Calibrating a Greenland ice sheet model using historical simulations between 1996-2022

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summary

- We want a calibrated Greenland wide ice sheet model to use to make projections of ice loss under scenarios of future climate change
- To do this we use an ice sheet model to simulate the last two decades and we prescribe as much known forcing as possible, to assess our model's ability to replicate observations
- We find it can indeed replicate observations, but only with both surface mass balance forcing and an evolving calving front
- To come: future projections using the calibrated model!

motivation and aims

Future projections of ice loss from the Greenland ice sheet are subject to large and often poorly quantified uncertainties. In particular, ice sheet models (or the modellers!) often struggle to replicate observations over the recent decades giving us little confidence in their predictive abilities into the future. Constraining models against observations is therefore a key step towards improving this confidence.

Here we aim to answer the following questions:

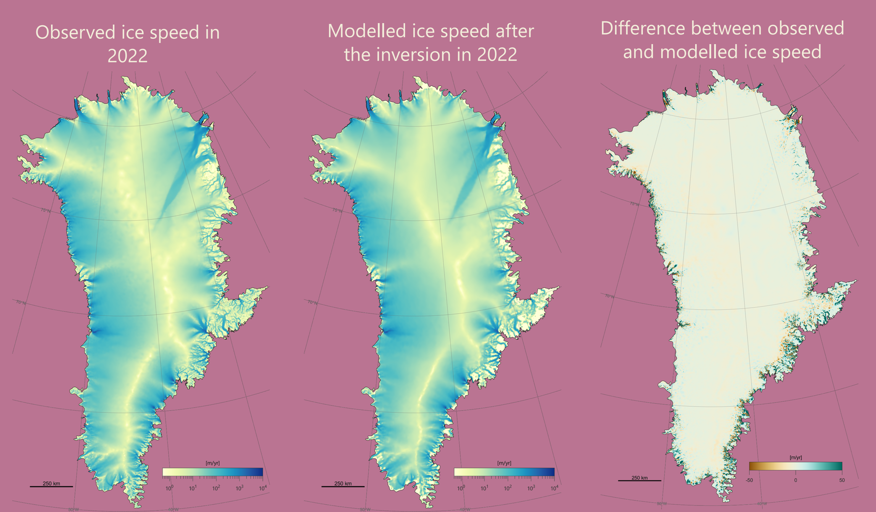
1. When we incorporate as much known forcing on the surface mass balance and calving front changes, can our model replicate observations and be reliably used as a predictor?
2. What model parameter values are needed to best replicate observations?

model initialisation

We use the ice flow model[1] Úa (Access the code here)

Our Greenland ice sheet domain is the boundary of the earliest satellite recorded extent in 1972[2]. Within that we use a 1996 mask[2]. Mesh has 120,000 linear elements ranging from 300m-33km, with a median of 3.5km.

1. **Model inversion** using BedMachine geometry[3] and 2022 Copernicus CCI velocities[4] to estimate basal slipperiness and ice rheology parameters

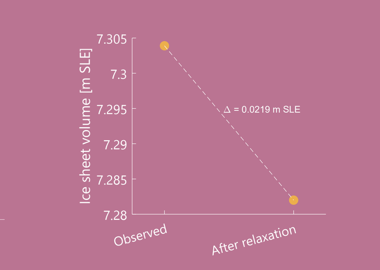


Here we use typical parameters for our inversion, including using Weertman sliding law m=3, and Glen's flow law n=3.

2. **Steady-state spin up simulation** to account for model drift we get at the beginning of our simulations (in the opposite direction to the trend in observed mass loss)

To relax the ice sheet surface we run the model for 5000 years using a fixed period of SMB (1961-1990) from MAR[5] and no prescribed changes in front position (ice is allowed to advance within the domain, up to the maximum extent of 1996).

At most major Greenland outlet glaciers the final ice flux after relaxation agrees with observations for 1996[6,7]. There is a 0.02 m change in ice sheet wide sea level equivalent volume from observations.



methods

historical forward in time simulations from 1996-2022

We use our initial model state in 1996 and prescribe as much known forcing and examine the performance of our model compared with observations

Surface mass balance

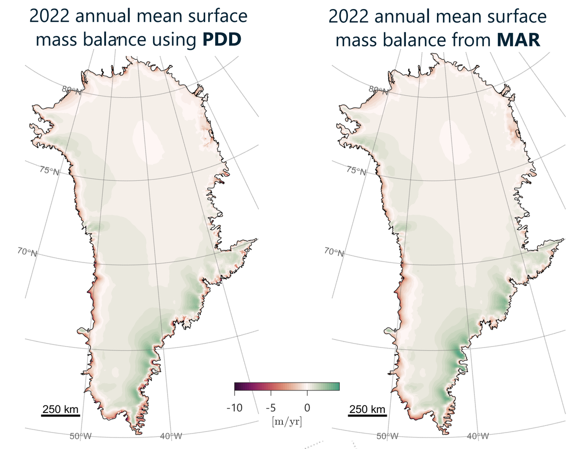
→ We take monthly temperature (T_{obs}) and precipitation (P_{obs}) fields from MAR[5]

→ scale these to changes in surface elevation s through time

$$T = T_{\mathrm{obs}} - \gamma(s - s_{\mathrm{obs}})$$

$$P = P_{\mathrm{obs}}\, e^{\beta_P (T - T_{\mathrm{obs}})}$$

→ use these as input to a positive degree day scheme[8,9] to calculate the surface mass balance through time applied as anomalies to our spin-up SMB



Calving front positions

→ Use monthly Greenland wide ice masks from MEaSUREs ITS_LIVE[2]

→ Directly prescribe ice front positions through time using the level-set function in-built in Úa

Melt rates at floating ice tongues

→ We apply sub-shelf melt rates to floating ice tongues (both past and present) using a piecewise linear function of ice shelf draft

→ Use observations[10] for annual maximum melt rates at depth from early 2000s-2022

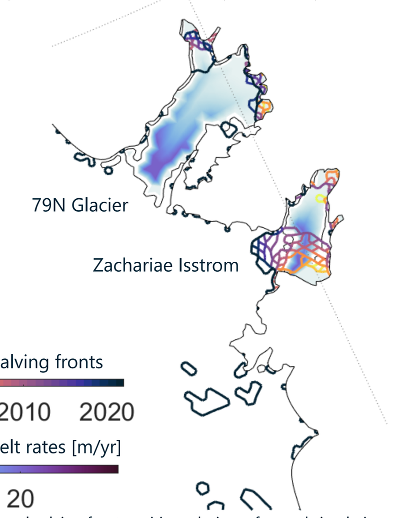
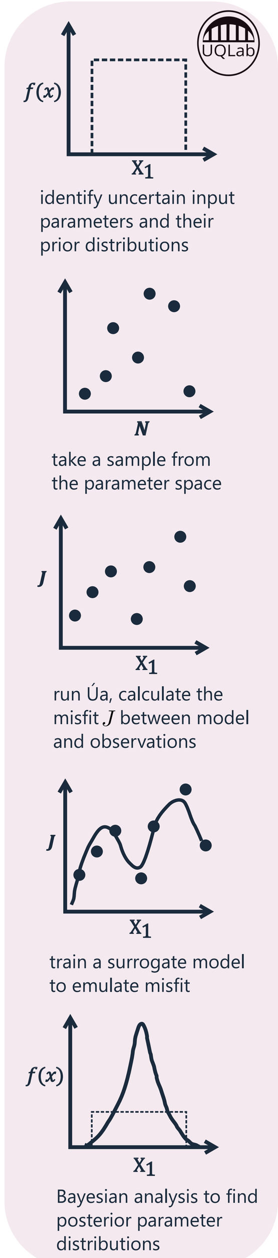


Figure shows annual calving front positions during a forward simulation at glaciers draining the NEGIS and sub-shelf melt rates at the end of the simulation

calibration of model forcing parameters

We use an uncertainty quantification approach (using the UQLab toolbox) to constrain uncertain parmeters (controlling the forcing) to best fit our model output to observed elevation changes



Parameter	Description	Range	Units
γ	Lapse rate	$5-7$	°C km^{-1}
β_P, β_E	Increase in precipitation/evaporation	$5-8$	% per °C
f_s	Degree day factor for melting of snow	$2-6$	mm w.e.°C^{-1}day^{-1}
f_i	Degree day factor for melting of ice	$6-12$	mm w.e.°C^{-1}day^{-1}
σ_{pdd}	Standard deviation of air temperature	$2.5-5.5$	°C
N	Calving fronts on or off	0 or 1	–
z_{fac}	Factor for ice shelf draft	0.75–1.25	–

→ parameters controlling melt-elevation feedback (γ, β_P, β_E)
→ parameters controlling PDD surface mass balance (f_s, f_i, σ_{pdd})
→ binary calving fronts on or off parameter (N)
→ parameter for maximum sub-shelf melt depth (z_{fac})

We take a sample of 150 points from our parameter space using a Sobol sequence

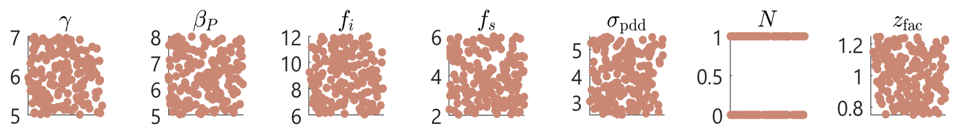


Figure shows 150 point parameter sample evaludate in our ice sheet model and then used as training data for our surrogate model

Run ensemble of Úa simulations and then compare the final state of our model in 2022 to observed surface elevation changes[11].

We calculate the misfit J as:

$$J(\boldsymbol{\theta}) = \frac{1}{2\mathscr{A}} \int_{\mathscr{A}} \frac{\left(\dot{h}_{\mathrm{mod}}(\mathbf{x};\boldsymbol{\theta}) - \dot{h}_{\mathrm{obs}}(\mathbf{x})\right)^2}{\varepsilon^2_{\mathrm{obs}}(\mathbf{x})}\, d\mathscr{A}$$

(model; observed; observed errors; ice-covered area)

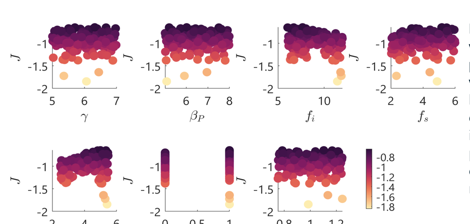


Figure shows J versus each parameter value coloured by the value of J. Giving an initial sense of parameters controlling the misfit.

We train a kriging surrogate model to learn the relationship between model inputs $\boldsymbol{\theta}$ and outputs (misfit J). The surrogate performs well on un-seen data

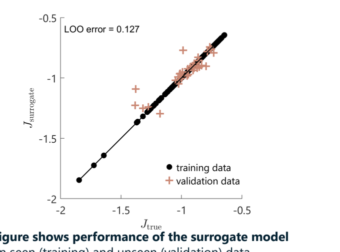


Figure shows performance of the surrogate model on seen (training) and unseen (validation) data

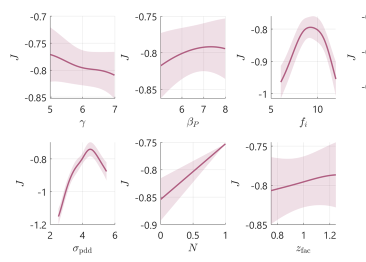


Figure shows the individual parameter to misfit relationship using the surrogate model and keeping all other parameters fixed

Using our surrogate model and MCMC sampling we estimate posterior distribution of model parameters $\boldsymbol{\theta}$ that best reproduce observations, using a log likelihood

$$\log L(\boldsymbol{\theta}) = -\mathcal{A}\, J(\boldsymbol{\theta})$$

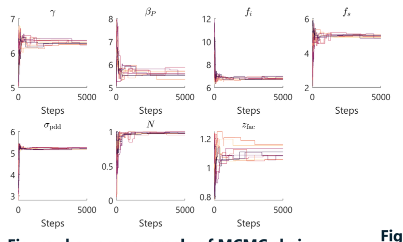


Figure shows an example of MCMC chain convergence for each parameter

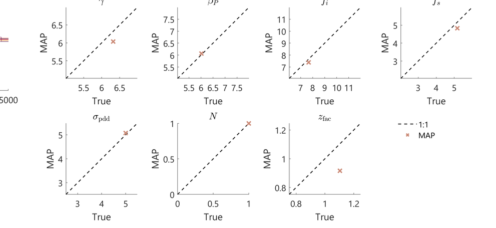


Figure shows a synthetic test in which we substitute the observations for a model run to check the input parameters can be recovered by our analysis

results

1 our model can replicate observations of ice surface elevation changes

but it matters if we include the calving front positions or not

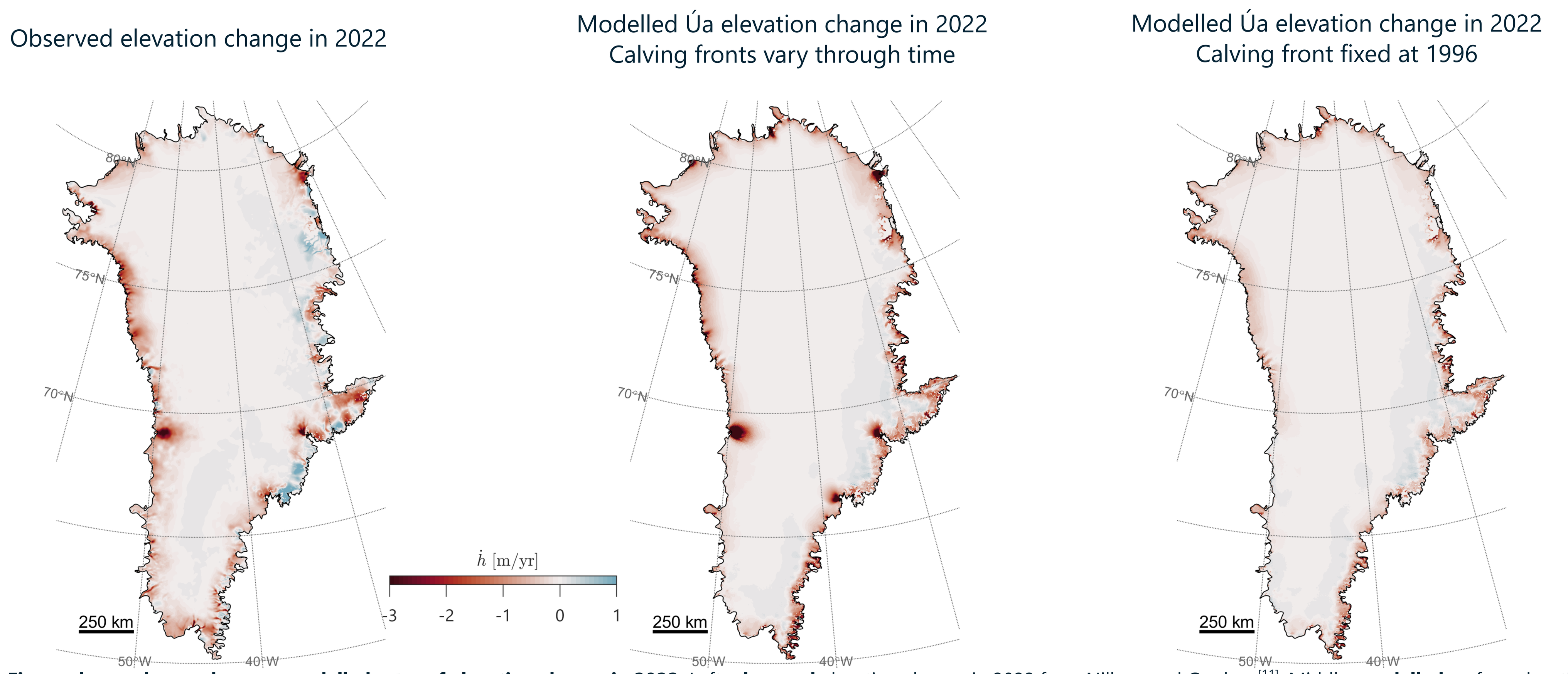


Figure shows observed versus modelled rates of elevation change in 2022. Left: **observed** elevation change in 2022 from Nillsen and Gardner[11]. Middle: **modelled** surface elevation change from Úa in 2022 (calculated as h_{2022}-h_{1996}/27 years), using the "best" parameter combination, i.e. the parameter values that lead to the smallest misfit (highest log likelihood) between observed and modelled results, and including time varying monthly calving front position updates. Right: **modelled** surface elevation change from Úa in 2022 using the same parameter values as the middle plot but keeping the calving fronts fixed at the start (1996) position through time.

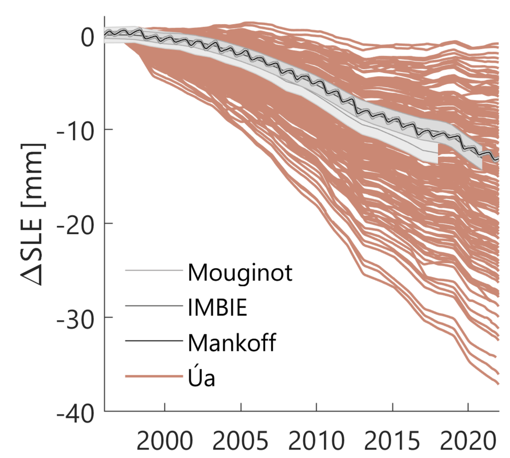


Figure shows change in sea level equivalent (SLE) ice loss during our forward in time simulations (negative = sea level rise)**.** Coloured lines represent each ensemble member. Observations are taken from Mouginot et al.[6], the latest IMBIE assessment[12] and Mankoff et al.[7]

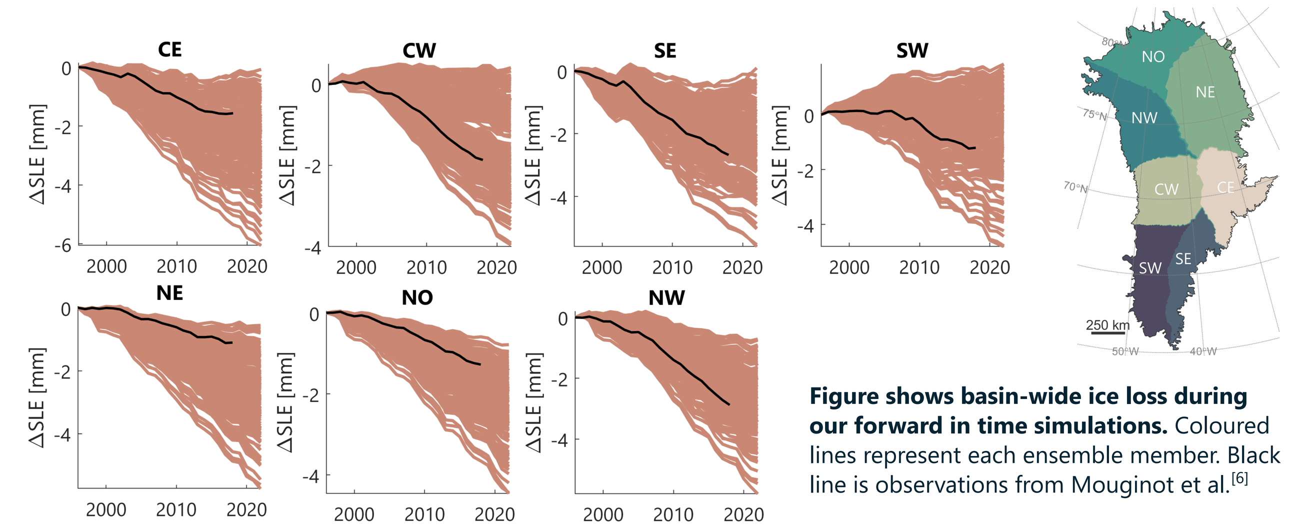


Figure shows basin-wide ice loss during our forward in time simulations. Coloured lines represent each ensemble member. Black line is observations from Mouginot et al.[6]

2 we find posterior parameter distributions that improve the fit to observations

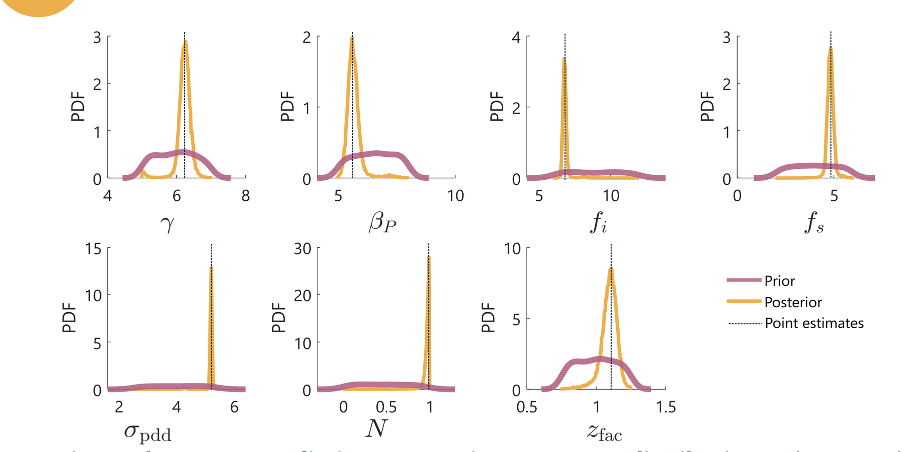
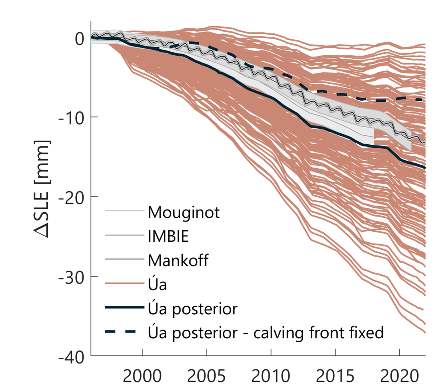


Figure shows very preliminary posterior parameter distributions. These are the output of our initial Bayesian inference. They show tight distributions for most parameters, in particular those most strongly controlling the SMB: the degree day factor for ice and standard deviation of air temperature

We re-evaluate our ice flow using the point estimates from our posterior distributions and find that simulation indeed has the best fit to observations (lowest misfit)



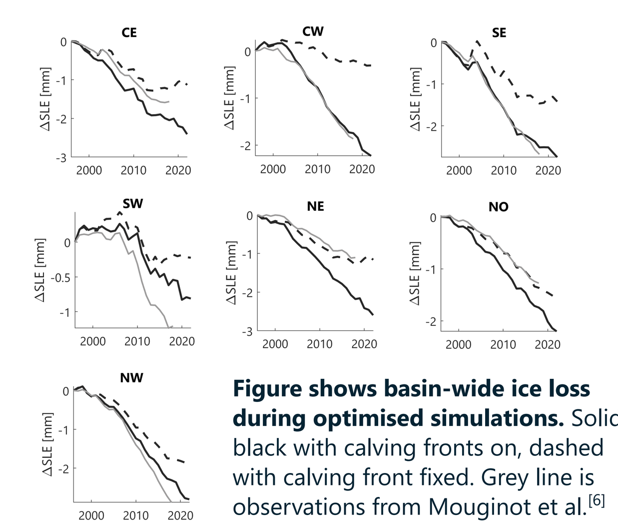


Figure shows basin-wide ice loss during optimised simulations. Solid black with calving fronts on, dashed with calving front fixed. Grey line is observations from Mouginot et al.[6]

conclusions, caveats, and future work

- We have shown that with the correct forcing and with the correct parameter values for that forcing, our ice sheet model can closely replicate observations of ice loss from the Greenland ice sheet
- But crucially only when we include changes in ice front position through time. But that doesn't exactly help us decide how to force calving front position changes in the future - that's for future work!

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