Regional Climate of the Larsen B embayment 1980-2014

SUPPLEMENTARY INFORMATION

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S1 Supplementary Methods

S1.1 Multivariate Changepoint Analysis

Intuitively, in order to uncover if/when climatological parameters change, we need to determine when they have shifted from one mode to another. In order to automatically determine when this occurs, we use changepoint analysis (see Eckley et al., 2011 for an introduction). Formally, a changepoint is a point in time where the statistical properties of prior data are different from the statistical properties of subsequent data; the data between two changepoints is a segment.

There are various ways that one can determine when a changepoint should occur, but the best fit for our data is to consider changes in both the mean and variance of our estimates. As we have several time series that are related we use multivariate changepoint detection to automatically determine if there is a change in any or all of the series (here: PDDs, Melting and Snowfall). In order to automate this, we use the \texttt{cpt.mv} function in the R changepoint.mv package (soon to be released on CRAN, available from Killick). This function uses the PELT and ASMOP algorithms (Killick et al., 2012, Pickering et al., 2016) for fast and exact detection of multiple changes in a subset of series. The function returns changepoint locations and estimates of the mean and variance between changes. We use the penalty values of alpha=2*log(p) and beta=log(n)*log(p), where beta controls the addition of a new changepoint and alpha controls the addition of one series having the same changepoint as another.

S2 Supplementary Figures

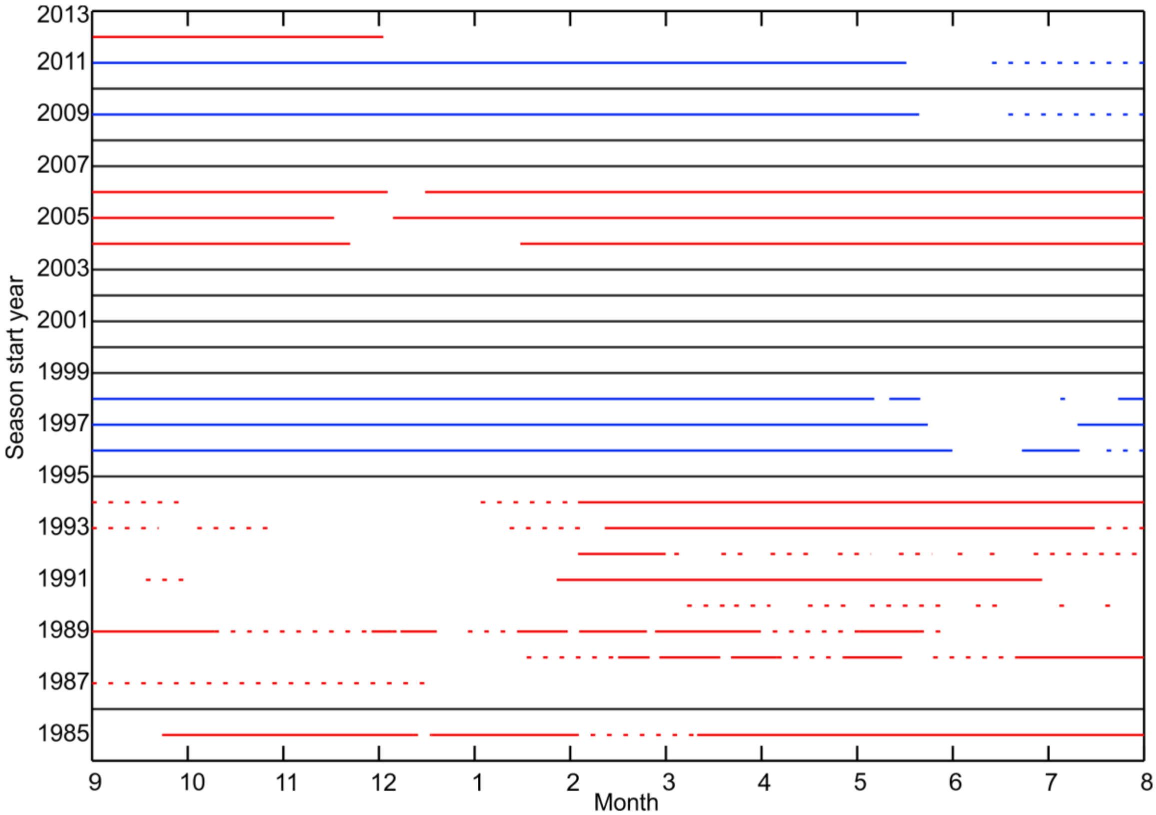

Figure S1. Availability of observations at Larsen C AWS. Solid lines indicate continuous data, dotted lines indicate fragmented data. Black denotes a full year of data, blue indicates continuous data available during the main melt months (DJF), red indicates years for which there is insufficient data to quantify observed melt. We do not present a similar inventory for Matienzo since the record there is complete during our study period, with the exception of 84 days between March and May in 2004.

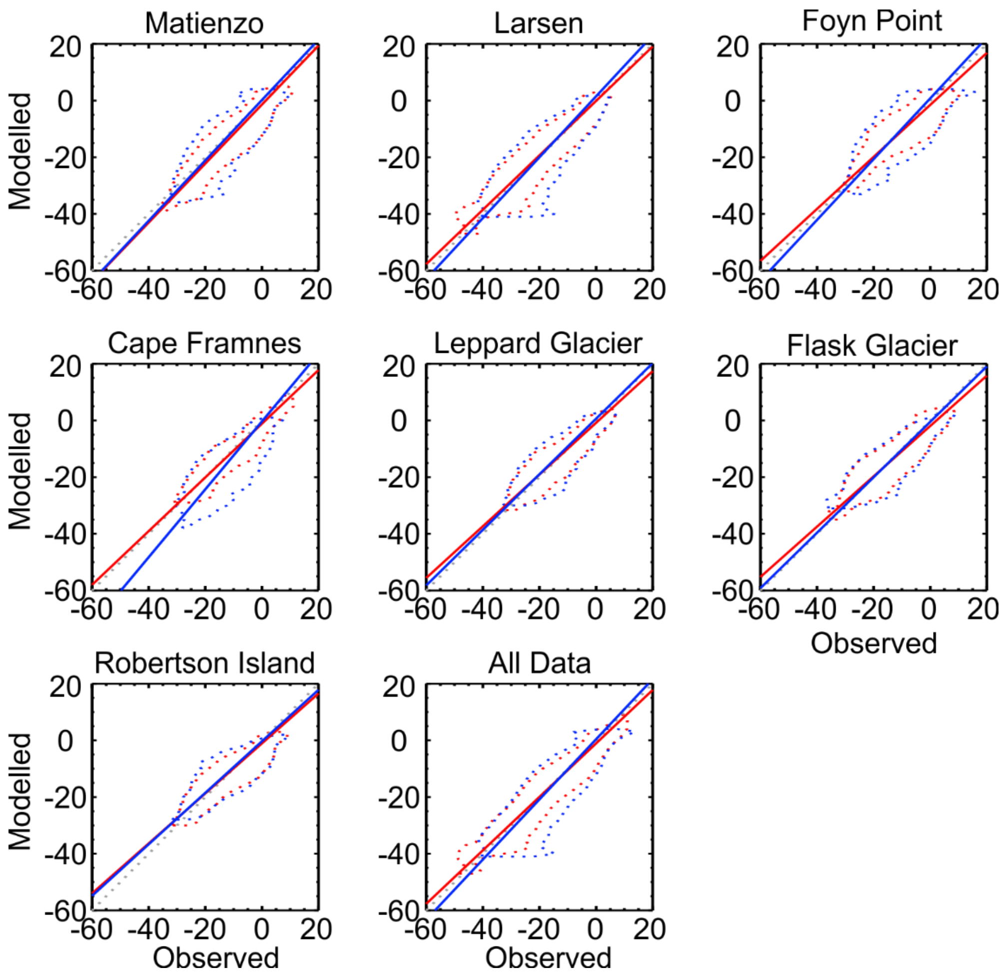

Figure S2. Modelled vs observed 2 m temperature (all data). Simulated values are given in blue (RACMO2.3/27) and red (RACMO2.3/5.5). Dashed polygon delineates 95% of data, solid lines indicate linear fit to these data, dashed line indicates 1:1 relationship. Where the gradient of the regression line is steeper than the 1:1 line, high values are underestimated by the model and low values are overestimated.

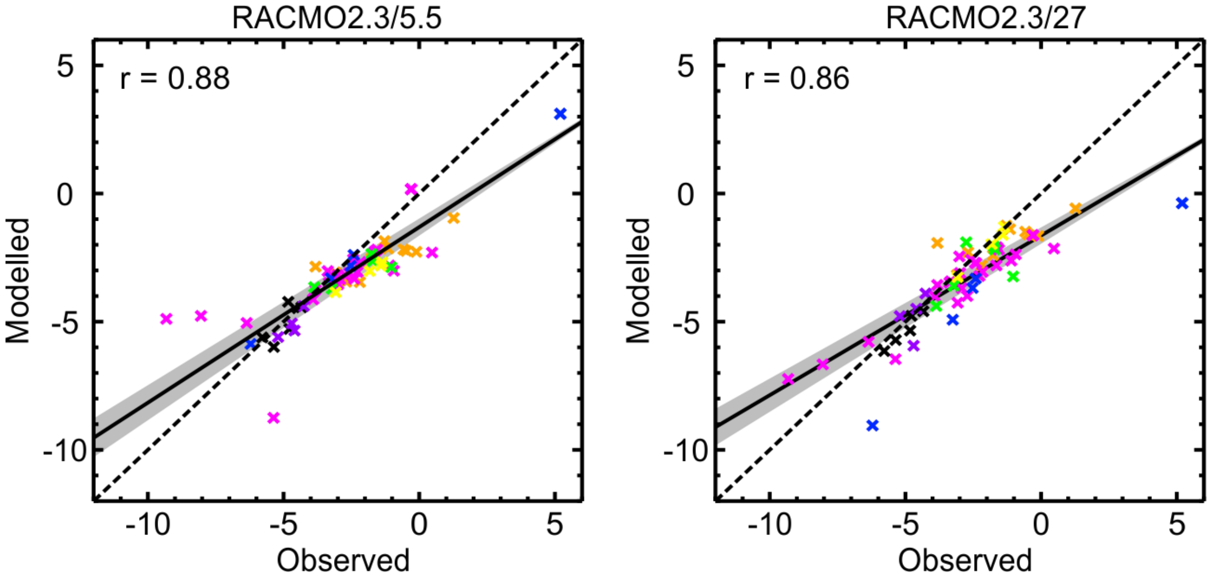

Figure S3. Mean summer (DJF) temperature from observations and RACMO2 simulations. Colours represent different weather stations: black – Flask Glacier, purple – Leppard Glacier, Green – Foyn Point, Blue – Cape Framnes, Yellow – Robertson Island, Pink - Larsen C AWS and Orange - Matienzo AWS. Dashed lines indicates an ideal 1:1 relationship between modelled and observed values, solid lines indicates the actual fit, grey shading denotes +- 1 σ uncertainty on the fit. Pearson's correlation co-efficient (r) is annotated.

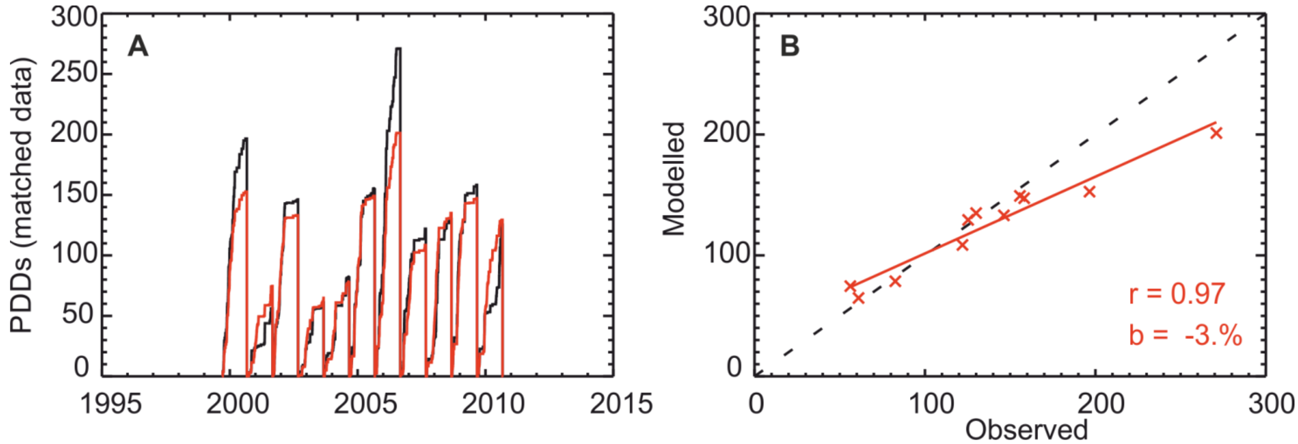

Figure S4. Cumulative Positive Degree Days at Matienzo AWS. Black indicates observed values, red indicates RACMO2.3/5.5 estimate with bias correction applied to modelled temperature data. Panel B shows modelled vs observed total annual PDDs, Pearson's correlation co-efficient (r) and mean bias (b) between the observed and modelled values are annotated.

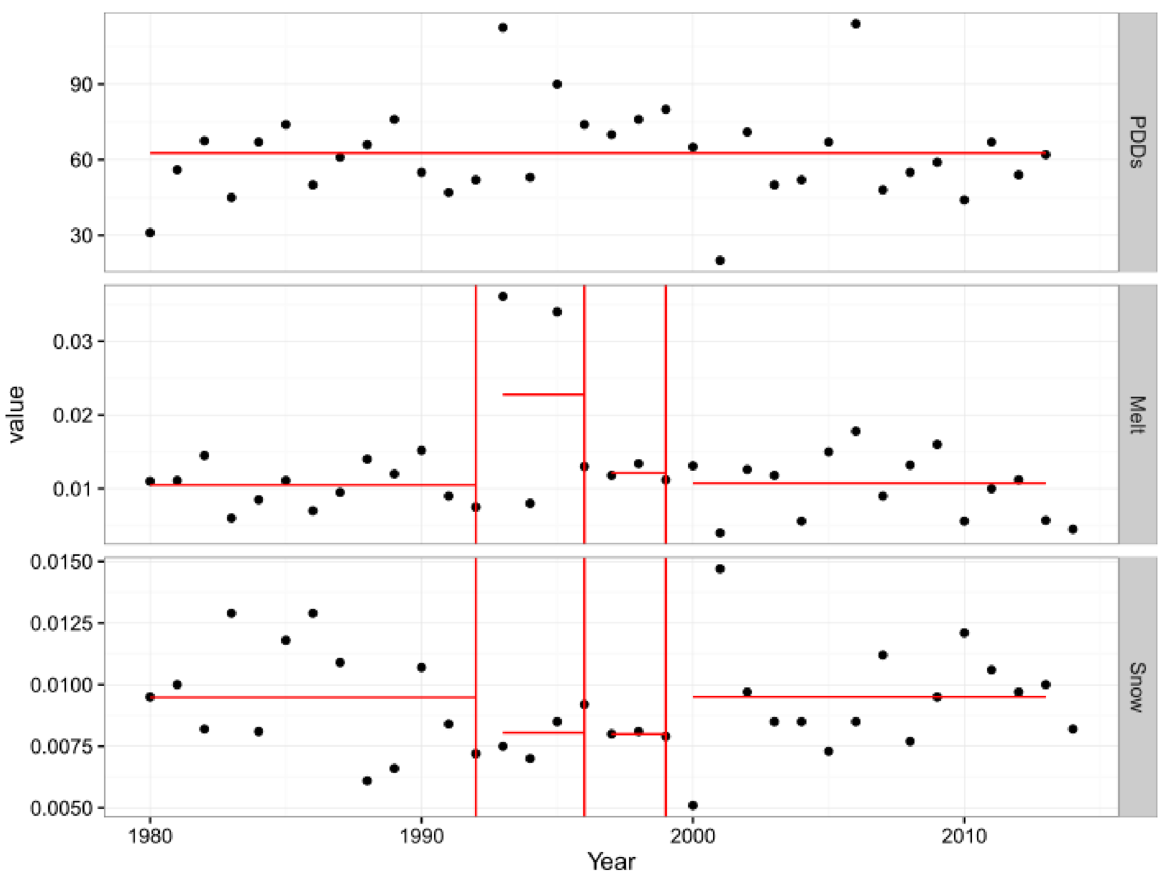

Figure S5. Results of multivariate changepoint analysis applied to RACMO2 simulated melting and snowfall over the pre-collapse Larsen B between 1980 and 2014.

Station	Lon	Lat	Z (m a.s.l.)	RACMO2.3/5.5			RACMO2.3/27		
				Lon	Lat	Z	Lon	Lat	Z
Matienzo	-60.07	-64.98	25	-60.12	-65.00	14	-60.20	-64.94	17
Larsen C	-61.47	-67.00	45	-61.41	-67.00	39	-61.24	-66.89	18
Foyn Point	-61.65	-65.25	65	-61.79	-65.24	82	-61.73	-65.40	26
Cape Framnes	-60.56	-66.01	100	-60.86	-66.05	108	-60.61	-66.03	82
Flask Glacier	-62.90	-65.75	583	-62.80	-65.77	568	-62.72	-65.78	568
Leppard Glacier	-62.90	-65.95	602	-62.81	-65.87	614	-62.72	-65.78	568
Robertson Island	-59.44	-65.25	58	-59.52	-65.15	64	-59.45	-65.09	14

Table S1. Latitude, longitude and elevation of each AWS. Also given in the latitude, longitude and elevation of the RACMO grid cell closest to each location.

Supplementary References

Eckley, I.A., Fearnhead, P. and Killick, R. (2011) Analysis of changepoint models. Chapter 10 in Bayesian Time Series Models, eds. D. Barber, A.T. Cemgil and S. Chiappa, Cambridge University Press

Pickering, B. (2016) Changepoint Detection for Acoustic Sensing Signals, PhD Thesis, Lancaster University