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# Antarctic Surface Mass Balance: Natural Variability, Noise, and Detecting New Trends

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**Key Points:**
- We examine the natural variability within Antarctic surface mass balance recorded in ice cores and models, testing a range of noise models
- We find that a Generalized Gauss Markov or power law model is preferred over simple white noise, or widely used autoregressive [1], models
- Over the longest timescales considered, linear trend uncertainties are up to ~10 times larger with a power-law-like model compared to an AR1 model

**Supporting Information:**
- Supporting Information S1

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**Abstract** The emergence of new, statistically robust trends in Antarctic surface mass balance (SMB) requires an understanding of the underlying SMB variability (noise). We show that simple white or AR[1] noise models do not adequately represent the variability of SMB in both the RACMO2.3p2 SMB model output (1979–2017) and composite ice core records (1800–2010), underestimating low-frequency variability. By testing a range of noise models, we find that a Generalized Gauss Markov (GGM) model better approximates the noise around a linear trend. The general preference for GGM noise applies over spatial scales from the total ice sheet down to individual drainage basins. Over the longest timescales considered, trend uncertainties are 1.3–2.3 times larger using a GGM model compared to using an AR1 model at the ice sheet scale. Overall, our results suggest that larger trends or longer periods are required before new SMB trends can be robustly separated from background noise.

**Plain Language Summary** The rate of snowfall in Antarctica varies over months to millennia. Snowfall is expected to increase over coming decades as the climate warms and evaporates more water from the Southern Ocean and then falls as snow. The question we focus on is "when can we be sure a new trend has emerged?". To help answer this question we examine the variability of snowfall since 1800 as recorded in ice cores and as predicted since 1979 by a weather model. We find that variations in snowfall are largest over longer periods (decades) and that traditional ways of estimating the natural variability underestimate the "noise" at these long periods, by a factor of up to about 10. As a result, it is harder to detect genuine changes in trends in Antarctic snowfall than previously thought—they will need to be larger or persist for longer to confidently detect them. It is clear, nonetheless, that Antarctica is losing overall mass due to increased discharge from key glaciers, and this is expected to dominate any changes to snowfall.

## 1. Introduction

Antarctica's total mass balance, and hence contribution to sea-level change, is largely the difference between surface mass balance and ice discharge, with small contributions from other sources of mass flux such as subglacial meltwater. Surface mass balance varies over wide timescales due to a combination of natural variation and longer-term trends driven by large-scale climate change. For example, Antarctic surface mass balance increased overall during the Holocene due to climate warming and is expected to increase further in the coming decades as the climate warms further (e.g., Jouzel et al., 2007; Lenaerts et al., 2016; Palerme et al., 2017).

Robustly detecting a change in rate of surface mass balance, often modeled as a constant or simple parametric function, depends on one's understanding of the timescales and magnitude of natural variability plus measurement or model error (hereafter referred to as "noise"). Likewise, understanding of the uncertainty of rates of surface mass balance depends on the noise being robustly characterized within the context of the adopted function model. Failure to understand this noise could result in overconfidence or underconfidence in estimated trends or the significance of changing trends.

It is common within studies of surface mass balance or total mass balance to adopt simple noise models about a linear or quadratic functional model such as white noise, where temporal correlations within the data are assumed to be negligible, or auto-regressive-1 (AR[1]) noise. With few exceptions, the suitability of the adopted noise model to a given surface mass balance dataset is not tested. Studies adopting white noise models adopt, for instance, standard root-mean-square type statistics whereas more sophisticated approaches are required to consider temporal correlations. For example, different studies examining changes in surface mass balance rates over the twentieth century have considered both white and AR[1] models (Medley & Thomas, 2019; Monaghan et al., 2006) but with no apparent justification for either selection.

A notable exception is the study of Wouters et al. (2013) who examined noise characteristics of modeled Antarctic (and Greenland) surface mass balance time series over 1979–2011, testing a range of different noise models for their suitability in the presence of trends or accelerations. Their analysis focused on an $n$-th order autoregressive noise model (typically $n = 1$), although they note that the shortness of the time series may mean that their analysis underestimates noise at the lowest frequencies and hence underestimate trend and acceleration uncertainties.

Analysis of geodetic records of Antarctic ice elevation or mass change has also highlighted that temporal correlations exist within these records (Ferguson et al., 2004; Horwath & Dietrich, 2009; Williams et al., 2014) with Williams et al. (2014) finding a factor of 4–6 larger uncertainties for GRACE-derived trends and accelerations when adopting preferred, temporally correlated noise models (power-law or AR) compared with a purely white-noise model. It is not yet clear if variation in ice dynamics contributes substantially to these temporal correlations or if they are dominated by surface mass balance. Overall, then, while there is significant evidence for temporally correlated noise in Antarctic surface mass balance over multidecadal timescales, the studies of it are limited in terms of the timespans and noise models considered.

In this study we build on the work of Wouters et al. (2013) by (i) extending the duration of the data set through longer numerical model output and recently published centennial-scale composite ice core records; (ii) considering optimal noise models for not just the entire ice sheet (AIS) but also regions down to individual drainage basins; and (iii) testing the applicability of a larger range of noise models. We determine optimal noise models for these regions and quantify the duration required to separate trends from noise in each of them.

## 2. Surface Mass Balance Data Sets

### 2.1. Numerical Model Output (1979–2017)

We considered surface mass balance outputs from RACMO2.3p2 (van Wessem et al., 2018) over 1979–2017 inclusive at monthly intervals and at approximately 27 km resolution. We spatially interpolated these data to a regular 5 km grid and then computed surface mass balance anomalies relative to the mean over the full period. We summed the anomalies over different spatial regions to produce anomaly time series in units of Gt for grounded portions of the ice sheets for all of Antarctica (AIS), West Antarctica (WAIS), East Antarctica (EAIS), the Antarctic Peninsula (APIS), and 27 individual drainage basins as defined by the Goddard drainage systems (EAIS is taken as basins 2–17; WAIS as basins 1,18–23; APIS as basins 24–27) (Zwally et al., 2012). These anomalies were then cumulatively summed to produce mass time series. The time series were then detrended to yield anomalies to the linear trend in units of Gt.

### 2.2. Composite Ice Core Records (1800–2000)

To expand the temporal coverage of the study beyond the 39 years covered by RACMO, we also considered the record of snow accumulation from composite ice core records from Thomas et al. (2017). We adopted the data sets converted, by approximation by Thomas et al. (2017), to units of gigatons per year, and limited the time period to 1800–2000 inclusive when the most cores were available to produce the composite records. For closer comparison with the analysis of the RACMO output we also consider the ice-core record limited to time period 1979–2010 inclusive. We again cumulatively summed the time series and then detrended to produce anomalies to the linear trend in units of Gt.

We consider time series for composite records for the entire AIS, WAIS, EAIS, and APIS, noting that due to sampling limitations these regions do not correspond identically to the ones we consider for RACMO using the same names. To produce a single EAIS record we sum individual records from the East Antarctic Plateau, Wilkes Land, Victoria Land, Droning Maud Land, and the Weddell Sea. For AIS, WAIS, and APIS we used the values as provided by Thomas et al. (2017). The composite ice core records are subject to measurement error, especially errors in detecting the peak of the annual cycle for a given year, something that would introduce some mid-to-high frequency noise. RACMO could have time-varying bias due to, for example, changing quality of its boundary conditions.

## 3. Methods

We examine time series of surface mass balance from each of the data sets using the HECTOR software v1.7.2 (Bos et al., 2013) available online (http://segal.ubi.pt/hector/). HECTOR allows for simultaneous estimation of, among other parameters, time series trends, periodic signals, offsets, and noise parameters for one of a range of noise models. Here, we estimated just a single linear trend together with, in turn, parameters for five different noise models: white noise, AR[1], AR[5], power-law (PL), and Generalized Gauss-Markov (GGM) models. For the RACMO time series we also estimated periodic terms at 1.0 and 2.0 cycles per year. These models were chosen due to their use in previous ice sheet/core studies (AR[1] and white) or where they have been shown to fit a wide set of geophysical data (PL, GGM), such as ice-sheet mass change (Williams et al., 2014). We included AR[5] as a higher-order variant of AR[1], with order 5 chosen arbitrarily. When computing the PL parameters we used an approach which closely approximates PL by using GGM and holding its parameter fixed close to 1 (Bos et al., 2013). We also considered white noise added to the other noise models but found that these did not improve the noise characterization and so considered the single-type noise models only.

For each ice sheet and basin we commence by identifying the preferred noise model by ranking them based on the Bayesian Information Criteria (BIC), which agreed with the ranking using the Akaike Information Criteria (AIC) in about half the cases; we adopt the BIC, but this model uncertainty also needs to be considered when interpreting results (Akaike, 1974; Schwarz, 1978) (see supporting information Table S1 for the BIC/AIC for the major ice sheets and supplied data for the others).

Given the general stability of the background climate over the late Holocene, we assume that the surface mass balance over the study period has been either stable or changing at a constant rate (Medley & Thomas, 2019), implying that all other change is an expression of noise. The consequence of simultaneously estimating a linear trend and noise parameters is that adopting a different functional definition of the underlying trend or trends, such as adding a quadratic term, could produce a different noise model. In that context, we note that accumulation has accelerated in the APIS over the ice core data period (Thomas et al., 2008), and we consider this further in the discussion.

## 4. Results

The time series of mass anomalies are shown in Figure 1a for AIS, WAIS, EAIS, and APIS from both RACMO (thin lines) and the ice core composites (thick lines). The composite records show larger variations at periods longer than are sampled by the RACMO output. Among these are the post-1850 acceleration in accumulation in APIS over long timescales, but decadal variability is also seen as is particularly evident in WAIS. The RACMO anomalies are computed relative to the RACMO data period, and hence, some of the mass trends since 1979 are distinct from those in the composite records. Beside these, however, there are differences in interannual variability, presumably a result of increased spatial averaging in RACMO and model and measurement errors.

Figures 1b and 1c show the power spectra of these data, revealing the power-law-like characteristics of the data sets, with power increasing toward the lowest frequency. While there are differences in the ordering of lines between the two sets of spectra, they both show increasing power at lower frequencies. Some of the time series suggest a slight flattening in parts of the spectra, particularly at high frequency (e.g., EAIS and AIS in Figure 1b), but in general there is a steady increase in power from the Nyquist frequency throughout the spectrum. This simple visualization of the data suggests that these time series will not be well represented by a white noise model in which data are temporally uncorrelated, expressed as a flat spectrum.

The preferred noise model from the HECTOR analysis is never white noise over the timescales considered, confirming our visual interpretation of the time series and spectra. For the RACMO outputs, GGM noise was preferred for the AIS, WAIS, EAIS, APIS, and 26 of 27 drainage basins. For one drainage basin (basin 13, which includes the Aurora subglacial basin), AR[5] noise was preferred but with GGM ranked second. The second-ranked model otherwise varied between AR[1] and AR[5]. In all

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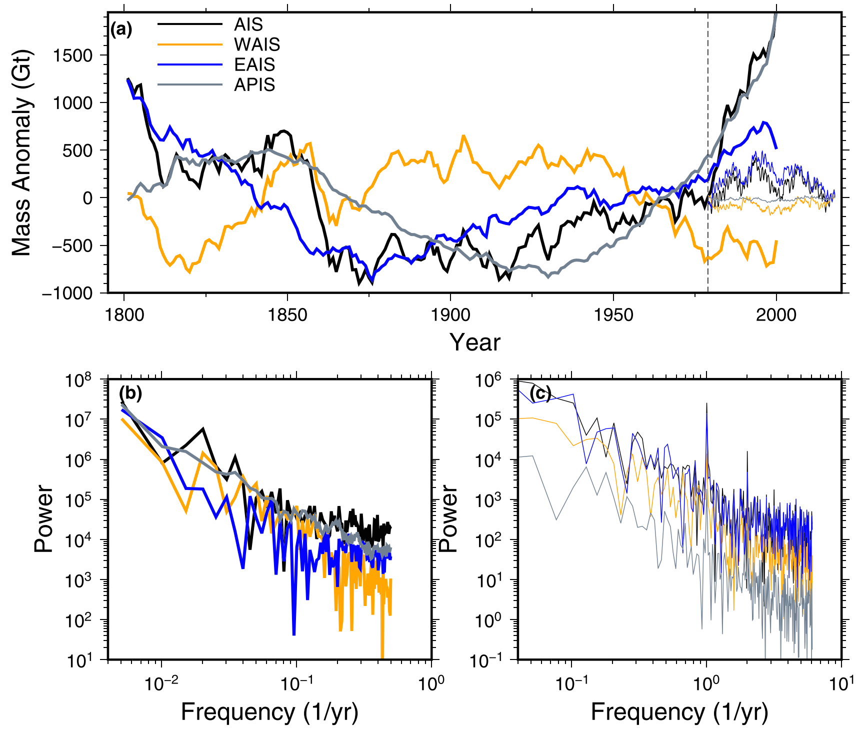


**Figure 1.** Detrended, cumulative surface mass balance from RACMO (thin lines post 1979) and ice core composites (thick lines). Shown are (a) mass anomaly time series after detrending and (b and c) Lomb-Scargle Power Spectra for ice core composites and RACMO, respectively. Note the shift in scales between (b) and (c). The anomalies are computed relative to linear fits to the full data sets. The vertical dashed line in (a) marks the start of the RACMO record.

cases, white-noise only was the lowest ranked noise model. Using AIC, the top-ranked model was split, approximately evenly, between GGM and AR[5]. Inspecting the AR[1] stochastic coefficients reveals them all to be ~0.98; a coefficient of 1 makes AR[1] equivalent to a random walk model (power-law with spectral index of −2). The spectral indices for GGM and PL were −2.3 to −2.7 and −2.2 to −2.3, respectively (Table S1), above that for random walk.

For the longer ice core composites, GGM noise was again preferred for all four ice sheets. In each case, the order in decreasing preference was GGM, AR[5], PL, AR[1], and white noise. Considering the composite records over just 1979–2010 showed a slight variation in that AR[5] was preferred to GGM for AIS and APIS, with GGM ranked second, although GGM was preferred for EAIS and WAIS. The AR[1] coefficients were again close to 1, and the spectral indices for GGM and PL were −2.8 to −3.3 and −2.6 to −3.0, respectively (Table S2).

The spectra of the preferred noise models for the ice sheets are shown in Figure S1 (RACMO) and Figure S2 (ice core composites) in the supporting information. The fit to the ice core composites (Figure S2) particularly reveals a tendency for an AR[1] noise model to overestimate the noise at high frequencies and underestimate it at low frequencies. This effect is also evident in the RACMO data set (Figure S1). A common feature of the (best-fitting) GGM model is a flattening of the spectra at low frequencies.

Our conclusion from the HECTOR tests is that, of the models tested, GGM is the preferred model across a wide range of areas and temporal scales although with some caveats for PL discussed below. Our subsequent analysis focuses on GGM and the effect of adopting it instead of the often-adopted AR[1] when determining trends and their uncertainties.

To explore the effect of the presence of GGM noise on estimates of linear trends we performed a Monte Carlo simulation considering a range of time periods. To do this we used HECTOR to produce 100 simulated time series for each ice sheet and (for shorter periods only) 27 basins. These were defined using different realizations of the specified noise but with no underlying trend. The time series were simulated at annual time steps with a total length of 40 years (RACMO) or 100 years (composite ice cores). We then estimated trends over

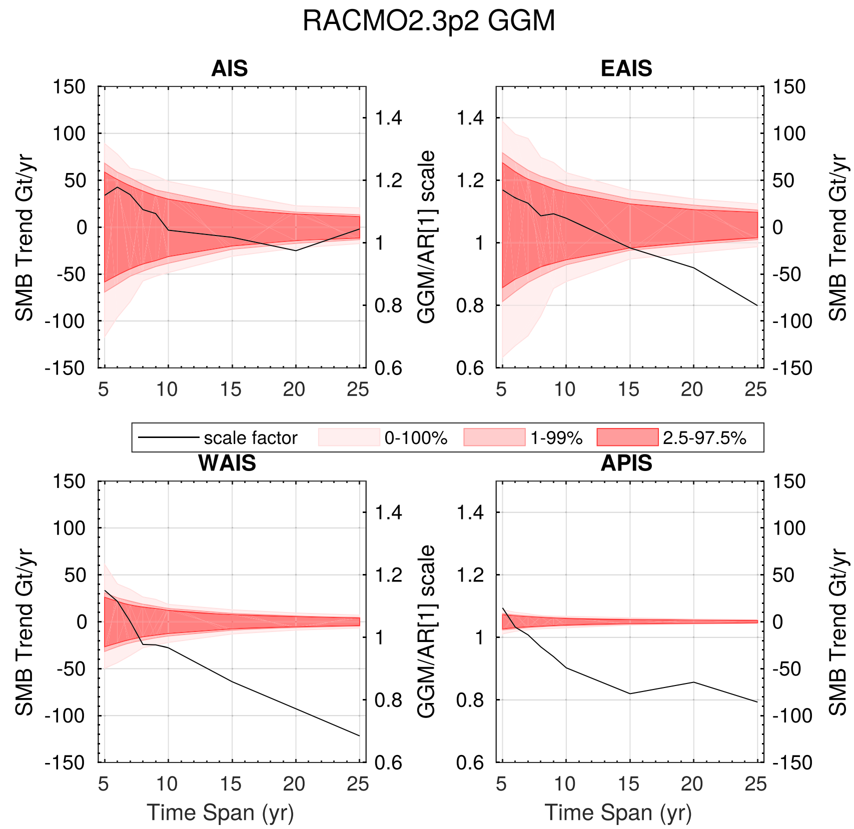


**Figure 2.** Fan plots showing the range of trends determined from simulated time series over different durations using GGM noise determined from RACMO2.3p2 for each ice sheet. The ratio of the of the 0–100% range for GGM noise versus AR[1] noise is also shown. Trend Y scales are each consistent with Figure 3 aside from AIS.

different durations of the simulated series, again using HECTOR, interpreting the distribution of these trends as an indicator of trend uncertainty in the presence of GGM noise.

The results are shown in Figure 2 (RACMO) and Figure 3 (ice core composites) in terms of fan plots reflecting the range of estimated trends over different data spans. The analysis based on RACMO output (Figure 2) shows substantially greater range of values for EAIS and AIS (top panels) compared to WAIS and especially APIS over all periods up to 25 years. The variability within the EAIS analysis dominates the AIS variability (compare also the absolute power in Figure S1 between EAIS and WAIS/APIS). Over 25 years, the uncertainty on trends in EAIS/AIS surface mass balance is around ±15 Gt/yr (95% interval) while the WAIS and APIS uncertainties are ±5 Gt/yr at most.

Figures 1, S1, and S2 suggest, however, that low frequency (long period) noise continues to increase in power over periods longer than sampled by the RACMO data set. Consequently, the fan plots for the ice core composites (Figure 3) show dramatically increased trend ranges at 25 years, especially for AIS, WAIS, and APIS; for EAIS they are ±40 Gt/yr, for WAIS ±40 Gt/yr, for APIS ±45 Gt/yr, and AIS ±70 Gt/yr (all 95% confidence limits). For the longer time spans, the limits reduce almost negligibly for APIS, more substantially for WAIS and only slowly for EAIS and AIS.

Given the common use of AR[1] noise in various surface mass balance and accumulation studies, we compared the trend variability obtained when adopting the GGM model for the simulations with those obtained when adopting an AR[1] model. To do this, we repeated the simulations using the best-fit AR[1] coefficient and computed the scale factors between the trend ranges (0–100%) for each timespan. The results are shown in Figures 2 and 3 (black lines). The results are displayed in Figures 2 and 3 and show that GGM noise produces trends with a range generally larger than AR[1] by a factor of 1.5–2.5. The scale is smaller for WAIS and larger for APIS, where it ranges up to a factor of 4. For the shorter period of RACMO (Figure 2), the

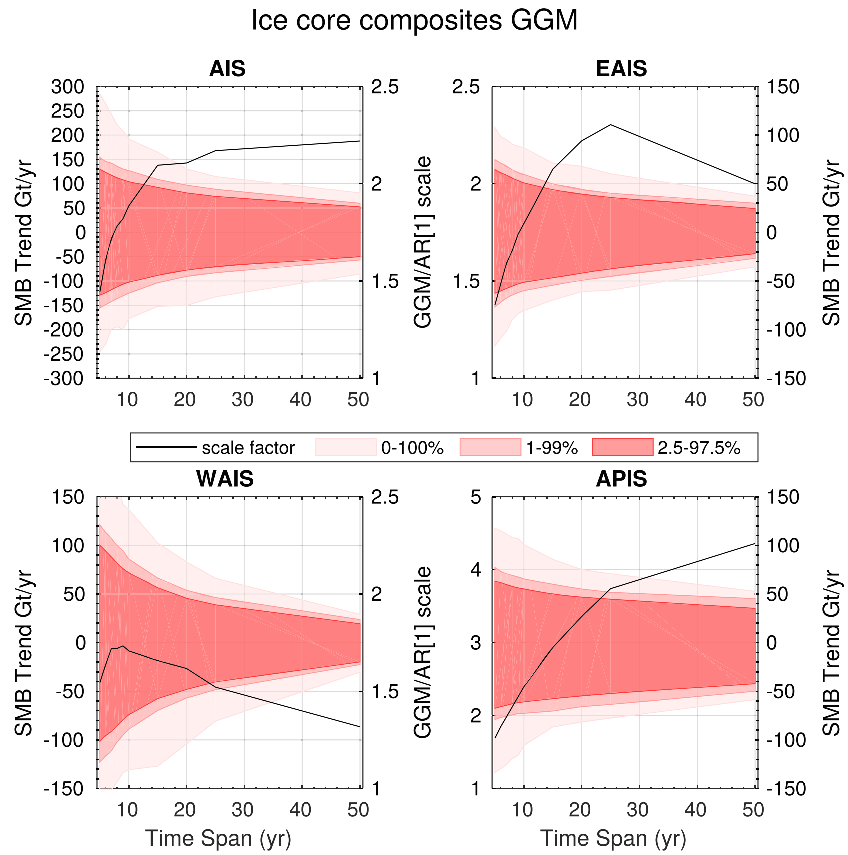


**Figure 3.** As for Figure 2 but for the ice core composites. Note the different Y scale for AIS trends compared to Figure 2 and GGM/AR[1] scale for APIS.

scale factors are closer to 1 and even below 1 (suggesting that GGM noise would produce smaller trend uncertainties than AR[1] in this case).

## 5. Discussion

Our analysis highlights that the choice of noise model used when estimating trends or changing trends in Antarctic surface mass balance requires careful consideration. Making simple assumptions of noise properties is likely to result in erroneous estimates of trend uncertainty. We illustrate this point by showing that the widely used AR[1] noise model significantly underestimates trend uncertainties in many cases; this would be even more dramatically illustrated if we compared it to a white noise only model, which substantially underestimates noise at low frequencies and overestimates noise at high frequencies (Figures S1 and S2).

Our results require some caution as they are based on residuals to a linear fit to the data, assuming the data are otherwise stationary over their respective time series lengths. While our results over several data sets are consistent in preferring GGM noise model in almost all cases, the APIS is known to have experienced accelerated rates of accumulation over the last 150 years. As such, the APIS results in Figure 3 should be viewed with some caution given the underlying model is most likely nonlinear.

To examine the effects of nonlinearity in the time series further, we repeated the analysis of the ice core composites using a linear-plus-quadratic model, which provides more realistic fit to the four time series (Figure S3). The estimates of the linear and quadratic terms for the different ice sheets and noise models are shown in Table 1, noting that the quadratic and linear terms are for SMB anomalies in which the mean rate of SMB has already been subtracted from the respective data sets. For all ice sheets the GGM noise model is preferred, showing the lowest BIC/AIC aside from EAIS where the AIC indicates a narrow preference for AR[5] over GGM, with the least preferred noise model always white noise only followed by AR[1] (here, effectively pure random walk). Aside from APIS, uncertainties for trends are 3.8–5.0 times higher with

**Table 1**
*Estimates of Trends and Quadratic (Half Accelerations) in SMB Within the Ice Core Composites (1801–2000) for the AIS, APIS, EAIS, and WAIS*

| Noise model | BIC | AIC | Trend (Gt/yr) | Half acceleration (Gt/yr$^2$) |
|---|---|---|---|---|
| AIS | | | | |
| GGM | 2,316.834 | 2,308.101 | 1.0 ± 1.5 | 0.208 ± 0.028 |
| AR[5] | 2,323.004 | 2,309.905 | 1.3 ± 1.8 | 0.215 ± 0.031 |
| PowerlawApprox | 2,344.237 | 2,336.960 | 5.8 ± 20.2 | 0.284 ± 0.119 |
| AR[1] | 2,347.802 | 2,340.525 | 2.1 ± 2.2 | 0.227 ± 0.034 |
| White | 2,862.270 | 2,856.448 | 0.1 ± 0.4 | 0.180 ± 0.007 |
| ***APIS*** | | | | |
| GGM | 1,894.971 | 1,886.239 | 14.1 ± 5.7 | 0.180 ± 0.068 |
| AR[5] | 1,899.548 | 1,886.450 | 11.7 ± 4.8 | 0.180 ± 0.063 |
| PowerlawApprox | 1,908.861 | 1,901.583 | 23.4 ± 25.9 | 0.181 ± 0.086 |
| AR[1] | 1,996.670 | 1,989.393 | 8.3 ± 1.63 | 0.147 ± 0.020 |
| White | 2,919.806 | 2,913.985 | −0.1 ± 0.4 | 0.146 ± 0.009 |
| ***EAIS*** | | | | |
| GGM | 2,039.081 | 2,030.349 | −1.4 ± 1.2 | 0.133 ± 0.020 |
| AR[5] | 2,040.972 | 2,027.873 | −1.9 ± 1.4 | 0.134 ± 0.022 |
| PowerlawApprox | 2,057.869 | 2,050.591 | −5.8 ± 8.6 | 0.122 ± 0.053 |
| AR[1] | 2,059.677 | 2,052.400 | −2.3 ± 1.5 | 0.134 ± 0.020 |
| White | 2,667.521 | 2,661.700 | 0.1 ± 0.2 | 0.142 ± 0.005 |
| ***WAIS*** | | | | |
| GGM | 2,201.926 | 2,193.194 | −0.3 ± 1.1 | −0.082 ± 0.019 |
| AR[5] | 2,210.122 | 2,197.023 | −0.4 ± 1.2 | −0.075 ± 0.022 |
| PowerlawApprox | 2,236.991 | 2,229.714 | −3.3 ± 23.1 | 0.019 ± 0.116 |
| AR[1] | 2,249.439 | 2,242.162 | −1.6 ± 1.8 | −0.053 ± 0.028 |
| White | 2,733.606 | 2,727.785 | 0.0 ± 0.3 | −0.108 ± 0.005 |

*Note*. Uncertainties are 1-sigma.

GGM than white noise, with AR[1] showing the highest uncertainty, highlighting that an inappropriate noise model can produce pessimistic as well as optimistic uncertainties. The uncertainties of the quadratic terms show similar patterns to the linear terms as a function of noise type.

For APIS, GGM uncertainties are 12.9 times higher than those from a white noise model, but the data are not well fit by a quadratic model (Figure S3). The APIS results highlight the interplay between the deterministic and stochastic models, in that changing the noise model can result in different estimates for trends and other unknowns in the presence of significant low-frequency variability.

There are some limitations in using BIC or AIC to determine preferred models, especially so for time series with relatively few data points. In particular, the role of PL noise in a time series can be downplayed, especially when a trend is estimated. To explore this, we considered 100 × 100 year simulated time series based on the analysis of the AIS ice core record to generate a representative PL noise model. We found that PL was not preferred using BIC and AIC but rather GGM (92%), AR[5] (6%), and AR[1] (2%). As such, PL may be more appropriate than GGM for this case. However, in a stable climate we assume that time series of SMB would be stationary, unlike PL noise where the highest power is at the lowest frequencies. In the face of model uncertainty, adopting the noise model which produces the largest uncertainty may be the most appropriate approach. In the case of PL noise for the linear-plus-quadratic model, trend uncertainties for the ice core composite records are 5–20 times greater than for GGM (Table 1).

For studies of ice sheet mass balance using the mass budget method, the relevant time period of interest is the period over which the velocities are estimated—typically months to years. Figure 1 suggests that even over this time period some temporal correlation in SMB exists, and adopting a simple white noise model (e.g., root-mean-square) is likely to produce over-optimistic uncertainties of mass balance trends. Other approaches to estimating ice sheet mass balance (e.g., altimetry and gravimetry) should also consider temporal correlations and appropriate noise models as discussed previously (Ferguson et al., 2004; Horwath & Dietrich, 2009; Williams et al., 2014) as they will contain signal from surface mass balance variations in addition to other time-varying signals (e.g., firn densification and/or mass discharge).

## 6. Conclusions

We show that substantial temporal correlations exist in records of Antarctic surface mass balance and accumulation from ice core composites covering the last two centuries. In almost every region and timescale considered—from the full ice sheet down to individual drainage basins and from periods of decades to two centuries—a Generalized Gauss Markov noise model was preferred, based on Bayesian Information Criteria, over white noise or autoregressive noise models assuming the presence of an underlying trend or acceleration.

Our results build on the previous work of Wouters et al. (2013) who identified temporal correlation in records of Greenland and Antarctic SMB and GRACE-derived mass change, suggesting temporal correlations exist in Antarctic SMB data and that an AR[n] model was preferred over a white noise only model. Our study extends this conclusion from a few decades to the period since 1800, to regions down to the size of individual drainage basins (1979–2010) and suggests that a GGM noise model is preferred over AR[1] models over almost all regions and timescales tested. The selection of noise models tested here is limited, and other models may offer improved performance and hence result in different parameter estimates and uncertainties; nonetheless, the GGM fits the spectra of the data well, and the reduced power at the lowest and highest frequencies is physically reasonable.

Our findings have important ramifications for the statistically significant detection of changes in trends in surface mass balance—either in the past or as new ones emerge as expected with a warming climate—especially given the common use of largely untested white noise or autoregressive [1] noise models in such studies. In our tests, white noise models always resulted in underestimated uncertainty when compared with those derived using more sophisticated noise models, by a factor of around 4–5, while uncertainties derived using a GGM model are generally much larger, but sometimes smaller, than those derived using less-well-fitting autoregressive noise models. A PL model is not preferred by Bayesian Information Criteria, but simulations suggest it could still be dominant, even if not detected, given we estimate a trend which can absorb low frequency noise; adopting it produces uncertainties up to 20 times larger.

Ultimately, the most appropriate noise model for a given data set cannot be predetermined as each data set has its own noise properties and even the definition of noise varies depending on the functional model adopted. Fortunately, software tools such as HECTOR are freely available (http://segal.ubi.pt/hector/) and offer straightforward opportunities to test a range of functional and stochastic models for application in studies exploring temporal evolution of surface mass balance and other Cryospheric time series (e.g., sea ice extent).

## Conflict of Interest

There are no real or perceived conflicts of interest for any author.

### Data Availability Statement

Data supporting the conclusions of the paper is available online (https://data.utas.edu.au/metadata/9f7cc90a-bebb-4f9b-b851-bfbb702cc875). The underlying gridded RACMO model data may be obtained from the website (https://www.projects.science.uu.nl/iceclimate/models/antarctica.php) while the ice core composite data are in the supplementary material of Thomas et al. (2017), and the data converted to Gt were obtained from E.R. Thomas directly.

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## References

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*(6), 716–723. https://doi.org/10.1109/TAC.1974.1100705

Bos, M. S., Fernandes, R. M. S., Williams, S. D. P., & Bastos, L. (2013). Fast error analysis of continuous GNSS observations with missing data. *Journal of Geodesy*, *87*(4), 351–360. https://doi.org/10.1007/s00190-012-0605-0

Ferguson, A. C., Davis, C. H., & Cavanaugh, J. E. (2004). An autoregressive model for analysis of ice sheet elevation change time series. *IEEE Transactions on Geoscience and Remote Sensing*, *42*(11), 2426–2436. https://doi.org/10.1109/tgrs.2004.836788

Horwath, M., & Dietrich, R. (2009). Signal and error in mass change inferences from GRACE: The case of Antarctica. *Geophysical Journal International*, *177*(3), 849–864. https://doi.org/10.1111/j.1365-246X.2009.04139.x

Jouzel, J., Masson-Delmotte, V., Cattani, O., Dreyfus, G., Falourd, S., Hoffmann, G., et al. (2007). Orbital and millennial Antarctic climate variability over the past 800,000 years. *Science*, *317*(5839), 793–796. https://doi.org/10.1126/science.1141038

Lenaerts, J. T. M., Vizcaino, M., Fyke, J., van Kampenhout, L., & van den Broeke, M. R. (2016). Present-day and future Antarctic ice sheet climate and surface mass balance in the community earth system model. *Climate Dynamics*, *47*(5-6), 1367–1381. https://doi.org/10.1007/s00382-015-2907-4

Medley, B., & Thomas, E. R. (2019). Increased snowfall over the Antarctic ice sheet mitigated twentieth-century sea-level rise. *Nature Climate Change*, *9*(1), 34–39. https://doi.org/10.1038/s41558-018-0356-x

Monaghan, A. J., Bromwich, D. H., Fogt, R. L., Wang, S. H., Mayewski, P. A., Dixon, D. A., et al. (2006). Insignificant change in Antarctic snowfall since the international geophysical year. *Science*, *313*(5788), 827–831. https://doi.org/10.1126/science.1128243

Palerme, C., Genthon, C., Claud, C., Kay, J. E., Wood, N. B., & L'Ecuyer, T. (2017). Evaluation of current and projected Antarctic precipitation in CMIP5 models. *Climate Dynamics*, *48*(1–2), 225–239. https://doi.org/10.1007/s00382-016-3071-1

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, *6*(2), 461–464. https://doi.org/10.1214/aos/1176344136

Thomas, E. R., Marshall, G. J., & McConnell, J. R. (2008). A doubling in snow accumulation in the western Antarctic Peninsula since 1850. *Geophysical Research Letters*, *35*, L01706. https://doi.org/10.1029/2007GL032529

Thomas, E. R., van Wessem, J. M., Roberts, J., Isaksson, E., Schlosser, E., Fudge, T. J., et al. (2017). Regional Antarctic snow accumulation over the past 1000 years. *Climate of the Past*, *13*(11), 1491–1513. https://doi.org/10.5194/cp-13-1491-2017

van Wessem, J. M., van de Berg, W. J., Noël, B. P. Y., van Meijgaard, E., Amory, C., Birnbaum, G., et al. (2018). Modelling the climate and surface mass balance of polar ice sheets using RACMO2 – Part 2: Antarctica (1979–2016). *The Cryosphere*, *12*(4), 1479–1498. https://doi.org/10.5194/tc-12-1479-2018

Williams, S. D. P., Moore, P., King, M. A., & Whitehouse, P. L. (2014). Revisiting GRACE Antarctic ice mass trends and accelerations considering autocorrelation. *Earth and Planetary Science Letters*, *385*, 12–21. https://doi.org/10.1016/j.epsl.2013.10.016

Wouters, B., Bamber, J. L., van den Broeke, M. R., Lenaerts, J. T. M., & Sasgen, I. (2013). Limits in detecting acceleration of ice sheet mass loss due to climate variability. *Nature Geoscience*, *6*(8), 613–616. https://doi.org/10.1038/Ngeo1874

Zwally, H. J., Giovinetto, M. B., Beckley, M. A., & Saba, J. L. (2012). Antarctic and Greenland Drainage Systems, GSFC Cryospheric Sciences Laboratory. Retrieved from http://icesat4.gsfc.nasa.gov/cryo_data/ant_grn_drainage_systems.php