



State and parameter estimation for Ronne Ice Shelf over 1992-2018

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Abstract. Projections of sea level change require ice sheet models that reconcile observations with ice flow dynamics to constrain poorly observed processes and parameters. We use the Ice-sheet and Sea-level System Model (ISSM) to construct a state and parameter estimate of Ronne Ice Shelf and its drainage basin from 1992 to 2018. We assimilate time-varying observations of surface velocity and elevation change to reconstruct dynamically consistent time-mean fields of basal friction coefficient and ice rheology, as well as spatio-temporally varying sub-shelf basal melting rates. Relative to existing data assimilation methods, we reduce uncertainty-weighted root mean square error in elevation change and velocity by 21.2% and 43.6%, respectively. Our inferred basal melt estimates capture spatio-temporal patterns driven by ocean currents at 5 km spatial resolution, and match monthly amplitudes 36.7% closer to observations relative to existing estimates. Mass change in the upstream grounded basin exhibits an excellent correlation with Gravity Recovery and Climate Experiment (GRACE) estimates ($R = 0.75$). This dynamically consistent 26-year reconstruction of Ronne Ice Shelf establishes a prototype for state estimation across Antarctica and Greenland, enabling better-constrained ice sheet models and more credible sea level projections.

1 Introduction

Uncertainty in the dynamic behavior of the Antarctic Ice Sheet (AIS) remains a major limitation on projections of future sea level change (Seroussi et al., 2020; Edwards et al., 2021; Fox-Kemper et al., 2021). Several key processes governing ice sheet response to climate change operate at the ice-ocean interface, making it essential to understand and predict the evolution of floating ice shelves and their interactions with the ocean. Although these shelves do not directly contribute to sea level, they buttress grounded ice and regulate its discharge across grounding lines. Sub-shelf basal melting and refreezing, or "basal melt", modifies ice shelf thickness and geometry; this alters stress transmission and buttressing, with potentially rapid consequences for grounded ice discharge (Pritchard et al., 2012; Gudmundsson et al., 2019). Accurately constraining basal melt is therefore critical, particularly near grounding lines and shear margins, where changes in ice shelf thickness exert strong influence on upstream grounded ice dynamics (Goldberg et al., 2019).

Over the past three decades, multi-mission satellite and in situ observations have transformed our ability to monitor the coupled ice-sheet/ice-shelf system. Laser altimetry resolves surface elevation change; synthetic aperture radar and image feature tracking constrain ice velocity change; and gravimetry informs basin-scale mass change (Smith et al., 2020; Nilsson et al., 2022; Gardner et al., 2024; Sasgen et al., 2019). Airborne surveys and in situ measurements provide complementary constraints on ice thickness, subglacial topography, ice shelf cavity geometry, ocean properties, and basal melt (Morlighem, 2022;



Vaňková and Nicholls, 2022; Cook et al., 2022; Anselin et al., 2025). Yet these records differ in spatial coverage, temporal sampling, and uncertainty; furthermore, direct observations of the ice-ocean interface remain especially sparse beneath ice shelves. Even when combined, these observations cannot uniquely identify processes driving changes in elevation, velocity, and mass because those changes reflect overlapping effects, including ice advection, deformation, surface mass balance, firm evolution, and basal melt. Their joint interpretation therefore calls for a framework that can infer poorly-observed parameters while constraining them using physically-consistent ice dynamics processes and measurements.

Data assimilation provides such a framework by combining observations with a physical model to estimate the evolving state of a system and its uncertain parameters (Morlighem and Goldberg, 2023). Four-dimensional variational (4D-Var) methods and Kalman filtering have long been used for time-dependent state and parameter estimation in meteorology and oceanography (Stammer et al., 2002; Errico, 1997; Wunsch and Heimbach, 2013; Forget et al., 2015). Within ice sheet modeling, inverse methods have traditionally taken the form of time-independent, or snapshot, inversions, which use single-epoch or time-mean surface velocity fields to infer basal friction or ice rheology (MacAyeal, 1989; Larour et al., 2012a; Morlighem et al., 2013). Although these inversions can reproduce observed flow at the assimilation epoch, they neither constrain the transient evolution of ice geometry and flow under past atmospheric and ocean forcing nor ensure consistency with observed rates of change; subsequent forward simulations may therefore exhibit artificial drift (Goldberg and Heimbach, 2013; Gillet-Chaulet, 2020; Choi et al., 2023). By contrast, time-dependent state and parameter estimation seeks a dynamically consistent model trajectory that minimizes misfit to observations throughout an assimilation interval while satisfying stress balance and mass conservation.

Building on the development of a time-dependent adjoint framework for marine ice sheet state estimation (Goldberg and Heimbach, 2013), an early application assimilated ICESat altimetry over Northeast Greenland Ice Stream to jointly infer basal friction and surface mass balance (Larour et al., 2014b). Annually resolved surface elevation and velocity observations over Smith, Pope, and Kohler glaciers were later assimilated to estimate an evolving state and spatially varying, time-mean parameters (Goldberg et al., 2015). Transiently calibrated ice state was subsequently used to initialize coupled ice-ocean simulations (Goldberg and Holland, 2022). More recent applications have assimilated time-varying velocity records at Kjer Glacier and in northwestern Greenland, improving agreement with observed evolution and yielding projections that differ materially from those based on snapshot initialization (Choi et al., 2023; Badgeley et al., 2025). At Thwaites Glacier, transient calibration using both velocity and surface elevation has further demonstrated that observations selected for assimilation strongly affect reconstructed evolution and projected mass loss (Goldberg et al., 2026). Beyond these predominantly adjoint-based variational applications, ensemble Kalman methods provide a complementary approach to joint state and parameter estimation (Gillet-Chaulet, 2020; Choi et al., 2025). Together, these studies demonstrate the value of time-dependent assimilation. However, existing applications have focused primarily on outlet glaciers; where ice shelves are represented, they have generally prescribed basal melt rather than estimated it as a spatially and temporally varying model control.

In parallel, observation-based approaches have produced Antarctic-wide estimates of ice shelf basal melt, ranging from multiyear mean fields to multi-decadal quarterly reconstructions (Rignot et al., 2013; Adusumilli et al., 2020; Paolo et al., 2023). These products diagnose basal melt kinematically through mass continuity, combining estimates of thickness change, surface mass balance, and horizontal ice flux divergence; time-varying reconstructions also largely assume time-invariant

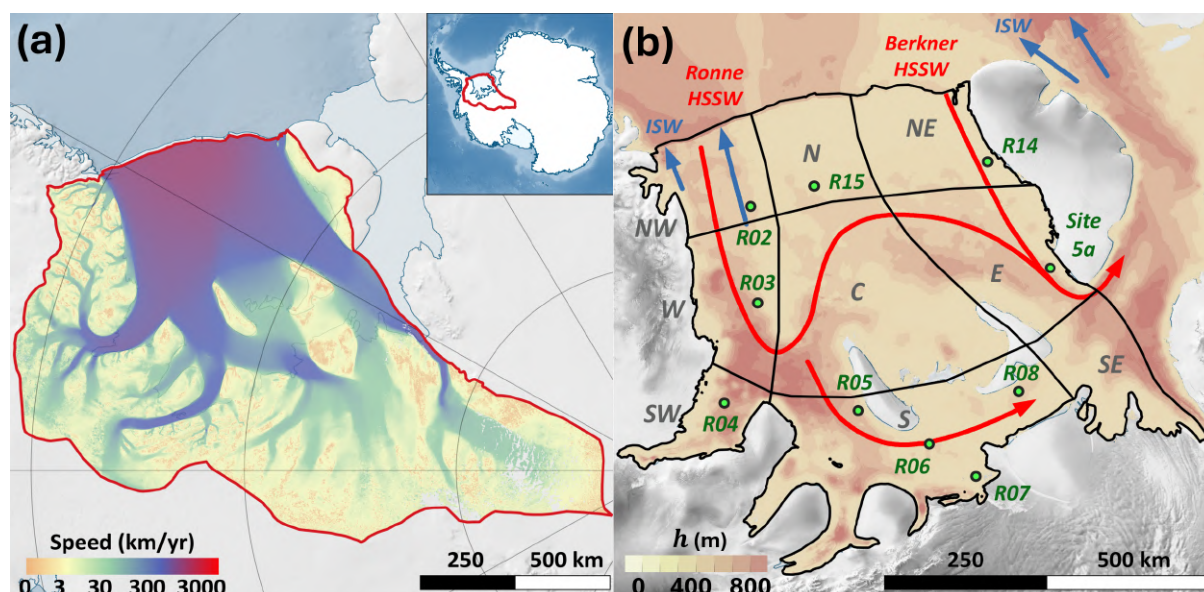


Figure 1. (a) Ice sheet velocity mosaic plotted over region of interest Ronne Ice Shelf (RIS) and surrounding drainage basin (Rignot et al., 2017). (b) RIS water column thickness h with regional cardinal designations delineated in black/gray; ocean current flow of dense Ronne and Berkner High Salinity Shelf Water (HSSW) inflows in red; buoyant Ice-Shelf Water (ISW) outflows in blue; observational melt measurement sites shown in green (Vaňková and Nicholls, 2022).

ice velocity outside the Amundsen Sea Embayment (Adusumilli et al., 2020; Paolo et al., 2023). However, while invaluable for characterizing spatial-temporal variability of basal melt, these inferred patterns are not constrained to reproduce coupled evolution of geometry and flow across ice-sheet/ice-shelf systems within a prognostic ice dynamics model. No study has yet demonstrated joint transient calibration of multiple physical parameters on a major Antarctic ice shelf that is consistent with physical laws as well as observational data.

To address this, we use the Ice-sheet and Sea-level System Model (ISSM) to construct a 26-year state and parameter estimate of Ronne Ice Shelf (RIS) and its drainage basin spanning 1992-2018 (Fig. 1). We jointly assimilate time-varying observations of surface velocity and elevation change to infer spatially varying, time-mean basal friction and ice rheology, together with a spatially and temporally varying basal melt field. This approach yields, to our knowledge, the first multidecadal state estimate of a major Antarctic ice shelf in which basal melt is treated as a time-dependent model control. We evaluate the resulting reconstruction against in situ basal melt observations (Vaňková and Nicholls, 2022) and basin-scale mass change estimates for the upstream grounded ice sheet from the Gravity Recovery and Climate Experiment (GRACE) mission (Sasgen et al., 2019).



2 Data and methods

75 2.1 State estimation

State estimation is the process of combining observations with a numerical physical model over a finite time interval to infer a system's retrospective behavior. In practice, this smoothing problem is a massive, non-linear least-squares optimization. The procedure generates a dynamically and kinematically self-consistent time-trajectory of a system whose residual misfits between the underlying physical model and the observed data are ideally within prior expectations (Wunsch and Heimbach, 2007; Wunsch, 2019). Existing efforts such as the Estimating the Circulation and Climate of the Ocean (ECCO) consortium pioneered this modeling method in the oceanographic community, and has led to support for its usage in the cryosphere community with this study (Wunsch and Heimbach, 2007; Forget et al., 2015). In our work, the model describes glacier flow via a coupled system of stress balance and mass transport equations, along with boundary conditions and forcings at the ice-bed, ice-atmosphere, and ice-ocean interfaces (Larour et al., 2014a). Formal representation of this problem is taken from existing 80 works (Stammer et al., 2002; Wunsch, 2019; Goldberg and Heimbach, 2013; Larour et al., 2016), and is adapted as follows:

$$\mathbf{x}_{t+1} = \mathcal{M}(\mathbf{x}_t, \mathbf{q}_t, \mathbf{u}_t) \quad \text{for } t = t_0, \dots, t_f, \quad (1)$$

$$\mathbf{y}_t = \mathbf{E}_t \mathbf{x}_t + \mathbf{n}_t. \quad (2)$$

Here, $\mathbf{x}_t$ is model glacier state at time t , describing state variables such as ice thickness and ice velocity; $\mathcal{M}$ is the nonlinear glacier dynamics model (Larour et al., 2012b); $\mathbf{q}_t$ denotes prescribed external forcings and boundary conditions such as surface mass balance (SMB) in model space; $\mathbf{u}_t$ denotes unknown "controls", which in this study comprises adjustments in the model physics parameters basal friction, ice rheology, and basal melt; $\mathbf{y}_t$ is the observation vector, comprising available spatio-temporal measurements such as surface velocity and elevation change data; $\mathbf{E}_t$ maps state variables from model space to observation space; i.e., this operator extracts state variables at discrete points in time and space where observations are available; and $\mathbf{n}_t$ is observational noise or error. 90

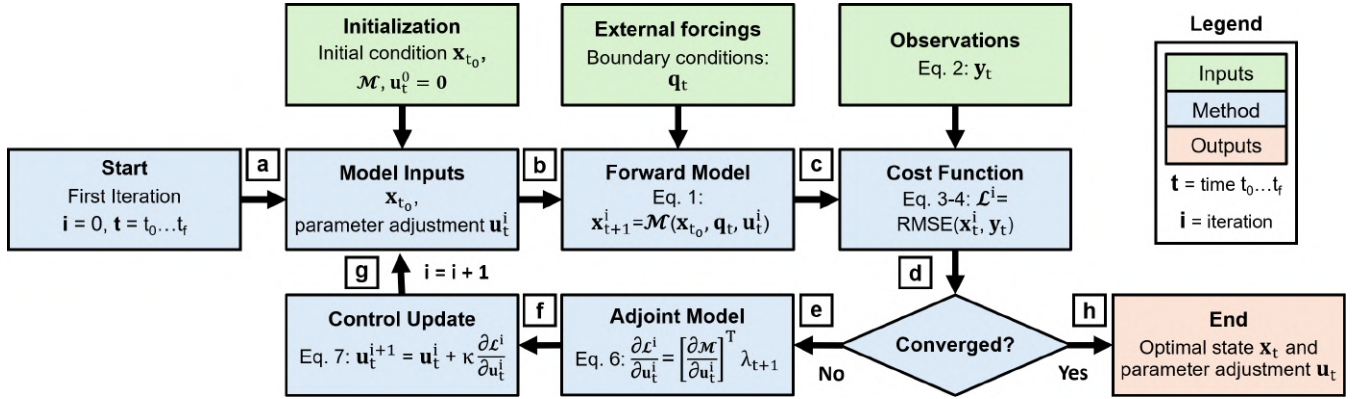


Figure 2. State estimation optimization workflow. (a) Begin with first-guesses of model initial conditions $\mathbf{x}_0$ and model parameters in $\mathcal{M}$. (b) Forward model generates time trajectory state variables $\mathbf{x}_t^i = \mathcal{M}(\mathbf{x}_0, \mathbf{q}_t, \mathbf{u}_t^i)$ for $t = t_0, \dots, t_f$. (c) Cost function $\mathcal{L}^i$ is calculated from the difference between predicted and observed state. (d) Convergence criteria are checked (i.e., $\frac{\|\nabla \mathcal{L}^i\|}{\|\nabla \mathcal{L}^i=0\|} < 10^{-5}$), and if they are not yet met, (e) the adjoint model is run to obtain a gradient of the cost with respect to the control parameters. (f) Optimal control adjustments determined from the gradient are applied to parameters, before (g) iteration $i+1$ begins. Once convergence criteria are met, (h) optimal model parameters and states are retrieved.

95 Assuming that model parameters in $\mathcal{M}$ and initial conditions $\mathbf{x}_0$ are initialized sufficiently well via "snapshot inversion" (time-invariant inverse control method, see Larour et al. (2005); Morlighem et al. (2013)), the main goal of state estimation is then to find optimal model parameter adjustments $\mathbf{u}_t$ with uncertainty $\mathbf{Q}_t$, and model state $\mathbf{x}_t$ with uncertainty $\mathbf{P}_t$ that is consistent with observations $\mathbf{y}_t$ with uncertainty $\mathbf{R}_t$, such that overall model-data misfit is minimized. The function $\mathcal{J}$ that measures this misfit is:

$$100 \quad \mathcal{J} = \sum_{t=1}^{t_f} [\mathbf{y}_t - \mathbf{E}_t \mathbf{x}_t]^T \mathbf{R}_t^{-1} [\mathbf{y}_t - \mathbf{E}_t \mathbf{x}_t]. \quad (3)$$

Constraints are incorporated by appending them to $\mathcal{J}$ in the form of Lagrangian $\mathcal{L}$:

$$\mathcal{L} = \mathcal{J} + \sum_{t=1}^{t_f} \mathbf{u}_t^T \mathbf{Q}^{-1} \mathbf{u}_t - \sum_{t=0}^{t_f-1} \lambda_{t+1} [\mathbf{x}_{t+1} - \mathcal{M}(\mathbf{x}_t, \mathbf{q}_t, \mathbf{u}_t)], \quad (4)$$

105 where the first sum encourages minimal necessary control adjustments conditioned on uncertainty $\mathbf{Q}_t$, the second sum enforces adherence to forward model physics constraints, and λ_t are the Lagrange multipliers, or adjoint variables. By setting the derivatives of $\mathcal{L}$ with respect to $\mathbf{u}_t$, λ_t , and specifically $\mathbf{x}_t$ to 0 (see Stammer et al. (2002) Eq. 4, Wunsch (2019) Eq. 6.3.18), we arrive at a system including the adjoint model equation:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{x}_t} \equiv \lambda_t = \left[\frac{\partial \mathcal{M}}{\partial \mathbf{x}_t} \right]^T \lambda_{t+1} + \left[\frac{\partial \mathbf{E}_t}{\partial \mathbf{x}_t} \right]^T \mathbf{R}_t^{-1} [\mathbf{y}_t - \mathbf{E}_t \mathbf{x}_t]. \quad (5)$$

Terminal value λ_{t_f} is assumed to be given by the second term on the right side of the above equation as λ_{t_f+1} is undefined. This accumulates sensitivities of $\mathcal{L}$ with respect to all model states $\mathbf{x}_t$ at all times. In this application, model parameters affect



110 the cost function indirectly via model state (see Eq. 3). Desired cost gradients are derived as follows:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{u}_t} = \left[\frac{\partial \mathcal{M}}{\partial \mathbf{u}_t} \right]^T \lambda_{t+1}. \quad (6)$$

These gradients indicate adjustments to control parameters $\mathbf{u}_t$ such that cost function $\mathcal{L}$ is minimized. Unknown parameters are then updated for subsequent forward run $i + 1$ (Fig. 2f-g) as follows:

$$\mathbf{u}_t^{i+1} = \mathbf{u}_t^i - \kappa \frac{\partial \mathcal{L}}{\partial \mathbf{u}_t}, \quad (7)$$

115 where κ controls step size in the descent direction, and is determined via quasi-newton methods detailed in Sect. 2.3. Iterative forward-adjoint simulations continue until the cost function converges sufficiently ($\kappa < 10^{-7}$, $\frac{\|\nabla \mathcal{L}^i\|}{\|\nabla \mathcal{L}^0\|} < 10^{-5}$, or as a fallback, $i > 125$). The final $\mathbf{x}_t$ and $\mathbf{u}_t$ represent optimal model state and parameter adjustments.

2.2 Forward and inverse model

Model $\mathcal{M}$ (Eq. 1) is evaluated in practice using the Ice-sheet and Sea-level System Model (ISSM). ISSM is a thermomechanical
120 finite-element ice flow model that implements conservation laws, constitutive material laws, and boundary conditions (Larour et al., 2012b). Model setup for each of the physical modules (stress balance, mass transport, thermal, and grounding line migration) follows existing work (Schlegel et al., 2018). The stress balance module uses 2D Shelfy Stream Approximation (SSA), as it is computationally efficient and sufficiently accurate for large, relatively thin ice sheets (MacAyeal, 1989).

Ice rheology B is based on Glen's flow law, where Glen's flow law exponent is 3; it is dependent on ice temperature, crystal
125 fabric alignment/structure, and large scale damage from rifts and crevasses (Glen and Perutz, 1955; Cuffey and Paterson, 2010). Basal friction α is implemented as the linear friction law equation: $\tau_b = -\alpha^2 \mathbf{v}_b$, where τ_b is the basal stress vector, $\mathbf{v}_b$ is the basal velocity vector, and α is the basal drag coefficient (Budd et al., 1979; Cuffey and Paterson, 2010). Rheology and friction formulations are chosen due to their effectiveness as shown in previous studies (Morlighem et al., 2013; Schlegel et al., 2018; Larour et al., 2012b; Seroussi et al., 2017).

130 The grounding line module assumes a perfect connection to the ocean with no hydrological flow. Relation $N = g(\rho_i H + \rho_w z_b)$ is used to approximate effective pressure of water at the glacier base, where g is gravity, H is ice thickness, ρ_i is ice density, ρ_w is water density, and z_b is bedrock elevation relative to sea level (Cuffey and Paterson, 2010). The grounding line evolves assuming hydrostatic equilibrium and incorporates sub-element migration (Seroussi et al., 2014). The mass transport module uses a depth-integrated mass conservation equation and reads: $\Delta H \equiv \frac{\partial H}{\partial t} = -\nabla \cdot (H \bar{\mathbf{v}}) + \dot{m}_s - \dot{m}$, where $\bar{\mathbf{v}}$ is depth-
135 averaged velocity, H is ice thickness, $\dot{m}_s$ is surface accumulation (in m yr^{-1} of ice equivalent), and $\dot{m}$ is basal melt (in m yr^{-1} of ice equivalent). Bed elevation is from BedMachine Antarctica (Morlighem, 2022). Ice surface elevation, or the digital elevation model (DEM), is taken from REMA (Howat et al., 2022). Ice thickness is initialized to be the surface-bed difference on grounded ice, and derived from surface elevation alone assuming hydrostatic equilibrium on the ice shelf. Surface mass balance (SMB) represents net change in ice mass from precipitation, evaporation, and melt at the ice surface. The Glacier
140 Energy and Mass Balance v1.3 (GEMB v1.3) model provides 5 km gridded monthly SMB values, from 1992-2024 (Gardner et al., 2023). GEMB v1.3 uses the same dynamical core as ISSM, minimizing representation error that may arise when using



SMB products from other frameworks such as RACMO. Firn Air Content (FAC) is a correction that converts altimetric surface elevation to ice-equivalent thickness, accounting for variable firn density due to uncompacted snow. GEMB v1.3 is used to prescribe physically-consistent FAC at the same spatial and temporal resolutions as SMB.

145 The inverse model is implemented within ISSM using the CoDiPack algorithmic differentiation library to automatically calculate the model adjoint for an arbitrary cost function (Eq. 3-6) and its associated control parameter adjustment gradients (Eq. 7) (Larour et al., 2016; Morlighem et al., 2021; Sagebaum et al., 2017). These gradients capture sensitivity of model-data misfit relative to each control parameter, and reduce model-data misfit over many (~ 100) iterations.

2.3 Cost function

150 Cost function $\mathcal{L}$ (Eq. 4) is implemented in practice as a weighted sum of velocity misfit, elevation change misfit, and regularization terms intended to enforce spatial smoothness and prevent non-physical high frequency spatial oscillations in the control fields. It takes the explicit form:

$$\mathcal{L} = \frac{1}{2} \sum_t \int_S \gamma_1 \frac{(v - v_{\text{obs}})^2}{\sigma_{v_{\text{obs}}}^2} + \gamma_2 \frac{(\Delta H - \Delta H_{\text{obs}})^2}{\sigma_{\Delta H_{\text{obs}}}^2} + \gamma_3 \frac{\|\nabla \dot{m}\|^2}{\sigma_{\dot{m}}^2} dS, \quad (8)$$

where v^t , v_{obs}^t , and $\sigma_{v_{\text{obs}}^t}$ denote modeled, observed, and uncertainty in surface velocity at time t , respectively; ΔH^t , ΔH_{obs}^t , and $\sigma_{\Delta H_{\text{obs}}^t}$ denote modeled, observed, and uncertainty in surface elevation change at time t , respectively; $\|\nabla \dot{m}\|$ represents basal melt control gradient magnitude, used to regularize/penalize high frequency noise in the solution; and $\gamma_1 - \gamma_3$ are weighting parameters such that each term contributes comparably to total cost. Several caveats are to be noted in this optimization routine. In order to assure each control (i.e., friction, ice rheology, and melt rate) contributes to cost function reduction equally despite their large difference in scales, control adjustments are scaled relative to the magnitude of their uncertainties in the process known as non-dimensionalization (on the order of $\sigma_\alpha \approx 10$, $\sigma_B \approx 10^8$, and $\sigma_{\dot{m}} \approx 1$). These values are incorporated into $\mathcal{L}$ as baseline weights for $\gamma_1, \gamma_2, \gamma_3$. To facilitate efficient optimization, the L-BFGS quasi-newton method is used to approximate the Hessian (second derivative) of cost function $\mathcal{L}$, which optimizes step size κ (Eq. 7) and the direction to descend down the gradient, thus achieving faster convergence (Liu and Nocedal, 1989).

Uncertainty terms used in $\mathcal{L}$ and model initialization incorporate prior information into the algorithm through error propagation. Observational uncertainty $\mathbf{R}_t$ is incorporated in $\mathcal{L}$ as $\sigma_{v_{\text{obs}}^t}$ and $\sigma_{\Delta H_{\text{obs}}^t}$. Ice elevation change uncertainty (time-mean $\sigma_{\overline{\Delta H}}$, Fig. 3d) is processed from original dataset source providers, and accounts for assorted altimetric, tidal, atmospheric, and cross-sensor errors (Nilsson et al., 2022; Paolo et al., 2023). Ice surface velocity uncertainty ($\sigma_{\overline{v}}$, Fig. 3f) is derived from dataset providers, with processing to remove outliers and add a formal error component accounting for spatio-temporal processing discrepancies Gardner et al. (2024). Control parameter uncertainty $\mathbf{Q}_t$ is incorporated in model initialization as σ_α as well as σ_B , and in $\mathcal{L}$ as $\sigma_{\dot{m}}$. Basal friction uncertainty (σ_α , Fig. 6d) is derived from surface height and velocity observational uncertainty propagated through a linearized version the initialization equation: $\sigma_\alpha = \sigma_v \left(\frac{\rho_i g H \|\nabla s\|}{2\alpha(\|v\| + \epsilon_v)} \right)^{1/2} - \sigma_v \frac{(\rho_i g H \|\nabla s\|)^{1/2}}{2\|v\|^{3/2}}$, assuming velocity uncertainty is small relative to bed uncertainty. Ice rheology uncertainty (σ_B in Fig. 6h) is derived from modeled temperature uncertainty and estimated model representation error along grounding line/shear margins. Basal melt



uncertainty (time invariant $\sigma_{\dot{m}}$ in Fig. 8b) is computed from variance of existing basal melt estimates. Model state uncertainty
 175 $\mathbf{P}_t$ is not utilized in this implementation.

2.4 Input data

This study is carried out on Ronne Ice Shelf (RIS) and its surrounding drainage basin, from 1992 to 2018. Boundaries are defined using IMBIE (MEaSURES Antarctic Boundaries for IPY 2007-2009 from Satellite Radar (NSIDC-0709)) (Zwally et al., 2012). The ice front is static, and is forced to the 2007-2009 mean. Model mesh resolution varies from 2km near the
 180 grounding line, 8km over the ice shelf, to 40km in the interior, resulting in a ~ 41000 element mesh. Control parameters are limited to basal friction α , ice rheology B , and time-varying basal melt $\dot{m}$.

Table 1. Summary of model data inputs, constraints, and controls. Values are approximate and domain-averaged over the RIS basin.

Category	Name (symbol)	Time range	Reference	Typical range (units)
Observed states ($\mathbf{y}$)	Ice surface velocity ($\mathbf{v}$)	1992 - 2018	Gardner et al. (2024)	[0, 1500] (m yr^{-1})
	Elevation change (ΔH)	1992 - 2018	Nilsson et al. (2022); Paolo et al. (2023)	[-2, 2] (m yr^{-1})
Control parameters ($\mathbf{u}$)	Basal friction (α)	Time-invariant	Morlighem et al. (2013)	[10^2 , 10^4] (Pa s m^{-1})
	Ice rheology (B)	Time-invariant	Seroussi et al. (2013)	[10^7 , 10^8] ($\text{Pa s}^{1/3}$)
	Basal melt ($\dot{m}$)	1992 - 2018	Rignot et al. (2013)	[-3, 3] (m yr^{-1})
Validation data	Basal melt ($\dot{m}_{V22}$)	2016 - 2018	Vaňková and Nicholls (2022)	[-1, 2] (m yr^{-1})
	Basal melt ($\dot{m}_{P23}$)	1992 - 2020	Paolo et al. (2023)	[-3, 3] (m yr^{-1})
	Basal melt ($\dot{m}_{A20}$)	2010 - 2018	Adusumilli et al. (2020)	[-3, 3] (m yr^{-1})
	Mass change (ΔM)	2002 - 2022	Sasgen et al. (2019)	[-5, 5] (Gt/yr)

First-guesses for each control parameter $\mathbf{u}_t$ are estimated during model spin-up using snapshot inversions, which enables better convergence during optimization. Key model inputs, constraints, and controls are listed in Table 1 and described below. First-guess basal ice shelf melt rate is obtained from Rignot et al. (2013) in meters per year. The basal melt parameterization
 185 assumes vertical melting only. Seasonal variation is used as a proxy for uncertainty, which is derived from the standard deviation of the Paolo et al. (2023) melt rate time series. First-guess ice rheology (a parameterization of ice viscosity, ice fabric, and damage) is derived from ice temperature computed from a thermal steady state model simulation on the grounded ice following (Seroussi et al., 2013)). The three-dimensional higher-order (Blatter, 1995; Pattyn, 2003) thermal simulation uses geothermal heat flux (Maule et al., 2005) and surface temperatures (van Wessem et al., 2018) to converge upon a temperature gradient.
 190 Temperature is then depth-averaged, and ice rheology B is derived from it using the relation $\mu = \frac{(1-D)B}{2\dot{\epsilon}_e \frac{n}{n-1}}$. Ice rheology is inferred on the ice shelf from time-mean ice velocity via snapshot inversion, following Larour et al. (2005). These simulations are only used to set initial temperature/rheology, as temperature/rheology profiles of AIS on grounded ice are generally stable over century time scales (Seroussi et al., 2013). First-guess friction is initialized according to Eq. 31 from Morlighem et al.



(2013): $\alpha = \left(\frac{\rho_i g H \|\nabla s\|}{\|v_{obs}\| + \epsilon_v} \right)^{1/2}$ where $\|\nabla s\|$ is bed slope, H is ice thickness, $\|v_{obs}\|$ is ice speed, and ϵ_v is set to 0.1 m yr^{-1} . This
195 initialization speeds up optimization by setting basal friction equal to driving stress and assuming basal velocity is equal to
observed surface velocity. First-guess friction and ice rheology are then refined using a series of snapshot inversions constrained
to observed ice velocity.

Observational constraints y_t comprise ice surface velocities derived from Landsat/Sentinel data (Gardner et al., 2024; Rignot
et al., 2022) and ice elevation change derived from ERS1/2, Cryosat, and ICESat-1 (Paolo et al., 2023; Adusumilli et al., 2020).
200 Input forcings q_t such as temperature and surface mass fluxes are based on other model (GEMB) estimates. Unknown model
parameters include ice shelf geometry, time-varying basal melt, and freshwater mass fluxes across the grounding line. Table 1
lists typical ranges, units, and sources for each of the above fields.

3 Results and Discussion

3.1 State variables

205 Control adjustments result in corrections to ice velocity and elevation change state variables x_t that can be compared against
observations y_t while considering observational uncertainty R_t . These changes are evaluated via unweighted and weighted
root mean square error (RMSE).

We improve average elevation change error $RMSE_{\Delta H}$ by 10.51%, reduced from $RMSE_{\Delta H_0} = 0.753 \text{ m yr}^{-1}$ to $RMSE_{\Delta H_f} =$
 0.674 m yr^{-1} (Fig. 3c-d). Unweighted improvement is visible on the shelf and is primarily attributable to basal melt adjust-
210 ments. Weighted $RMSE_{\Delta H \sigma^{-1}}$ is improved by 21.2% (Fig. 3e). Weights on shear margins are zeroed to minimize interference
from optimizing for an area where elevation change has known and un-capturable model-data discrepancies; weights on the
shelf are higher due to uncertainty in tidal corrections/altimetry from source data. Weighted improvement is seen on shear
margins near the grounding line and in the interior. Near shear margins on grounded ice, improvement is interpreted as trying
to match effects of unmodeled physical processes and due to ungrounding effects. In the interior, these elevation change im-
215 provements are interpreted as corrections for measurement error due to slope, and are primarily attributable to basal friction
adjustments. Note that elevation differences of $\sim 0.5\text{m}$ are small relative to ice thickness H , which ranges from 100m on the
ice shelf to several kilometers in the interior. As a consequence, accurate representation of elevation change is less a necessity
for proper ice dynamics modeling and more an important observational constraint on control parameters. For specific observa-
tional locations on RIS, pre-optimized initial elevation change ΔH_{ini} deviates beyond accepted uncertainty bounds $\sigma_{\Delta H_{obs}}$, and
220 in some cases exhibits runaway behavior (Fig. 4a,e,f). Post-optimization modeled ΔH exhibits a smoother record of elevation
change than observations would suggest, but still largely falls within uncertainty bounds. This smoothness is attributable to
model resolution limits/representation error, but could also indicate noisiness in the observational record due to actual high
frequency variations or measurement error.

We improve average velocity error $RMSE_{\bar{v}}$ by 30.8%, reduced from $RMSE_{\bar{v}_0} = 40.3 \text{ m yr}^{-1}$ to $RMSE_{\bar{v}_f} = 27.9 \text{ m}$
225 yr^{-1} (Fig. 3g-h). Weighted $RMSE_{\bar{v} \sigma^{-1}}$ is improved by 43.6% (Fig. 3j). Weights in the interior near the pole are zeroed out

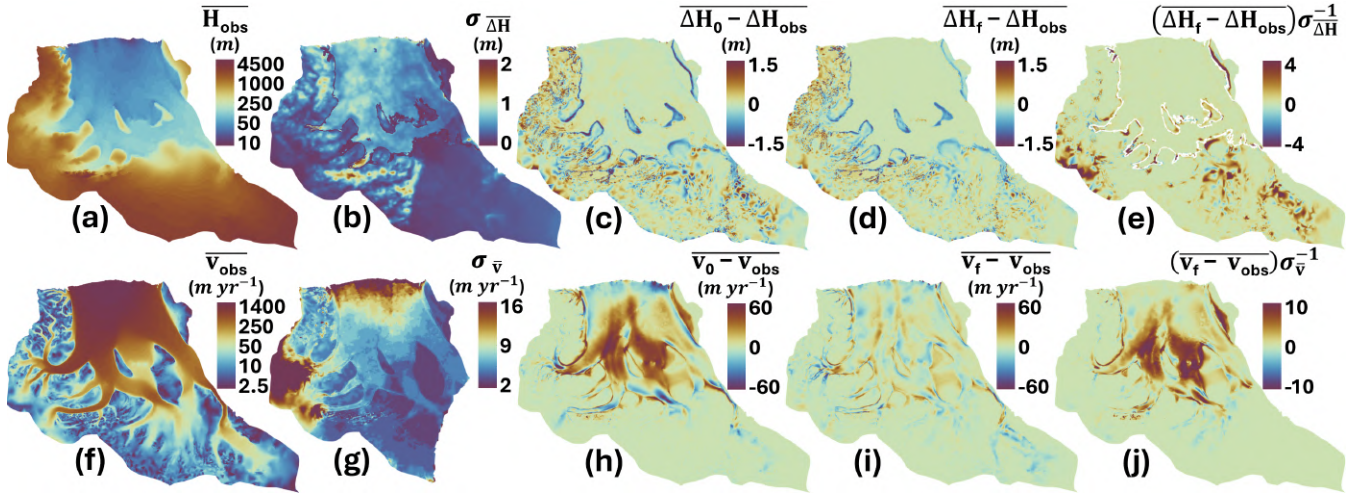


Figure 3. (a) Mean observed $\overline{H_{obs}}$ in log-scaled meters, averaged over 1992-2018. (b) Elevation change uncertainty $\sigma_{\Delta H}$. (c) Initial misfit $\overline{\Delta H_0} - \overline{\Delta H_{obs}}$ with $RMSE_{\overline{\Delta H_0}} = 19.2\text{m}$ is optimized to (d) $\overline{\Delta H_f} - \overline{\Delta H_{obs}}$ with $RMSE_{\overline{\Delta H_f}} = 16.0\text{m}$. (e) Improvement in uncertainty-weighted misfit cost ($\|\overline{\Delta H_0} - \overline{\Delta H_f}\| \sigma_{\Delta H}^{-1}$) is primarily on the shear margins and the interior, while misfit on the shelf has been reduced to be on the order of elevation change uncertainty levels. (f) Mean observed $\overline{V_{obs}}$ in log-scaled meters per year, averaged over 1992-2018. (g) Velocity uncertainty $\sigma_{v_{obs}}$. (h) Initial misfit $\overline{V_0} - \overline{V_{obs}}$ with $RMSE_{\overline{V_0}} = 30.5\text{m yr}^{-1}$ is optimized to (i) $\overline{V_f} - \overline{V_{obs}}$ with $RMSE_{\overline{V_f}} = 25.5\text{m yr}^{-1}$. (j) Improvement in uncertainty-weighted misfit cost ($\|\overline{V_0} - \overline{V_f}\| \sigma_v^{-1}$) is primarily on the shelf, and worsens slightly in areas throughout the domain.

due to lack of coverage, slow ice, and consequent high uncertainty in velocity measurement; weights in western RIS and calving front are high due to large uncertainty in source data. Improvement is seen on the ice shelf, both in free-floating areas as well as the central region where ice rises and tenuously grounded ice, which is primarily attributable to ice rheology adjustments. Note that optimized velocities $\overline{v}$ tend towards time-mean mosaic $\overline{v_{mos}}$, and does not vary in time as much as v_{obs} would suggest. We attribute this discrepancy to measurement error, as ice velocity on RIS should not vary so quickly over multi-year/decadal timescales, and v still falls roughly within uncertainty bounds $\sigma_{v_{obs}}$. For specific observational locations on RIS, pre-optimized initial velocity v_{ini} deviates beyond accepted uncertainty bounds $\sigma_{v_{obs}}$ significantly, and in many cases exhibits runaway behavior (Fig. 5a,b,c,f,i). Post-optimization modeled v exhibits a more static velocity record than time-varying observations v_{obs} would suggest, but again modeled v largely falls roughly within $\sigma_{v_{obs}}$. Similar to modeled elevation changes, we attribute these velocity patterns to model limits/representation error, though these patterns could also indicate variations or measurement error in the observational record beyond provided uncertainties.

3.2 Time-mean parameter estimates α and B

Control adjustments to time-invariant basal friction α and ice rheology B reveal spatial patterns that reflect both physical processes and observational constraints (Fig. 6). Basal friction is adjusted by a median of 3.2% across the grounded ice,

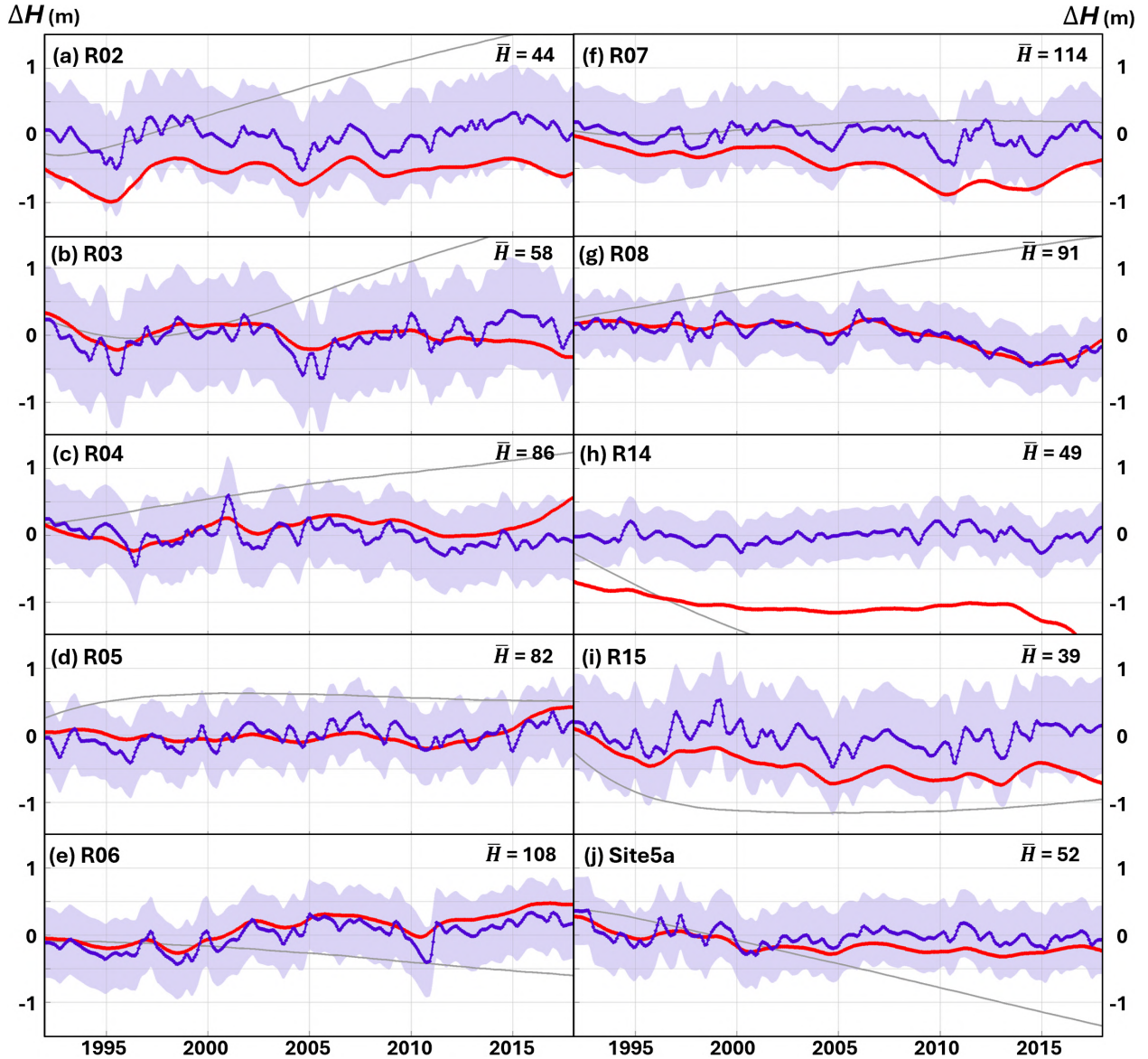


Figure 4. Elevation change ΔH from 1992-2018 for locations R02-R15 and Site5a on RIS, relative to time-mean $\bar{H}$ (a-j). Optimized elevation change ΔH (red) are compared against initial pre-optimized elevation change ΔH_{ini} (solid gray) and elevation change observations ΔH_{obs} (blue); $\sigma_{\Delta H_{obs}}$ uncertainty bound envelope shaded in light blue (Paolo et al., 2023; Nilsson et al., 2022).

240 indicating sufficient initialization with modest corrections contributing to overall misfit improvement. Spatial patterns of larger adjustments correlate with areas of high surface slope, low mesh resolution, and low surface velocity in more mountainous interior regions. Adjustments near the grounding line are minimal, supporting that the initialization procedure based on driving stress balance provides reasonable first-guess friction in these dynamically important and more heavily constrained regions

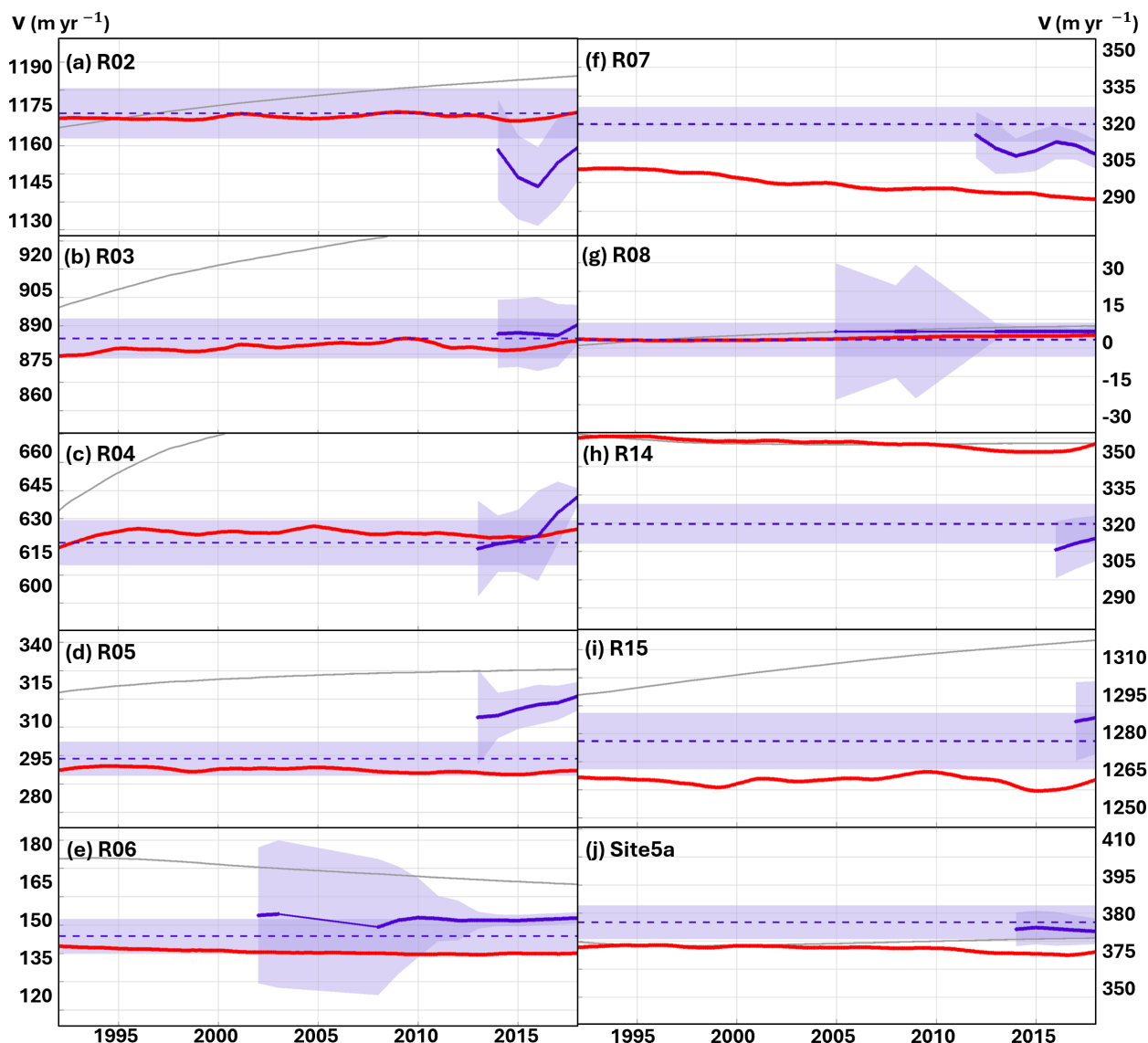


Figure 5. Velocity time series from 1992–2018 for locations R02–R15 and Site5a on RIS (a–j). Optimized velocities v (red) are compared against first-guess velocity v_{ini} (solid gray), time-varying velocities v_{obs} (solid blue) and time-mean velocity mosaics $\overline{v_{mos}}$ (dashed blue); $\sigma_{v_{obs}}$ uncertainty bound envelopes shaded in light blue (Gardner et al., 2024).

(Morlighem et al., 2013). Additional changes are made in the tributary glaciers feeding RIS. Together, these adjustments
 245 compensate for a combination of potential issues, including topographic representation errors, altimetry measurement error due to slope, unresolved bed roughness features, and insufficient velocity constraints in slow-flowing regions. These corrections are primarily correcting for geometric errors rather than mis-characterization of the basal hydrology, for which basal friction is a proxy. This conjecture is made with the assumption that time-invariant basal friction is sufficient to parameterize hydrological

processes in Antarctica due to seasonal stability of subglacial channels; only in Greenland is it potentially worthwhile to include
 250 time-varying basal friction so as to capture seasonal meltwater-intrusion-driven hydrological patterns (Dow et al., 2022).

Ice rheology is adjusted by a median of 3.7% across the domain, and by 16.5% on the ice shelf, indicating sufficient
 initialization on the grounded ice, but improvements to be desired on the ice shelf. Decreases in ice rheology are high along
 shear margins on the shelf where damage processes due to shear stress or deformational heating may soften ice. Additional
 decreases on the shelf imply a weakening of the ice through refreezing of soft, nearly melted ice, as supported by regional basal
 255 melt trends seen in Sect. 10. Increases on the shelf show where more rigid plates of ice form within the ice stream, primarily
 around ice rises in the southern/central and along the western/eastern margins of the shelf. Additional increases in ice rheology
 are found along the shear margins on the grounded ice, which correspond to a slow-down in ice flow feeding perpendicular to
 the shelf, though these adjustments may be less geophysical and more compensating for the representative limitations of the
 model. Along grounded RIS tributaries, small adjustments are made along areas of ice flow, but the majority of ice rheology in
 260 the interior is otherwise unadjusted. Given prior uncertainty conditioned on temperature, velocity, and elevation change, more
 adjustments are made than expected over shear margins. We attribute this discrepancy to a lack of knowledge and constraints
 in the interior as well as sub-surface conditions. Overall, adjustments correspond to areas of high shear, deformational heating,
 and large-scale damage accumulation; these processes were not captured via temperature-initialized/inversion-based values set
 in Sect. 2.4.

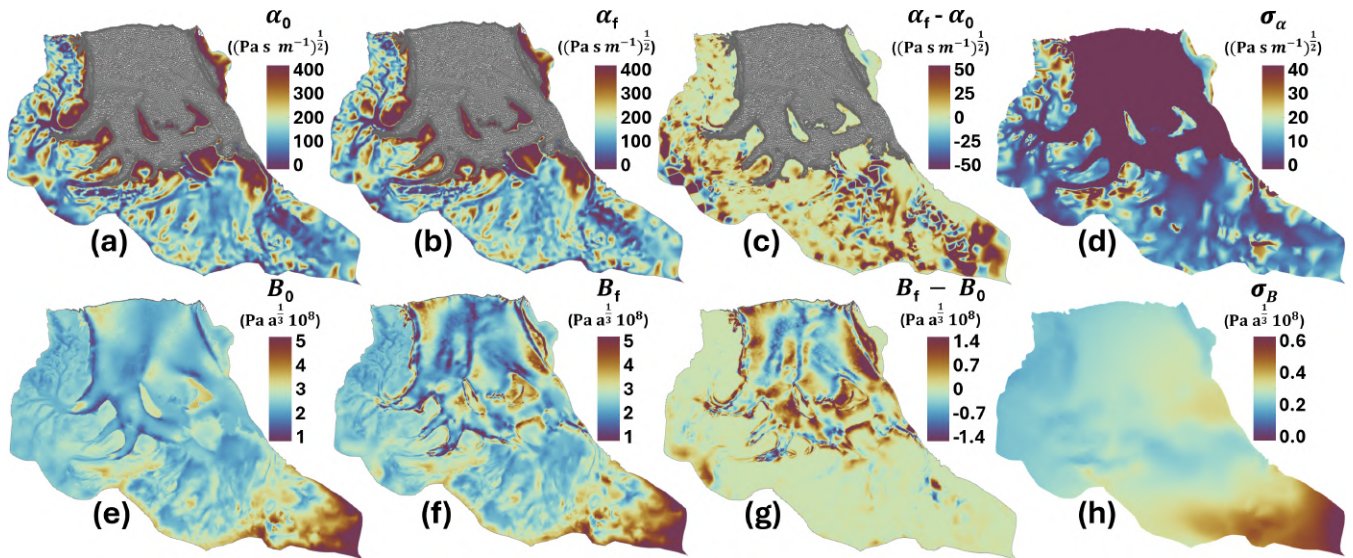


Figure 6. (a) Initial basal friction α_0 , (b) final basal friction α_f , and (c) control adjustment difference $\alpha_f - \alpha_0$. Positive adjustments represent increases in final values relative to initial values. (d) Time-invariant uncertainty σ_α . (e) Initial ice rheology B_0 , (f) final ice rheology B_f , and (g) control adjustment difference $B_f - B_0$. Positive adjustments represent increases in final values relative to initial values. (h) Time-invariant uncertainty σ_B .



265 3.3 Time-varying parameter estimate $\dot{m}$

Time-varying control adjustments to basal melt are shown in Fig. 7. Melt rate adjustments are largest in the first year (up to $\pm 5 \text{ m yr}^{-1}$ in 1992), which we attribute to transient initialization shock and sparse observational constraints. Subsequent years show monthly seasonal changes (on average $\pm 2 \text{ m yr}^{-1}$) relative to their initial values. Adjustments are made relative to time-mean melt rates from Rignot et al. (2013).

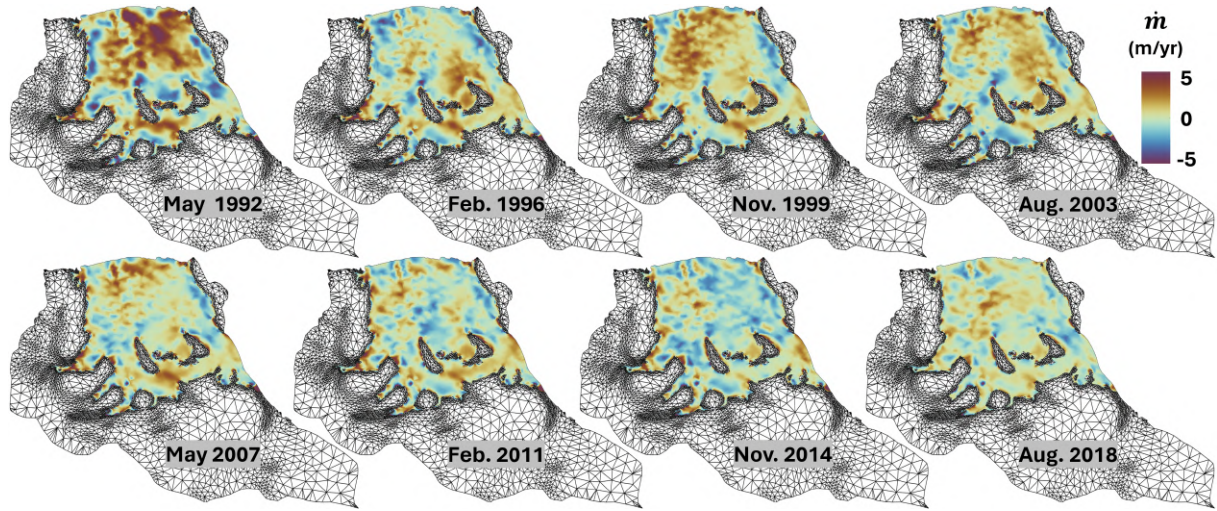


Figure 7. Modeled time-varying basal melt $\dot{m}$ for RIS, 1992-2018.

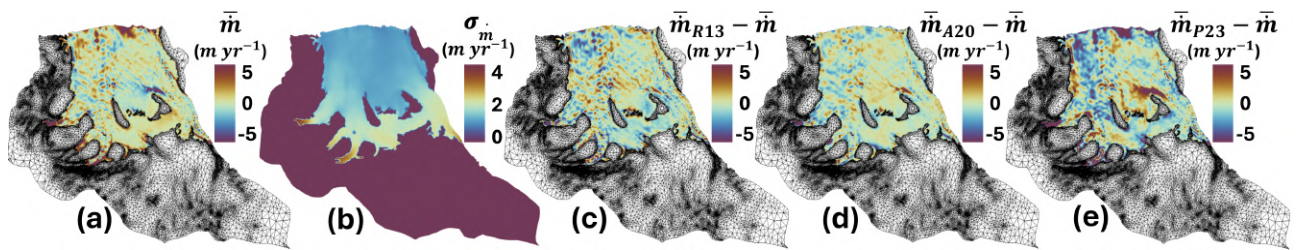


Figure 8. (a) Mean basal melt $\bar{m}$ for 2008. (b) Time-invariant uncertainty $\sigma_{\dot{m}}$. (c) Difference between Adusumilli et al. (2020) and our melt rates ($\bar{m}_{A21} - \bar{m}$) over 2010-2018. (d) Difference between Adusumilli et al. (2020) and our melt rates ($\bar{m}_{A20} - \bar{m}$). (e) Difference between Paolo et al. (2023) and our melt rates ($\bar{m}_{P23} - \bar{m}$). Positive adjustments represent increases relative to estimates from (Rignot et al., 2013).

270 For comparison, we evaluate the 2008 time-mean of our melt rates $\bar{m}$ against values from Rignot et al. (2013) ($\bar{m}_{R13}$), Adusumilli et al. (2020) ($\bar{m}_{A20}$), Paolo et al. (2023) ($\bar{m}_{P23}$), and point observations from (Vaňková and Nicholls, 2022) ($\bar{m}_{V22}$). $\dot{m}_{R13}$ is a 2007-2009 mean melt rate used to initialize our model. $\dot{m}_{A20}$ is a 2010-2018 mean melt rate. $\dot{m}_{P23}$ is a quarterly time series from 1992-2018, derived from corrections made to satellite altimetry records of RIS (Paolo et al., 2023). $\dot{m}_{V22}$ are monthly-averaged 2016-2018 observations at limited locations on RIS. Comparing $\dot{m}$ against these others in Fig.



275 8 shows that differences $\dot{m} - \dot{m}_{A20}$ (Fig. 8c) and $\dot{m} - \dot{m}_{R13}$ (Fig. 8d) are within 3 sigma uncertainty ranges (Fig. 8b); we attribute larger differences in $\dot{m} - \dot{m}_{P23}$ (Fig. 8e) more so to the large relative amplitude of $\dot{m}_{P23}$ relative to observations in $\dot{m}_{V22}$ rather than to errors in our estimate $\dot{m}$.

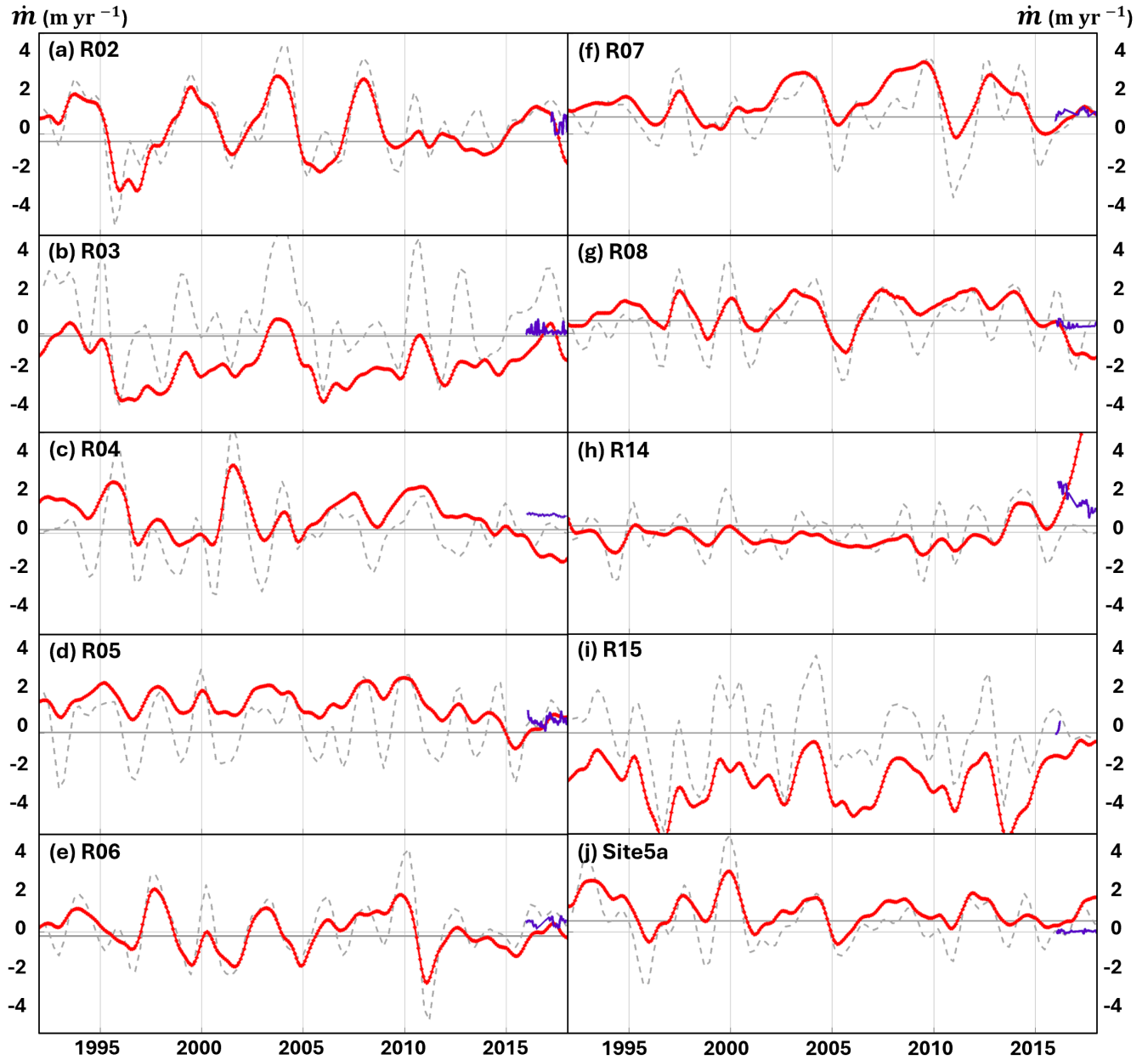


Figure 9. Basal melt $\dot{m}$ from 1992-2018 for locations R02-R15 and Site5a on RIS in frames (a-j), respectively. Reference velocity field for RIS is plotted on the left. Our optimized rates (red) are compared against first-guess time-mean Rignot et al. (2013) ($\dot{m}_{ini} \equiv \dot{m}_{R13}$, solid gray), time-varying Paolo et al. (2023) ($\dot{m}_{P23}$, dashed gray), and observations Vaňková and Nicholls (2022) ($\dot{m}_{V22}$, blue).



Fig. 9 compares $\dot{m}$ against $\dot{m}_{P23}$, $\dot{m}_{R13}$, and $\dot{m}_{V22}$ over time at 10 observational locations. Our model $\dot{m}$ better matches
 observed seasonal amplitudes from $\dot{m}_{V22}$ 36.7% more closely than $\dot{m}_{P23}$. Across these sites, $\dot{m}$ and $\dot{m}_{P23}$ share similar
 280 seasonal phase, but differ in mean and amplitude. Inaccuracy is attributable to the chosen spatio-temporal resolution on the shelf
 (5 km, monthly), which by design is incapable of capturing higher frequency trends. Overestimation of the melt rate amplitude
 is also attributable to uncertainties and potential bias in the ice shelf altimetry corrections derived from Paolo et al. (2023).
 Additionally, the prescribed static calving front may partially explain misfit in modeled trends at nearby locations R02, R14,
 and R15. Further discrepancies may be explained by differences in melt rate parameterizations chosen by different instruments
 285 versus models including ours. These limitations highlight the need for further observations in general to constrain these errors.
 Nevertheless, the overall improvements demonstrates the strength of jointly inferring basal melt within a physically-consistent
 ice flow model over diagnosing it kinematically from altimetry alone, resulting in a melt rate estimate more consistent with
 observations.

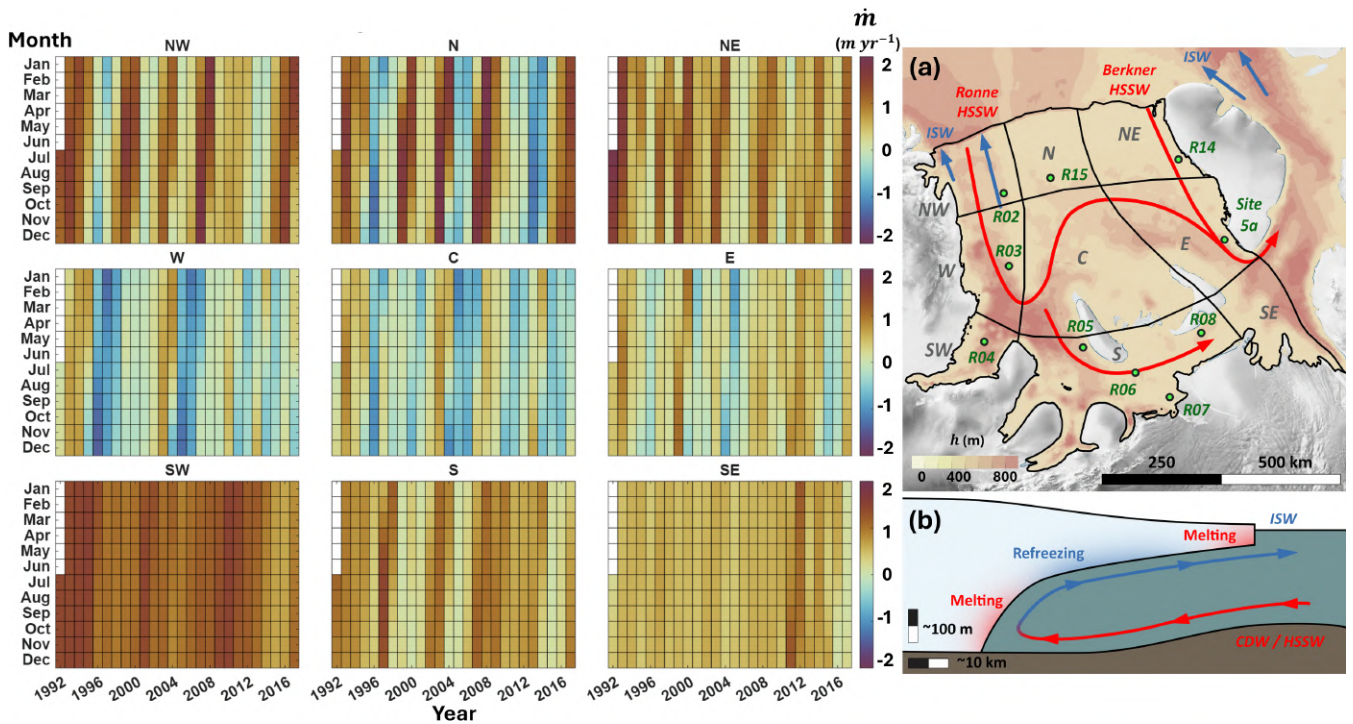


Figure 10. Regionally averaged median basal melt, in meters/year. (a) Planview schematic of RIS overlaid with corresponding cardinal regions and ocean currents. (b) Flowline schematic of ice-ocean interface, showing dominant mode of ocean driven melting/refreezing under the RIS (Jacobs et al., 1992). Circumpolar Dense Water (CDW)/High Salinity Shelf Water (HSSW) causes the highest melting at the grounding line, after which ice shelf refreezing occurs mid-shelf as buoyant subglacial discharge and melt water travels out of the shelf cavity, which is then followed by additional ice shelf mass loss/frontal ablation at the calving front due to surface heat before currents are discharged as Ice Shelf Water (ISW).



Changes to the 26-year basal melt time series $\dot{m}$ provide insight into regional trends, which exhibit strong spatial-temporal patterns consistent with ocean induced melting and refreezing due to ocean current changes. This supports the hypothesis that ocean–ice interactions are a key driver of basal mass balance in the region (Nicholls et al., 2009). We observe high melt rates in the southern regions where warm High Salinity Shelf Water (HSSW) flows into the shelf cavity along the ocean bed to induce melting at the grounding line. As the buoyant freshwater flux from melt and subglacial discharge combines with HSSW to become Ice-Shelf Water (ISW) outflows, it flows up along the base of the ice shelf, where lower basal melt and refreezing in the central regions is observed (Fig. 10). Spatial patterns associated with Ronne HSSW flow (from north to south, and from west to east) are also highlighted in Fig. 10, where more melt is seen in the southwestern sector, followed by less melt in the south and southeastern sectors. Basal melt in the northeastern, eastern, and southeastern sectors is bolstered by inflows of Berkner HSSW along the relatively shallower bed in these areas. Refreezing is supported by virtue of negative adjustments to ice rheology (see Fig. 6g) in these central regions as newly refrozen ice is still close to its melting point, and is thus weaker than initial rheology B_0 (derived from depth averaged temperature of the ice column) would suggest. Northern regions differ in patterns that can again be explained by ocean currents underlying the ice shelf. In northern regions, melting at the calving front and proximity to warm surface waters induce greater melting rates. High melt is observed in the NE region due to the lack of ISW outflow, contrasted with lower melt rates in the north/north-west regions which we attribute to the presence of such ISW outflows. Additionally, inter-annual trends can be observed in the regional melt rates as well. Lower melting is observed during the cold winters of years like 1996, 2004, and 2013, and may be related to the El Niño–Southern Oscillation (ENSO).

3.4 Mass change comparison

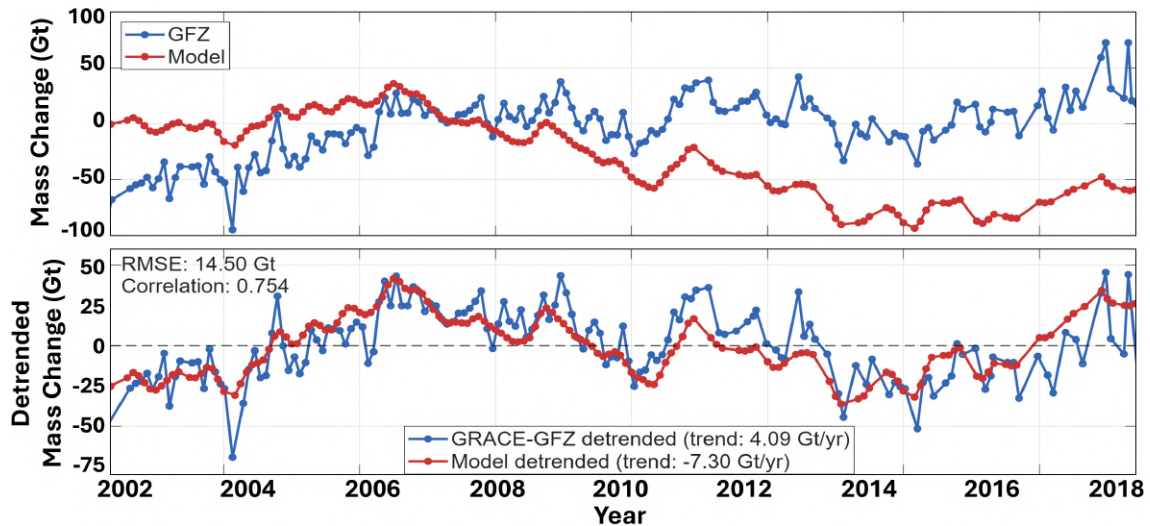


Figure 11. (a) Mass change on the grounded RIS domain relative to the 2004-2010 mean for GRACE-GFZ (blue) and our model (red) from 2002-2018, in Gigatons (Gt). (b) Detrended mass changes for GRACE-GFZ (blue) and our model (red) show high correlation ($R_{GFZ} = 0.75$).



Our model produces mass change estimates that can be validated against GRACE mass change solutions, which were explicitly excluded as constraints for this study. We integrate GRACE solutions from the German Research Centre for Geosciences's (GFZ) RL06 v5 monthly gridded land mass change data (GRACE-GFZ) over RIS's grounded ice and compare it against our total modeled mass change, from 2002-2018 (Fig. 11) (Sasgen et al., 2019). The GRACE-GFZ solution is specifically chosen for comparison over GRACE-JPL and GRACE-CSR solutions due to GFZ's specific handling of ice mass change over Antarctica and Greenland (Dahle et al., 2025). Signal leakage due to differences in model and mascon boundaries is not quantified, as these values are for intercomparison only and not to be taken as actual estimates of mass change.

We find general agreement between the model and GRACE-based mass change estimates. In particular, the detrended mass changes are highly correlated ($R_{GFZ} = 0.75$), underscoring the model's excellent representation of dynamic mass transport on interannual timescales. We attribute part of the discrepancy in secular trends to uncertainty in the glacial isostatic adjustment (GIA) correction applied to the GRACE-GFZ solution. This correction is based on a radially symmetric, one-dimensional Earth viscosity structure and primarily represents the solid Earth response to glacial-cycle loading (Dahle et al., 2025; Richard Peltier et al., 2018). Regional variations in three-dimensional Earth structure and uncertainties in historical ice loading may therefore not be fully represented in the applied GIA correction. Accounting for these effects could modify the GRACE-derived secular trend. Part of the discrepancy may also arise from limitations of our forward model and state estimation. In particular, we prescribe a static calving front during a period when RIS increased in area by $736 \text{ km}^2 \text{ yr}^{-1}$ ($0.22\% \text{ yr}^{-1}$) from 2011 to 2019. The associated changes in ice shelf extent and mass could have altered buttressing and promoted upstream accumulation of grounded ice that is not captured by the model (Andreassen et al., 2023). Although matching the secular trend remains difficult and seasonal variations remain uncertain, the comparison nevertheless provides an independent validation of the model's self-consistent reconstruction of interannual mass change across the RIS basin from 2002 to 2018.

4 Conclusions

We present a 26-year state and parameter estimate of Ronne Ice Shelf and its drainage basin, jointly inferring basal friction and ice rheology alongside time-varying basal melt by assimilating surface velocity and elevation change observations. Optimization reduces uncertainty-weighted root mean squared error for elevation change and velocity by 21.2% and 43.6%, respectively. Detrended mass change in the upstream grounded basin correlates excellently with independent GRACE estimates ($R = 0.75$), providing cross-validation of basin-scale inter-annual mass change variability.

Geophysical insights are given by adjustments to inferred parameter fields. Basal friction adjustments are concentrated in steep, poorly resolved parts of the low velocity interior, where it is least constrained and may compensate for topographic and slope-related errors. Ice rheology adjustments are largest along shear margins and across the shelf, highlighting limitations of temperature-based initialization where fabric, damage, and unresolved stresses alter effective rheology. Basal melt adjustments exhibit characteristic patterns consistent with sub-shelf ocean circulation: enhanced melting near the grounding line, refreezing as buoyant meltwater ascends beneath the shelf, and renewed melting toward the calving front due to surface processes and heating. At sites with in situ measurements, inferred seasonal melt-rate amplitude (0.86 m yr^{-1}) is substantially closer to the



340 observed amplitude (0.41 m yr^{-1}) than that of existing estimates from Paolo et al. (2023) (2.03 m yr^{-1}). Unlike the existing estimates, our reconstructed melt history is estimated jointly with basal friction and ice rheology and constrained to reproduce the coupled evolution of geometry and flow across RIS and its drainage basin.

The estimate nevertheless remains non-unique, and residual misfit indicates that more observations are needed to disentangle parameter effects and constrain variability over shorter timescales. Model development may entail increasing basal melt spatial
 345 resolution 2.5km, integrating dynamic calving fronts, and interactive treatments of ice-ocean, ice-atmosphere, and ice-bed processes. More specifically, future treatments may integrate ice-ocean interactions via coupling with ocean models like ECCO, ice-atmosphere interactions via energy balance models like GEMB, direct integration of satellite observations from ICESat-2, dynamic calving front forcings, and crevasse/damage mapping via emerging datasets from satellites like NISAR. Additional future work would involve expanding coverage into the Amundsen Sea embayment, West Antarctica, and beyond. Overall, the
 350 state estimation framework demonstrated here can yield dynamically consistent, data-constrained representations of present-day ice dynamics, improve initial conditions for prognostic simulations, and strengthen the rigor of future sea level projections.

Code and data availability. The Ronne Ice Shelf basin 1992-2018 monthly 5km gridded dataset (velocity, elevation change, basal melt, basal friction, and ice rheology), model, and source code for ISSM are available at <https://doi.org/10.5281/zenodo.22968210>.

Author contributions. DC, EL, and IF contributed to the method, code, model, and data processing. IF and EL provided key direction for the
 355 overall study and outputs. DC, SA, IF, and EL contributed to the results analysis and discussion topics. DC wrote the manuscript with critical input from SA. All authors reviewed and approved the manuscript.

Competing interests. The authors declare no competing interests.

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References

- Adusumilli, S., Fricker, H. A., Medley, B., Padman, L., and Siegfried, M. R.: Interannual variations in meltwater input to the Southern Ocean
 365 from Antarctic ice shelves, *Nature Geoscience*, 13, 616–620, <https://doi.org/10.1038/s41561-020-0616-z>, 2020.
- Andreasen, J. R., Hogg, A. E., and Selley, H. L.: Change in Antarctic ice shelf area from 2009 to 2019, *The Cryosphere*, 17, 2059–2072,
<https://doi.org/10.5194/tc-17-2059-2023>, 2023.
- Anselin, J., Nicholls, K. W., Holland, P. R., Taylor, J. R., Østerhus, S., and Makinson, K.: Basal Melt Rate Variability and Tidal Current Ver-
 tical Structure From Observations Beneath Ronne Ice Shelf, Antarctica, *Journal of Geophysical Research: Oceans*, 130, e2025JC022524,
 370 <https://doi.org/10.1029/2025JC022524>, _eprint: <https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2025JC022524>, 2025.
- Badgeley, J. A., Morlighem, M., and Seroussi, H.: Increased Sea-Level Contribution from Northwestern Greenland for Models That Re-
 produce Observations, *Proceedings of the National Academy of Sciences*, 122, e2411904 122, <https://doi.org/10.1073/pnas.2411904122>,
 2025.
- Blatter, H.: Velocity and stress fields in grounded glaciers: a simple algorithm for including deviatoric stress gradients, *Journal of Glaciology*,
 375 41, 333–344, <https://doi.org/10.3189/S002214300001621X>, 1995.
- Budd, W. F., Keage, P. L., and Blundy, N. A.: Empirical Studies of Ice Sliding, *Journal of Glaciology*, 23, 157–170,
<https://doi.org/10.3189/S0022143000029804>, 1979.
- Choi, Y., Seroussi, H., Morlighem, M., Schlegel, N.-J., and Gardner, A.: Impact of time-dependent data assimilation on ice flow model
 initialization and projections: a case study of Kjer Glacier, Greenland, *The Cryosphere*, 17, 5499–5517, <https://doi.org/10.5194/tc-17->
 380 5499-2023, 2023.
- Choi, Y., Petty, A., Felikson, D., and Poterjoy, J.: Estimation of the state and parameters in ice sheet model using an ensemble Kalman filter
 and Observing System Simulation Experiments, <https://doi.org/10.5194/egusphere-2025-301>, 2025.
- Cook, S., Nicholls, K. W., Vaňková, I., Thompson, S. S., and Galton-Fenzi, B. K.: Data initiatives for ocean-driven melt of Antarctic ice
 shelves, *Annals of Glaciology*, 63, 27–32, <https://doi.org/10.1017/aog.2023.6>, 2022.
- 385 Cramer, F., Shephard, G. E., and Heron, P. J.: The misuse of colour in science communication, *Nature Communications*, 11, 5444,
<https://doi.org/10.1038/s41467-020-19160-7>, 2020.
- Cuffey, K. and Paterson, W.: *The Physics of Glaciers*, Academic Press, ISBN 978-0-08-091912-6, [https://shop.elsevier.com/books/](https://shop.elsevier.com/books/the-physics-of-glaciers/cuffey/978-0-12-369461-4)
[the-physics-of-glaciers/cuffey/978-0-12-369461-4](https://shop.elsevier.com/books/the-physics-of-glaciers/cuffey/978-0-12-369461-4), 2010.
- Dahle, C., Boergens, E., Sasgen, I., Döhne, T., Reißland, S., Dobslaw, H., Klemann, V., Murböck, M., König, R., Dill, R., Sips, M., Sylla,
 390 U., Groh, A., Horwath, M., and Flechtner, F.: GravIS: mass anomaly products from satellite gravimetry, *Earth System Science Data*, 17,
 611–631, <https://doi.org/10.5194/essd-17-611-2025>, 2025.
- Dow, C. F., Ross, N., Jeofry, H., Siu, K., and Siegert, M. J.: Antarctic basal environment shaped by high-pressure flow through a subglacial
 river system, *Nature Geoscience*, 15, 892–898, <https://doi.org/10.1038/s41561-022-01059-1>, 2022.
- Edwards, T. L., Nowicki, S., Marzeion, B., Hock, R., Goelzer, H., Seroussi, H., Jourdain, N. C., Slater, D. A., Turner, F. E., Smith, C. J.,
 395 McKenna, C. M., Simon, E., Abe-Ouchi, A., Gregory, J. M., Larour, E., Lipscomb, W. H., Payne, A. J., Shepherd, A., Agosta, C.,
 Alexander, P., Albrecht, T., Anderson, B., Asay-Davis, X., Aschwanden, A., Barthel, A., Bliss, A., Calov, R., Chambers, C., Champollion,
 N., Choi, Y., Cullather, R., Cuzzone, J., Dumas, C., Felikson, D., Fettweis, X., Fujita, K., Galton-Fenzi, B. K., Gladstone, R., Golledge,
 N. R., Greve, R., Hattermann, T., Hoffman, M. J., Humbert, A., Huss, M., Huybrechts, P., Immerzeel, W., Kleiner, T., Kraaijenbrink, P.,
 Le clec'h, S., Lee, V., Leguy, G. R., Little, C. M., Lowry, D. P., Malles, J.-H., Martin, D. F., Maussion, F., Morlighem, M., O'Neill, J. F.,



- 400 Nias, I., Pattyn, F., Pelle, T., Price, S. F., Quiquet, A., Radić, V., Reese, R., Rounce, D. R., Rückamp, M., Sakai, A., Shafer, C., Schlegel, N.-J., Shannon, S., Smith, R. S., Straneo, F., Sun, S., Tarasov, L., Trusel, L. D., Van Breedam, J., van de Wal, R., van den Broeke, M., Winkelmann, R., Zekollari, H., Zhao, C., Zhang, T., and Zwinger, T.: Projected land ice contributions to twenty-first-century sea level rise, *Nature*, 593, 74–82, <https://doi.org/10.1038/s41586-021-03302-y>, number: 7857, 2021.
- Errico, R. M.: What Is an Adjoint Model?, *Bulletin of the American Meteorological Society*, 78, 2577–2592, [https://doi.org/10.1175/1520-0477\(1997\)078<2577:WIAAM>2.0.CO;2](https://doi.org/10.1175/1520-0477(1997)078<2577:WIAAM>2.0.CO;2), 1997.
- 405 Forget, G., Campin, J.-M., Heimbach, P., Hill, C. N., Ponte, R. M., and Wunsch, C.: ECCO version 4: an integrated framework for non-linear inverse modeling and global ocean state estimation, *Geoscientific Model Development*, 8, 3071–3104, <https://doi.org/10.5194/gmd-8-3071-2015>, 2015.
- Fox-Kemper, B., Hewitt, H. T., Xiao, C., Aðalgeirsdóttir, G., Drijfhout, S. S., Edwards, T. L., Golledge, N. R., Hemer, M., Kopp, R. E., Krinner, G., Mix, A., Notz, D., Nowicki, S., Nurhati, I. S., Ruiz, L., Sallée, J.-B., Slangen, A. B. A., and Yu, Y.: Ocean, Cryosphere and Sea Level Change, in: *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M. I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J. B. R., Maycock, T. K., Waterfield, T., Yelekçi, O., Yu, R., and Zhou, B., pp. 1211–1362, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, <https://doi.org/10.1017/9781009157896.011>, 2021.
- 415 Gardner, A., Fahnestock, M., Greene, C., Kennedy, J., Liukis, M., Lopez, L., and Scambos, T.: MEASURES ITS_LIVE Regional Glacier and Ice Sheet Surface Velocities, Version 2, <https://doi.org/10.5067/JQ6337239C96>, 2024.
- Gardner, A. S., Schlegel, N.-J., and Larour, E.: Glacier Energy and Mass Balance (GEMB): a model of firn processes for cryosphere research, *Geoscientific Model Development*, 16, 2277–2302, <https://doi.org/10.5194/gmd-16-2277-2023>, 2023.
- 420 Gillet-Chaulet, F.: Assimilation of Surface Observations in a Transient Marine Ice Sheet Model Using an Ensemble Kalman Filter, *The Cryosphere*, 14, 811–832, <https://doi.org/10.5194/tc-14-811-2020>, 2020.
- Glen, J. W. and Perutz, M. F.: The creep of polycrystalline ice, *Proceedings of the Royal Society of London. Series A. Mathematical and Physical Sciences*, 228, 519–538, <https://doi.org/10.1098/rspa.1955.0066>, 1955.
- Goldberg, D. N. and Heimbach, P.: Parameter and state estimation with a time-dependent adjoint marine ice sheet model, *The Cryosphere*, 7, 1659–1678, <https://doi.org/10.5194/tc-7-1659-2013>, 2013.
- 425 Goldberg, D. N. and Holland, P. R.: The Relative Impacts of Initialization and Climate Forcing in Coupled Ice Sheet–Ocean Modeling: Application to Pope, Smith, and Kohler Glaciers, *Journal of Geophysical Research: Earth Surface*, 127, e2021JF006570, <https://doi.org/10.1029/2021JF006570>, 2022.
- Goldberg, D. N., Heimbach, P., Joughin, I., and Smith, B.: Committed Retreat of Smith, Pope, and Kohler Glaciers over the Next 30 Years Inferred by Transient Model Calibration, *The Cryosphere*, 9, 2429–2446, <https://doi.org/10.5194/tc-9-2429-2015>, 2015.
- 430 Goldberg, D. N., Gourmelen, N., Kimura, S., Millan, R., and Snow, K.: How Accurately Should We Model Ice Shelf Melt Rates?, *Geophysical Research Letters*, 46, 189–199, <https://doi.org/10.1029/2018GL080383>, 2019.
- Goldberg, D. N., Morlighem, M., and Gourmelen, N.: Recent Observations of Thwaites Glacier, West Antarctica, Are Consistent with High Rates of Loss in the Next 50 Years, *Geophysical Research Letters*, 53, e2025GL118823, <https://doi.org/10.1029/2025GL118823>, 2026.
- 435 Gudmundsson, G. H., Paolo, F. S., Adusumilli, S., and Fricker, H. A.: Instantaneous Antarctic Ice Sheet Mass Loss Driven by Thinning Ice Shelves, *Geophysical Research Letters*, 46, 13 903–13 909, <https://doi.org/10.1029/2019GL085027>, 2019.



- Howat, I., Porter, C., Noh, M.-J., Husby, E., Khuvis, S., Danish, E., Tomko, K., Gardiner, J., Negrete, A., Yadav, B., Klassen, J., Kelleher, C., Cloutier, M., Bakker, J., Enos, J., Arnold, G., Bauer, G., and Morin, P.: The Reference Elevation Model of Antarctica - Mosaics, Version 2, <https://doi.org/10.7910/DVN/EBW8UC>, 2022.
- 440 Jacobs, S. S., Helmer, H. H., Doake, C. S. M., Jenkins, A., and Frolich, R. M.: Melting of ice shelves and the mass balance of Antarctica, *Journal of Glaciology*, 38, 375–387, <https://doi.org/10.3189/S0022143000002252>, 1992.
- Larour, E., Rignot, E., Joughin, I., and Aubry, D.: Rheology of the Ronne Ice Shelf, Antarctica, inferred from satellite radar interferometry data using an inverse control method, *Geophysical Research Letters*, 32, <https://doi.org/10.1029/2004GL021693>, _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2004GL021693>, 2005.
- 445 Larour, E., Morlighem, M., Seroussi, H., Schiermeier, J., and Rignot, E.: Ice flow sensitivity to geothermal heat flux of Pine Island Glacier, Antarctica, *Journal of Geophysical Research: Earth Surface*, 117, <https://doi.org/10.1029/2012JF002371>, _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2012JF002371>, 2012a.
- Larour, E., Seroussi, H., Morlighem, M., and Rignot, E.: Continental scale, high order, high spatial resolution, ice sheet modeling using the Ice Sheet System Model (ISSM), *Journal of Geophysical Research: Earth Surface*, 117, 1022, <https://doi.org/10.1029/2011JF002140>,
450 2012b.
- Larour, E., Khazendar, A., P.Borstad, C., Seroussi, H., Morlighem, M., and Rignot, E.: Representation of sharp rifts and faults mechanics in modeling ice shelf flow dynamics: Application to Brunt/Stancomb-Wills Ice Shelf, Antarctica, *Journal of Geophysical Research: Earth Surface*, 119, 1918–1935, <https://doi.org/10.1002/2014JF003157>, 2014a.
- Larour, E., Utke, J., Csatho, B., Schenk, A., Seroussi, H., Morlighem, M., Rignot, E., Schlegel, N., and Khazendar, A.: Inferred basal friction
455 and surface mass balance of the Northeast Greenland Ice Stream using data assimilation of ICESat (Ice Cloud and land Elevation Satellite) surface altimetry and ISSM (Ice Sheet System Model), *The Cryosphere*, 8, 2335–2351, <https://doi.org/10.5194/tc-8-2335-2014>, 2014b.
- Larour, E., Utke, J., Bovin, A., Morlighem, M., and Perez, G.: An approach to computing discrete adjoints for MPI-parallelized models applied to Ice Sheet System Model 4.11, *Geoscientific Model Development*, 9, 3907–3918, <https://doi.org/10.5194/gmd-9-3907-2016>, 2016.
- 460 Liu, D. C. and Nocedal, J.: On the limited memory BFGS method for large scale optimization, *Mathematical Programming*, 45, 503–528, <https://doi.org/10.1007/BF01589116>, 1989.
- MacAyeal, D. R.: Large-scale ice flow over a viscous basal sediment: Theory and application to ice stream B, Antarctica, *Journal of Geophysical Research: Solid Earth*, 94, 4071–4087, <https://doi.org/10.1029/JB094iB04p04071>, _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1029/JB094iB04p04071>, 1989.
- 465 Maule, C. F., Purucker, M. E., Olsen, N., and Mosegaard, K.: Heat Flux Anomalies in Antarctica Revealed by Satellite Magnetic Data, *Science*, 309, 464–467, <https://doi.org/10.1126/science.1106888>, 2005.
- Morlighem, M.: MEaSURES BedMachine Antarctica, Version 3, <https://doi.org/10.5067/FPSU0V1MWUB6>, 2022.
- Morlighem, M. and Goldberg, D. N.: Data Assimilation in Glaciology, in: *Applications of Data Assimilation and Inverse Problems in the Earth Sciences*, edited by Ismail-Zadeh, A., Castelli, F., Jones, D., and Sanchez, S., pp. 93–111, Cambridge University Press,
470 <https://doi.org/10.1017/9781009180412.007>, 2023.
- Morlighem, M., Seroussi, H., Larour, E., and Rignot, E.: Inversion of basal friction in Antarctica using exact and incomplete adjoints of a higher-order model, *Journal of Geophysical Research: Earth Surface*, 118, 1746–1753, <https://doi.org/10.1002/jgrf.20125>, _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1002/jgrf.20125>, 2013.



- Morlighem, M., Goldberg, D., Dias dos Santos, T., Lee, J., and Sagebaum, M.: Mapping the Sensitivity of the Amundsen Sea Embayment to Changes in External Forcings Using Automatic Differentiation, *Geophysical Research Letters*, 48, e2021GL095440, <https://doi.org/10.1029/2021GL095440>, _eprint: <https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2021GL095440>, 2021.
- Nicholls, K. W., Østerhus, S., Makinson, K., Gammelsrød, T., and Fahrbach, E.: Ice-ocean processes over the continental shelf of the southern Weddell Sea, Antarctica: A review, *Reviews of Geophysics*, 47, <https://doi.org/10.1029/2007RG000250>, _eprint: <https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2007RG000250>, 2009.
- Nilsson, J., Gardner, A. S., and Paolo, F. S.: Elevation change of the Antarctic Ice Sheet: 1985 to 2020, *Earth System Science Data*, 14, 3573–3598, <https://doi.org/10.5194/essd-14-3573-2022>, 2022.
- Paolo, F. S., Gardner, A. S., Greene, C. A., Nilsson, J., Schodlok, M. P., Schlegel, N.-J., and Fricker, H. A.: Widespread slowdown in thinning rates of West Antarctic ice shelves, *The Cryosphere*, 17, 3409–3433, <https://doi.org/10.5194/tc-17-3409-2023>, 2023.
- Pattyn, F.: A new three-dimensional higher-order thermomechanical ice sheet model: Basic sensitivity, ice stream development, and ice flow across subglacial lakes, *Journal of Geophysical Research: Solid Earth*, 108, <https://doi.org/10.1029/2002JB002329>, _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1029/2002JB002329>, 2003.
- Pritchard, H. D., Ligtenberg, S. R. M., Fricker, H. A., Vaughan, D. G., van den Broeke, M. R., and Padman, L.: Antarctic ice-sheet loss driven by basal melting of ice shelves, *Nature*, 484, 502–505, <https://doi.org/10.1038/nature10968>, 2012.
- Richard Peltier, W., Argus, D. F., and Drummond, R.: Comment on “An Assessment of the ICE-6G_C (VM5a) Glacial Isostatic Adjustment Model” by Purcell et al., *Journal of Geophysical Research: Solid Earth*, 123, 2019–2028, <https://doi.org/10.1002/2016JB013844>, 2018.
- Rignot, E., Jacobs, S., Mouginot, J., and Scheuchl, B.: Ice-Shelf Melting Around Antarctica, *Science*, 341, 266–270, <https://doi.org/10.1126/science.1235798>, 2013.
- Rignot, E., Mouginot, J., and Scheuchl, B.: MEaSUREs InSAR-Based Antarctica Ice Velocity Map, Version 2, <https://doi.org/10.5067/D7GK8F5J8M8R>, 2017.
- Rignot, E., Mouginot, J., Scheuchl, B., and Jeong, S.: Changes in Antarctic Ice Sheet Motion Derived From Satellite Radar Interferometry Between 1995 and 2022, *Geophysical Research Letters*, 49, e2022GL100141, <https://doi.org/10.1029/2022GL100141>, _eprint: <https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2022GL100141>, 2022.
- Sagebaum, M., Albring, T., and Gauger, N. R.: High-Performance Derivative Computations using CoDiPack, <https://doi.org/10.48550/arXiv.1709.07229>, arXiv:1709.07229 [cs], 2017.
- Sasgen, I., Groh, A., and Horwath, M.: GFZ GravIS RL06 Ice-Mass Change Products, https://doi.org/10.5880/GFZ.GRAVIS_06_L3_ICE, 2019.
- Schlegel, N.-J., Seroussi, H., Schodlok, M. P., Larour, E. Y., Boening, C., Limonadi, D., Watkins, M. M., Morlighem, M., and van den Broeke, M. R.: Exploration of Antarctic Ice Sheet 100-year contribution to sea level rise and associated model uncertainties using the ISSM framework, *The Cryosphere*, 12, 3511–3534, <https://doi.org/10.5194/tc-12-3511-2018>, 2018.
- Seroussi, H., Morlighem, M., Rignot, E., Khazendar, A., Larour, E., and Mouginot, J.: Dependence of century-scale projections of the Greenland ice sheet on its thermal regime, *Journal of Glaciology*, 59, 1024–1034, <https://doi.org/10.3189/2013JoG13J054>, 2013.
- Seroussi, H., Morlighem, M., Rignot, E., Mouginot, J., Larour, E., Schodlok, M., and Khazendar, A.: Sensitivity of the dynamics of Pine Island Glacier, West Antarctica, to climate forcing for the next 50 years, *Cryosphere*, 8, 1699–1710, <https://doi.org/10.5194/tc-8-1699-2014>, 2014.



- 510 Seroussi, H., Nakayama, Y., Larour, E., Menemenlis, D., Morlighem, M., Rignot, E., and Khazendar, A.: Continued retreat of Thwaites Glacier, West Antarctica, controlled by bed topography and ocean circulation, *Geophysical Research Letters*, 44, 6191–6199, <https://doi.org/10.1002/2017GL072910>, _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1002/2017GL072910>, 2017.
- Seroussi, H., Nowicki, S., Payne, A. J., Goelzer, H., Lipscomb, W. H., Abe-Ouchi, A., Agosta, C., Albrecht, T., Asay-Davis, X., Barthel, A., Calov, R., Cullather, R., Dumas, C., Galton-Fenzi, B. K., Gladstone, R., Golledge, N. R., Gregory, J. M., Greve, R., Hattermann, T., Hoffman, M. J., Humbert, A., Huybrechts, P., Jourdain, N. C., Kleiner, T., Larour, E., Leguy, G. R., Lowry, D. P., Little, C. M., Morlighem, M., Pattyn, F., Pelle, T., Price, S. F., Quiquet, A., Reese, R., Schlegel, N.-J., Shepherd, A., Simon, E., Smith, R. S., Straneo, F., Sun, S., Trusel, L. D., Van Breedam, J., van de Wal, R. S. W., Winkelmann, R., Zhao, C., Zhang, T., and Zwinger, T.: ISMIP6 Antarctica: a multi-model ensemble of the Antarctic ice sheet evolution over the 21st century, *The Cryosphere*, 14, 3033–3070, <https://doi.org/10.5194/tc-14-3033-2020>, 2020.
- 520 Smith, B., Fricker, H. A., Gardner, A. S., Medley, B., Nilsson, J., Paolo, F. S., Holschuh, N., Adusumilli, S., Brunt, K. M., Csatho, B., Harbeck, K., Markus, T., Neumann, T., Siegfried, M. R., and Zwally, H. J.: Pervasive Ice Sheet Mass Loss Reflects Competing Ocean and Atmosphere Processes, *Science*, 368, 1239–1242, <https://doi.org/10.1126/science.aaz5845>, 2020.
- Stammer, D., Wunsch, C., Giering, R., Eckert, C., Heimbach, P., Marotzke, J., Adcroft, A., Hill, C. N., and Marshall, J.: Global ocean circulation during 1992–1997, estimated from ocean observations and a general circulation model, *Journal of Geophysical Research: Oceans*, 107, 1–1–1–27, <https://doi.org/10.1029/2001JC000888>, _eprint: <https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2001JC000888>, 2002.
- 525 van Wessem, J. M., van de Berg, W. J., Noël, B. P. Y., van Meijgaard, E., Amory, C., Birnbaum, G., Jakobs, C. L., Krüger, K., Lenaerts, J. T. M., Lhermitte, S., Ligtenberg, S. R. M., Medley, B., Reijmer, C. H., van Tricht, K., Trusel, L. D., van Uft, L. H., Wouters, B., Wuite, J., and van den Broeke, M. R.: Modelling the climate and surface mass balance of polar ice sheets using RACMO2 – Part 2: Antarctica (1979–2016), *The Cryosphere*, 12, 1479–1498, <https://doi.org/10.5194/tc-12-1479-2018>, 2018.
- 530 Vaňková, I. and Nicholls, K. W.: Ocean Variability Beneath the Filchner-Ronne Ice Shelf Inferred From Basal Melt Rate Time Series, *Journal of Geophysical Research: Oceans*, 127, e2022JC018879, <https://doi.org/10.1029/2022JC018879>, _eprint: <https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2022JC018879>, 2022.
- Wunsch, C.: Inverse Problems, Inverse Methods, and Inverse Models, in: *Encyclopedia of Ocean Sciences*, vol. 5, pp. 502–512, Cambridge University Press, third edn., ISBN 978-0-521-48090-1, <https://doi.org/10.1017/CBO9780511629570>, 2019.
- 535 Wunsch, C. and Heimbach, P.: Practical global oceanic state estimation, *Physica D: Nonlinear Phenomena*, 230, 197–208, <https://doi.org/10.1016/j.physd.2006.09.040>, 2007.
- Wunsch, C. and Heimbach, P.: Two Decades of the Atlantic Meridional Overturning Circulation: Anatomy, Variations, Extremes, Prediction, and Overcoming Its Limitations, *Journal of Climate*, <https://doi.org/10.1175/JCLI-D-12-00478.1>, 2013.
- 540 Zwally, H. J., Giovinetto, M. B., Beckley, M. A., and Saba, J. L.: Antarctic and Greenland Drainage Systems, <https://earth.gsfc.nasa.gov/cryo/data/polar-altimetry/antarctic-and-greenland-drainage-systems>, 2012.