Dear Editor and Reviewers,

Thanks for the constructive feedback to improve the manuscript entitled “Changes in 1958-2019 Greenland Surface Mass Balance are Attributable to both Greenhouse Gases and Anthropogenic Aerosols” for the revision. Please find a point-by-point reply below, with the comments in black and our answers in blue.

Sincerely,
Yan-Ning Kuo, on behalf of the coauthors

Reviewer #1

General comments

The manuscript presents a rigorous detection and attribution analysis on historical Greenland Ice Sheet (GrIS) surface mass balance (SMB) changes, using a Bayesian total least square (TLS) regression framework that explicitly accounts for multiple sources of uncertainty. Using CESM2 large ensemble and single forcing large ensemble, with regional climate model RACMO outputs as a reference, the authors show that historical GrIS SMB changes can be attributed not only to greenhouse gases (GHG) but also to anthropogenic aerosols (AAER) through their forced changes on runoff. The study finds that GHG primarily drive the long-term trend, whereas AAER contribute through decadal atmospheric circulation variability, particularly a Greenland blocking pattern. The authors further explain the lower signal-to-noise ratio associated with AAER attribution and address the temperature state dependence of such attribution, highlighting the need for future methodological improvements.

Overall, the manuscript is very well written, clearly structured, and the results are well presented with helpful supportive information. The Bayesian TLS regression approach provides a robust quantification of regression uncertainties, addressing a key challenge in detection and attribution studies of ice sheet changes given the limited data. The work also demonstrates that parts of the historical GrIS SMB change are attributable to AAER for the first time. I find the work novel and inspirational, and I expect the results will be of broad interest to the community. One thing related to the key conclusion needs to be justified further is whether GHG forcing also contributes to the decadal variability of GrIS SMB and runoff changes. Additional comments can be found below to improve clarity and strengthen the discussion. Once these issues are addressed, I would be very happy to support prompt publication of this paper in *The Cryosphere*.

We thank the reviewer for a supportive review with constructive comments to improve the manuscript.

Specific comments

Line 30-31: in addition to calving, ice discharge can also come from oceanic melting

The reviewer is right that both calving and oceanic melting are contributing to the ice discharge. We will revise Line 30-31 by mentioning the oceanic melting (**BOLD**):

"...(2) changes in ice discharge related to glacial dynamics, manifested in calving and **oceanic melting** trends."

Line 36: "surface melting" would be more accurate than "ice melting"

Thanks for the reviewer's comment. We will revise L36 from ice melting to surface melting.

Line 103: Can add a citation for the statement "as GHG and AAER are two dominant anthropogenic forcings for historical climate change."

There are a few studies in the literature to support this argument: such as Deser et al. (2020) and the reference therein. We will add citations for these papers in the revised manuscript.

Deser, C., Phillips, A. S., Simpson, I. R., Rosenbloom, N., Coleman, D., Lehner, F., ... & Stevenson, S. (2020). Isolating the evolving contributions of anthropogenic aerosols and greenhouse gases: A new CESM1 large ensemble community resource. Journal of climate, 33(18), 7835-7858.

Line 182: It seems that the Frederikse et al. (2020) reconstruction does include RACMO SMB data in its input-output estimate (Mouginot et al., 2019). Therefore, it will be more accurate to just say something like "by the fact that the reconstructed GrIS mass loss includes RACMO-simulated SMB."

Thanks for the comment. We will revise L182 as suggested by the reviewer.

Figure 2, 3: Maybe it can add more clarity to restate the y (RACMO-ERA) and x (ensemble mean of CESM2) for regression in the captions.

Thanks for the comment. We will add the information in the figure captions as one additional sentence:

"Here, scaling factor (β) is derived by the Bayesian Total Least Square regression with y from RACMO-ERA and x from ensemble mean of CESM2-LE."

Figure S4: It seems that xAAER has larger increase in runoff or decrease in SMB than GHG. What do you think could be the possible reason, e.g., related to the temperature state dependence?

Yes. We would speculate the xAAER has stronger runoff increase due to its warmer mean-state temperature.

Line 225: Maybe add something like “usually” to the statement “βAAER > 1 and also > βGHG”

Thanks, we will revise L225 as: “usually β_{AAER} > 1 and also > β_{GHG}”

Section 3.3 and Figure 4: The same Bayesian TLS regression is applied to estimate the temperature sensitivity of SMB and R to TAS. Although it is pointed to Table S1 in Section 2.2.1, it will add more clarity by stating what the y and x are for the regression, either in the figure caption or in the text. Does each regression use the annual SMB and TAS from the corresponding simulation? Does the sensitivity (Gt per year per 1K warming) equal to the scaling factor?

Thanks for the comment. We will add the clarifying descriptions on the regression in figure caption, as the other above-mentioned comment. For the temperature sensitivity, we would not call it “scaling factor”, which is a term defined in the detection and attribution method for a case to quantify how well the simulated forced response matches the observed forced response. In this case, both x and y are the same variable with the same unit. This is why it is defined as a detectable and attributable signal when the scaling factor is around 1 and significantly greater than 0 (i.e., the modeled forced response matches the observed forced response perfectly).

Figure S6: in panel (a), is the GBI time series in black calculated from RACMO output or directly from ERA5?

The GBI time series is taken directly from ERA5 to be comparable to the large-scale circulation map taken from ERA5. We will add clarification in the revised manuscript.

Section 3.4 and Figure 5: It is well illustrated that there is an AAER-forced change in the variability of circulation, imprinted onto a pattern that reinforces Greenland blocking, by comparing the correlation patterns in AAER and ERA5 (Fig.5f,e). However, another question remains that if GHG also contribute to circulation variability in addition to the long-term linear trend. Thus, I am curious what the correlation map for GHG would look like (e.g., whether it will have a similar pattern as panel (e) and (f)).

We thank the reviewer for this comment. Indeed, the GHG-induced runoff increase plateaued after 2000, hinting at GHG-forced decadal variability. The correlation between

R and Z500 in GHG has an emerging Greenland blocking-like pattern (Figure R1 left panel), distinct from the GHG-induced trend pattern (Figure 5c). The Greenland blocking pattern is still significant in the correlation map when the linear trends in the ensemble means in GHG are removed (Figure R1 right panel). This supports the reviewer's viewpoint that GHG contributes to both the long-term uniform linear trend and the decadal variability.

We speculate that the plateaued GHG-induced GrIS runoff increase after 2000 may come from feedback due to the cold blob in the North Atlantic subpolar gyre, which is linked to a more positive North Atlantic Oscillation (Fan et al., 2023). Idealized experiments are necessary to isolate GHG-induced circulation change from direct GHG radiative forced response versus GHG-induced SST (i.e., the cold blob), though such experiments are beyond the scope of this project. We will revise Section 3.4 to discuss these results (new text highlighted in **BOLD**):

"What are the mechanisms by which GHG and AAER forcing drive long-term trends and decadal variability in GrIS SMB through runoff changes? Here, we focus on the summer (JJA) temperature and circulation patterns to explain the GrIS runoff changes, which are linked to the melting-induced runoff changes (Sherman et al., 2020; Hanna et al., 2014; Tedesco and Fettweis 2020). The trend map for 1958-2019 from ERA5 shows overall JJA polar warming and increasing Z500 over Greenland (Figure 5a), consistent with the Greenland Block Index (GBI) time series (Figure S6a). **The correlation between annual GrIS runoff and JJA near-surface temperature and JJA Z500 from ERA5 shows positive correlations between GrIS runoff and near-surface temperature and Z500, i.e., a Greenland blocking pattern (Figure 5e). Greenland blocking provides more cloudless days and subsidence-induced warming (Sherman et al., 2020), as well as warm air advection towards Western Greenland (Hanna et al., 2014; Tedesco and Fettweis 2020) due to the anti-cyclone over Greenland. The correlation pattern in ERA5 remains consistent even after detrending and temporal smoothing (Figure S8). Thus, the long-term linear trend has little impact on the correlation pattern seen in ERA5.**

JJA near-surface warming and Z500 increasing **trends** over the North Atlantic sector are visible in both ALL (Figure 5b) and GHG (Figure 5c). **Though the ALL-forced Z500 is weaker than the observed Z500 trend (consistent with GBI in Figure S6 and Delhasse et al. (2020)), the observed trend is within the range of possible trends from the 50-member ALL ensemble. The forced temperature and Z500 trends from ALL and GHG are overall alike, confirming that GHG contributes to the long-term linear trend seen in these atmospheric variables related to GrIS runoff changes.** However, in GHG, the Atlantic Meridional Overturning Circulation (AMOC) declines more rapidly than in ALL, as it lacks the offsetting North Atlantic cooling from AAER

(Figure 9 in Simpson et al., 2023), leading to cooling in the Subpolar Gyre. Additionally, ALL-forced JJA Z500 increases with a blocking-like structure over Greenland, while GHG-forced JJA Z500 increases more uniformly (Figure 5b vs Figure 5c contours). A cooling of the Subpolar Gyre in GHG simulation and a stronger subsidence trend in ALL together lead to \textit{less} warming in GHG than in ALL (Figure 5b vs 5c).

In addition, the Subpolar Gyre cooling correlates with a more positive NAO (Fan et al., 2023). This implies a less negative NAO/reduced Greenland blocking as a result of this air-sea coupled feedback over the Subpolar Gyre, which may explain why GHG-forced runoff (Figure 3e) and GBI (Figure S6b) plateaus after 2000 when the Subpolar Gyre cooling intensifies. This is also supported by the significant correlations of an emerging Greenland blocking pattern in GHG that differs from its uniform warming and Z500 trends (Figure 5c), regardless of whether linear trends in GHG are removed or not (Figure S9). Beyond the scope of this study, idealized experiments to distinguish the circulation changes originating from direct GHG radiative forcing versus from GHG-induced Subpolar Gyre SSTs would help advance understanding of Greenland circulation and GrIS mass loss.

AAER, on the other hand, contributes almost nothing to this long-term trend pattern (Figure 5a vs 5d). These trend maps imply that the detected signal from AAER during 1958-2019 (Figure 3b, 3f) does not arise through the long-term linear trend but through forced decadal variability undergoing phase changes during this time period. We compare maps of the correlation from ERA5 (Figure 5e) and from the ensemble mean of AAER during 1958-2019 (Figure 5f). The AAER-based correlation map shows a pattern that is distinct from its long-term trend (Figure 5f vs Figure 5d); instead, the correlation map shows a pattern more similar to the ERA5-based correlation map (Figure 5e vs 5f). Both ERA5 and AAER have positive correlations between GrIS runoff and near-surface temperature and Z500. Figure 5f confirms a similar correlation pattern due to AAER, supporting an AAER-forced change in the variability of circulation, imprinted onto a pattern that reinforces Greenland blocking."

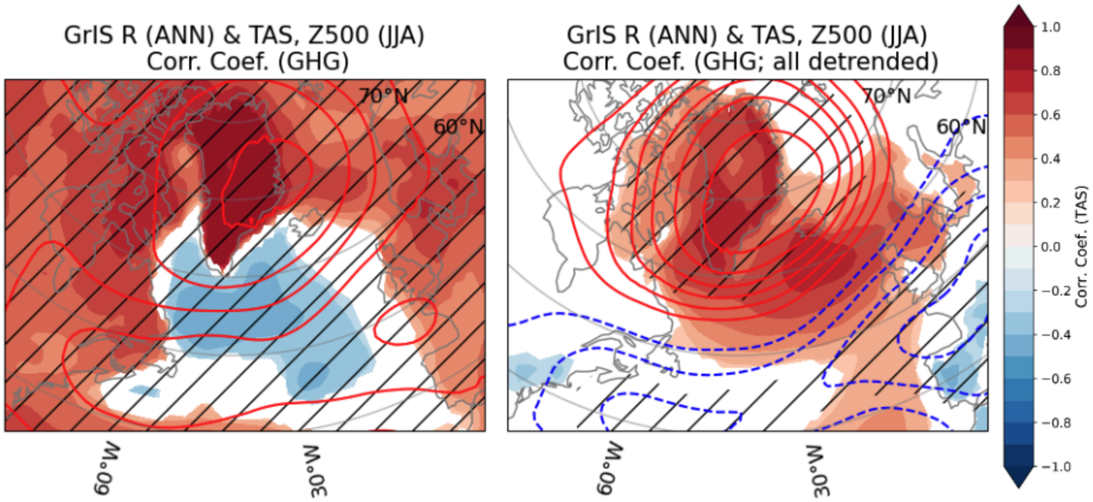

Figure R1 (the new Figure S9). Correlation map of GrIS R with Z500 (contours) and TAS (shading) during 1958-2019 in 15-member mean GHG (left panel) and the linearly detrended 15-member mean GHG (right panel). Insignificant TAS correlations are masked out and significant Z500 correlations are hatched (95% confidence). Contours start from 0.1 with contour spacings 0.1. The significance level of the correlation coefficients is based on a t-test with the degrees of freedom corresponding to the length of data (1958-2019, 62 years).

Discussion: it can benefit from adding more discussion about the structural model uncertainty (of using one climate model CESM2 and one regional climate model RACMO).

Thanks for the comment. Indeed, we also noticed the potential impacts from model uncertainty after conversations with colleagues post-submission of this manuscript. We acknowledge model structural uncertainty can be a key uncertainty and will introduce an additional paragraph in the discussion to cover this:

"CESM2 and RACMO have shown reasonable simulated SMB and their water budgets (Noël et al., 2018; an Kampenhout et al., 2020); however, both are subject to model structural uncertainty. The model structural uncertainty accounts for most of the uncertainty in SMB future projections (Holube et al., 2022). The high model structural uncertainty in SMB does not come from the snow parameterization uncertainty (Holube et al., 2022). Instead, it comes from the model structural uncertainties in the atmospheric variables, as GrIS precipitation, temperature, and Z500 all show high model structural uncertainties in their future projections (Zhang et al., 2024). One motivation to conduct D&A with Bayesian regression, instead of a deterministic regression, is to account for the uncertainty in estimates of forced responses (from CESM2) and of observations (from RACMO). We acknowledge the caveat that this study does not fully sample the model structural uncertainty. Future work to extend the presented D&A with more climate models could enhance the robustness of the results presented here. Such efforts could also support the development of observational constraints on SMB projections, for example, based on the temperature sensitivity presented here."

Holube, K. M., Zolles, T., & Born, A. (2022). Sources of uncertainty in Greenland surface mass balance in the 21st century. The Cryosphere, 16(1), 315-331.

Zhang, Q., Huai, B., Ding, M., Sun, W., Liu, W., Yan, J., ... & Kang, L. (2024). Projections of Greenland climate change from CMIP5 and CMIP6. Global and Planetary Change, 232, 104340.

Technical corrections

Line 84: “ran” to “run”

Line 181: “by the GrIS”

Figure 1: 2nd line in caption: maybe rephrase as “The anomalous (long-term mean subtracted) annual GrIS mass loss from the Frederikse et al., (2020) reconstruction”

Figure 4: 3rd line in caption: the annotation “(ALL, GHG, AAER; purple, red, blue, light blue respectively)” needs to be completed or can be removed since it is already stated for panel (a)

Line 243: reverse the order of “AAER and GHG”

Line 252: This sentence “to explain the GrIS runoff changes, which are linked to the melting-induced runoff changes” seems repetitive.

Figure 5: Maybe remove “GrIS” in the titles of panel (a)-(d)

Line 262: Consider adding “trend” after “All-forced Z500”

Line 304: “than” to “that”

Supplementary Information:

S1: first line: add space to “implement a Markov Chain…”

S1: 13th line: “(green line in Figure S1a)”?

We thank the reviewer for catching these typos and sentences that require corrections. We will revise them accordingly in the revised manuscript.

Reviewer #2

General comments

This study investigates the trend and variability of surface mass balance (SMB) and surface run-off over the Greenland icesheet (GrIS) and how these detectable signals can be attributed to anthropogenic aerosols (AAER) and Greenhouse Gases (GHG). Using a large ensemble of climate simulations from CESM2 with different sets of external forcings, combining with a Bayesian regression of fingerprints, the authors show that AAER contributes to the decadal variability of GrIS surface run-off and SMB through feedback to large-scale circulation pattern, i.e., strengthening Greenland blocking pattern, meanwhile GHG has an impact on long-term increase in surface air temperature. The study also addresses the issue of low signal-to-noise in attributing the impact of AAER due to the dependence on mean state temperature. This emphasises the need for improvement of method used in detection and attribution of climate change.

This study fits well to the scope of The Cryosphere, and to the best of my knowledge, is a missing piece in the literature. The manuscript is well-written with reasonable research questions and providing sufficient evidence to support the main findings. One major concern that should be addressed is to discuss further how AAER and GHG might have an impact on the NAO, the dominant of climate variability over the north Atlantic given that the authors refer to the NAO in the 3rd and 4th paragraph in the introduction and hypothesise that AAER contributes to GrIS SMB changes by modifying the circulation pattern projected into NAO. Although the manuscript discusses Greenland blocking, its relationship with the negative NAO in the summer, when SMB decrease happens, is less strong than in the winter. In addition, the positive NAO might contribute (equally to the AMOC) to the cold blob over the sub-polar gyre (Fan et al., 2023). Could this suggest a decrease in negative NAO (and hence Greenland blocking) in the GHG simulations? When this issue is addressed, I would be happy to accept this manuscript to be published in The Cryosphere.

We thank the reviewer for the overview comment. The reviewer is right that the sea level pressure used to define NAO index may be mixed with the signal driven by the sub-polar dyre cold blob, which would lead to a less strong GBI and NAO relationship. We will revise the wording of “projecting onto NAO” to “projecting onto Greenland blocking pattern” to be more concise with the Z500 results used to support our results.

The GHG-forced GrIS runoff increase plateaued after 2000, which we haven’t discussed this result prior to the submission. The reviewer’s suggested literature is helpful, and we speculate the cold blob over the Subpolar Gyre may decrease the Greenland blocking/negative NAO (Fan et al., 2023). Idealized experiments are necessary to isolate the impacts of the GHG-forced sea surface temperature on circulation, while it is beyond the scope of this study. Together with the comment from Reviewer #1 on GHG-induced variability, we will revise Section 3.4 to discuss these results (new text highlighted in **BOLD**):

“What are the mechanisms by which GHG and AAER forcing drive long-term trends and decadal variability in GrIS SMB through runoff changes? Here, we focus on the summer (JJA) temperature and circulation patterns to explain the GrIS runoff changes, which are linked to the melting-induced runoff changes (Sherman et al., 2020; Hanna et al., 2014; Tedesco and Fettweis 2020). The trend map for 1958-2019 from ERA5 shows overall JJA polar warming and increasing Z500 over Greenland (Figure 5a), consistent with the Greenland Block Index (GBI) time series (Figure S6a). **The correlation between annual GrIS runoff and JJA near-surface temperature and JJA Z500 from ERA5 shows positive correlations between GrIS runoff and near-surface temperature and Z500, i.e., a Greenland blocking pattern (Figure 5e). Greenland blocking provides more cloudless days and subsidence-induced warming (Sherman et al., 2020), as well as warm air advection towards Western Greenland (Hanna et al., 2014; Tedesco and Fettweis 2020) due to the anti-cyclone over Greenland. The correlation pattern in ERA5 remains consistent even after detrending and temporal smoothing (Figure S8). Thus, the long-term linear trend has little impact on the correlation pattern seen in ERA5.**

JJA near-surface warming and Z500 increasing **trends** over the North Atlantic sector are visible in both ALL (Figure 5b) and GHG (Figure 5c). **Though the ALL-forced Z500 is weaker than the observed Z500 trend (consistent with GBI in Figure S6 and Delhasse et al. (2020)), the observed trend is within the range of possible trends from the 50-member ALL ensemble. The forced temperature and Z500 trends from ALL and GHG are overall alike, confirming that GHG contributes to the long-term linear trend seen in these atmospheric variables related to GrIS runoff changes.** However, in GHG, the Atlantic Meridional Overturning Circulation (AMOC) declines more rapidly than in ALL, as it lacks the offsetting North Atlantic cooling from AAER (Figure 9 in Simpson et al., 2023), leading to cooling in the Subpolar Gyre. Additionally, ALL-forced JJA Z500 increases with a blocking-like structure over Greenland, while GHG-forced JJA Z500 increases more uniformly (Figure 5b vs Figure 5c contours). A cooling of the Subpolar Gyre in GHG simulation and a stronger subsidence trend in ALL together lead to \textit{less} warming in GHG than in ALL (Figure 5b vs 5c).

In addition, the Subpolar Gyre cooling correlates with a more positive NAO (Fan et al., 2023). This implies a less negative NAO/reduced Greenland blocking as a result of this air-sea coupled feedback over the Subpolar Gyre, which may explain why GHG-forced runoff (Figure 3e) and GBI (Figure S6b) plateaus after 2000 when

the Subpolar Gyre cooling intensifies. This is also supported by the significant correlations of an emerging Greenland blocking pattern in GHG that differs from its uniform warming and Z500 trends (Figure 5c), regardless of whether linear trends in GHG are removed or not (Figure S9). Beyond the scope of this study, idealized experiments to distinguish the circulation changes originating from direct GHG radiative forcing versus from GHG-induced Subpolar Gyre SSTs would help advance understanding of Greenland circulation and GrIS mass loss.

AAER, on the other hand, contributes almost nothing to this long-term trend pattern (Figure 5a vs 5d). These trend maps imply that the detected signal from AAER during 1958-2019 (Figure 3b, 3f) does not arise through the long-term linear trend but through forced decadal variability undergoing phase changes during this time period. We compare maps of the correlation from ERA5 (Figure 5e) and from the ensemble mean of AAER during 1958-2019 (Figure 5f). The AAER-based correlation map shows a pattern that is distinct from its long-term trend (Figure 5f vs Figure 5d); instead, the correlation map shows a pattern more similar to the ERA5-based correlation map (Figure 5e vs 5f). Both ERA5 and AAER have positive correlations between GrIS runoff and near-surface temperature and Z500. Figure 5f confirms a similar correlation pattern due to AAER, supporting an AAER-forced change in the variability of circulation, imprinted onto a pattern that reinforces Greenland blocking."

Specific comments

Section 2.2.1: Did the author normalise both observed variable and fingerprints by internal variability (e.g., estimated from control runs) beforehand? Should this help with maximising signal-to-noise ratio?

In the Bayesian regression, we do not normalize the internal variability. The goal of developing this Bayesian total least square regression here is not to maximize signal-to-noise ratio. Instead, we developed the method to address concerns in detection and attribution about (1) the upward bias in regression coefficient in deterministic total least square regression and (2) the potential climate model bias in estimating internal variability (L136-143).

L238: If I understand correctly, xAAER is equivalent to GHG forcing plus natural variability, and ALL-minus-xAAER is equivalent to AAER forcing plus nonlinear response, right?

Yes, we treated xAAER as equivalent to GHG and ALL-minus-xAAER as AAER. Indeed xAAER simulations include all radiative forcings other than AAER, which is dominated by GHG. The reviewer is correct that ALL-minus-xAAER includes AAER plus nonlinear response by the interactions of these radiative forcings. The original L238 intended to say the mean temperature over GrIS has a weaker forced response in AAER than in GHG and this statement also holds in the paired experiment of ALL-minus-xAAER and xAAER. We will revise L238 to make this clearer.

Original L238: In addition, the mean temperature over GrIS has a weaker forced response in AAER (ALL-minus-xAAER) than in GHG (xAAER) (Figure S5).

Revised L238: In addition, the mean temperature over GrIS has a weaker forced response in AAER than in GHG (Figure S5; *also true using ALL-minus-xAAER and xAAER*).

Figure 4: The SMB sensitivity to TAS from AAER is close to zero, while it is significantly positive in ALL-minus-xAAER simulation (opposite to RACMO-ERA). However, the sensitivity of run-off to TAS in this ALL-minus-xAAER is close to RACMO-ERA, while the sensitivity in AAER is much lower than RACMO-ERA. Could another unknown factor play a role here?

We thank the reviewer for the comment. Precipitation usually increases under warming (e.g., Held and Soden 2006), so we also assessed its influence when preparing the manuscript. All the simulations show positive precipitation (P) sensitivity to warming, although these CESM2 simulations tend to have a higher P sensitivity than RACMO-ERA (Figure R2, new Figure S7). P sensitivity is much higher in the ALL-minus-xAAER simulation, so we think that it contributes to the more positive SMB sensitivity to warming, as SMB can be approximated as precipitation minus runoff (P-R). We did not include this result when we submitted the manuscript because Figure 2-3 showed there is no detectable forced change in P and the manuscript after Figure 3 focuses on R.

We will include this additional figure on precipitation sensitivity to warming in the supplementary and some descriptions of this new figure to explain the SMB sensitivity in ALL-minus_xAAER in the resubmitted manuscript:

"P sensitivity to warming is generally positive, as precipitation usually increases under warming (Held and Soden, 2006). Note that P sensitivity is much higher in the ALL-minus-xAAER simulation (Figure S7) than in the AAER simulations, explaining the slightly positive SMB sensitivity in ALL-minus-xAAER (Figure 4a). "

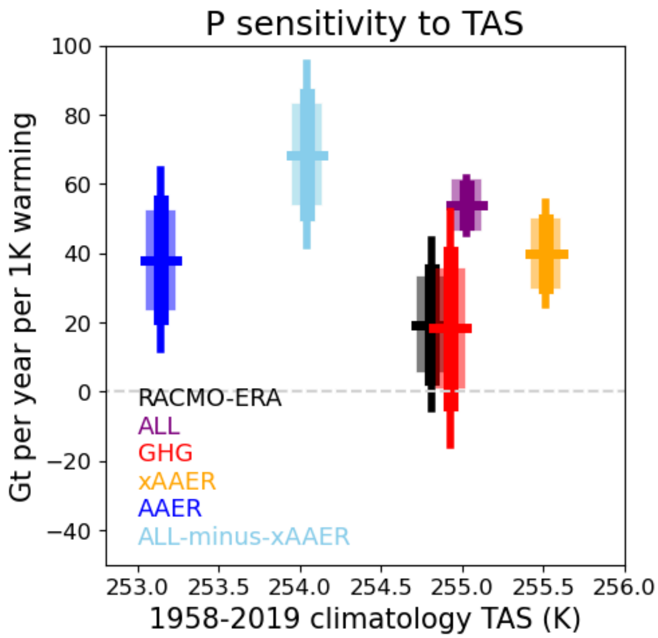

Figure R2 (new Figure S7). The observed (RACMO-ERA; black) and forced (ALL, GHG, xAAER, AAER, ALL-minus-xAAER; purple, red, orange, blue, light blue respectively) GrIS P sensitivity to near-surface temperature during 1958-2019 sorted by the climatological mean near-surface temperature.

Held, I. M., & Soden, B. J. (2006). Robust responses of the hydrological cycle to global warming. Journal of climate, 19(21), 5686-5699.

L242-243: swapping order of AAER and GHG.

Thanks for catching this. We will swap the order in the revised manuscript.

L255: GBI is mentioned for the first time, so it should be defined here. Besides, the time series of Greenland blocking indices were analysed in recent studies (e.g., Maddison et al., 2024; Luu et al., 2024) which suggested a sharp increase and well above zero since 2000 in observations. This seems different in Figure S6a which shows negative GBI values in a couple of years after 2000. Did the authors compute GBI from ERA5 or from RACMO-ERA?

Thanks for the comment and the reference literature. First, we calculated GBI from ERA5. Maddison et al (2024) and Luu et al. (2024) showed their GBI with 20-year and 10-year running mean, respectively, while we showed annual values. When GBI is smoothed with 10-year or 20-year running mean, our GBI also stays positive after 2000 (Figure R3).

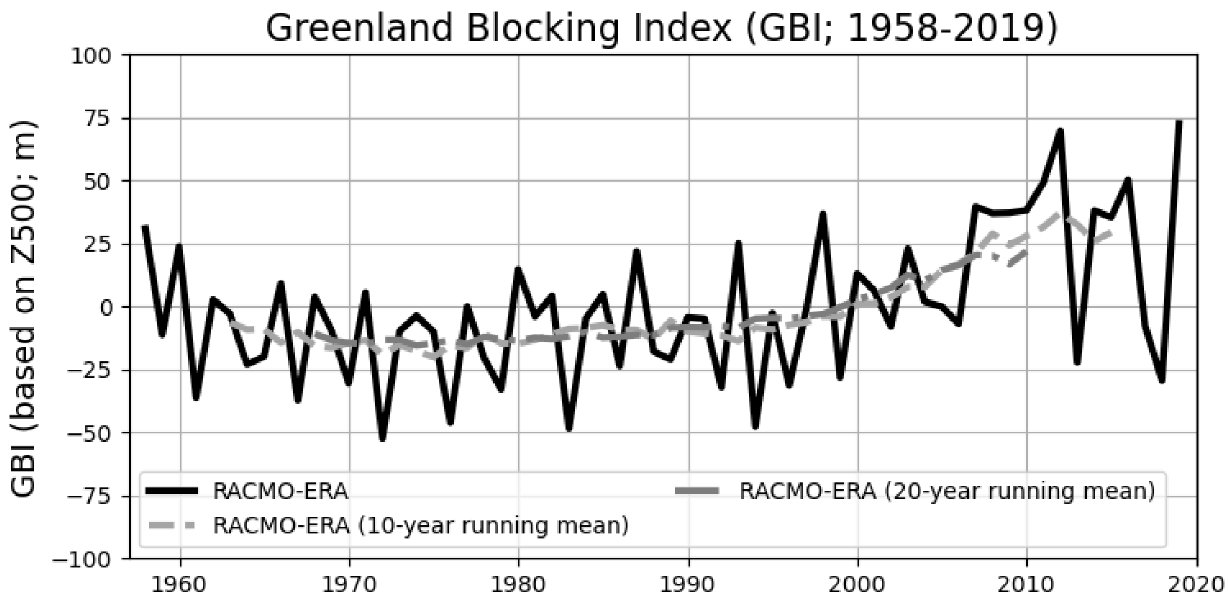

Figure R3. Time series of Greenland Blocking Index (GBI) since 1958 from RACMO-ERA (black), 10-year running mean (light gray dash-dot), and 20-year running mean (dark gray dashed).

L277-279: Perhaps it's worth to compare with findings from Maddison et al. (2024) which also suggested AAER simulations (larger set of CMIP6) show some predictable signals of observed GBI variability, but the signals of the response to AAER is too weak in those simulations.

We thank the reviewer for the reference. We will reference Maddison et al. (2024) in the revised L277-279 and in the conclusion and discussion section.

Revised: Figure 5f confirms a similar correlation pattern due to AAER, supporting an AAER-forced change in the variability of circulation, imprinted onto a pattern that reinforces Greenland blocking *consistent with (Maddison et al., 2024)*.

Section 4: I suggest adding a few sentences discussing the caveat of using only one GCM (CESM2) and the uncertainty of RACMO-ERA, although there are no other choices for observations of SMB.

Thanks for the comment. We will incorporate this comment with the comment from Reviewer #1 that suggested discussions on model uncertainty for an additional paragraph in discussion:

"CESM2 and RACMO have shown reasonable simulated SMB and their water budgets (Noël et al., 2018; an Kampenhout et al., 2020); however, both are subject to model structural uncertainty. The model structural uncertainty accounts for most of the uncertainty in SMB future projections (Holube et al., 2022). The high model structural uncertainty in SMB does not come from the snow parameterization uncertainty (Holube et al., 2022). Instead, it comes from the model structural uncertainties in the atmospheric variables, as GrIS precipitation, temperature, and Z500 all show high model structural uncertainties in their future projections (Zhang et al., 2024). One motivation to conduct D&A with Bayesian regression, instead of a deterministic regression, is to account for the uncertainty in estimates of forced responses (from CESM2) and of observations (from RACMO). We acknowledge the caveat that this study does not fully sample the model structural uncertainty. Future work to extend the presented D&A with more climate models could enhance the robustness of the results presented here. Such efforts could also support the development of observational constraints on SMB projections, for example, based on the temperature sensitivity presented here."

Fan, Y., Liu, W., Zhang, P., Chen, R., and Li, L.: North Atlantic Oscillation contributes to the subpolar North Atlantic cooling in the past century, Climate Dynamics, 61, 5199-5215, 10.1007/s00382-023-06847-y, 2023.

Luu, L. N., Hanna, E., de Alwis Pitts, D., Maddison, J., Screen, J. A., Catto, J. L., and Fettweis, X.: Greenland summer blocking characteristics: an evaluation of a high-resolution multi-model ensemble, Climate Dynamics, 10.1007/s00382-024-07453-2, 2024.

Maddison, J. W., Catto, J. L., Hanna, E., Luu, L. N., and Screen, J. A.: Missing decadal variability of summer Greenland blocking in climate models, Submitted to Geophysical Research Letters, 2024.

We thank the reviewer for the list of literature.