or shading corresponding to those colours. Lower plots (c,d) show historical simulations and three scenarios for the CMIP6 r1-ensemble. Three observational products are shown in black. Thick coloured lines denote multi-model means and faint lines show individual model trajectories. The number of models included in each mean is noted in brackets in the legend.

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Data availability: All model output is available through https://esgf-node.llnl 345 .gov/projects/esgf-llnl/ (Table S1). All observational products are publicly avail-346 able: OSISAF from http://osisaf.met.no/p/ice/ice_conc_reprocessed.html to 2015 347 and http://www.osi-saf.org/?q=content/global-sea-ice-concentration-interim 348 -climate-data-record-release-2 from 2016 onwards (Lavergne et al., 2019); NASA-349 Team and Bootstrap from https://nsidc.org/data/g02202 (Meier et al., 2017); Berke-350 ley from http://berkeleyearth.org/data/ (Rohde et al., 2013); NOAA globaltemp 351 v5.0.0 from https://www.ncdc.noaa.gov/noaa-merged-land-ocean-global-surface 352 -temperature-analysis-noaaglobaltemp-v5 (Vose et al., 2012; H.-M. Zhang et al., 353 2020), GISTEMPv4 from https://data.giss.nasa.gov/gistemp/ (GISTEMP Team, 354

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- 2019; Lenssen et al., 2019); and HadCRUT4.6.0.0 from https://www.metoffice.gov
- .uk/hadobs/hadcrut4/ (Morice et al., 2012).
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- formed the analysis. All authors contributed to the manuscript. SO, EB and TR addi-
- tionally provided model data before they were available on ESGF.

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