Dear authors

Thanks for submitting your responses. I would like to invite you to submit the revised manuscript for the full consideration.

Kenny Matsuoka

TC/TCD Editor

Dear Editor,

We would like to thank you for editing our manuscript. We have updated it according to the comments of the reviewers as suggested in our responses. You can find below the point by point response to each reviewer's comment as well as the final version of our manuscript with track changes.

On behalf of all co-authors,

Dalaiden Quentin

The Referee's comments below are in italics, our answer in plain font in blue

*The authors present the ability of CMIP5 GCMs to be used, together with ice core and d18O proxies, as a tool to reconstruct by data assimilation Antarctic temperature and SMB. They explore regionally the relation between these two variables by using different reconstruction techniques, and conclude that using both SMB and d18O proxies is most optimal. Doing this they can now better reconstruct SMB in the last two centuries. The paper is well written, with clear figures and a new, at least to me, approach in reconstructing temperature and SMB far back in time based on physical models. The results are robust, well presented, sufficiently new and original, and I do not feel that any information is missing. I therefore strongly recommend publication in The Cryosphere. However, I do have some comments on the clarity of the paper and would also recommend to make the data assimilation explanation more clear, as I will explain below.*

We would like to thank the Referee for the positive evaluation and for the useful comments.

*P1, Title: To me the title does not really catch the main conclusions and content of the manuscript. To me, the paper comes across as a new temperature and SMB reconstruction based on a new/better technique. Do the authors feel that the main content of the paper is the link of SMB and temperature? The current title seems to"state the obvious", and did not really attract me at first to review the manuscript.*

We agree with the referee that the title does not totally correspond to the main content of the manuscript. We have decided to change it to: "How useful is snow accumulation in reconstructing surface temperature in Antarctica? A study combining ice core records and climate models."

*P1, Abstract, l7: This sentence is confusing, as d18O and temperature could also be the same. You mean the SMB-temperature relationship is stronger than the relationship between d180 and temperature? Maybe write out this sentence and omit the -dash.*

We have changed this sentence. "We find that, on the regional scale, the modeled relationship between surface temperature and SMB is generally stronger than between temperature and $\delta^{18}O$."

*P1, Abstract, l13: This is not clear. Which reconstruction method is used for the SMB?*

We agree that this sentence is ambiguous. We have changed it by:

Finally, we provide a spatial SMB reconstruction of the AIS over the last two centuries showing 1) large variability in SMB trends at regional scale; and 2) a large SMB increase (0.82 Gt year$^{-2}$) in West Antarctica over 1957–2000 while at the same time, East Antarctica has experienced a large SMB decrease (-3.3 Gt year$^{-2}$), which is consistent with a recent reconstruction.

by:

Finally, using the same data assimilation method as for the surface temperature reconstruction, we provide a spatial SMB reconstruction for the AIS over the last two centuries showing large variability in SMB trends at regional scale, with an increase (0.82 Gt year$^{-2}$) in West Antarctica over 1957–2000 and a decrease in East Antarctica during the same period (-3.3 Gt year$^{-2}$). As expected, this is consistent with the recent reconstruction used as a constraint in the data assimilation.

*P1, Abstract, general: The abstract (and title) should be reconsidered. The abstract is the first thing people read, and should be instantaneously clear. I had to re-read the abstract several times to understand it. Of course I understood it after reading the whole manuscript, but the abstract should be standalone in my opinion.*

As suggested by the reviewer, we have rewritten the abstract to highlight our main conclusions.

*P3, l17: what is meant here with "estimated by d180"? This relation comes out of the blue.*

We wanted to point out here that the $\delta^{18}O$ is used as a proxy of surface temperature in some studies analyzing the link between surface temperature and SMB. Therefore, those studies (e.g. Fudge et al., 2016; Altnau et al., 2015; Philippe et al., 2016; Goursaud et al., 2019) have analyzed the link between $\delta^{18}O$ and SMB rather than the link between surface temperature and SMB. In other words, they are not based on observed surface temperature but on estimated surface temperature derived from $\delta^{18}O$.

We have changed this sentence to illustrate this:

However, some studies (Fudge et al., 2016; Altnau et al., 2015; Philippe et al., 2016; Goursaud et al., 2019) indicate that this SMB-surface temperature relationship (estimated by $\delta^{18}O$) is not always positive, and varies spatially and temporally.

by:

However, some studies using surface temperature reconstructions based on $\delta^{18}O$ data (Fudge et al., 2016; Altnau et al., 2015; Philippe et al., 2016; Goursaud et al., 2019) suggest that this SMB-surface temperature relationship is not always positive and varies spatially and temporally.

*P10, Figure 3: Where does the very low reconstructed value for West Antarctica in∼1700 come from?*

This very low value is likely related to the low number of ice cores used for the SMB composite of the West Antarctica region at this time. As shown by Thomas et al. (2017), the regional SMB composites before 1800 are based on very few records, which can lead to large uncertainties. We have decided to only display the 1800-2010 period for the reconstruction to avoid those uncertain values.

*P11, Figure 4: Please change the y-axis and x-axis labels. Slope West/Slope East is unclear.*

We agree that this plot is unclear. We have changed the plot to make it clearer (see the response to the second review).

*P12, Figure5: why is this shown in a contour plot? To me this is confusing. Can't you make a scatter plot (such as Fig. 7) showing the correlations?*

We think it is important to display the correlations between SMB and surface temperatures on a map instead of a scatter plot to keep the spatial dimension. For example, by analyzing the results for RACMO2, we observe that the coastal regions of East Antarctica display weak correlations between the two variables. Replacing this map by a scatter plot will remove this spatial information, which is important in our interpretation.

*P17, Discussion and conclusions: Same comments for this section as for the abstract:*
*I miss a clear emphasis on the main conclusion of the manuscript. How can these datasets be used in future work? What's the relevance of the study? What's the most important take-home message? I expect that the authors can easily strengthen the relevance of the study by giving this some extra thoughts.*

We will change our conclusion in order to strengthen our main findings as asked by the referee.

The Referee's comments below are in italics, our answer in plain font in blue

*This paper from Dalaiden and co-authors addresses the question of the relationship between surface air temperature (SAT) and surface mass balance (SMB) in Antarctica, from the past 1000 years to the last decades, in view of using the SMB information for reconstructing past SAT. Given the short and sparse observational coverage in Antarctica, reconstruction of the Antarctic climate further than the last decades rely on the interpretation of proxies. The isotopic composition of the snow (in particularδ18O in ice cores) is the most widely used proxy of SAT in Antarctica. First the authors show that the strong link between SMB and SAT, already acknowledged in the literature (e.g. Frieler et al 2015), remain valid in GCMs during the past1000 years and the past 200 years. They also show that the relationship does not stand when considering the last two reconstructions of surface air temperature (based on ice cores δ18O, Stenni et al., 2017) and surface mass balance (based on ice cores accumulation, Thomas et al., 2017), but does exist when using an Antarctic SAT reconstruction based on weather stations (Nicolas and Bromwich 2014, NB14) instead of the SAT reconstruction based on ice cores δ18O. Then the authors use isotope-enabled global climate models to perform an offline data assimilation of δ18O and SMB over the past 200 years. They obtain more consistent results with NB14 SAT over West and East Antarctic ice sheets when combining the assimilation of δ18O and SMB. I think using both SMB and δ18O for reconstructing SAT with an assimilation method is novel and relevant for the cryosphere and climate community. The overall presentation is clear and figures are nicely shaped. Conclusions seem robust and interesting. However I have some concerns about some of the interpretations, and I also have comments on the methodology. Therefore I recommend this article to be published after addressing the following issues.*

We would like to thank the Referee for the careful evaluation and for all the suggestions that helped to improve the manuscript.

*Major*

*1) I think the GCM evaluation is of interest, in particular the plots comparing SMB by elevation bins, but I disagree with the conclusion that GCM are doing a good job in Antarctica. I think this is not a critical point for this study, so the authors should minimize or remove the section about GCM evaluation (Section 4.1, one or two sentences and citing supplementary would be enough) and extend the analysis on the SMB/SAT relationship (Section 4.2). Fig. 2 is not necessary, Fig. 3 and Fig. 4 could be moved to the SAM/SAT section, Fig. 4 could be extended with a scatterplot comparing SMB/SAT sensitivity factors (% K-1) of West vs East. This way the result section would follow the plan detailed in the introduction: i) SMB/SAT in GCMS over the past millennia and* centuries ii) data assimilation for the past centuries.

As suggested by the reviewer, we have trimmed the GCM evaluation. The evaluation over the recent past (1979-2005; i.e. the comparison to RACMO outputs) has been moved to Supplementary Materials. However, we have kept the section on the comparison between the simulated and reconstructed (i.e. Thomas et al., 2017) SMB changes during the last two centuries. Therefore, we have adapted the title section: "Reconstructed and simulated SMB changes over the last centuries".

The Fig. 4 has been extended with a scatter plot comparing the SMB/SAT sensitivity factors:

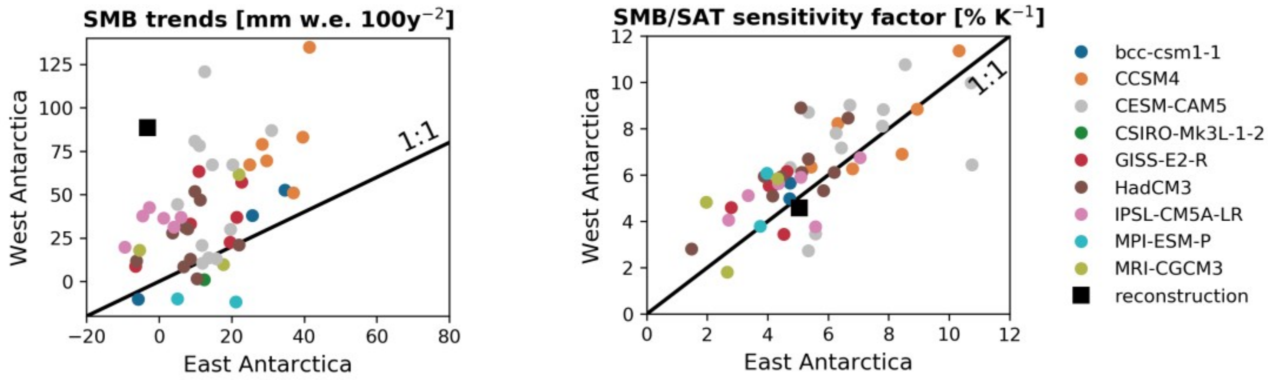


**Figure 4.** (left) Comparison between the reconstructed and the simulated SMB trends (mm w.e./100y$^{-2}$) over the period 1950–2000 CE in West Antarctica (y axis) and East Antarctica (x axis). (right) As on the left but for SMB/SAT sensitivity factors (% K$^{-1}$). For the reconstruction, data from Thomas et al. (2017) and Nicolas and Bromwich (2014) are used.

*In detail:*
** Abstract "Here, we show that Global Climate Models (GCMs) can reproduce the present-day (1979–2005) AIS SMB and the temporal variations over the last two centuries."*

We have removed this sentence to stay focused in the abstract on the SMB-SAT relationship and on our reconstructions.

** P17 "The GCMs are able to simulate relativity well the current AIS SMB"*
*-> Should be rephrased or removed (see hereafter).*

We have removed the SMB evaluation in the discussion/conclusions section.

** P8 "Overall, the AIS SMB simulated by GCMs is in good agreement with the SMB simulated by the regional climate model RACMO2 over the last decades (1979–2005,R2 = 0.53; Fig. 2 and S1 for the SMB of each model)."*
*-> I see huge differences, spatially and integrated over the ice sheet (Fig. S1 and S2). How is computed this correlation coefficient? What is the bias?*

We have made a correlation plot (new figure: see below, Fig. S2) of the SMB climatology as simulated by the average of the GCMs as a function of the climatology of RACMO over the 1979-2005 period. The correlation is computed between the model mean spatial distribution (averaged over 1979-2005) and the spatial distribution of RACMO over the same period. The model mean has been interpolated on the RACMO grid to compute the correlations. The bias is the average of the difference between the GCM mean and RACMO (in mm w.e. year$^{-1}$).

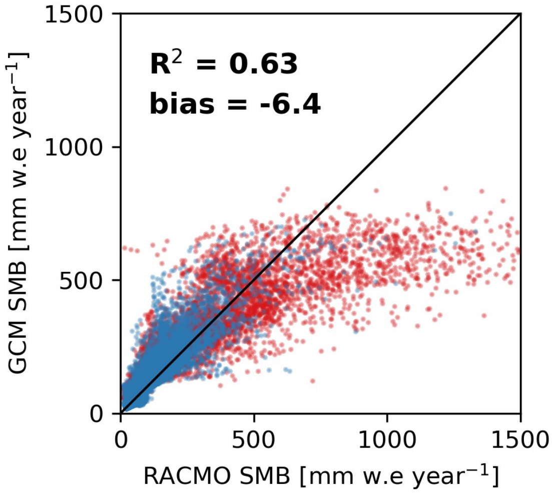


**Figure S2.** Correlation plot of SMB climatology from GCM mean (average over all the GCMs including isotope-enabled models) as a function of SMB RACMO over the 1979–2005 period at the same location. $R^2$ is the determination coefficient and the estimation of the bias is the average of the difference between GCM mean and RACMO (in mm w.e. year$^{-1}$). Red (blue) dots are for places where the altitude is lower (higher) than 1500m. See Fig. S4 for the equivalent for each model.

Because we have added the isotope-enable models in the evaluation, we have updated the following sentence:

"The mean of the SMB over the entire AIS simulated by the selected CMIP5 models is 87 Gt year -1 higher than the SMB simulated by RACMO2 (relative bias: -3.7%; see Fig. S2 for the integrated SMB over the entire AIS for each model)."

by:

"The mean of the SMB over the entire AIS simulated by the selected models (including isotope-enable models) is 6.4 mm w.e. year -1 lower than the SMB simulated by RACMO2 over the 1979-2005 period (relative bias: -3.4%; see Fig. S4 for the correlation plots for each model and Fig. S5 for the integrated SMB over the entire AIS for each model)."

** P8 "Both display high values of SMB along the coast (>300 mm w.e. year-1) – especially for West Antarctica and the Antarctic Peninsula – and lower values at high elevations (e.g. the Plateau: <100 mm w.e. year-1)."*
*-> This is really the minimum feature a model can do, because of the general circulation and the ice sheet topography.*

Yes, we totally agree with your remark, but we think that it is important to notice the main Antarctic SMB pattern. Therefore, we have added "As expected" at the beginning of the sentence to show that is not something surprising.

*2) I found interpretations in contradiction with the figures.*
** P9 "Nevertheless, when analyzing the individual simulations of the ensemble performed with CESM1-CAM5, the contrast between East Antarctica and West Antarctica is as large as in recent observations (Fig. 4). This indicates that 1) the observed SMB trends between the two regions are within the range of the simulated values; 2) internal variability has an important role in the current Antarctic SMB changes."*
*-> Reconstruction is a clear outlier of the GCM's scatterplots, so reformulate the conclusion in agreement with your figure.*

We have changed the paragraph following the suggestion to be in better agreement with the figure:

"When analyzing the ensemble of simulations performed with CESM1-CAM5, the ensemble mean also shows a relatively homogeneous increase, but some simulations display a contrast between East Antarctica and West Antarctica close to the one observed in the reconstruction (Fig. 3). This suggests that internal variability has a dominant contribution in the current Antarctic SMB changes and might explain why the observed contrast between East and West Antarctica is only present in a few simulations."

** P12 "For most regions, the link between surface temperature and SMB (r=0.70 on average over the seven subregions for the 1850–2000 period) is higher than that between surface temperatures andδ18O (r=0.55 on average over the seven subregions for the 1850–2000 period)." (...) "The results with the outputs of ECHAM5-wiso and ECHAM5/MPI-OM are similar (Figs. S6 and S7)."*
*-> It does not appear to be true when looking at Fig. S6 and S7: blue dots (SAT/δ18O) are often higher than green dots (SMB/SAT). I regret this over-interpretation and the fact that the authors focused on the iHadCM3 in the main text without specifying it and explaining this choice.*

We mostly focused on iHadCM3 outputs and not on the other isotope-enable models in the main the text because, in contrast to the other isotope-enabled models (ECHAM5-wiso and ECHAM5/MPI-OM), iHadCM3 offers an ensemble of simulations which is a significant advantage for data assimilation. Indeed, dealing with an ensemble of simulations allows increasing the probability to find a good match between the assimilated records and model results during the assimilation process.

Regarding the ECHAM5-wiso and ECHAM5/MPI-OM models, we have modified the figures S6 and S7 to replace them by the Figure S9:

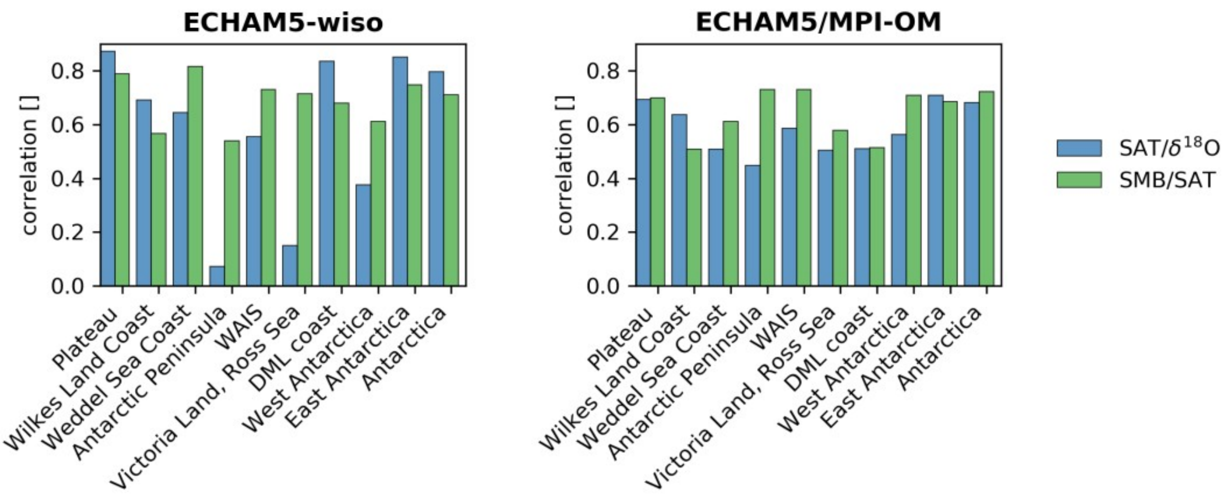


**Figure S9.** 5-year mean correlations between surface temperature and $\delta^{18}O$ (blue) and, SMB and surface temperature (green) for the seven Antarctic regions for the entire period simulation (1871–2010 for ECHAM5-wiso and 801–2000 for ECHAM5/MPI-OM).

This new figure allows for an easier comparison between the potential of SMB and $\delta^{18}O$ in reconstructing regional surface temperatures. As the reviewer mentioned, the results of ECHAM models are a little different than those of iHadCM3. We thus propose to discuss in more details those results of the ECHAM in the main text:

“The results of ECHAM5-wiso and ECHAM5/MPI-OM confirm this strong link between SMB and temperature but, in contrast to iHadCM3, the correlations are not systematically higher than between $\delta^{18}O$ and temperature (Fig. S9). When analyzing the long ECHAM5/MPI-OM simulation (800–2000), the relationship between SMB and surface temperature is generally higher than between $\delta^{18}O$ and surface temperature but the difference is small. For some regions, the SMB-surface temperature link is much higher than the $\delta^{18}O$-surface temperature link but it is weaker for other regions. In contrast to the $\delta^{18}O$-surface temperature link, the SMB-surface temperature is less spatially variable (minimum regional correlation is 0.54 against 0.07 for the $\delta^{18}O$-surface temperature link).”

*P18 "On the one hand, models show a strong correlation between δ18O and SMB for all the Antarctic regions"-*
*> It’s not true: red dots in Fig 7, S6 and S7. Is there a typo here? But even SAT-SMB relationship is not strong for all regions (Fig S5).*

Indeed, we made a mistake here (it is the SAT-SMB relationship and not the $\delta^{18}O$-SMB relationship that shows a strong correlation for all regions). Thank you for that.

We propose to replace “for all the Antarctic regions” by “many Antarctic regions”.

*"we showed that the relationship between SMB and surface temperature is often higher than the one between surface temperature andδ18O. This is true both on the continental and regional scale."*
*-> That’s not true when considering ECHAMwiso and ECHAM/MPI-OM*

Even though the ECHAM models do not always display stronger regional correlations between SMB and surface temperature than between $\delta^{18}O$ and surface temperature, on average over all the isotope-enable models, the SMB-surface temperature link is stronger (90% of the time for iHadCM3, 80% for ECHAM/MPI-OM and 50% for ECHAM5-wiso) and more stable than the $\delta^{18}O$ -surface temperature link. We propose to modify slightly this sentence:

“By analyzing isotope-enabled climate models, we show that the relationship between SMB and surface temperature is often higher than the one between surface temperature and δ 18 O.”

by:

“By analyzing isotope-enabled climate models, we showed that on average over the models, the relationship between SMB and surface temperature is often higher (or at least equivalent) and more stable than the one between surface temperature and $\delta^{18}O$.”

*3) Methodology*
*Data assimilation (DA) must be evaluated with independent datasets. It is the case for SAT (NB14 is not assimilated) but not for SMB. The authors assimilate SMB from Thomas et al. (2017) and evaluate their results with Thomas et al. (2017). I suggest to use independent and annually resolved datasets, such as the radar transects resolved annually in West Antarctica (Medley et al. 2014 https://doi.org/10.5194/tc-8-1375-2014) and stake line transects (JARE, CHINARE).*
** P19 "Considering our good results regarding surface temperatures and SMB reconstructions,"*
*-> This sentence is not fair if you evaluate your result with the data you assimilate.*

We totally agree with the reviewer. Our goal is to propose a new reconstruction method for surface temperature. It is thus needed to evaluate this new reconstruction with an independent dataset. Unfortunately, we did not find any suitable dataset to evaluate our data assimilation-based reconstruction. The radar transects that you suggest (Medley et al., 2014) cover a small part of the West Antarctic Ice Sheet over the 1985-2009 period. It is thus not possible to make an evaluation at the scale of Antarctica. Furthermore, because we applied a 5-year smoothing on our SMB and surface temperature reconstruction to remove the non-climatic noise, any validation would be based on a too small sample (applying a 5-year smoothing on the NB2014 dataset which covers the 1958-2012 period reduces the time series to 12 points which is already low for making correlations).

This absence of independent datasets forbids us to evaluate the skill of the new reconstruction. The comparison of our data assimilating-based SMB reconstruction to Thomas et al. (2017) is thus only done to check if the reconstruction is consistent with all the input information or if major incompatibilities are present. If model results (used as prior) and data are too different or if the uncertainty is not well estimated, the particle filter may degenerate. The resulting reconstruction can also be far away from the assimilated records if there is no model result that fits with the signal recorded in those data. Our comparison to Thomas et al. (2017) is not independent but at least shows that our reconstruction is consistent with Thomas et al. (2017). This is indeed expected but good to verify.

We specified in the experimental design (section 3.2) that we are not able to independently evaluate our SMB reconstruction:

“SMB estimates are also available for the last decades (e.g. Medley et al. 2014), but they cover a too short period or have a too small spatial coverage to provide an independent validation of our reconstruction. It is thus not possible to estimate if the assimilation of SMB and $\delta^{18}O$ measurements provides an improvement for this field.”

We have also specified in the discussion/conclusions section that we cannot independently simulate our SMB reconstruction:

“Although it is not possible to independently evaluate our SMB reconstruction, our good results regarding surface temperatures and SMB reconstructions suggest that the strong simulated correlation between surface temperatures and SMB in GCMs is not a model artefact.”

** P19 "our data assimilation-based reconstructions suggest that the strong simulated correlation between surface temperatures and SMB in GCMs is not a model artefact"*
*-> DA is a weighted average, so if the SMB-SAT relationship exists in the models, isn’tit conserved in the reconstruction by construction?*

Yes, this link should be preserved as the reconstruction is based on the covariance between those two variables as displayed in models. However, if the models were overestimating this link, the particle filter would give more weight to the model results that display the weakest correlation. Furthermore, the increased skill of the surface temperature reconstruction when including SMB data also indicates that the model covariance is bringing additional information. This is not a formal proof. This is the reason why in the corresponding sentence, we propose to use ‘suggest’ (see the new proposed sentence just above), but it remains consistent with the fact that the strong correlation between SMB and surface temperature is not a model artefact.

*4) A remark*
*Results of data assimilation seem less variable than the other reconstructions (Fig 8 and Fig 9). Is it due to the assimilation method? What is the confidence on the DA temporal variability?*

The mean reconstruction provided by data assimilation may underestimate the variability if the data is too uncertain or if there is not enough data. In the extreme case when you have no data (or with data displaying a very large uncertainty), the particle filter will just give a reconstruction that is the model ensemble mean which consists here, because of the experiment design, in a value of zero for the whole period. However, in that case, the uncertainty of the ensemble would be very large, and this of course must be taken into account when discussing the temporal variability of the reconstruction. More specifically, with only a few uncertain data, it is expected that the reconstruction based on our data assimilation method may show less variance than reconstructions provided by some other methods (as observed previously; e.g. Goosse et al. 2010). Nevertheless, we did not discuss much this point in the manuscript as it critically depends on the uncertainty of the input data, that is itself not well known.

Reference:

Goosse, H., E. Crespin, A. de Montety, M. E. Mann, H. Renssen, and A. Timmermann (2010), Reconstructing surface temperature changes over the past 600 years using climate model simulations with data assimilation, J. Geophys. Res.,115, D09108, doi:10.1029/2009JD012737.

*Minor*
*Abstract*
*"with a linear correlation coefficient with the observed surface temperatures (1958–2010 CE) of 0.73"*
*I don't think this number is meaningful, I suggest to remove it.*

It has been removed.

*P2*
*"(Rignot et al., 2011)"*
*Update with Rignot et al. (2019) https://www.pnas.org/content/116/4/1095"*

Thank you for the updated reference. It has been updated in the new version of the manuscript.

*(Wouters et al., 2013).*
*"Idem, update the reference.*

It is done: we have replaced the old reference by the new one: Martín-Español, A., et al. (2016), *Spatial and temporal Antarctic Ice Sheet mass trends, glacio-isostatic adjustment, and surface processes from a joint inversion of satellite altimeter, gravity, and GPS data*, J. Geophys. Res. Earth Surf.,121, 182–200, doi:10.1002/2015JF003550.

*"from stable isotope ratios of oxygen"*
*From water stable isotopes, and in particular δ18O*

Thank you for the specification. We have added it in the text.

*P3*
*"According to Monaghan et al. (2008), the observed sensitivity of Antarctic snowfall accumulation to surface temperature was about 5% K-1 during the 1960–1999 period."*
*Why Monaghan and not a most recent and complete reference? (e.g. Frieler 2015)*

We have replaced Monaghan et al. by Frieler et al. as suggested.

*"These results suggest that in some regions, especially along the AIS coasts, the variability of thermodynamic processes (such as the Clausius-Clapeyron effect) on SMB is dominated by the large-scale atmospheric circulation, limiting the correlation with δ18O."*
*Do you mean: SMB variability is dominated by large-scale atmospheric circulation rather than by thermodynamic processes?*

Yes, as mentioned by Philippe et al. (2016), we think that the SMB variability along the coasts is more related to large-scale atmospheric circulation than the thermodynamic processes.

We have changed the sentence to make it clearer:

"These results suggest that in some regions, especially along the AIS coasts, the variability of thermodynamic processes (such as the Clausius-Clapeyron effect) on SMB is dominated by the large-scale atmospheric circulation, limiting the correlation with δ18O."

by this:

"These results suggest that in some regions, especially along the AIS coasts, the SMB variability is dominated by large-scale atmospheric circulation rather than by thermodynamic processes (such as the Clausius-Clapeyron relation), limiting the correlation with $\delta^{18}$O."

*"While the statistical methods classically used to infer past surface temperature (see for instance Stenni et al., 2017) rely on the length of the calibration period, on the quality of the record during this period, and on the stationarity of the link between the proxy and the variable of interest, which can be strong assumptions in the case of the δ18O-temperature relationship (Klein et al., 2019), data assimilation does not.*
*"Doesn't data assimilation rely on the quality of the assimilated record too? One step further, a short sentence about the limits of the assimilation method is missing, to be fair. E.g. changes in the number and quality of assimilated data?*

We agree that all the reconstruction methods, including data assimilation, rely on the quality of the input data. The point here is that statistical methods are based on strong assumptions such as the stationarity of the link between the proxy and the climate variable. As this relationship is estimated over the instrumental period (i.e. calibration period), statistical methods highly depend on the data quality during this period. Because data assimilation methods do not require any calibration period, these methods are not dependent on the quality of assimilated records over the calibration period used in the statistical periods. Therefore, we propose to keep this sentence in the text, but we have added a general sentence to state that all methods depend on the quality of the input records to be fair:

"All reconstruction methods depend on the number and quality of the input data."

*P4*
*"The simulation of ECHAM5-wiso, which only includes an atmospheric component, was performed by Steiger et al. (2017) and covers the period 1871–2011 CE at 1◦resolution. The model is driven by the sea surface temperature and sea ice from the Rayner et al. (2003) dataset."*
*You have to mention that the Rayner et al. (2003) dataset is not relevant before 1973: "2.1.3. Antarctic Atlas Climatologies Before the advent of satellite area based imagery in 1973, sea ice concentration data for the Antarctic are not available, and sea ice extent data are not readily available for individual months, seasons or years, although some visible and infrared data do exist for 1966–1972 [Zwally et al., 1983] and some undigitized charts reside in national archives (e.g.,*

*V. Smolyanitsky, personal communication,2002). Readily available information was limited to two historical climatologies of sea ice extent. Therefore our sea ice concentration analysis before 1973 is derived indirectly, and does not include any interannual variability, though there are some trends resulting from the differences between climatologies for different periods."*

Thank you for the specification. We have added this information in the text:

"Due to a lack of Antarctic sea ice data before 1973, this dataset is based on historical climatologies of sea ice concentration for the period 1871-1973 CE, with no interannual variability."

*"Comparisons of the results of these three isotope-enabled models with modern δ18O observations indicate that they all reproduce the main characteristics of the spatial distribution of the isotopic composition of precipitation over Antarctica (see reference for each model)."*
*Add a word about their known biases.*

We have added a few sentences in the text regarding the modelled biases:

"According to Tindall et al. (2009) and Sime et al. (2008), the small biases in $\delta^{18}O$ (for example, an underestimation of the spatial $\delta^{18}O$ variability in rugged areas) in the iHadCM3 simulation mainly come from the coarse horizontal resolution of the model and not from the isotopic model itself. ECHAM5-wiso and ECHAM5/MPI-OM display an overall underestimation of $\delta^{18}O$ in Antarctica but reproduce well the general Antarctic $\delta^{18}O$ pattern (Goursaud et al., 2018; Klein et al., 2019, see reference of each model for more details)."

*P5*
*"(4) the output of RACMO2 for the AIS SMB agrees very well with available measurements (correlation coefficient with observations of 0.9; van Wessem et al., 2018)."*
*A high correlation coefficient alone is not a proof of good performance. Correlation can be equal to one with a very large bias.*

Thank you for your remark. We have removed the part with the correlation and modified the previous sentence:

"(4) the output of RACMO2 for the AIS SMB agrees very well with available measurements (correlation coefficient with observations of 0.9; van Wessem et al., 2018)."

by this:

"(4) RACMO2 has been extensively evaluated against available measurements and displays a very good agreement (e.g. van Wessem et al., 2018; Lenaerts et al., 2012)."

References:

Lenaerts, J. T. M., M. R. van den Broeke, W. J. van de Berg, E. van Meijgaard, and P. Kuipers Munneke (2012), A new, high-resolution surface mass balance map of Antarctica (1979–2010) based on regional atmospheric climate modeling, Geophys. Res. Lett.,39, L04501, doi:10.1029/2011GL050713.

*P6*
*"This temporal averaging reduces uncertainties in dating linked to the noise induced by non-climatic processes (e.g. Laepple et al., 2018; Fan et al., 2014)."*

*The temporal averaging is not described before, and I understood latter in the paragraph that you were talking about the 5-year and 10-year average. The whole paragraph is strangely shaped, please rephrase.*

Thank you for your remark. We made a mistake here. This sentence is not at the right location. We have moved it at the end of the third paragraph of the experimental design section (3.2).

*P7*
*"each ensemble member, called particle, is compared to the proxy-based reconstruction by computing its likelihood, taking into account data uncertainties."*
*Give a description of this likelihood function. How do you compute it?*

In our data assimilation method, the weights given to each particle are computed using a Gaussian likelihood. All the details can be found in Dubinkina et al. (2011). It is now specified in the new version of the manuscript:

"At each time step of the data assimilation procedure (yearly, see Sec. 3.2), each ensemble member, called particle, is compared to the proxy-based reconstruction by computing its likelihood, assumed here to be Gaussian, taking into account data uncertainties (see Dubinkina et al. (2011) for details)."

Reference:

Dubinkina, S., Goosse, H., Sallaz-Damaz, Y., Crespin, E., and Crucifix, M.: Testing a Particle Filter To Reconstruct Climate Changes Over the Past Centuries (2011), International Journal of Bifurcation and Chaos, 21, 3611–3618, https://doi.org/10.1142/S0218127411030763.

*P8*
*"The median of the SMB over the entire AIS simulated by CMIP5 models is 1.16"*
*A median computed from 12 values is not robust. This number is hiding large discrepancies between the models.*

We have replaced the median by the mean in the text (absolute and relative biases):

"The SMB integrated over the entire AIS is 87 Gt year $^{-1}$ higher for the mean of the selected CMIP5 models than in RACMO2 (relative bias: -3.7%; see Fig. S2 for the integrated SMB over the entire AIS for each model)."

As mentioned in the comment, there are large discrepancies between the models. Especially the MRI-CGCM3 model largely overestimates the AIS SMB compared to RACMO2 (+1320 Gt year $^{-1}$, see the figure below).

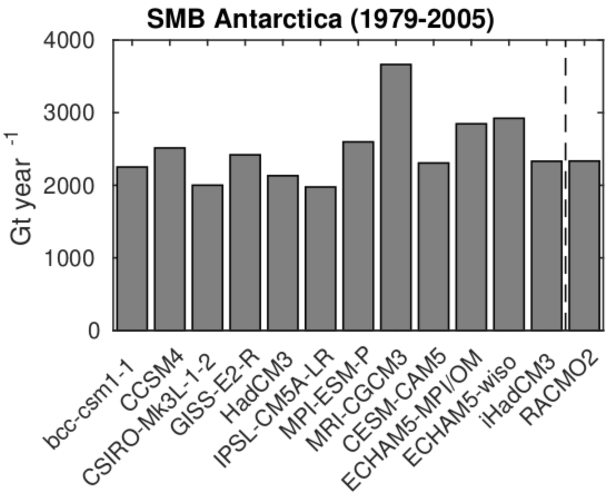


**Figure S5.** Mean Antarctic Ice Sheet surface mass balance (Gt year$^{-1}$) simulated by all the models used in this study.

**Figure 2:* You show the average while above you give the number for the median.*

We have now replaced the median by the average.

*"who have shown that due to the lower spatial resolution of GCMs in comparison to the regional model, SMB is underestimated at the coasts while an overestimation occurs in the interior of the ice sheet."*
*Resolution might play a role but model's physics also plays a major role. E.g. Fig S1 shows that MRI-CGCM3 and ECHAM-wiso have much large SMB at the margins than RACMO2, whereas they have a lower resolution.*

Thank for your remark. We have added this sentence in the text:

However, models with similar resolutions may also have very different results, in particular in coastal regions (relative SMB biases of +47% and +100% for CCSM4 and MRI-CGCM3 respectively compared to RACMO for DML coast over the 1979-2005 period), suggesting a critical role of model physics in some of the GCM biases.

**Fig. S3:* Add the isotope-enabled models*

As suggested, the isotope-enabled models have been added on the figure.

*"confirming that the spatial resolution has a crucial impact on the simulated SMB."*
*This is not convincing and not the dominant factor in my point of view.*

We have added a new sentence on the role of the model's physics in the new version of the manuscript (see the previous answer on the same topic).

*P11*
*"According to these reconstructions, this sensitivity has increased a lot for the recent period (1950–2005; 15.52 Do you think it is realistic? I don't find such an increase in sensitivity in Frieler et al. (2015)?*

We totally agree that this large increase in the SMB sensitivity to surface temperature using these reconstructions is quite surprising. Actually, as you mentioned, Frieler et al. (2015) do not obtain such an increase. This could suggest that the reconstructions used in this study suffer from issues. We have added a sentence accordingly to this result:

“However, Frieler et al. (2015) do not obtain such an increase in SMB sensitivity (only ∼+40%).”

**Figure 6:* I don’t understand why for WAIS and AP, ‘reconstructions’ (black line) is lower than model mean, while for the combination of both (West Antarctica), ‘reconstructions’ is larger than the model mean? + typos in the legend.*

The sensitivity factor for West Antarctica is not the average of the sensitivity factors of AP and WAIS. For the three aggregated regions (i.e. West Antarctica, East Antarctica, and Antarctica), our resulting sensitivity factors are based on SMB and SAT averaged over the regions. Because of some compensations between regions, what is observed for AP and WAIS can be different from what is observed for West Antarctica. The same behavior is noticed for Antarctica as a whole. Sensitivity factors deduced from the reconstruction for all sub-Antarctic regions are lower than the model mean, while for the continent as a whole, the value for the reconstruction is very close to the model mean.

*P12*
*"The analysis of isotope-enabled model results reinforces this hypothesis (Fig. 7): the iHadCM3 outputs show high correlations between these two variables."*
*In the sub-section 4.3, you only focus on the iHadCM3 outputs without explicitly announcing it and explaining why you did this choice.*

Throughout the text we mainly focused on the iHadCM3 model because, in contrast to the other isotope-enabled models (ECHAM5-wiso and ECHAM5/MPI-OM), iHadCM3 offers an ensemble of simulations, which is a significant advantage for data assimilation.

We added a few words on the reason of our choice at the end of the section 3.1.:

“Because iHadCM3 offers an ensemble of seven simulations, while the other isotope-enable models have only a single realization, we mainly focus on the iHadCM3 outputs in the manuscript. Dealing with an ensemble instead of a single simulation increases the probability of finding model results close to the assimilated records during the data assimilation process.”

*P16*
*"(estimated by the weighted variance of the particles with non-zero weight)"*
*Define this weight/metric in the method section. What is the threshold?*

After each particle has received a weight depending on its likelihood, all the weights are multiplied by the total particle number. Then, the weights are rounded to the nearest integer toward negative infinity. Therefore, the maximum value of the weight is the number of particles and the minimum value is zero. We have specified in the new version of the manuscript how the weights are computed:

“Depending on its likelihood, each particle receives a weight. Then, all the weights are multiplied by the number of particles and rounded to the nearest integer toward negative infinity by ensuring that the sum of the weights equals the number of particles throughout the data assimilation process (see Dubinkina et al., 2011 for details).”

*"When assimilating both $\delta^{18}O$ and SMB, the SMB reconstruction is in good agreement with the reconstruction of Thomas et al. (2017)."*

*As expected as Thomas is assimilated.*

Indeed, this is expected. However, we assimilate both $\delta^{18}O$ and SMB and not only SMB. Therefore, we constrain the model with two types of information. This can lead to a SMB reconstruction different from the reconstruction of Thomas et al. (2017) and indeed the reconstruction is different than the one assimilating only SMB (Figure S8). Additionally, if model outputs and assimilated records are too different, the resulting data assimilation-based reconstruction can highly differ from the data assimilated. If the resulting data assimilation-based reconstruction is close to the assimilated records, it means that no inconsistency is found between model results and the assimilate records.

Nevertheless, as this is not a surprising result, we have added "as expected" at the end of the sentence.

*P18*
*"who suggest an increase of the SMB sensitivity to surface temperature for the future in Antarctica,"*
*Can you give a number?*

According to Frierler et al. (2015), this increase is about 40% (Table 1). It has been added in the new version of the manuscript.

*"The GCMs may have biases in the simulated temperature changes or in their response to anthropogenic forcing."*
*This is very general, what are the known biases in GCMs?*

We agree that this sentence in the discussion/conclusions section is very general. We have added a couple of sentences regarding the GCM biases:

"The GCMs may have biases in the simulated temperature changes. For example, as shown by Klein et al. (2019), GCMs display on average a homogeneous warming over Antarctica during the last decades while observations mainly show a warming for West Antarctica with no significant change for East Antarctica. Additionally, climate model simulations generally display a warming starting in the $19^{th}$ century in Antarctica while it begins much later in proxy-based reconstructions (Abram et al., 2016)."

*"This may contribute to an overestimation of the contribution of the simple thermodynamic link between temperature and precipitation and thus snow accumulation while it underestimates the role of changes in atmospheric circulation variability.*
*"Any reference on this point?*

We have added three papers supporting this point.

1. Abram, N. J., McGregor, H. V., Tierney, J. E., Evans, M. N., McKay, N. P., Kaufman, D. S., Thirumalai, K., Martrat, B., Goosse, H., Phipps,S. J., Steig, E. J., Kilbourne, K. H., Saenger, C. P., Zinke, J., Leduc, G., Addison, J. A., Mortyn, P. G., Seidenkrantz, M. S., Sicre, M. A.,Selvaraj, K., Filipsson, H. L., Neukom, R., Gergis, J., Curran, M. A., and Von Gunten, L. (2016): Early onset of industrial-era warming across the oceans and continents, Nature, 536, 411–418, https://doi.org/10.1038/nature19082.

2. Klein, F., Abram, N. J., Curran, M. A. J., Goosse, H., Goursaud, S., Masson-Delmotte, V., Moy, A., Neukom, R., Orsi, A., Sjolte, J., Steiger, N., Stenni, B., and Werner, M. (2019): Assessing the

robustness of Antarctic temperature reconstructions over the past 2 millennia using pseudoproxy and data assimilation experiments, Clim. Past, 15, 661–684, https://doi.org/10.5194/cp-15-661-2019.

3. PAGES 2k-PMIP3 group: Continental-scale temperature variability in PMIP3 simulations and PAGES 2k regional temperature reconstructions over the past millennium (2015), Clim. Past, 11, 1673–1699, https://doi.org/10.5194/cp-11-1673-2015.

The first paper shows that GCMs may imperfectly simulate the main mode of atmospheric variability over the last millennium. The other papers suggest that the model response to anthropogenic forcing (radiative forcing) is too important relatively to changes in general atmospheric circulation.

*"According to Neukom et al. (2018), uncertainties in the reconstructions (the noise in proxy data and the deficiencies in the reconstruction methods) and the data sampling could be an explanation of the observed discrepancy between models and reconstructions."*
*Give some key details on how it is proven.*

We have added the method used by Neukom et al. (2018) in the new version of the manuscript:

"To understand the potential origin of the disagreements between model results and reconstructions over the last millennium, Neukom et al. (2018) used pseudoproxy experiments. They found that uncertainties in the reconstructions (the noise in proxy data and the properties of the reconstruction methods) and the data sampling could be an explanation for many observed discrepancies between models and reconstructions."

*"surface temperature over the period 1958–2010"*
*Add the reference (Nicolas and Bromwich, 2014)*

Done.

*P19*
*"Regarding changes in SMB over the last two centuries, our reconstruction shows large regional differences in SMB trends, both in magnitude and in sign, in accordance with Medley and Thomas (2019; Fig. S12)."*
*A word on the fact that DA assimilate Thomas 2017, which use the same ice core dataset as in Medley and Thomas 2019? So it is not surprising that patterns are similar?*

As the method used by Medley and Thomas (2019) is different than ours, we could have had different results (even if the ice core dataset is the same). Unlike their method, we do not make any assumption on the stationarity of the link between the reanalysis (that they use) and the ice core dataset. Getting similar results thus shows that by using different methods, we obtain similar results, which gives more robustness to these results. However, we have added something in the corresponding sentence accordingly:

"Regarding changes in SMB over the last two centuries, our reconstruction shows large regional differences in SMB trends, both in magnitude and in sign, in accordance with Medley and Thomas (2019; Fig. S12) who used the same ice core dataset but a different method."

*"This is supported by a strong link between these two variables in observations, in particular for East Antarctica (r=0.82, statistically significant)."*
*Specify that is between Thomas et al 2017 and NB14, and does not work with Stenni2017*

The specification has been added in the text:

“This is supported by a strong link between these two variables in observations when using snow accumulation data from Thomas et al. (2017) and surface temperatures from Nicolas and Bromwich (2014), in particular for East Antarctica (r=0.82, statistically significant).”

*"By using data assimilation, no assumption such as stationarity or long calibration periods is required to estimate the link between variables"*
*Please also include the limitations of the data assimilation method*

We propose to add this sentence:

“However, to get a skillful data assimilation-based reconstruction, it is essential that the selected climate models have an adequate representation of climate variability and that good uncertainty estimates are available for the chosen datasets.”

# ~~Surface Mass Balance of the Antarctic Ice Sheet and its link with~~ How useful is snow accumulation in reconstructing surface temperature ~~change~~ in ~~model simulations~~ Antarctica? A study combining ice core records and ~~reconstructions~~climate models

Quentin Dalaiden[1], Hugues Goosse[1], François Klein[1], Jan T. M. Lenaerts[2], Max Holloway[3,4], Louise Sime[3], and Elizabeth R. Thomas[3]

[1]Georges Lemaître Centre for Earth and Climate Research (TECLIM), Earth and Life Institute (ELI), Université catholique de Louvain (UCL), Louvain-la-Neuve Belgium
[2]Department of Atmospheric and Oceanic Sciences, University of Colorado Boulder, Boulder CO, USA
[3]British Antarctic Survey, Madingley Road, Cambridge, CB3 0ET, UK
[4]Scottish Association for Marine Science, Oban, UK

**Correspondence:** Quentin Dalaiden (quentin.dalaiden@uclouvain.be)

**Abstract.** Improving our knowledge of the temporal and spatial variability of the Antarctic Ice Sheet (AIS) Surface Mass Balance (SMB) is crucial to reduce the uncertainties of past, present and future Antarctic ~~contributions~~ contribution to sea level rise. ~~Here, we show that Global Climate Models (GCMs) can reproduce the present-day (1979–2005) AIS SMB and the temporal variations over the last two centuries.~~ An examination of the surface temperature–SMB relationship in model simulations demonstrates a strong link between the two. Reconstructions based on ice cores display a weaker relationship, indicating a model-data discrepancy that may be due to model biases or to the non-climatic noise present in the records. We find that, on the regional scale, the modelled ~~temperature-SMB relationship is stronger than the relationship between~~ relationship between surface temperature and SMB is often stronger than between temperature and $\delta^{18}$~~O-temperature~~O. This suggests that SMB data can be used to reconstruct past surface temperatures. Using this finding, we assimilate isotope-enabled model SMB and $\delta^{18}$O output with ice-core observations, to generate a new surface temperature reconstruction. Although an independent evaluation of the skill is difficult because of the short observational time series, this new reconstruction outperforms the previous reconstructions for the continental-mean temperature that were based on $\delta^{18}$O alone~~with a linear correlation coefficient with the observed surface temperatures (1958–2010 CE) of 0.73~~. The improvement is largest for the East Antarctic region, where the uncertainties are particularly large. Finally, using the same data assimilation method as for the surface temperature reconstruction, we provide a spatial SMB reconstruction ~~of~~ for the AIS over the last two centuries showing ~~1)~~ large variability in SMB trends at regional scale~~; and 2) a large SMB~~ , with an increase (0.82 Gt year$^{-2}$) in West Antarctica over 1957–2000 ~~while at the same time, East Antarctica has experienced a large SMB decrease~~ and a decrease in East Antarctica during the same period (-3.3 Gt year$^{-2}$)~~, which~~ . As expected, this is consistent with ~~a recent reconstruction~~ the recent reconstruction used as a constraint in the data assimilation.

## 1 Introduction

The spatial coverage of climate observations in Antarctica and the Southern Ocean is sparse (e.g. Jones et al., 2016; Neukom et al., 2018). Consequently, the climate dynamics of the high southern latitudes are still poorly understood, leading to large uncertainties in the processes governing climate variability (Church et al., 2013). Since around 1995, the contribution to the global sea level rise from the ice sheets – Greenland Ice Sheet (GrIS) and the Antarctic Ice Sheet (AIS) – has strongly increased, and are slowly outpacing the contributions from mountain glaciers and ocean thermal expansion (Shepherd et al., 2018). The GrIS has been dominating the ice sheet contribution so far ~~(Rignot et al., 2011)~~(Rignot et al., 2019), but AIS mass loss has increased ~~five-fold~~ fivefold in 2012–2017 relative to 1992–1997, with current AIS mass loss values that approach those of the GrIS.

The (grounded) AIS Mass Balance (MB) is the difference between the surface mass balance (SMB) and the solid ice discharge (Lenaerts et al., 2019; Fyke et al., 2018). Reliable estimates of AIS MB and its relationship with internal climate variability and transient climate forcing are needed to constrain future climate and sea level projections (Bamber et al., 2018). The current AIS MB is negative (~~Rignot et al., 2011~~Rignot et al., 2019) because of large values of ice discharge (IMBIE team, 2018). ~~The AIS SMB displays large spatial variations that mask the trend at the continental scale (Wouters et al., 2013).~~

The SMB is defined as the difference between the incoming and outgoing mass at the surface of the ice sheet. In Antarctica, the main source term of the SMB, and its interannual variations, is precipitation in the form of snow (e.g. Lenaerts et al., 2012; Agosta et al., 2018). Unlike Greenland, AIS surface melt is small, and most surface melt water refreezes in place, not contributing to SMB (Trusel et al., 2015; Kuipers Munneke et al., 2012). As a result, the surface sublimation and sublimation of blowing snow are the main sink terms of the AIS SMB (e.g. Frezzotti et al., 2013; van Wessem et al., 2018).

Ice cores provide information on past changes in surface temperature and SMB across Antarctica on time scales of centuries to millennia (e.g. Stenni et al., 2017; Thomas et al., 2017). In particular, it has become standard to reconstruct past temperature changes from ~~stable isotope ratios of oxygen (~~water stable isotopes, and in particular $\delta^{18}$O ~~; (~~(e.g. Jouzel, 2003; Masson-Delmotte et al., 2006). However, ice core studies suffer from several limitations: 1) the ice core network is still relatively sparse, despite recent coordinated international drilling efforts (Thomas et al., 2017; Stenni et al., 2017); 2) annually resolved surface temperature and SMB records are not available from extremely dry areas, such as the East Antarctic Plateau; 3) changes in precipitation seasonality (e.g. Sime et al., 2008), moisture origin (e.g. Holloway et al., 2016a) and other processes can modify the expected relationship between $\delta^{18}$O and surface temperature (e.g. Jouzel et al., 1997; Klein et al., 2019). Combined, these factors lead to large uncertainties in the reconstruction of surface temperatures.

Until recently, AIS SMB had been considered to display no significant trends since the mid-twentieth century (Monaghan et al., 2006; Frezzotti et al., 2013). Based on recent work, this hypothesis has been revised: using a larger ice core network (PAGES2k database), Thomas et al. (2017) and Medley and Thomas (2019) have shown that AIS SMB has increased significantly since 1900, albeit with important regional differences. The Antarctic Peninsula has witnessed a considerable SMB increase during the twentieth century (e.g. Thomas et al., 2015; Goodwin et al., 2016), as well as some regions of Dronning Maud Land (e.g. Philippe et al., 2016; Lenaerts et al., 2013; Medley et al., 2018; Shepherd et al., 2012). In contrast, other regions of Droning Maud Land are subjected to a SMB decrease over the recent past (Schlosser et al., 2014; Altnau et al., 2015). All these studies point out the need to densify the ice-core network over Antarctica, but also to retrieve more insight in what is driving the trends in AIS SMB and its spatial signatures. For the latter, output of climate model simulations can be very useful (e.g Lenaerts et al., 2018).

In the last decade, output of several climate model simulations that cover the last millennium has become available (Schmidt et al., 2011). Thus far, model evaluation has been mainly focussed on surface temperature (PAGES 2k-PMIP3 group, 2015). These results have shown discrepancies in AIS surface temperature between climate model simulations and reconstructions during the last millennium. In contrast to climate model results, surface temperature reconstructions show no clear warming over the 20$^{\text{th}}$ century at the continental scale (Goosse et al., 2012; Stenni et al., 2017; PAGES 2k-PMIP3 group, 2015; Neukom et al., 2018). This mismatch can be explained by an overestimation of the response of climate models to external forcing, or ~~by an underestimation of the signal from proxy overwhelmed by a~~ the strong natural variability occurring in Antarctica or an underestimation of the signal in proxy-based reconstructions, or by a combination of ~~both~~ all those (Jones et al., 2016; Neukom et al., 2018). Unlike temperature changes, modelled AIS SMB variations over the past millennium are poorly documented.

In a warmer climate, AIS SMB is expected to increase due to higher snowfall associated to the greater moisture holding capacity ~~of warmer air (e.g. Lenaerts et al., 2016)~~at higher air temperature (e.g. Lenaerts et al., 2016). Taken alone, this straightforward thermodynamical effect would mitigate the sea level rise (Huybrechts et al., 2004; Krinner et al., 2007; Frieler et al., 2015). According to ~~Monaghan et al. (2008)~~Frieler et al. (2015), the observed sensitivity of Antarctic snowfall accumulation to surface temperature was about 5% K$^{-1}$ during the ~~1960–1999~~ 1960–1999 period. Based on climate model simulations, this sensitivity is expected to increase in future with an estimated conversion value of 7.4% K$^{-1}$ for the end of the ~~21th~~ 21st century (2080–2099; Palerme et al., 2017). The link between surface temperature and SMB has been confirmed for small regions at the centennial time scale (200 years; e.g. Oerter et al., 2000; Medley et al., 2018) and on longer time scales (glacial-interglacial; Frieler et al., 2015) for the full AIS using climate models and ice cores. However, some studies ~~(Fudge et al., 2016; Altnau et al., 2015; Philippe et al., 2016; Goursaud et al., 2019) indicate~~ using surface temperature reconstructions based on $\delta^{18}$O data (Fudge et al., 2016; Altnau et al., 2015; Philippe et al., 2016; Goursaud et al., 2019) suggest that this SMB-surface temperature relationship ~~(estimated by $\delta^{18}$O)~~ is not always positive ~~,~~ and varies spatially and temporally. These results suggest that in some regions, especially along the AIS coasts, the ~~variability of~~ SMB variability is dominated by large-scale atmospheric circulation rather than by thermodynamic processes (such as the Clausius-Clapeyron ~~effect)on SMB is dominated by the large-scale atmospheric circulation~~relation), limiting the correlation with $\delta^{18}$O.

The first goal of this study is to document the relationship between surface temperature and SMB in Antarctica on a regional scale using climate models and ice-core records over the two past centuries and over the last millennium. The final goal is to use the covariance between both variables to reconstruct past changes over the last two centuries by using a data assimilation procedure. ~~While~~ All reconstruction methods depend on the number and quality of the input data. However, while the statistical methods classically used to infer past surface temperature (see for instance Stenni et al., 2017) rely on the length of the calibration period, on the quality of the record during this period, and on the stationarity of the link between the proxy and the variable of interest, which can be strong assumptions in the case of the $\delta^{18}$O-temperature relationship (Klein et al., 2019), data assimilation does not. In recent years, data assimilation has become a standard procedure in paleoclimatology to optimally combine the information from model results and proxies and to provide estimates of past climate states (e.g. Hakim et al., 2016; Widmann et al., 2010; Goosse et al., 2010; Matsikaris et al., 2015; Steiger et al., 2014). ~~However~~Nevertheless, Antarctic SMB to the best of our knowledge has never been assimilated in a climate model. The biggest advantage of using data assimilation is that it takes into account information brought by both SMB and $\delta^{18}$O without making the strong assumptions that the statistical methods do. Additionally, using the covariance between them might lead to better estimates of past changes in the two variables, particularly ~~over time periods~~ when proxy records are scarce and few instrumental data are available, which is the case for the Antarctica. The resulting reconstructions will have the benefit of being compatible with the physics of the climate system as represented by the models.

## 2 Data: model simulations and observations

### 2.1 Global climate model simulations

The climate model simulations selected for this study are those for which the required variables (i.e. precipitation and sublimation/evaporation) are available for the last millennium from the PMIP3-CMIP5 database (Otto-Bliesner et al., 2009; Taylor et al., 2012). In addition to these simulations, the CESM1-CAM5 model simulations covering the last millennium (~~Lehner et al., 2015~~Otto-Bliesner et al., 2015) are also used. The characteristics and references of each model are described in Tab. A1. All these GCMs use the GMTED2010 elevation dataset (Danielson and Gesch, 2011) as topography, adapted to their spatial horizontal resolution. The simulations are driven by both natural (orbital, solar and volcanic) and anthropogenic (greenhouse gases, land use, aerosol and ozone) forcings through the last millennium (Schmidt et al., 2011, 2012). Except for CESM1-CAM5, CSIRO- Mk3L-1-2 and MPI-ESM-P, the simulations do not cover the entire millennium. Historical simulations covering 1851-2005 CE were launched independently of simulations covering 850-1850 CE (referred to as past1000 experiment). In order to obtain results over the full millennium, we adopt the approach from Klein and Goosse (2018) and merge the first ensemble members (r1i1p1) of the past1000 experiment with the corresponding ensemble members of the historical experiment. Although not continuous, there is no large discrepancy between the two merged simulations (e.g. Klein and Goosse, 2018).

Simulations performed with the isotope-enabled climate models, ECHAM5-MPI/OM (Sjolte et al., 2018), ECHAM5-wiso (Steiger et al., 2017) and iHadCM3 (Tindall et al., 2009; Holloway et al., 2016b) are also analyzed. These simulations allow for a direct comparison with observed water isotope content. ECHAM5/MPI-OM is a fully coupled General Circulation Model (GCM). The simulation used here covers the period 800–2000 CE forced by natural and anthropogenic forcing (Sjolte et al., 2018). The horizontal resolution of the atmospheric model is $3.75° \times 3.75°$. The simulation of ECHAM5-wiso, which only includes an atmospheric component, was performed by Steiger et al. (2017) and covers the period 1871–2011 CE at $\sim 1°$ resolution. The model is driven by the sea surface temperature and sea ice from the Rayner et al. (2003) dataset. Due to a lack of Antarctic sea ice data before 1973, this dataset is based on historical climatologies of sea ice concentration for the period 1871–1973 CE, with no interannual variability. Finally, iHadCM3 is the version of HadCM3 (fully coupled climate model;

Turner et al., 2016) which has an explicit representation of the water isotopes. The resolution of the atmospheric model is $3.75° \times 2.5°$. While only one simulation is available for ECHAM5-MPI/OM and ECHAM5-wiso, we have an ensemble of seven iHadCM3 simulations spanning the industrial period from 1851 to 2003 CE. The initial conditions for each of these simulations correspond to different years in the pre-industrial control simulation of the iHadCM3 model. Comparisons of the results of these three isotope-enabled models with modern $\delta^{18}O$ observations indicate that they all reproduce the main characteristics of the spatial distribution of the isotopic composition of precipitation over Antarctica ~~(see reference for each model)~~ including the latitudinal distribution (negative $\delta^{18}O$ gradient from the coasts to the Plateau). According to Tindall et al. (2009) and Sime et al. (2008), the small biases in $\delta^{18}O$ (for example, an underestimation of the spatial $\delta^{18}O$ variability in rugged areas) in the iHadCM3 simulation mainly come from the coarse horizontal resolution of the model and not from the isotopic model itself. ECHAM5-wiso and ECHAM5/MPI-OM display an overall underestimation of $\delta^{18}O$ in Antarctica but reproduce well the general Antarctic $\delta^{18}O$ pattern (Goursaud et al., 2018; Klein et al., 2019, see reference of each model for more details).

Klein et al. (2019) has recently described an evaluation of Antarctic surface temperature in reconstructions and model simulations over the last millennium. In accordance with Abram et al. (2016), they highlighted the early onset of industrial warming simulated by the PMIP/CMIP models, which is not observed in the $\delta^{18}O$-based temperature reconstructions of Stenni et al. (2017). This suggests that the Antarctic surface temperatures simulated by the models are too sensitive to the anthropogenic forcing.

### 2.2 The regional climate model RACMO2 simulation

The evaluation of AIS SMB simulated by GCMs for the present period (1979–2005) is mainly based on the results of the regional atmospheric climate model RACMO2.3p_2 (RACMO2 hereafter) covering the entire AIS over 1979–2016 (van Wessem et al., 2018). This is because 1) the SMB observations are very sparse on the AIS (Favier et al., 2013); 2) the interannual (year-to-year) variability is different between observations and GCMs given that the latter are freely-evolving coupled models. Consequently, the comparison can be only made on multi-decadal time scales (> 20 years), which drastically reduces the availability of observations; 3) unlike observations, RACMO2 provides a complete SMB field over the entire AIS; and, finally, (4) ~~the output of~~ RACMO2 ~~for the AIS SMB agrees very well with available measurements (correlation coefficient with observations of 0.9; van Wessem et al., 2018)~~has been extensively evaluated against available measurements and displays a very good agreement (e.g. van Wessem et al., 2018; Lenaerts et al., 2012). In an intercomparison of AIS SMB from reanalysis, atmospheric models and observations, Wang et al. (2016) showed that the RACMO2 model best fits the recent AIS SMB observations compared to all other available datasets.

RACMO2 combines the physics package of the European Centre for Medium- Range Weather Forecasts (ECMWF, 2008) integrated Forecast System and the hydrostatic dynamics of the High Resolution Limited Area Model (HIRLAM, Unden et al., 2002). RACMO2 is specially adapted to polar regions since it includes the interactions between the atmosphere and the multi-layered snow model that calculates physical processes occurring in the firn: meltwater production, percolation, runoff, refreezing, as well as snow grain size and resulting snow albedo (Greuell and Thomas, 1994; Ettema et al., 2010). RACMO2 also includes a drifting snow scheme simulating the interactions between the near-surface air with snow (Lenaerts et al., 2010).

All the SMB components are explicitly calculated by this regional model on a 27 km resolution grid. The Digital Elevation Model of Bamber et al. (2009) is taken as reference of the Antarctic topography. ERA-Interim reanalysis data (Dee et al., 2011) are used to force the regional model at its lateral boundaries. For more details on RACMO2, see van Wessem et al. (2018).

### 2.3 Snow accumulation database from Antarctica2k

The annually resolved Antarctica2k (Ant2k) snow accumulation database (Thomas et al., 2017) is used for the evaluation of AIS SMB simulated by GCMs before 1979. The estimate of the SMB from ice cores is based on the physical distance between suitable age markers within the ice core. The age markers used depend on the timescale of interest ranging from glacial cycles (e.g. bulk changes in isotopic compositions) to seasonal variations reflected by changes in stable water isotopes, while volcanic eruptions can inform on decadal to millennial timescales (Dansgaard and Johnsen, 1969). Once the age markers are identified, since the firn density generally increases with depth in the ice core, it is necessary to consider those variations to convert the age and depth to mass (Van Den Broeke et al., 2008). Doing so, SMB is converted to meters of water equivalent based on measured density and corrected for the vertical strain rate effect – the differential vertical velocity with depth leading to layer thinning with depth (Thomas et al., 2017).

This database is composed of 79 records that are assigned to seven geographical regions (Fig. 1) with distinctly different climates. East Antarctica above 2000 m elevation constitutes the East Antarctica Plateau (EAP). West Antarctica is separated into two parts: the Antarctic Peninsula (AP) and the West Antarctica Ice Sheet (WAIS), with a division at 88° W. The coastal region of East Antarctica is divided into four regions: Victoria Land (VL; 150-170° E), the Wilkes Land Coast (WL; 70-150° E), Dronning Maud Land (DML; 15° W-150° E) and the Weddell Sea Coast (WS; 15-60° E). For each region, this database covers the past 1000 years except for EAP, AP and DML, for which the period covered is ~~1240–2005 CE, 1703–2010 CE and 1737–2010~~ 1240–2005 CE, 1703–2010 CE and 1737–2010 CE, respectively. Hereafter, West Antarctica is composed of WAIS and AP, while East Antarctica comprises all of the other regions. Since some Antarctic regions lack long-term data, the SMB reconstruction for the whole Antarctic ice sheet is only available from 1737 AD. This regional SMB reconstruction has been compared to RACMO2, concluding that the reconstruction captures a large proportion of the regional spatial SMB variability as defined by RACMO2 for the ~~1979-2010~~ 1979–2010 period (Thomas et al., 2017).

### 2.4 Water stable isotopes records and surface temperatures reconstructions from Antarctica2k

Stenni et al. (2017) built $\delta^{18}$O regional composites from 112 individual ice cores compiled in the framework of the PAGES Antarctica2k working group for similar seven Antarctic subregions as in Thomas et al. (2017; see Sec. 2.3) over the last two millennia. ~~This temporal averaging reduces uncertainties in dating linked to the noise induced by non-climatic processes (e.g. Laepple et al., 2018; Fan et al., 2014).~~ Based on those $\delta^{18}$O composites, they reconstructed regional surface temperatures over the last two millennia based on the statistical relationship between $\delta^{18}$O and surface temperature. Three methods have been used to scale the $\delta^{18}$O composites. The second reconstruction (*borehole* reconstruction) is used throughout this study for two reasons: 1) this is not based on surface temperature observations, which are used here to estimate the skill of the reconstructions which would have led to a bias; 2) because it is based on more information, the borehole reconstruction is expected to be ~~better~~

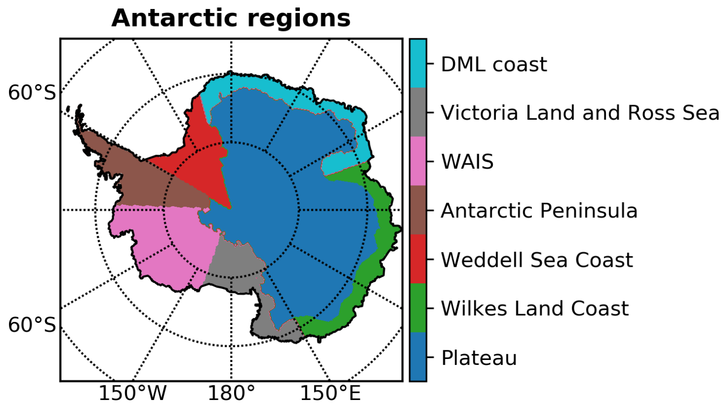


**Figure 1.** Antarctic regions used in this study. The definitions of the regions are those of Thomas et al. (2017).

~~(see Supplementary materials~~ more accurate (see section S1 for details). The temporal resolution is the same as for the $\delta^{18}$O composites: 10 years over 0–1800 and 5 years over 1800–2010.

## 3 Methods: Reconstructing SMB and surface temperatures using data assimilation

### 3.1 Data assimilation method: a particle filter using fixed ensembles

Data assimilation optimally combines observations (proxy data in our case) and climate model states. Two types of data assimilation methods are usually applied in paleoclimatology. First, online methods follow standard sequential data assimilation approaches, in which the analysis at a single time step depends on the state at the previous step. Information is thus propagated forward in time. However, because data assimilation requires a large ensemble of model simulations (tens to hundreds), for paleoclimate reconstructions, performing online data assimilation at high spatial climate model resolution (e.g. CMIP5 class as used here) becomes impractical. Second, when working with so-called offline methods, ensemble members are constructed from existing model simulations, which is of great interest in terms of computation time compared to online methods. Here, ensemble members are constructed by individual years and not by independent model simulations. Therefore, in contrast to online methods, offline methods do not maintain temporal consistency. However, when the predictability on inter-annual time-scales is limited, such as surface temperature or precipitation because of the dominant role of their chaotic nature, online methods do not outperform offline ones (Matsikaris et al., 2015). Indeed, offline methods have provided skilful data assimilation-based reconstructions for various types of data (e.g Steiger et al., 2017; Klein and Goosse, 2018; Hakim et al., 2016). Nevertheless, the online approach is preferred when focussing on ocean dynamics because of the ocean long memory (e.g. Goosse, 2017; Pendergrass et al., 2012).

The offline data assimilation method applied in this study is based on a particle filter (e.g. van Leeuwen, 2009; Dubinkina et al., 2011) using fixed ensembles from climate model outputs. The implementation described in Dubinkina et al. (2011)

is identical to previous studies (e.g. ~~Klein and Goosse, 2018; Goosse et al., 2012~~Klein and Goosse, 2018). Hence, only a brief description of the methodology will be given here. At each time step of the data assimilation procedure (yearly, see Sec. 3.2), each ensemble member, called particle, is compared to the proxy-based reconstruction by computing its likelihood, assumed here to be Gaussian, taking into account data uncertainties (see Dubinkina et al. (2011) for details). Depending on its likelihood, each particle receives a weight. Then, all the weights are multiplied by the number of particles and rounded to the nearest integer toward negative infinity by ensuring that the sum of the weights equals the number of particles throughout the data assimilation process (see Dubinkina et al. (2011) for details). Considering all particles weights, we can compute a weighted average, providing a reconstruction for this time step. In this study, the ensemble members are derived from three climate model outputs: ECHAM5-MPI/OM (Sjolte et al., 2018), ECHAM5-wiso (Steiger et al., 2017) and iHadCM3 (Tindall et al., 2009; Holloway et al., 2016b). These models have been chosen because they explicitly simulate $\delta^{18}$O. Because iHadCM3 offers an ensemble of seven simulations, while the other isotope-enable models have only a single realization, we mainly focus on the iHadCM3 outputs in the manuscript. Dealing with an ensemble instead of a single simulation increases the probability of finding model results close to the assimilated records during the data assimilation process.

### 3.2 Experiment design

Data assimilation is used in this study to reconstruct surface temperature and SMB by taking advantage of the covariance between these variables. They are assimilated together as well as separately in three different experiments. In the first experiment, the seven subregion composites of $\delta^{18}$O data (Stenni et al., 2017) are used to constrain model results. Assimilating $\delta^{18}$O instead of surface temperature potentially accounts for the non-stationary and the non-linearity of the stable oxygen ratios–surface temperature link (Masson-Delmotte et al., 2008; Klein et al., 2019). For the second experiment, the SMB reconstruction for the seven subregions (Thomas et al., 2017) is used in the data assimilation process. Finally, both $\delta^{18}$O and SMB are taken into account together in the last experiment. This allows us to estimate independently the consistency of the SMB and surface temperature reconstructed between the various records and model results. In addition, our experiments allow us to assess the information acquired on surface temperature by assimilating SMB, and on SMB by assimilating $\delta^{18}$O. In all the experiments, we assimilate annual-mean proxies. All modelled $\delta^{18}$O are precipitation-weighted as this quantity is most ~~realistic and comparable to ice cores which are themselves weighted~~similar to the one measured in ice cores.

Since the ~~number~~ amount of ice cores is limited before 1800 CE (both for $\delta^{18}$O and for SMB), which drastically decreases the quality of the regional composites (Thomas et al., 2017), the experiments are performed on the 1800–2010 period. Contrary to the SMB composites, which have an annual resolution, the composites of $\delta^{18}$O are 5-year averages. Consequently, the $\delta^{18}$O data have been interpolated linearly over the studied period to match the temporal resolution of the SMB reconstruction. However, as recommended by Stenni et al. (2017), the results are analyzed only for the 5-year averages. This temporal averaging reduces uncertainties in dating and the noise induced by non-climatic processes (e.g. Laepple et al., 2018; Fan et al., 2014).

In order to assess the skill our data assimilation-based surface temperature reconstructions, we evaluate them at first with the reconstructions of Stenni et al. (2017). But this is biased since they are only based on $\delta^{18}$O and we cannot thus evaluate the added value brought by SMB data and model physics in the data assimilation experiments. Therefore, independent data is needed to properly assess the potential of SMB and $\delta^{18}$O in reconstructing surface temperature. This is done here using the surface temperature reconstruction from Nicolas and Bromwich (2014), which is based on surface temperature records and not on $\delta^{18}$O data, over the 1958–2010 period. SMB estimates are also available for the last decades (e.g. Medley et al., 2014), but they cover a too short period or have a too small spatial coverage to provide an independent validation of our reconstruction. It is thus not possible to estimate if the assimilation of SMB and $\delta^{18}$O measurements provides an improvement for this field.

## 4 Results

### 4.1 ~~AIS SMB~~ Reconstructed and simulated ~~by GCMs~~ SMB changes over the ~~recent past and the past millennium~~last centuries

The AIS SMB over the last millennium has been estimated for each GCM by computing the difference between precipitation and sublimation/evaporation. Runoff is assumed to be negligible as surface meltwater generally refreezes in the cold firn (Magand et al., 2008; Kuipers Munneke et al., 2012). ~~Overall, the AIS~~ Our short evaluation of SMB simulated by GCMs ~~is in good agreement with the SMB simulated by the regional climate model RACMO2 over the last decades (1979–2005, $R^2$ = 0.53; Fig. S5 and S1 for the SMB of each model). Both display high values of SMB along the coast (>300 mm w.e. year$^{-1}$~~over the present-day (see section S3) suggests that the selected GCMs (including the isotope-enable models) ~~– especially for West Antarctica and the Antarctic Peninsula – and lower values at high elevations (e.g. the Plateau: <100 mm w.e. year$^{-1}$). The median of the SMB over the entire AIS simulated by CMIP5 models is 1.16% lower than the SMB simulated by RACMO2 (see Fig. S9 for the integrated SMB over the entire AIS for each model) .~~

~~Antarctic Ice Sheet Surface Mass Balance mm w.e. y$^{-1}$over 1979–2005 CE averaged over all the GCMs simulations (see Tab. A1 for the list) (top left), for RACMO2 (van Wessem et al., 2018) (top right), the difference between them (bottom left) and the distribution of the SMB simulated by RACMO2 and the GCMs as a function of elevation, binned in 400m elevation intervals (bottom right). The bars represent one standard deviation of the cell grids within each elevation bin. The equivalent of the latter panel for each model is provided on Fig. S10.~~

~~However, Figure S5 shows that the GCMs, compared to RACMO2, underestimate SMB in areas below 1500 m (mean bias of -55 mm w.e. year$^{-1}$; relative bias: -15%) over 1979–2005. For the areas above 1500 m, the mean bias of the simulated SMB by GCMs compared to RACMO2 is 11 mm w.e. year$^{-1}$ (relative bias: 11%). These results are in agreement with previous studies (e.g. Palerme et al., 2017; Genthon et al., 2009; Krinner et al., 2008) who have shown that due to the lower spatial resolution of GCMs in comparison to the regional model, SMB is underestimated at the coasts while an overestimation occurs in the interior of the ice sheet. The bias in the difference between the coastal and higher elevation regions are smaller for the models that have a higher spatial resolution, such as CCSM4 (Fig. S10) , confirming that the spatial resolution has a crucial impact on the simulated SMB~~ display reasonable SMB climatology when compared to RACMO outputs.

Before the 19$^{th}$th century, all GCMs simulations are characterized by large decadal variability, but no long-term trend (Fig. 2). A positive trend, albeit initiated at different times, is shown at the end of the simulation (around 1950 AD). All models agree on an AIS SMB increase from ∼1975 onwards, which is consistent with the SMB reconstruction of Thomas et al. (2017).

However, the contrast in the SMB trends between East Antarctica and West Antarctica is clearly stronger in the reconstruction based on ice cores than in GCMs on average. Indeed, over the last decades (1950–2000), the ice core SMB reconstruction shows a large increase for West Antarctica (25.6 Gt year$^{-1}$ per decade) and a small decrease (-3.6 Gt year$^{-1}$ per decade) for East Antarctica, while, on average, the GCMs simulate a strong SMB increase in both regions (8.9 $\pm$ 9.2 Gt year$^{-1}$ per decade and 14.2 $\pm$ 13.5 Gt year$^{-1}$ per decade respectively; Figs. 2 and 3 and Tab. S1). ~~Nevertheless, when analyzing the individual simulations of the ensemble~~ When analyzing the ensemble of simulations performed with CESM1-CAM5, the ensemble mean also shows a relatively homogeneous increase, but some simulations display a contrast between East Antarctica and West Antarctica ~~is as large as in recent observations~~ close to the one observed in the reconstruction (Fig. 3). This ~~indicates that 1) the observed SMB trends between the two regions are within the range of the simulated values; 2)~~ suggests that internal variability has ~~an important role~~ a dominant contribution in the current Antarctic SMB changes and might explain why the observed contrast between East and West Antarctica is only present in a few simulations.

## 4.2 Relationship between SMB and surface temperatures in Antarctica

Averaged across all GCMs, the relationship between SMB and surface temperature is positive for each Antarctic region (Fig. 4). A very similar result is obtained when the annual mean surface temperature and SMB derived from the RACMO2 simulation over the recent period (1979–2016) are used. The regional correlations are much weaker for the reconstructions based on ice cores than those obtained from model outputs (Fig. 4). These results are also true for detrended times series, indicating that this modelled link is valid at the inter-annual time-scale (not shown).

To quantify more precisely the link between surface temperature and SMB in model outputs and reconstructions, the SMB sensitivity to temperature – defined as the slope of the linear fit between near-surface air temperature and SMB – has been calculated. ~~On~~ Firstly, the GCMs and reconstruction (i.e. Thomas et al., 2017; Nicolas and Bromwich, 2014) suggest that this sensitivity is similar for both West Antarctica and East Antarctica over the 1950–2000 period (Fig. 3). Secondly, on average over the entire continent, this sensitivity reaches 3.6 % K$^{-1}$ in ice cores-based reconstructions for the 1850–1949 period. According to these reconstructions, this sensitivity has increased a lot for the recent period (1950–2005; 15.52 % K$^{-1}$), confirming the findings of Frieler et al. (2015). However, Frieler et al. (2015) do not obtain such an increase in SMB sensitivity (only ~+40%). Additionally, this recent increase found here in the reconstructions is not represented by the GCMs: on average, the simulated sensitivity of SMB to near-surface temperatures is 5.0 $\pm$ 1.1 % K$^{-1}$ over 1850–1949 and 5.4 $\pm$ 2.0 % K$^{-1}$ over 1950–2005. When looking at the regional scale over 1850–2005, the average SMB sensitivity over all models for West Antarctica (6.8 % K$^{-1}$) is in good agreement with the one deduced from the reconstructions (8.0 % K$^{-1}$; Fig. 5), while for East Antarctica, the sensitivity of the model mean is higher than the one obtained from the reconstructions (6.2 % K$^{-1}$ and 2.1 % K$^{-1}$ respectively). The very low SMB sensitivity in the reconstructions for East Antarctica, especially on the Antarctic Plateau (0.5 % K$^{-1}$) is somewhat unexpected, given that this region is continental and thus less affected by synoptic activities than coastal areas (Monaghan and Bromwich, 2008). Actually, when using the observed surface temperatures (e.g. Nicolas and Bromwich, 2014) instead of the reconstructed ones of Stenni et al. (2017), the Antarctic SMB sensitivity to temperature is strongly reduced (4.02 % K$^{-1}$ for the

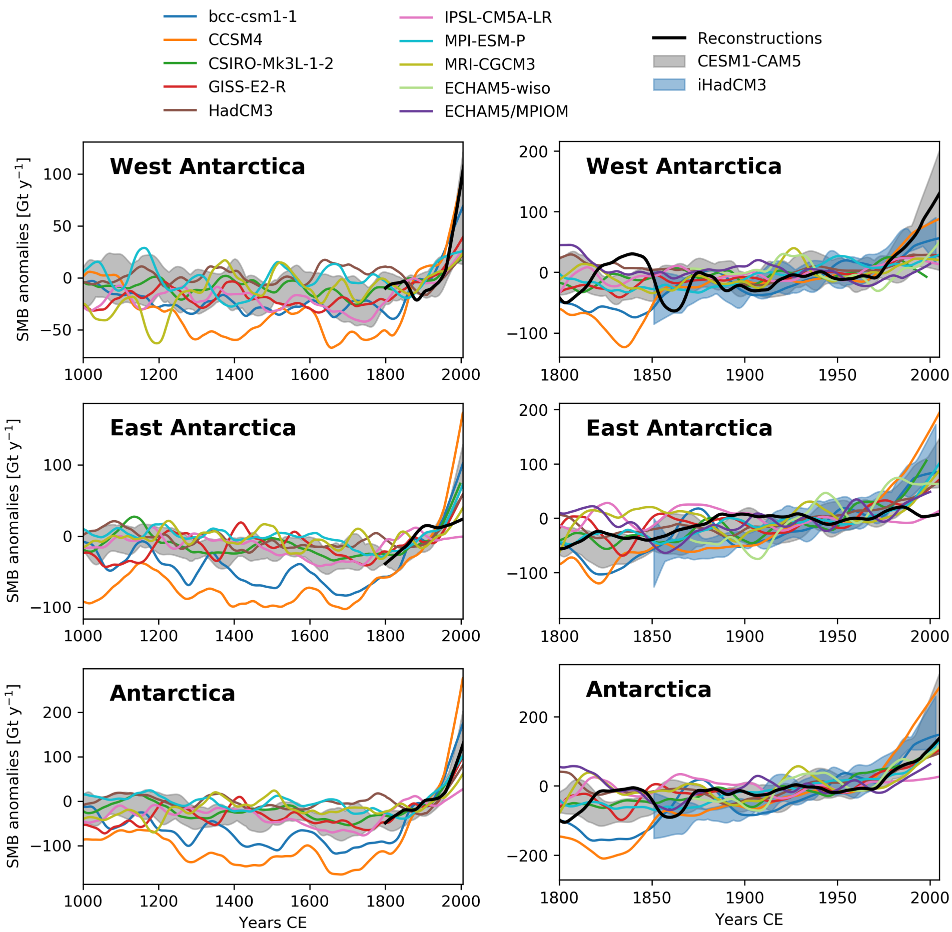


**Figure 2.** Surface Mass Balance anomalies [Gt y$^{-1}$] simulated by the GCMs (Tab. A1) and snow accumulation reconstructions (Thomas et al., 2017) during 1000 to 2005 and during 1800 to 2005 for West Antarctica, East Antarctica and Antarctica as a whole. Anomalies are ~~computed for~~ relative to the ~~period~~ 1871–2000 period. The shaded area corresponds to the range of the CESM1-CAM5 simulations. For visibility, data has been smoothed with a 100 years moving average for the last millennium and a 30 year moving average for the last 200 years. The equivalent for the seven subregions is given on Fig. S1.

1958–2010 period), and thus closer to the resulting sensitivity found in the GCMs (5.4 ± 2.0 % K$^{-1}$ for the 1950–2005 period).

In the study of Neukom et al. (2018), the authors ~~claim~~ argue that the data sampling, the noise in proxy data and the deficiencies in the reconstruction methods can partly explain the discrepancy between models and reconstructions for the surface temperature during the last millennium, especially for the southern hemisphere. The spatial coverage of the surface temperature and SMB reconstructions based on ice cores is poor, in particular for East Antarctica (Stenni et al., 2017; Thomas et al., 2017). Moreover, due to the low snow accumulation in some regions, the uncertainties of the reconstruction are large

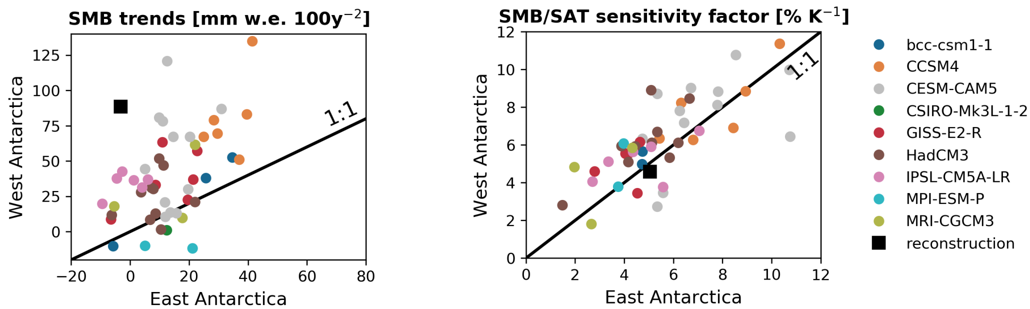


**Figure 3.** (left) Comparison between the reconstructed and the simulated ~~surface mass balance~~ SMB trends (mm w.e./100y$^{-2}$) over the period 1950–2000 CE in West Antarctica (y axis) and East Antarctica (x axis). ~~West Antarctica comprises both~~ (right) As on the ~~Antarctic Peninsula and WAIS here while East Antarctica comprises~~ left but for SMB/SAT sensitivity factors (% K$^{-1}$). For the ~~remaining regions of Antarctica~~reconstruction, data from Thomas et al. (2017) and Nicolas and Bromwich (2014) are used.

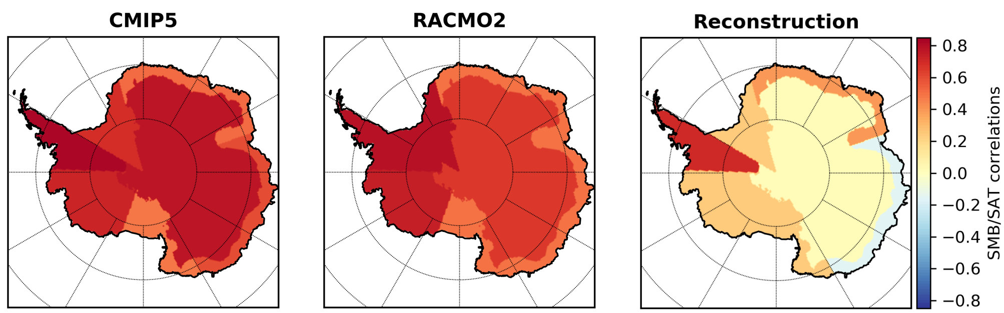


**Figure 4.** 5 yearly correlations (r) between SMB and surface temperature for seven Antarctic regions (see Fig. 1 for geographical definitions) for GCMs over the 1850–2000 CE (left), for RACMO2 over 1979–2016 CE (center) and for ice core reconstructions (Thomas et al., 2017; Stenni et al., 2017) for 1850–2000 CE (right). For the CMIP5 models and RACMO2, their correlations are all statistically significant (p-value<0.05). For the reconstructions, the statistically significant (p-value<0.05) correlations are obtained for the Antarctic Peninsula and Dronning Maud Land Coast. See Fig. S2 for the correlations for each CMIP5 model.

for both surface temperatures and SMB, leading to noise in the time series (Stenni et al., 2017; Thomas et al., 2017; Frezzotti et al., 2007). Since the SMB reconstruction is only based on direct snow accumulation measurements, this is expected to be more accurate than the $\delta^{18}$O-based temperature reconstruction, which is built by assuming a stationary link between $\delta^{18}$O and surface temperature. Because a lot of processes (such as precipitation seasonality or moisture origin) can significantly modify this relationship over time (e.g. Jouzel et al., 1997; Sime et al., 2008), this is computed over a short calibration period, but this might be too short to be representative (Klein et al., 2019). ~~Thus, the high sensitivity resulting from ice cores could arise from using $\delta^{18}$O as a surface temperature proxy. When using the observed surface temperatures (e.g. Nicolas and Bromwich, 2014) instead of the reconstructed ones of Stenni et al. (2017), the Antarctic~~ Consequently, all these processes could explain the large

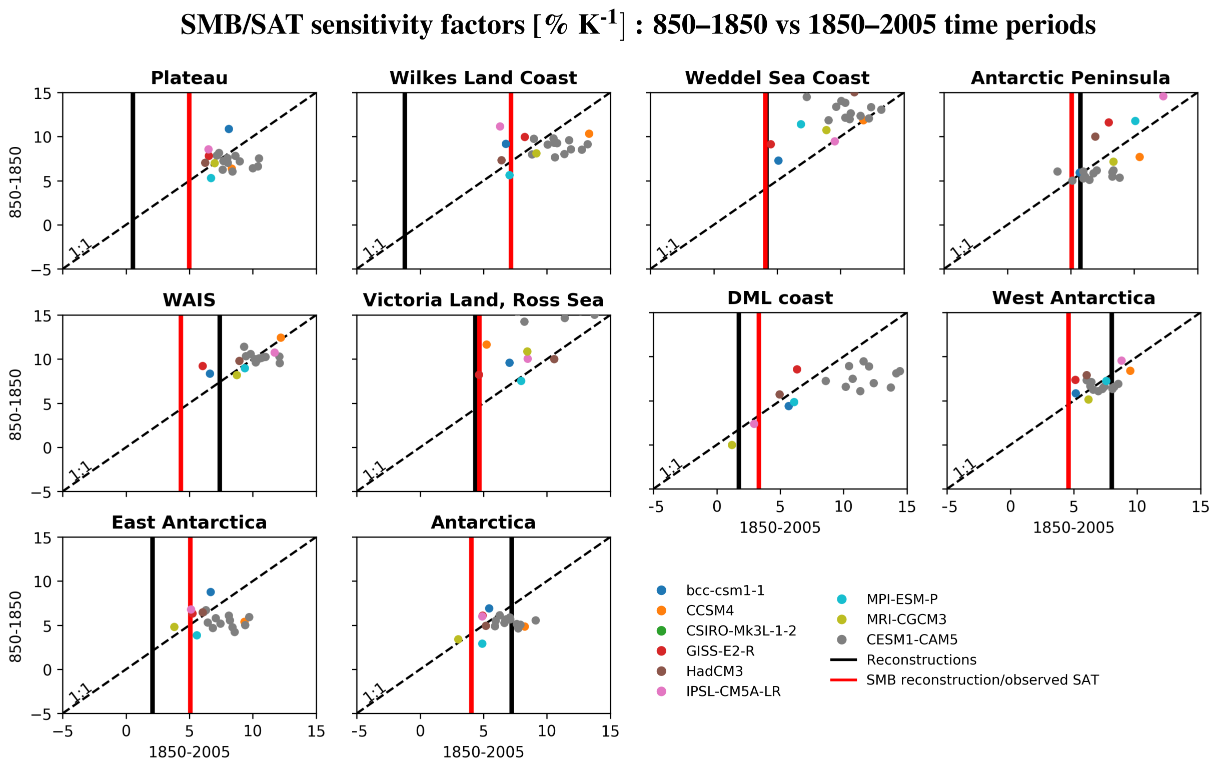


**Figure 5.** SMB sensitivity to Surface ~~Temperatures~~ Air Temperature (~~ST~~SAT) over the 850–1850 and the 1850–2005 periods for each Antarctic region (see Fig. 1 for geographical definitions) for GCM outputs. Additionally, the SMB-$\delta^{18}$O sensitivity for ice cores based-reconstructions (i.e Thomas et al., 2017; Stenni et al., 2017) over 1850–2005 is represented by a solid black vertical line while a solid red vertical line represents the SMB-observed surface ~~temperatures~~ temperature sensitivity ~~Thomas et al. (2017); Nicolas and Bromwich (2014)~~ (i.e. Thomas et al., 2017; Nicolas and Bromwich, 2014) over 1960–2010. For the CESM1-CAM5 model, the 12 simulations are plotted as grey points.

differences between models and proxy-based reconstructions in the estimation of SMB sensitivity to ~~temperature is strongly reduced (4.02 % K$^{-1}$ for the 1958–2010 period), and thus closer to the resulting sensitivity found in the GCMs (5.4 ± 2.0 % K$^{-1}$ for the 1950–2005 period).~~ surface temperatures.

### 4.3 SMB and surface temperature reconstructions from data assimilation

The high correlation values obtained between SMB and surface temperatures in GCMs suggest that we can potentially use SMB to reconstruct Antarctic near-surface temperature. The analysis of isotope-enabled ~~models~~ model results reinforces this hypothesis (Fig. 6): the iHadCM3 outputs show high correlations between these two variables. For most regions, the link between surface temperature and SMB (r=0.70 on average over the seven subregions for the 1850–2000 period) is higher than that between surface temperatures and $\delta^{18}$O (r=0.55 on average over the seven subregions for the 1850–2000 period). This is consistent with the observations: the regional correlations between SMB from ice cores (e.g. Thomas et al., 2017) and the observed surface temperatures (i.e. Nicolas and Bromwich, 2014) are high for several regions over the 1960–2010 period (using 5-year averages as for Stenni et al., 2017). In particular, this correlation for East Antarctica is 0.82 (statistically significant). The results with the outputs of ECHAM5-wiso and ECHAM5/MPI-OM are ~~similar (Figs. ?? and ??~~a bit more nuanced than those from iHadCM3 (Fig. S3). The results of ECHAM5-wiso and ECHAM5/MPI-OM confirm this strong link between SMB and temperature but, in contrast to iHadCM3, the correlations are not systematically higher than between $\delta^{18}$O and temperature. When analyzing the long ECHAM5/MPI-OM simulation (800–2000), the relationship between SMB and surface temperature is generally higher than between $\delta^{18}$O and surface temperature but the difference is small. For some regions, the SMB-surface temperature link is much higher than the $\delta^{18}$O-surface temperature link but it is weaker for other regions. Compared to the $\delta^{18}$O-surface temperature link, the SMB-surface temperature is also less spatially variable (minimum regional correlation is 0.54 against 0.07 for the $\delta^{18}$O-surface temperature link).

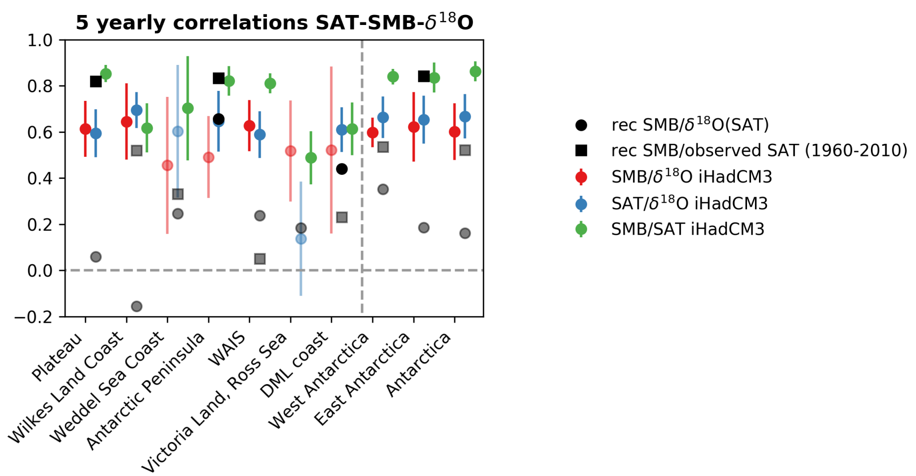


**Figure 6.** 5 year correlations between SMB and $\delta^{18}$O, surface temperature and $\delta^{18}$O, and SMB and surface temperature for the seven Antarctic regions over 1850–1995 period from the iHadCM3 outputs. The error bars correspond to the range (maximum and minimum) of the iHadCM3 simulations while the dot is the mean of the simulation ensemble. In black circles, the correlation between the SMB ice core reconstructions from Thomas et al. (2017) and the $\delta^{18}$O of Antarctic ice cores aggregated for the seven Antarctic regions (Stenni et al., 2017). In black squares, the correlation between the SMB reconstructions from Thomas et al. (2017) and the observed surface temperatures aggregated for the seven Antarctic regions (Nicolas and Bromwich, 2014). This latter dataset covers only the 1960–2010 period (5-year averages). Non-significant correlations (p-value>=0.05) are shown in pale.

#### 4.3.1 Surface temperatures reconstruction

When constraining the model with the SMB reconstruction of Thomas et al. (2017), the obtained surface temperature reconstruction is less well correlated with the reconstruction of Stenni et al. (2017) than for the data assimilation reconstruction constrained by only the $\delta^{18}$O (Fig. 7). However, the difference is relatively small, despite the fact that SMB and surface temperatures are more strongly correlated in models than in the ice core reconstruction (0.86 for iHadCM3 against 0.16 for ice cores; Fig. 6). When ~~comparing~~ compared to observed surface temperature over the 1958–2010 period (i.e. Nicolas and Bromwich, 2014), the surface temperature reconstruction of Stenni et al. (2017) as well as the reconstruction when only $\delta^{18}$O is assimilated is in good agreement with the observed surface temperatures for West Antarctica (Tab. 1, coefficient correlations are 0.79 and 0.69 respectively, both statistically significant) but not for East Antarctica (coefficient correlations are 0.10 and 0.13 respectively, both not statistically significant).

**Table 1.** 5-year mean correlations between the three surface temperature reconstructions from data assimilation experiments using the iHadCM3 outputs and the statistical reconstruction of Stenni et al. (2017), with the surface temperature reconstructions from Nicolas and Bromwich (2014) over the 1958–2010 period for West Antarctica, East Antartica and Antarctica as a whole. Stars represent statistically significant correlations (p-value<0.10).

| | West Antarctica | East Antarctica | Antarctica |
|---|---|---|---|
| DA $\delta^{18}$O | 0.69* | 0.13 | 0.34 |
| DA SMB | 0.55 | 0.60* | 0.65* |
| DA $\delta^{18}$O and SMB | 0.72* | 0.61* | 0.73* |
| Stenni et al. (2017) | 0.79* | 0.10 | 0.57* |

In contrast to the data assimilation experiment, in which only $\delta^{18}$O is assimilated, the skill of the surface temperature reconstruction is almost identical for both regions in the data assimilation experiment where only SMB is assimilated: r=0.55 (p-value<0.1) for West Antarctica and r=0.60 (p-value<0.1) for East Antarctica. Assimilating SMB thus provides a more spatially robust temperature reconstruction than when assimilating $\delta^{18}$O. When both $\delta^{18}$O and SMB are taken into account in the data assimilation process, the skill of the surface temperature reconstructions for the two sub-Antarctic regions is higher (r=0.72 and 0.61 for West Antarctica and for East Antarctica respectively, both significant) than when assimilating separately the $\delta^{18}$O or the SMB. Moreover, the only reconstruction that provides statistically significant results for all the regions (West, East and the entire Antarctica; p-value<0.1) is when both $\delta^{18}$O and SMB are assimilated, implying that assimilating both proxies offers more robust results than only assimilating one of them.

When looking at the linearly detrended time series, our final reconstruction (i.e. when $\delta^{18}$O and SMB are assimilated) displays a null correlation with observed surface temperature (p-value=0.99) for West Antarctica, but the correlation remains high for East Antarctica (r=0.60; p-value=0.07). During the 1958–2012 period, a significant warming is observed in West Antarctica while no significant change is noticed for East Antarctica (Nicolas and Bromwich, 2014). Consequently, data assimilation tends to reproduce the warming for West Antarctica and the inter-annual variability for East Antarctica, explaining our dif-

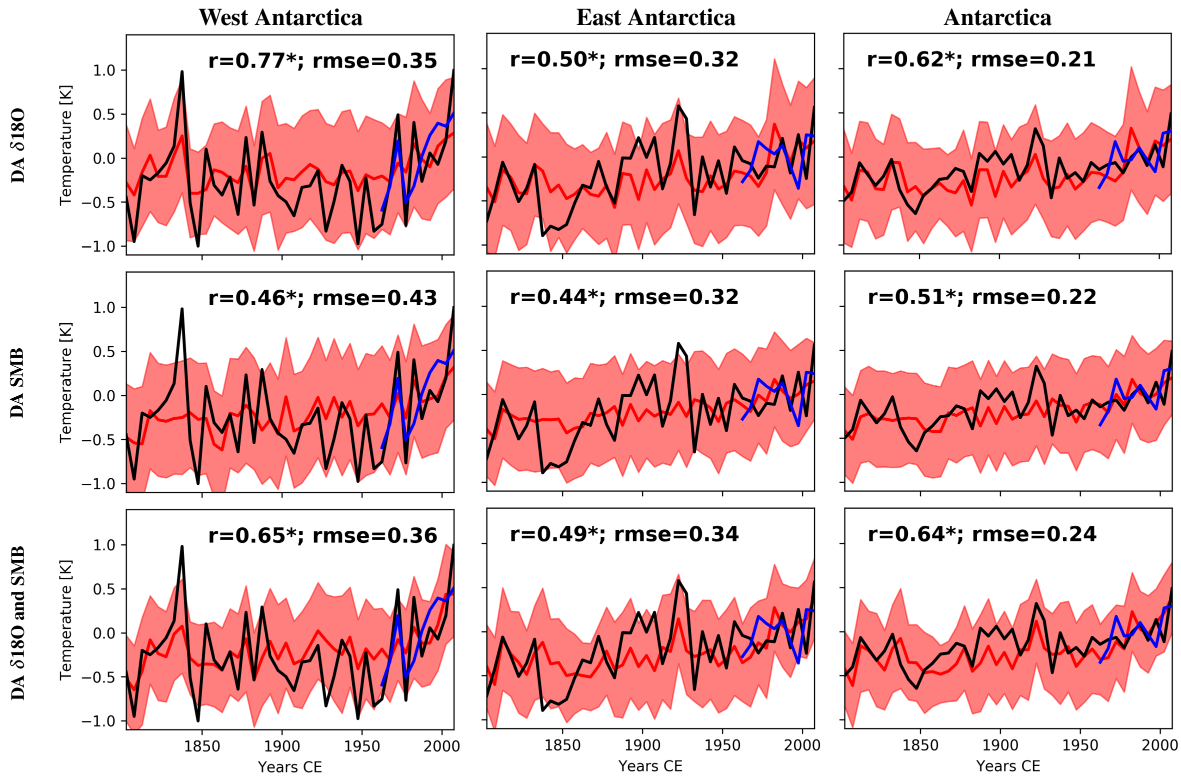


**Figure 7.** Reconstructed temperatures (5-year mean) for West Antarctica, East Antarctica and for Antarctica as a whole from data assimilation experiment (red) using the iHadCM3 outputs and $\delta^{18}$O (Stenni et al., 2017) and SMB reconstruction (Thomas et al., 2017) as constrain in the data assimilation process. The period is 1800–2010. The surface temperature reconstruction of Stenni et al. (2017) are represented in black and those from Nicolas and Bromwich (2014) are in blue. *DA $\delta^{18}O$* (first row) is the data assimilation experiment using only the $\delta^{18}$O data to constrain the model while *DA SMB* (second row) uses the SMB reconstruction and *DA $\delta^{18}O$ and SMB* (third row) uses both. For each experiment and each region, the correlation (*r*) between the reconstruction based on ice cores (in black) and that based on data assimilation is computed (in red). The shaded areas represent ± 1 standard deviation of the model particles. Stars represent the statistically significant correlation (p-value<0.05).

ferent results between the original and detrended time series. Additionally, as well as our reconstruction based on only $\delta^{18}$O, the correlation of the detrended $\delta^{18}$O-based temperature reconstruction of Stenni et al. (2017) with the observed one for East Antarctica is non-significant and negative suggesting that SMB constitutes a better proxy than $\delta^{18}$O for surface temperatures, at least at the inter-annual time-scale (see Tab. S2).

Regarding surface temperature trends over the last two centuries, our reconstructions displays an increase of 0.02°C per decade for West Antarctica and 0.023°C per decade for East Antarctica, which finally leads to an increase of 0.022°C per decade for Antarctica as a whole (all statistically significant). For the 1961–2010 period, our reconstruction is able to simulate the observed contrast between West and East Antarctica (0.22 °C per decade (significant) and 0.053 °C per decade (not significant), respectively, for Nicolas and Bromwich (2014) compared with 0.1 °C per decade and 0.06 °C per decade, respectively, for our reconstruction, both significant). The resulting contrast in our reconstruction is thus less large than observed (see Tab. S3 for details). However, because of the short time period considered, these values can highly vary depending on the time interval chosen (not shown).

#### 4.3.2 SMB reconstruction

Constraining the model with the $\delta^{18}$O data leads to a poor SMB reconstruction, especially for West Antarctica (correlation coefficient of 0.29; Fig. 8). Moreover, the constraint derived from observed $\delta^{18}$O on SMB is weak as illustrated by the large error band of the reconstruction (estimated by the weighted variance of the particles with non-zero weight). When assimilating both $\delta^{18}$O and SMB, the SMB reconstruction is in good agreement with the reconstruction of Thomas et al. (2017) as expected.

**Table 2.** SMB trends over grounded West Antarctica, East Antarctica and Antarctica as a whole from 1) our reconstruction based on data assimilation using iHadCM3 outputs and, SMB and $\delta^{18}$O data in the data assimilation procedure; 2) Medley and Thomas (2019); 3) RACMO2 outputs for various time intervals (in Gt year$^{-2}$). Stars stand for statistically significant trends at 5% level.

| | In this study | | | Medley and Thomas (2019) | | | RACMO2 |
|---|---|---|---|---|---|---|---|
| | 1801 – 2000 | 1957 – 2000 | 1979 – 2000 | 1801 – 2000 | 1957 – 2000 | 1979 – 2000 | 1979 – 2000 |
| West Antarctica | 0.07 | 0.82* | 1.6 | 0.1 | 1.3 | 1.7 | 2.0 |
| East Antarctica | 0.19* | -0.13 | -3.3* | 0.3* | -0.4 | -4.5* | -3.7 |
| Antarctica | 0.26* | 0.7 | -1.7 | 0.4* | 1 | -2.7 | -1.7 |

According to this data assimilation-based SMB reconstruction, the AIS SMB has increased at a 0.33 Gt year$^{-2}$ pace (p-value<0.001) during the 1801–2000 period and 0.88 Gt year$^{-2}$ (p-value=0.1) for the 1957–2000 period. Over this latter period, West Antarctica has witnessed an increase of 1.0 Gt year$^{-2}$ while East Antarctica was subjected to a decrease of 0.12 Gt year$^{-2}$ (p-values=0.7). Unlike West Antarctica, the ~~high~~ non statistical significance of the SMB trend for East Antarctica might imply that internal variability currently plays a large role in the SMB variability there (e.g. Jones et al., 2016). However, if we focus on the shorter 1979–2000 period, a significant decrease is obtained for East Antarctica (-3.9 Gt year$^{-2}$; p-value <0.01) while it is still positive for West Antarctica (1.9 Gt year$^{-2}$; p-value=0.2), which is consistent with RACMO2 outputs (-3.4 Gt year$^{-2}$ for East Antarctica and 2.1 Gt year$^{-2}$ for West Antarctica, both not significant).

## 5 Discussion and conclusions

This paper discusses the AIS SMB over the last two centuries and its links with surface temperature in reconstructions and model simulations. ~~The SMB simulated by GCMs has been evaluated using the regional climate model RACMO2 and~~

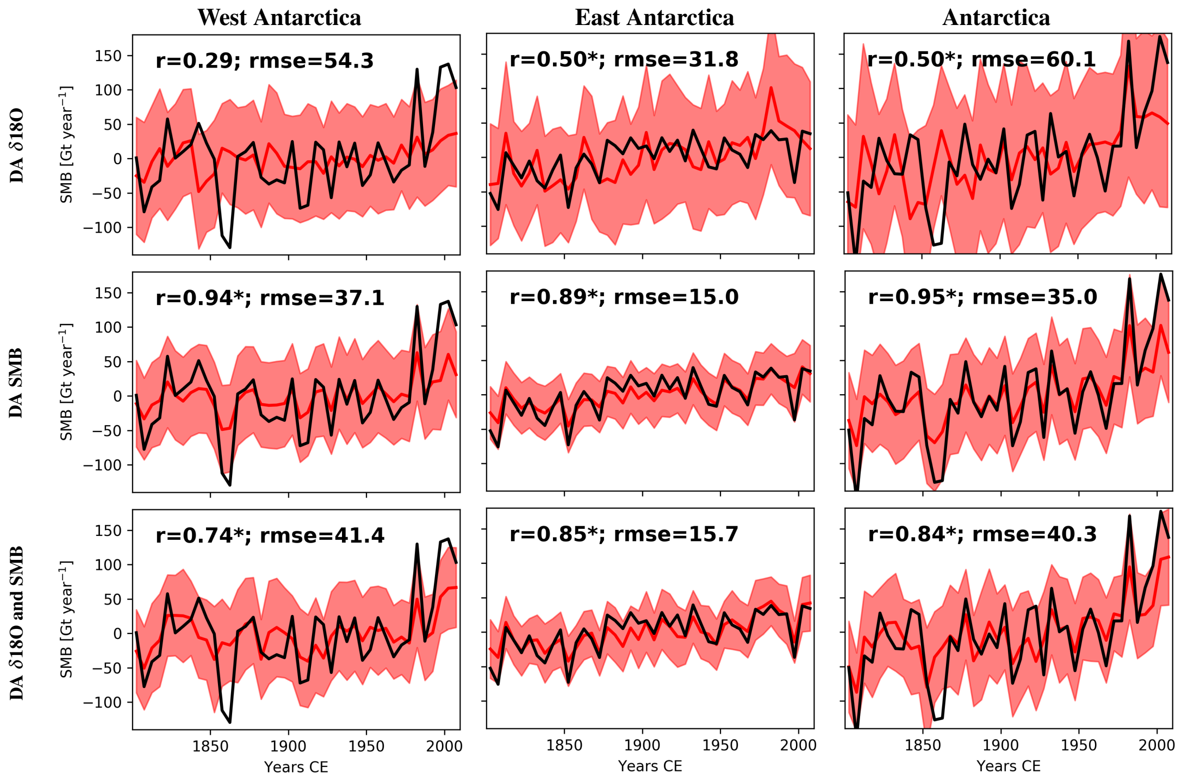


**Figure 8.** Reconstructed SMB (5-year mean) for West Antarctica, East Antarctica and Antarctica as a whole from data assimilation experiment using the iHadCM3 outputs and $\delta^{18}$O (Stenni et al., 2017) and SMB reconstruction (in black; Thomas et al., 2017) as constrain in the data assimilation process. The period is 1800–2010. *DA $\delta^{18}O$* (first row) is the data assimilation experiment using only the $\delta^{18}$O data to constraint the model while *DA SMB* (second row) uses the SMB reconstruction and *DA $\delta^{18}O$ and SMB* (third row) uses both. For each experiment and each region, the correlation (*r*) between the reconstruction based on ice cores (in black) and that based on data assimilation is computed (in red). The shaded areas represent ± 1 standard deviation of the model particles. Stars represent the statistically significant correlation (p-value<0.05).

~~reconstructions based on ice cores. The GCMs are able to simulate relativity well the current AIS SMB, as well as its temporal variations over the last two centuries, including the positive SMB trend since around 1960 AD. This evaluation gives confidence in the use of GCMs to study the SMB over Antarctica.~~

The analysis of the relationship between SMB and surface temperature in models and in ice core reconstructions highlighted the covariance between both variables that can potentially be used to reconstruct past changes. The relevance of SMB in the reconstruction of surface temperature in Antarctica is based on a relatively simple concept: Antarctic precipitation originates mainly from lower latitudes, in the form of warm and wet air masses (Goodwin et al., 2016; Turner et al., 2016; Clem et al., 2018). Nevertheless, $\delta^{18}$O also provides useful temperature-related information that can be used to complement the information provided by SMB, such as changes in moisture origin (e.g. Holloway et al., 2016a). Our analyses pointed out significant model-data discrepancies in the SMB-surface temperature relationship. On the one hand, models show a strong correlation between $\delta^{18}$O and SMB for ~~all the~~ many Antarctic regions and, on the other hand, the reconstructions based on ice cores display a weak relationship. Furthermore, unlike previous studies (e.g. Frieler et al., 2015) who suggest an increase of the SMB sensitivity to surface temperature for the future in Antarctica ($\sim$ 40%), we show that the current sensitivity is not exceptionally high compared to the last 200 years, according to CMIP5 models.

These large discrepancies between model results and reconstructions can be explained by different factors. The GCMs may have biases in the simulated temperature changes~~or in their~~. For example, as shown by Klein et al. (2019), GCMs display on average a homogeneous warming over Antarctica during the last decades while observations mainly show warming for West Antarctica with no significant change for East Antarctica. Additionally, climate model simulations generally display a warming starting in the 19th century in Antarctica while it begins much later in proxy-based reconstructions (Abram et al., 2016). This suggests that reconstructions underestimate the response to anthropogenic forcing ~~. This~~ or that climate models overestimate it. In this latter case, this may contribute to an overestimation of the contribution of the simple thermodynamic link between temperature and precipitation and thus snow accumulation while it underestimates the role of changes in atmospheric circulation variability (Abram et al., 2016; Klein et al., 2019; PAGES 2k-PMIP3 group, 2015). Nevertheless, by removing the linear trend of time series, we obtained similar results. ~~They~~ Models may also neglect processes such as blowing snow that can reduce the correlation between temperature and SMB. On the other hand, RACMO2, which includes a simple representation of blowing snow and is nudged to observed temperature and large-scale circulation changes, displays similar correlations to that of the GCMs. Another hypothesis is that differences could rather arise from uncertainties in the reconstructions. ~~According to Neukom et al. (2018), uncertainties in the reconstructions (the noise in proxy data and the deficiencies in the reconstruction methods)~~ To understand the potential origin of the disagreements between model results and reconstructions over the last millennium, Neukom et al. (2018) used pseudoproxy experiments. They found that uncertainties in the reconstructions and the data sampling could be an explanation ~~of the observed discrepancy~~ for many observed discrepancies between models and reconstructions.

By analyzing isotope-enabled climate models, we showed that on average over the models, the relationship between SMB and surface temperature is often higher (or at least equivalent) and more stable than the one between surface temperature and $\delta^{18}$O. This is true both on the continental and regional scale. Unlike SMB, $\delta^{18}$O can be subject to large uncertainties linked to precipitation seasonality (Sime et al., 2008) or changes in moisture origins (Holloway et al., 2016a), which can explain the weaker correlations.

Our data assimilation experiments confirm the benefits of using both proxies – SMB and $\delta^{18}$O – to reconstruct surface temperature. When assimilating both $\delta^{18}$O and SMB data, the resulting reconstruction shows a higher correlation with observed surface temperature over the period 1958–2010 (i.e. Nicolas and Bromwich, 2014) for the entire Antarctic continent (r=0.73) than the one obtained with the reconstruction based on the statistical method of Stenni et al. (2017; r=0.57). The difference is larger for East Antarctica, where the reconstruction skill is enhanced by incorporating SMB data (r=0.61 for our reconstruction against 0.10 for the reconstruction of Stenni et al., 2017). For West Antarctica, our reconstruction is very similar to Stenni et al.

(2017)'s statistical method. This improvement can be explained by the large uncertainties in $\delta^{18}O$ data for East Antarctica, probably because of the low ~~number~~ amount of ice cores and low snow accumulation in those areas. In comparison to Stenni et al. (2017) and Klein et al. (2019), who obtain a higher surface temperature trend over the last two centuries for East Antarctica (0.03 °C per decade and 0.018 °C per decade respectively, both significant) than for West Antarctica (0.011 °C per decade and 0.01 °C per decade respectively, both not significant), our data assimilation-based reconstruction reveals similar surface temperature trends for both regions (0.02 °C per decade and 0.023 °C per decade respectively, both significant). However, over the entire continent, the trend is almost the same between the different datasets (0.022 °C per decade in this study (significant), 0.019 °C per decade for Stenni et al., 2017, significant, and 0.016 °C per decade for Klein et al., 2019, not significant). Over the last decades (1961–2010), all the reconstructions are able to reproduce the observed contrast between West Antarctica (large warming) and East Antarctica (weak warming), but overall, they underestimate it (see Tab. S3 for details).

Regarding changes in SMB over the last two centuries, our reconstruction shows large regional differences in SMB trends, both in magnitude and in ~~sign~~signs, in accordance with Medley and Thomas (2019; Fig. S4) who used the same ice core dataset but a different method. While they obtain a statistically significant SMB increase of 0.4 Gt year$^{-2}$ over the grounded AIS for 1801–2000, our result ~~suggest~~ suggests a weaker increase (0.26 Gt year$^{-2}$; p-value<0.001; see Tab. 2 for details). A similar underestimation is noticed for the 1957–2000 period, (1.0 Gt year$^{-2}$ for Medley and Thomas (2019), not significant, and 0.70 Gt year$^{-2}$ for our reconstruction, p-value=0.130). Over the last decades (1979–2000), both Medley and Thomas (2019) and our results reveal that grounded West Antarctica gains mass at its surface (1.6 Gt year$^{-2}$ in this study and 1.7 Gt year$^{-2}$ for Medley and Thomas, 2019, both not significant) while grounded East Antarctica has experienced a very large SMB decrease (-3.3 Gt year$^{-2}$ and -4.5 Gt year$^{-2}$ respectively, both significant), which is consistent with the value obtained in the RACMO2 outputs (2.0 Gt year$^{-2}$ for West Antarctica -3.7 Gt year$^{-2}$ for East Antarctica, both not significant).

More generally, in contrast to statistical methods, data assimilation ensures that reconstructions are compatible with the physics of the system as represented in the models chosen. ~~Considering~~ Although it is not possible to independently evaluate our SMB reconstruction, our good results regarding surface temperatures and SMB reconstructions ~~, our data assimilation-based reconstructions~~ suggest that the strong simulated correlation between surface temperatures and SMB in GCMs is not a model artefact. This is supported by a strong link between these two variables in observations when using snow accumulation data from Thomas et al. (2017) and surface temperatures from Nicolas and Bromwich (2014), in particular for East Antarctica (r=0.82, statistically significant). Therefore, our study shows that SMB records seem to be a relevant proxy in reconstructing surface temperature in complementary with $\delta^{18}O$ records. Since only a few records are available before the instrumental period over Antarctica, any relevant record to reconstruct the Antarctic climate and more specifically surface temperature is welcome. Additionally, data assimilation appears particularly ~~well-adapted~~ well adapted for reconstructing surface temperatures ~~in this framework~~ as the covariance between variables is obtained directly from climate models that explicitly include physical processes while statistical approaches restrict the problem to empirical linear relationships. By using data assimilation, no assumption such as stationarity or long calibration periods is required to estimate ~~th~~ the link between variables, assumptions ~~which~~ whose validity can strongly vary in time and space (Klein et al., 2019). However, to get a skillful data assimilation-based reconstruction, it is essential that the selected climate models have an adequate representation of climate variability and that good uncertainty estimates are available for the chosen datasets.

## Appendix A: Characteristics of GCMs

**Table A1.** PMIP3/CMIP5 GCMs characteristics and references.

| Model name | Atmospheric model resolution (lat × lon) | Number of simulations for 850–1850 period | Number of simulations for 1850–2005 period | Reference |
|---|---|---|---|---|
| BCC-CSM1-1 | 64 × 128 | 1 | 3 | Wu et al. (2014) |
| CCSM4 | 192 × 288 | 1 | 6 | Gent et al. (2011) |
| CESM1-CAM5 | 96 × 144 | 12 | 12 | Otto-Bliesner et al. (2015) |
| CSIRO-Mk3L-1-2 | 56 × 64 | 1 | 1 | Rotstayn et al. (2010) |
| GISS-E2-R | 90 × 144 | 1 | 6 | Schmidt et al. (2014) |
| HadCM3 | 73 × 96 | 1 | 10 | Turner et al. (2006) |
| IPSL-CM5A-LR | 96 × 96 | 1 | 6 | Dufresne et al. (2013) |
| MPI-ESM-P | 96 × 192 | 1 | 2 | Stevens et al. (2013) |
| MRI-CGCM3 | 160 × 320 | 1 | 3 | Yukimoto et al. (2012) |

*Code and data availability.* The resulting Antarctic SMB and surface temperature reconstructions will be available when the manuscript is accepted. All CMIP5/PMIP3 model simulations can be directly downloaded on http://pcmdi9.llnl.gov. iHadCM3 data are available by request to Max Holloway (Max.Holloway@sams.ac.uk). ECHAM5-wiso data covering the 1871–2011 period can be downloaded from https://doi.org/10.5281/zenodo.1249604. Products from the ECHAM5/MPI-OM model simulation are available by request to Jesper Sjolte (jesper.sjolte@geol.lu.se). RACMO2 data are available by request to Jan Lenaerts (Jan.Lenaerts@Colorado.EDU). $\delta^{18}$O, surface temperature and SMB reconstructions are stored at UK Polar Data Centre and at NOAA World Data Center for Paleoclimatology (https://www.ncdc.noaa.gov/paleo-search/study/22589), or by a request from Elizabeth R. Thomas (lith@bas.ac.uk). Antarctic observed surface temperatures are available at http://polarmet.osu.edu/datasets/Antarctic_recon/.

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~~Antarctic Ice Sheet surface mass balance mm w.e. $y^{-1}$ for all the models used in this study over the 1979–2005 period.~~

~~Mean Antarctic Ice Sheet surface mass balance (Gt $year^{-1}$) simulated by all the models used in this study.~~

~~Distribution of the surface mass balance simulated by each GCM used in this study as a function of elevation, binned in 400m elevation intervals. The bars represent one standard deviation of the cell grids within each elevation bin.~~

~~Surface mass balance anomalies Gt $y^{-1}$ simulated by the GCMs (the average of all the available simulations has been represented; Tab. A1) and snow accumulation reconstructions (Thomas et al., 2017) for 1000–2005 and for 1800–2005 for all the Antarctic subregions. Anomalies are computed for the period 1800–2000. The shaded area corresponds to the range of the CESM1-CAM5 simulations. For visibility, data has been smoothed with a 100 year moving average for the last millennium and a 30 years moving average for the last 200 years.~~

~~Surface mass balance trends (in Gt $100y^{-2}$) for West Antarctica, East Antarctica and Antarctica as a whole in GCMs, in isotopic climate models (ECHAM5-wiso, ECHAM5/MPIOM and HadCM3) and in reconstructions based on ice cores (Thomas et al., 2017) over 1950–2000. The number in brackets is the number of simulations. The trend computation is based on yearly data.~~

~~Annual correlations (r) between surface mass balance and surface temperature for all seven Antarctic regions (see Fig. 1 for geographical definitions) for all the GCMs over the 1850–2005 AD. "1" is for the Plateau and "7" for DML Coast.~~

~~5 year correlations between SMB and $\delta^{18}$O, surface temperature and $\delta^{18}$O and, SMB and surface temperature for the seven Antarctic regions over 1870–199 time period from the ECHAM5-wiso outputs. In black, the correlation between the SMB reconstructions from Thomas et al. (2017) and the $\delta^{18}$O of the Antarctic ice cores aggregated for the seven Antarctic regions (Stenni et al., 2017).~~

~~5 year correlations between SMB and $\delta^{18}$O, surface temperature and $\delta^{18}$O and, SMB and surface temperature for the seven Antarctic regions over 1850–1995 from the ECHAM5/MPI-OM outputs. In black, the correlation between the SMB reconstructions from Thomas et al. (2017) and the $\delta^{18}$O of Antarctic ice cores aggregated for the seven Antarctic regions (Stenni et al., 2017).~~

~~Reconstructed surface temperatures (5-year mean) for West Antarctica, East Antarctica and Antarctica as a whole from our data assimilation experiment using the ECHAM5-wiso outputs and, $\delta$018 (Stenni et al., 2017) and SMB reconstruction (Thomas et al., 2017) as data. The period is 1800–2010. *DA $\delta^{18}O$* is the data assimilation experiment using only the $\delta^{18}$O data to constrain the model while *DA SMB* uses only the SMB reconstruction and *DA $\delta^{18}O$ and SMB* uses both. For each experiment and each region, the correlation ($r$) between the reconstruction based on ice cores and that based on data assimilation is computed. The shaded areas represent $\pm$ 1 standard deviation of the model particles.~~

~~Reconstructed surface temperatures (5-year mean) for West Antarctica, East Antarctica and Antarctica as a whole from data assimilation experiment using the ECHAM5-MPI/OM outputs and, $\delta$018 (Stenni et al., 2017) and SMB reconstruction (Thomas et al., 2017) as data. The period is 1800–2010. *DA $\delta^{18}O$* is the data assimilation experiment using only the $\delta^{18}$O data to constrain the model while *DA SMB* uses only the SMB reconstruction and *DA $\delta^{18}O$ and SMB* uses both. For each experiment and each region, the correlation ($r$) between the reconstruction based on ice cores and that based on data assimilation is computed. The shaded areas represent $\pm$ 1 standard deviation of the model particles.~~

~~Slopes (°C 100yr$^{-1}$) of each surface temperature reconstruction (Stenni et al., 2017; Klein et al., 2019; Nicolas and Bromwich, 2014 ; in this study) over the 1961–2010 period for West Antarctica, East Antarctica and the Antarctica. Statistically significant (p-value < 0.05) trends are represented by a star.~~

~~5-year mean correlations between the three surface temperature reconstructions from data assimilation experiments using the ECHAM5-MPI/OM outputs, ECHAM5-wiso outputs and the iHadCM3 outputs, and the surface temperature reconstructions from Nicolas and Bromwich (2014) over the 1958–2010 for the East, West and the whole Antarctica.~~

~~5-year mean correlations between the three surface temperature reconstructions from data assimilation experiments using the iHadCM3 outputs and the statistical reconstruction of Stenni et al. (2017), with the surface temperature reconstructions from Nicolas and Bromwich (2014) over the 1958–2010 period for East Antarctica, West Antartica and Antarctica as a whole. All the correlations are performed on detrended time series. Stars represent statistically significant correlations (p-value<0.10).~~

~~Reconstructed SMB (5-year mean) for West Antarctica, East Antarctica and Antarctica as a whole from data assimilation experiment using the ECHAM5-wiso outputs and, $\delta$018 (Stenni et al., 2017) and SMB reconstruction (Thomas et al., 2017) as data. The period is 1800–2010. *DA $\delta^{18}O$* is the data assimilation experiment using only the $\delta^{18}$O data to constrain the model while *DA SMB* uses only the SMB reconstruction and *DA $\delta^{18}O$ and SMB* uses both. For each experiment and each region, the correlation (*r*) between the reconstruction based on ice cores and that based on data assimilation is computed. The shaded areas represent $\pm$ 1 standard deviation of the model particles.~~

~~Reconstructed SMB (5-year mean) for West Antarctica, East Antarctica and Antarctica as a whole from data assimilation experiment using the ECHAM5-MPI/OM outputs and, $\delta$018 (Stenni et al., 2017) and SMB reconstruction (Thomas et al., 2017) as data. The period is 1800–2010. *DA $\delta^{18}O$* is the data assimilation experiment using only the $\delta^{18}$O data to constrain the model while *DA SMB* uses only the SMB reconstruction and *DA $\delta^{18}O$ and SMB* uses both. For each experiment and each region, the correlation (*r*) between the reconstruction based on ice cores and that based on data assimilation is computed. The shaded areas represent $\pm$ 1 standard deviation of the model particles.~~

~~Spatial Antarctic surfance mass balance trends (mm w.e. y$^{-1}$ decade$^{-1}$) over the 1801–2000, 1957–2000 and 1979–2000 periods from 1) our data assimilation-based reconstruction using the iHadCM3 outputs constrained by both $\delta^{18}$O and SMB (first row) and from 2) Medley and Thomas (2019; second row).~~

## S1: Statistical surface temperature reconstructions from Stenni et al. (2017)

~~Based on~~ Using the $\delta^{18}$O composites, Stenni et al. (2017) reconstructed regional surface temperature over the last two millennia based on the statistical relationship between $\delta^{18}$O and surface temperature. Three methods have been used to scale the $\delta^{18}$O composites. In the first approach, the regional slopes between $\delta^{18}$O and temperatures were computed from the outputs of the ECHAM5-wiso model forced by ERA-Interim atmospheric reanalysis (Goursaud et al., 2018) over the 1979–2013 period. In the second method, the reconstruction obtained from the first method for the WAIS region is corrected using an independent temperature record: the borehole temperature reconstruction at WAIS divide (Orsi et al., 2012). This allows to match the cooling trend over the 1000–1600 period (Stenni et al., 2017). This method provides a different reconstruction for the WAIS region – implying thus also the West Antarctic and the whole Antarctic reconstructions –, but not for the regions in East Antarctica. Finally, in the third method, the regional normalized $\delta^{18}$O composites have been scaled to the variance of the surface temperature observations (e.g. Nicolas and Bromwich, 2014) over the 1960–1990 period. The second reconstruction is used throughout this study for two reasons: 1) the third method is based on the surface temperature observations, which are used here to estimate the skill of the reconstructions which could lead to a bias; 2) the correction introduced in the second method is expected to improve the reconstruction compared to the previous method. The temporal resolution of these surface temperature reconstruction is the same as the $\delta^{18}$O composites: 10 years for 0–1800 period and 5 years for 1800–2010 period.

## S2: Defining uncertainties associated with proxy data used during data assimilation process

Data assimilation requires estimates of the uncertainty associated with the proxy data used. Unfortunately, uncertainty estimations are not provided with ~~the used published reconstructions~~ published reconstructions used here and the instrumental time series are too short to reliably derive the uncertainty. If we apply the same error for all the Antarctic regions, the assimilation will tend to give more weight to the time series that have more variance (i.e. the high-accumulation regions). On the other hand, if we apply an error proportional to the standard deviation of the time series, each region will tend to have the same weight. The uncertainly could also be related to the ~~number~~ amount of ice cores included in each regional composite, but the link between this number and the quality of the composite is not straightforward (Stenni et al., 2017). Several experiments have been performed to test the impact of different estimates of the data uncertainties on the data assimilation results. The results are qualitatively similar ~~for~~ to standard choices of the uncertainty (Klein et al., 2019). The experiments shown here assume a signal to noise ratio of 1 for each regional composite. This is probably an optimistic estimate but this has the advantage of providing a strong data constraint and the comparison of the reconstruction using data assimilation with instrumental data indicates a good skill of the methods using this value.

## S3: Present-day AIS SMB simulated by GCMs

Overall, the AIS SMB simulated by GCMs is in good agreement with the SMB simulated by the regional climate model RACMO2 over the last decades (1979–2005, $R^2$ = 0.63; Figs. S5, S6, S7 and S8). As expected, both display high values of SMB along the coast (>300 mm w.e. year$^{-1}$) – especially for West Antarctica and the Antarctic Peninsula – and lower values at high elevations (e.g. the Plateau: <100 mm w.e. year$^{-1}$). The mean of the SMB over the entire AIS simulated by the selected models (including isotope-enable models) is 6.4 mm w.e. year$^{-1}$ lower than the SMB simulated by RACMO2 over the 1979–2005 period (relative bias: -3.4%; Fig. S8 for the correlation plots for each model and Fig. S9 for the integrated SMB over the entire AIS for each model).

However, Figure S5 shows that the GCMs, compared to RACMO2, underestimate SMB in areas below 1500 m (mean bias of -55 mm w.e. year$^{-1}$; relative bias: -15%) over 1979–2005. For the areas above 1500 m, the mean bias of the simulated SMB by GCMs compared to RACMO2 is 11 mm w.e. year$^{-1}$ (relative bias: 11%). These results are in agreement with previous studies (e.g. Palerme et al., 2017; Genthon et al., 2009; Krinner et al., 2008) who have shown that due to the lower spatial resolution of GCMs in comparison to the regional model, SMB is underestimated at the coasts while an overestimation occurs in the interior of the ice sheet. The bias in the difference between the coastal and higher elevation regions are smaller for the models that have a higher spatial resolution, such as CCSM4 (Fig. S10), confirming that the spatial resolution has a crucial impact on the simulated SMB. However, models with similar resolutions may also have very different results, in particular in coastal regions (relative SMB biases of +47% and +100% for CCSM4 and MRI-CGCM3 respectively compared to RACMO for DML coast over the 1979–2005 period), suggesting a critical role of model physics in some of the GCM biases.

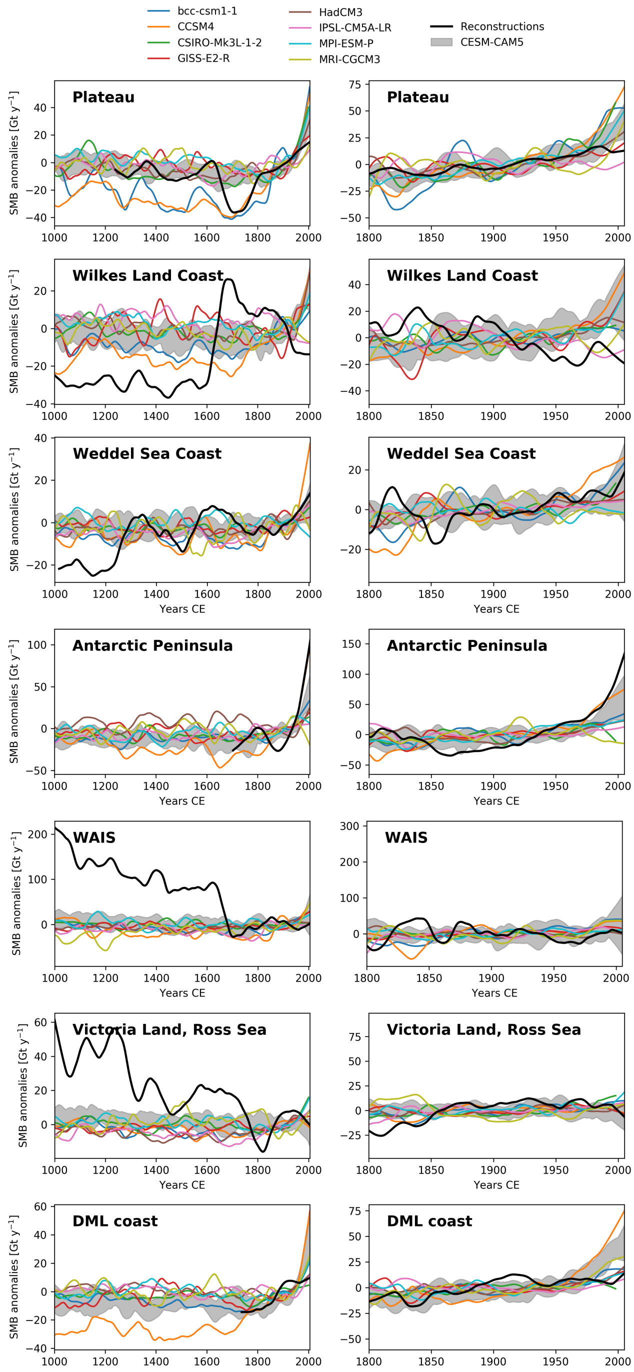


**Figure S1.** Surface mass balance anomalies [Gt y$^{-1}$] simulated by the GCMs (the average of all the available simulations has been represented; Tab. A1) and snow accumulation reconstructions (Thomas et al., 2017) for 1000–2005 and for 1800–2005 for all the Antarctic subregions. Anomalies are computed for the 1800–2000 period. The shaded area corresponds to the range of the CESM1-CAM5 simulations. For visibility, data has been smoothed with a 100 year moving average for the last millennium and a 30 years moving average for the last 200 years.

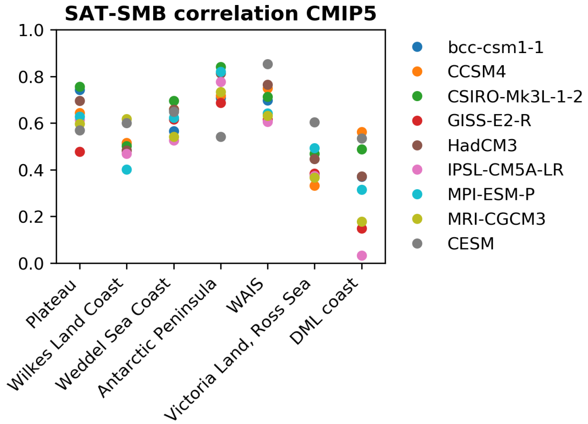


**Figure S2.** Annual correlations (r) between surface mass balance and surface temperature for all seven Antarctic regions (see Fig. 1 for geographical definitions) for all the GCMs over the 1850–2005 period.

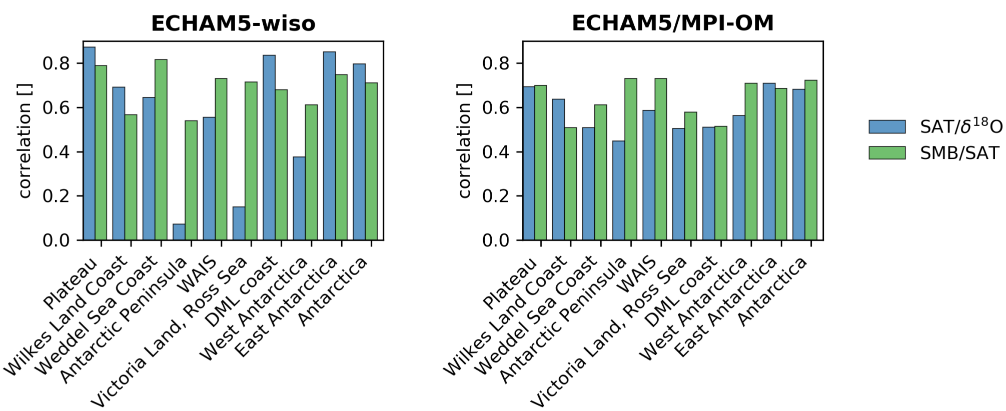


**Figure S3.** 5-year mean correlations between surface temperature and $\delta^{18}$O (blue) and between SMB and surface temperature (green) for the seven Antarctic regions for the entire period simulation (1871–2010 for ECHAM5-wiso and 801–2000 for ECHAM5/MPI-OM).

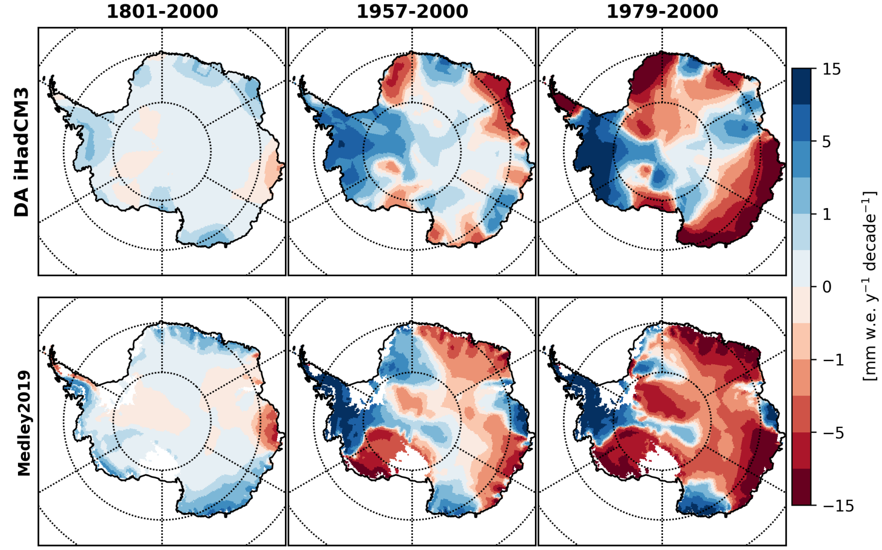


**Figure S4.** Spatial Antarctic surface mass balance trends (mm w.e. $y^{-1}$ $decade^{-1}$) over the 1801–2000, 1957–2000 and 1979–2000 periods from 1) our data assimilation-based reconstruction using the iHadCM3 outputs constrained by both $\delta^{18}O$ and SMB (first row) and from 2) Medley and Thomas (2019; second row).

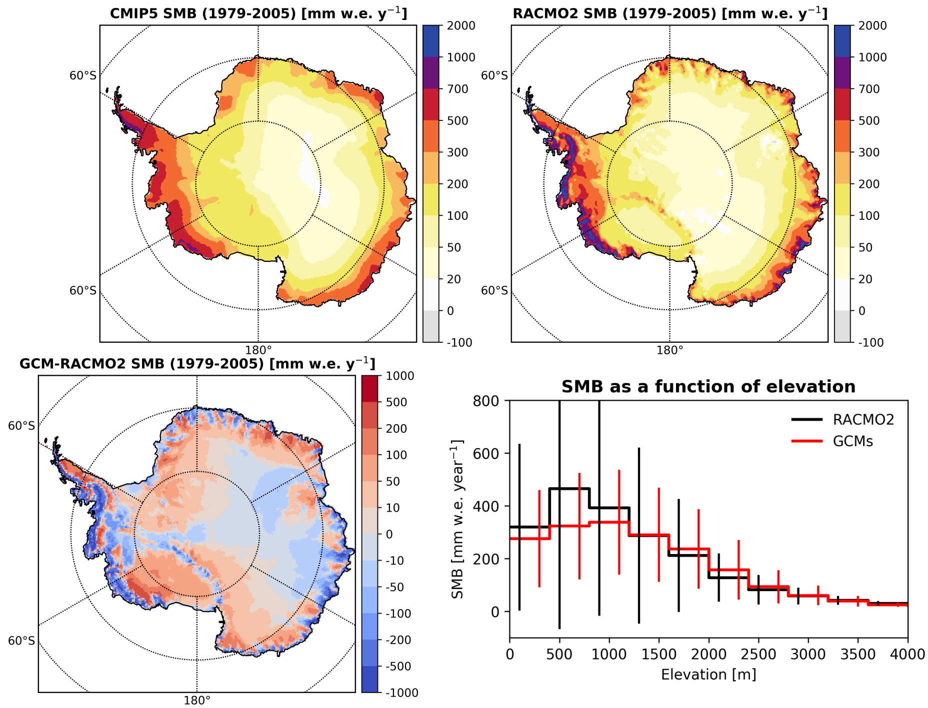


**Figure S5.** Antarctic Ice Sheet Surface Mass Balance [mm w.e. y$^{-1}$] over 1979–2005 CE averaged over all the GCMs simulations (see Tab. A1 for the list) (top left), for RACMO2 (van Wessem et al., 2018) (top right), the difference between them (bottom left) and the distribution of the SMB simulated by RACMO2 and the GCMs as a function of elevation, binned in 400m elevation intervals (bottom right). The bars represent one standard deviation of the cell grids within each elevation bin. The equivalent of the latter panel for each model is provided on Fig. S10.

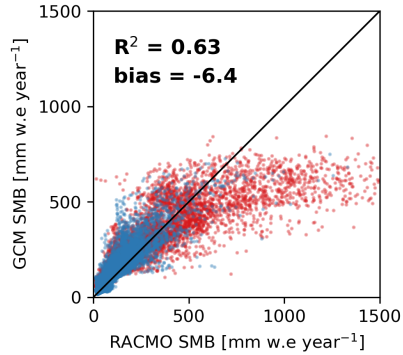


**Figure S6.** Correlation plot of SMB climatology from GCM mean (average over all the GCMs including isotope-enabled models) as a function of RACMO SMB over the 1979–2005 period. $R^2$ is the determination coefficient and bias the average of the difference between GCM mean and RACMO (in mm w.e. year$^{-1}$). Red (blue) dots are for places where the altitude is lower (higher) than 1500m. See Fig. S8 for each model.

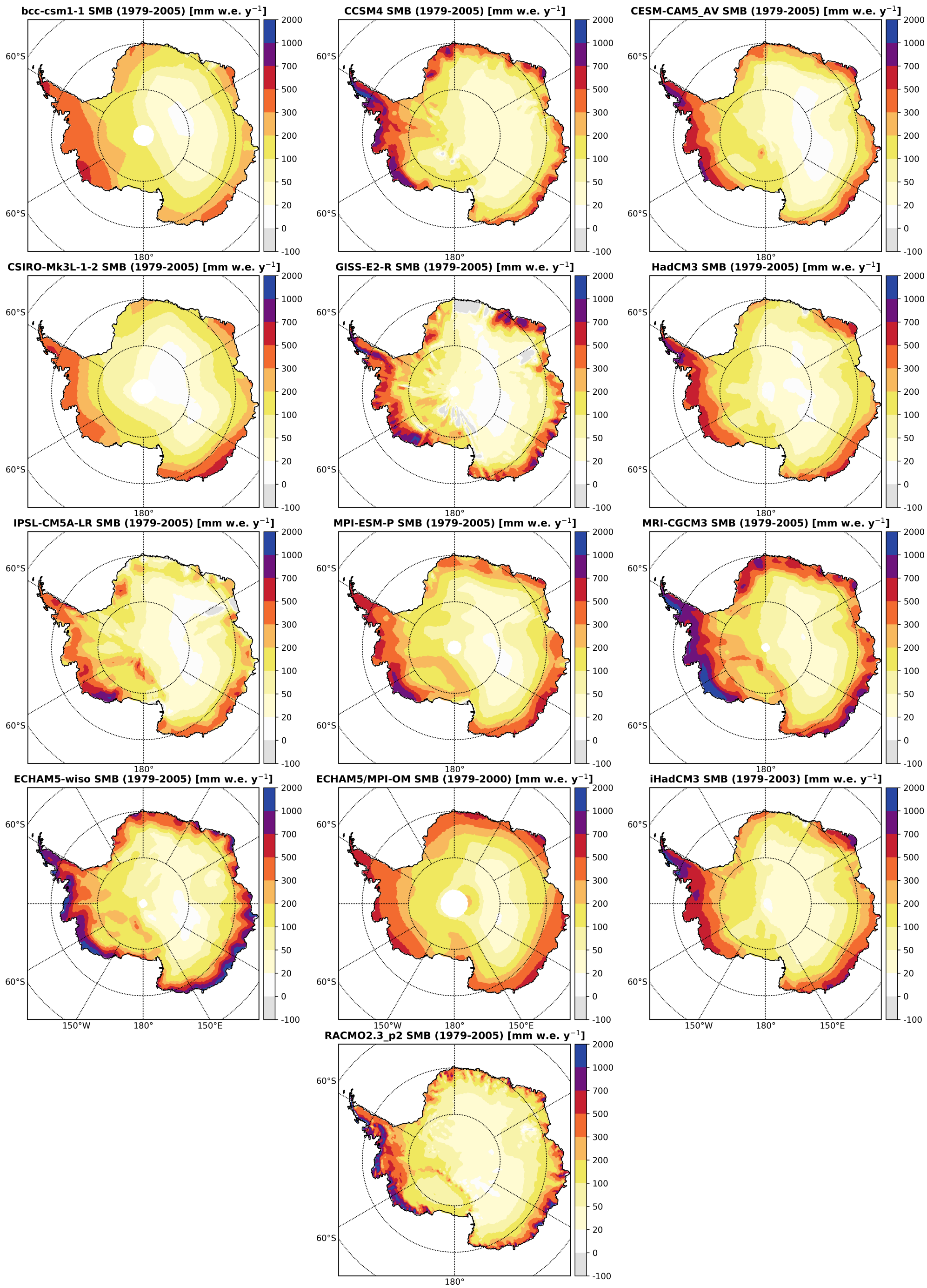


**Figure S7.** Antarctic Ice Sheet surface mass balance [mm w.e. y$^{-1}$] for all the models used in this study over the 1979–2005 period.

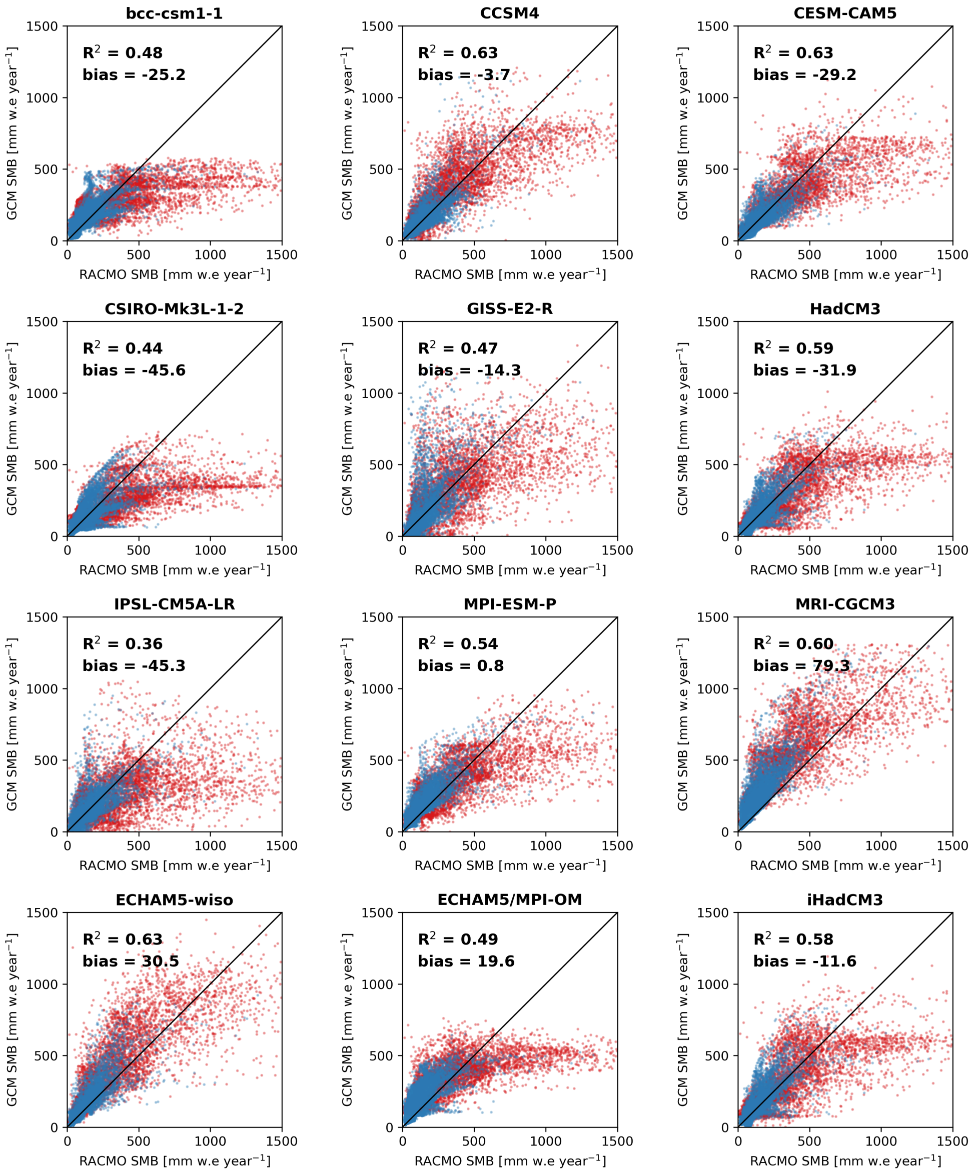


**Figure S8.** As in Fig. S6 but for all GCMs.

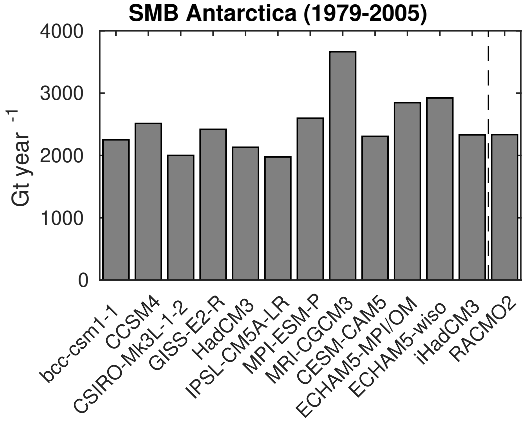


**Figure S9.** Mean Antarctic Ice Sheet surface mass balance (Gt year$^{-1}$) simulated by all the models used in this study.

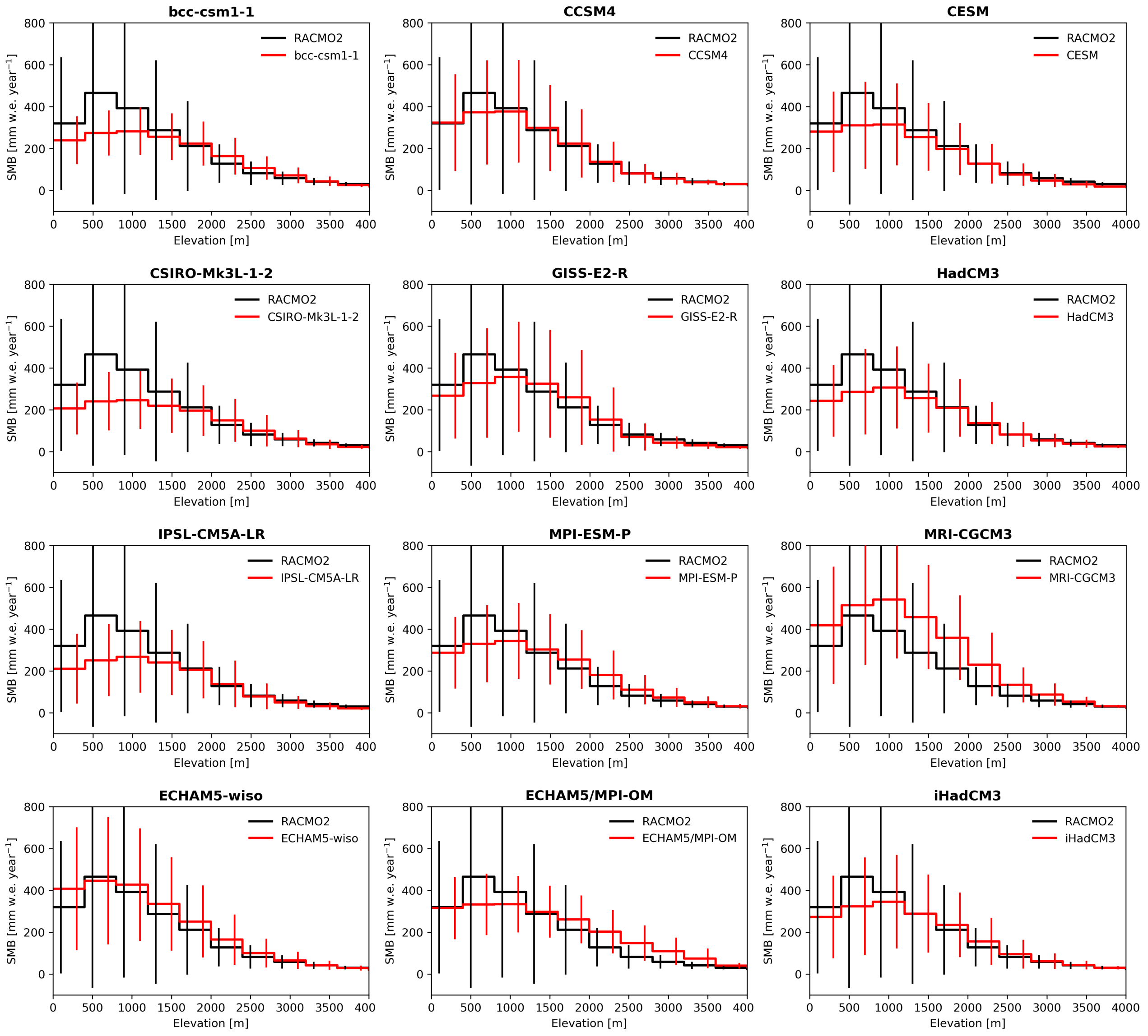


**Figure S10.** Distribution of the surface mass balance simulated by all climate models used in this study as a function of elevation, binned in 400m elevation intervals. The bars represent one standard deviation of the cell grids within each elevation bin.

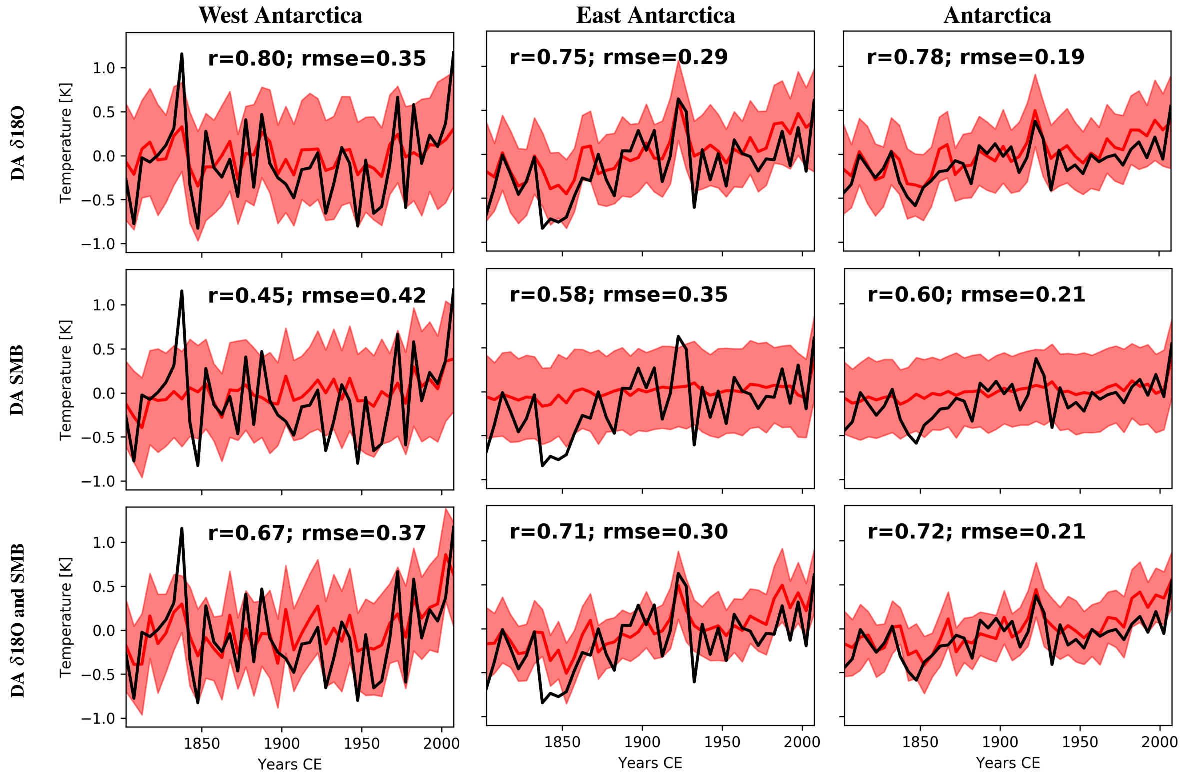


**Figure S11.** Reconstructed surface temperatures (5-year mean) for West Antarctica, East Antarctica and Antarctica as a whole from our data assimilation experiment using the ECHAM5-wiso outputs and, $\delta^{18}0$ (Stenni et al., 2017) and SMB reconstruction (Thomas et al., 2017) as data. The period is 1800–2010. *DA $\delta^{18}O$* is the data assimilation experiment using only the $\delta^{18}$O data to constrain the model while *DA SMB* uses only the SMB reconstruction and *DA $\delta^{18}O$ and SMB* uses both. For each experiment and each region, the correlation ($r$) between the reconstruction based on ice cores and that based on data assimilation is computed. The shaded areas represent $\pm$ 1 standard deviation of the model particles.

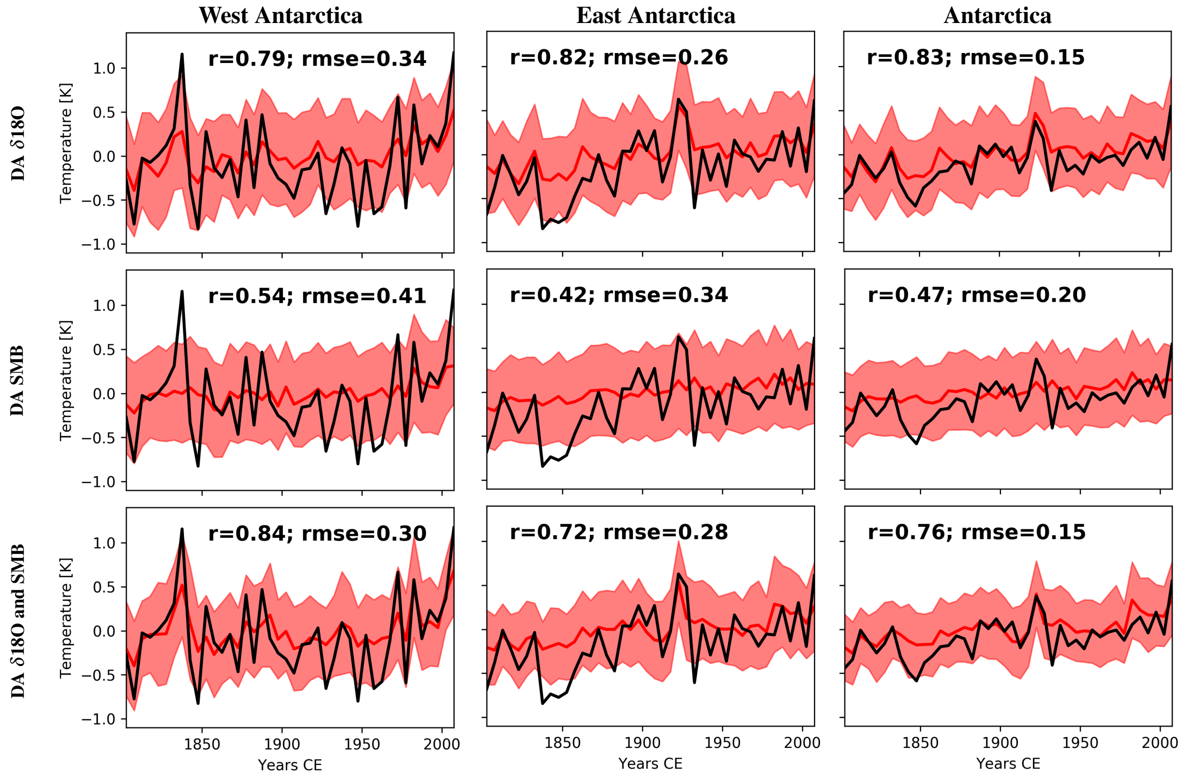


**Figure S12.** Reconstructed surface temperatures (5-year mean) for West Antarctica, East Antarctica and Antarctica as a whole from data assimilation experiment using the ECHAM5-MPI/OM outputs and, $\delta^{18}$O (Stenni et al., 2017) and SMB reconstruction (Thomas et al., 2017) as data. The period is 1800–2010. *DA $\delta^{18}O$* is the data assimilation experiment using only the $\delta^{18}$O data to constrain the model while *DA SMB* uses only the SMB reconstruction and *DA $\delta^{18}O$ and SMB* uses both. For each experiment and each region, the correlation (*r*) between the reconstruction based on ice cores and that based on data assimilation is computed. The shaded areas represent ± 1 standard deviation of the model particles.

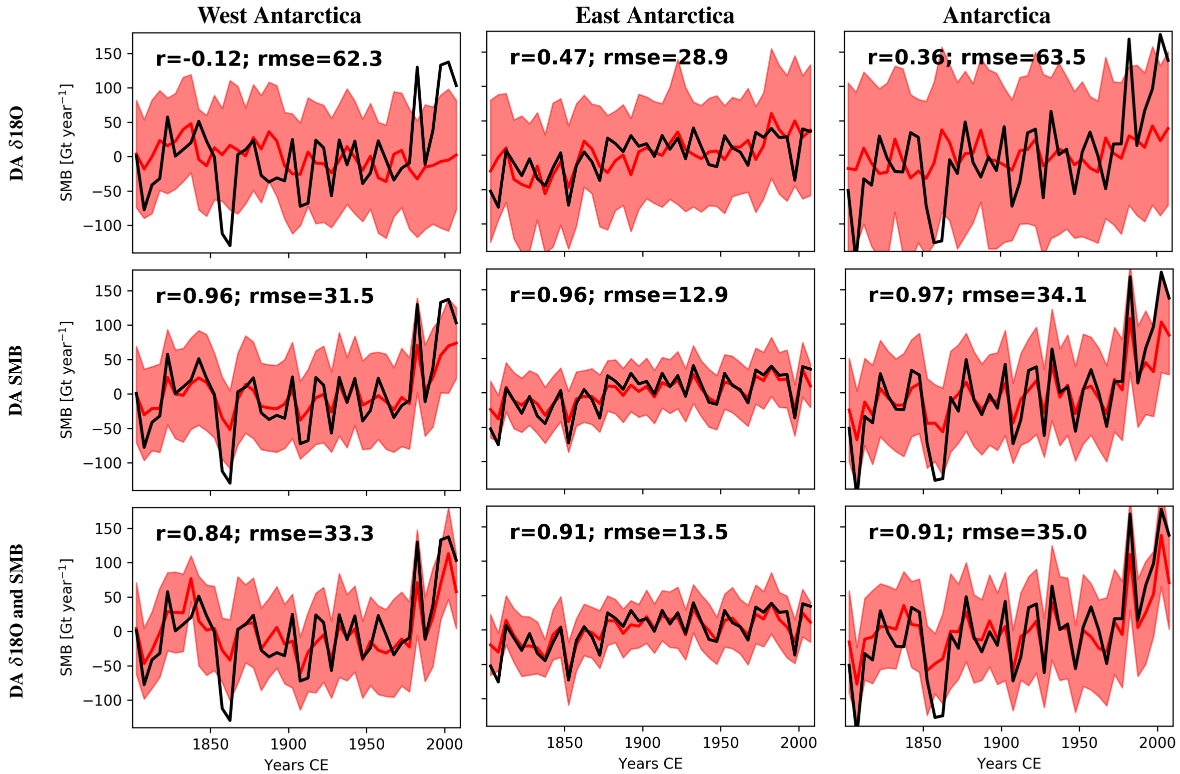


**Figure S13.** Reconstructed SMB (5-year mean) for West Antarctica, East Antarctica and Antarctica as a whole from data assimilation experiment using the ECHAM5-wiso outputs and, $\delta^{18}$O (Stenni et al., 2017) and SMB reconstruction (Thomas et al., 2017) as data. The period is 1800–2010. *DA $\delta^{18}O$* is the data assimilation experiment using only the $\delta^{18}$O data to constrain the model while *DA SMB* uses only the SMB reconstruction and *DA $\delta^{18}O$ and SMB* uses both. For each experiment and each region, the correlation (*r*) between the reconstruction based on ice cores and that based on data assimilation is computed. The shaded areas represent $\pm$ 1 standard deviation of the model particles.

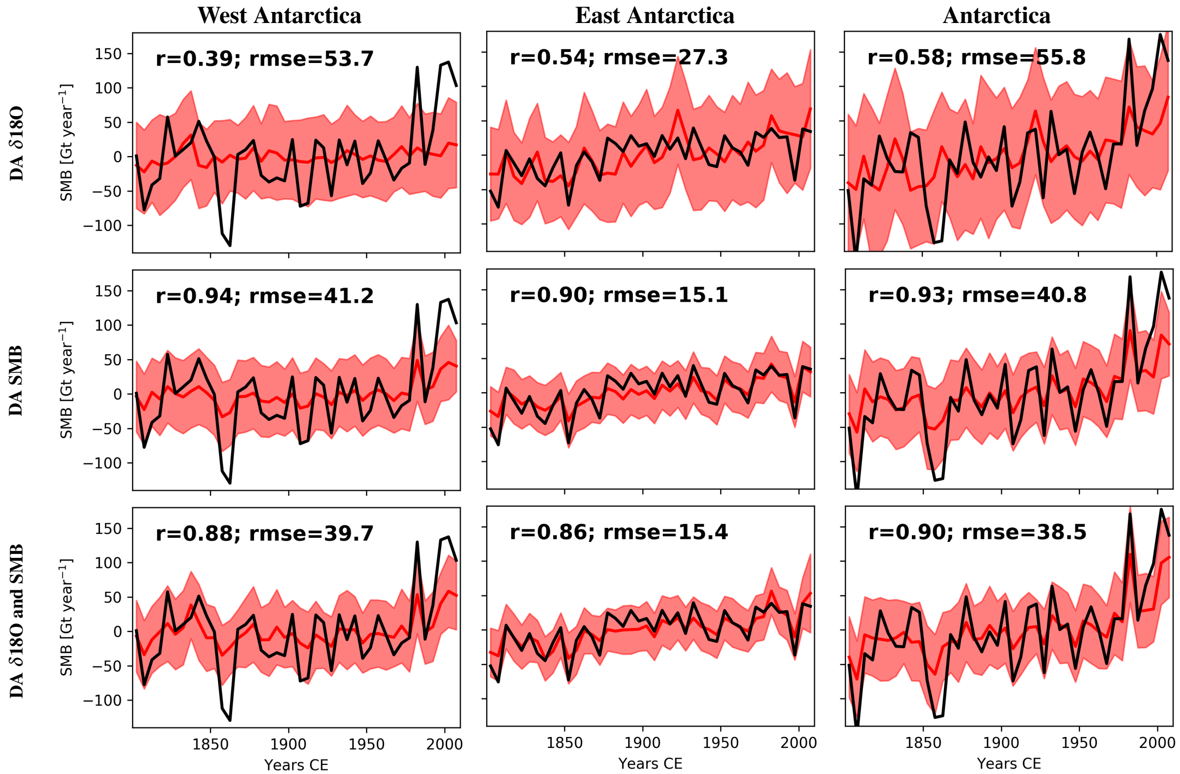


**Figure S14.** Reconstructed SMB (5-year mean) for West Antarctica, East Antarctica and Antarctica as a whole from data assimilation experiment using the ECHAM5-MPI/OM outputs and, $\delta^{18}$O (Stenni et al., 2017) and SMB reconstruction (Thomas et al., 2017) as data. The period is 1800–2010. *DA* $\delta^{18}O$ is the data assimilation experiment using only the $\delta^{18}$O data to constrain the model while *DA SMB* uses only the SMB reconstruction and *DA* $\delta^{18}O$ *and SMB* uses both. For each experiment and each region, the correlation ($r$) between the reconstruction based on ice cores and that based on data assimilation is computed. The shaded areas represent $\pm$ 1 standard deviation of the model particles.

**Table S1.** Surface mass balance trends (in Gt 100y$^{-2}$) for West Antarctica, East Antarctica and Antarctica as a whole in GCMs, in isotopic climate models (ECHAM5-wiso, ECHAM5/MPIOM and HadCM3) and in reconstructions based on ice cores (Thomas et al., 2017) over 1950–2000. The number in brackets is the number of simulations. The trend computation is based on yearly data.

| | West Antarctica | | | East Antarctica | | | Antarctica | | |
|---|---|---|---|---|---|---|---|---|---|
| | min | max | mean | min | max | mean | min | max | mean |
| bcc-csm1-1 (3) | -29.46 | 152.47 | 77.62 | -63.11 | 381.09 | 200.39 | -92.57 | 533.56 | 278.01 |
| CCSM4 (6) | 148.02 | 390.50 | 234.13 | 274.32 | 455.65 | 368.19 | 469.24 | 846.15 | 602.32 |
| CSIRO-Mk3L-1-2 (1) | | | 3.14 | | | 135.86 | | | 139.00 |
| GISS-E2-R (6) | 25.69 | 183.66 | 107.27 | -71.92 | 250.18 | 140.43 | -46.23 | 416.21 | 247.71 |
| HadCM3 (10) | 4.79 | 150.27 | 70.75 | -68.85 | 242.18 | 89.39 | -34.18 | 303.11 | 160.14 |
| IPSL-CM5A-LR (6) | 57.07 | 123.78 | 99.07 | -104.18 | 66.82 | -10.06 | -47.11 | 174.30 | 89.01 |
| MPI-ESM-P (2) | -33.85 | -28.74 | -31.30 | 54.75 | 231.84 | 143.29 | 26.01 | 197.99 | 112.00 |
| MRI-CGCM3 (3) | 28.62 | 178.64 | 86.45 | -59.28 | 242.24 | 125.66 | -7.19 | 420.89 | 212.11 |
| CESM1-CAM5 (12) | 30.90 | 349.67 | 153.07 | 55.72 | 340.24 | 162.27 | 161.99 | 592.43 | 315.34 |
| iHadCM3 (6) | 76.23 | 232.69 | 162.29 | 15.52 | 350.87 | 213.61 | 115.85 | 542.61 | 375.90 |
| ECHAM5-wiso (1) | | | -8.79 | | | 195.22 | | | 186.43 |
| ECHAM5/MPIOM (1) | | | 41.44 | | | 35.43 | | | 76.87 |
| Reconstructions (1) | | | 256.74 | | | -35.80 | | | 220.95 |

**Table S2.** 5-year mean correlations between the three surface temperature reconstructions from data assimilation experiments using the iHadCM3 outputs and the statistical reconstruction of Stenni et al. (2017), with the surface temperature reconstructions from Nicolas and Bromwich (2014) over the 1958–2010 period for East Antarctica, West Antartica and Antarctica as a whole. All the correlations are performed on detrended time series. Stars represent statistically significant correlations (p-value<0.10).

| | West Antarctica | East Antarctica | Antarctica |
|---|---|---|---|
| DA $\delta^{18}$O | -0.02 | -0.16 | -0.25 |
| DA SMB | -0.19 | 0.51 | 0.31 |
| DA $\delta^{18}$O and SMB | 0 | 0.60$^*$ | 0.44 |
| Stenni et al. (2017) | 0.45$^*$ | -0.20 | 0.12$^*$ |

**Table S3.** Slopes (°C 100yr$^{-1}$) of each surface temperature reconstruction (Stenni et al., 2017; Klein et al., 2019; Nicolas and Bromwich, 2014 ; in this study) over the 1961–2010 period for West Antarctica, East Antarctica and the Antarctica. Statistically significant (p-value < 0.05) trends are represented by a star.

| Dataset | West Antarctica | East Antarctica | Antarctica |
|---|---|---|---|
| Stenni et al. (2017) | | | |
| Stat ECHAMvariance | 1.69* | 0.75* | 1.27 |
| Stat borehole | 2.07* | 0.75* | 0.77* |
| Klein et al. (2018) | | | |
| DA ECHAM5-wiso | 1.15 | 0.94 | 0.98 |
| DA ECHAM5/MPI-OM | 1.0 | 0.48 | 0.59 |
| Nicolas and Bromwich (2014) | | | |
| | 2.22* | 0.53 | 0.90* |
| In this study | | | |
| DA $\delta^{18}$O and SMB iHadCM3 | 0.99* | 0.60* | 0.69* |

**Table S4.** 5-year mean correlations between the three surface temperature reconstructions from data assimilation experiments using the ECHAM5-MPI/OM outputs, ECHAM5-wiso outputs, the iHadCM3 outputs and the two surface temperature reconstructions of Stenni et al. (2017) with the surface temperature reconstruction from Nicolas and Bromwich (2014) over the 1958–2010 for East Antarctica, West Antarctica and Antarctica as a whole.

| | West Antarctica | | | East Antarctica | | | Antarctica | | |
|---|---|---|---|---|---|---|---|---|---|
| | ECHAM5-MPI/OM | ECHAM5-wiso | iHadCM3 | ECHAM5-MPI/OM | ECHAM5-wiso | iHadCM3 | ECHAM5-MPI/OM | ECHAM5-wiso | iHadCM3 |
| DA $\delta^{18}$O | 0.57 | 0.78 | 0.69 | 0.19 | 0.08 | 0.13 | 0.50 | 0.47 | 0.34 |
| DA SMB | 0.40 | 0.52 | 0.55 | 0.27 | 0.53 | 0.60 | 0.28 | 0.58 | 0.65 |
| DA $\delta^{18}$O and SMB | 0.53 | 0.65 | 0.72 | 0.34 | 0.48 | 0.61 | 0.59 | 0.71 | 0.73 |
| Stenni et al. (2017) | | 0.79 | | | 0.10 | | | 0.57 | |