



Brief communication: Sensitivity of Antarctic ice shelf melting to ocean warming across basal melt models

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Abstract. The uncertain sensitivity of Antarctic ice shelf basal melt to ocean warming strongly contributes to uncertainties in sea level projections. Here, we explore the response of five basal melt models to an idealised sub-thermocline warming. Total melt increases by 67 %–240 % (+1 °C) or by 141 %–680 % (+2 °C), showing a large inter-model spread. For deep regions of presently fast-melting ice shelves, this spread can reach 2 orders of magnitude. Therefore, a consistent calibration to present-day conditions does not guarantee consistent melt sensitivities, and several basal melt forcings should be applied to prevent underestimating uncertainties in sea level projections.

1 Introduction

The Antarctic Ice Sheet is losing mass at an accelerating rate, leading to an increasing contribution to sea level rise (Otosaka et al., 2023). This mass loss is mainly driven by increased ocean-induced melting at the base of Antarctic ice shelves (most recent estimates by Davison et al., 2023), leading to ice shelf thinning, reduced buttressing, and a consequential increase in the flux from the grounded ice toward the ocean. The future evolution of ocean-induced ice shelf melt therefore plays a crucial role in projections of the Antarctic Ice Sheet evolution and its contribution to sea level rise.

The most advanced way to simulate the ocean-induced ice shelf melt, here referred to as basal melt, is to use a coupled

ocean–ice-sheet model framework, where the ocean circulation in the cavities below the ice shelves is resolved and where the ice-sheet geometry responds to the melt at the ice shelf base. However, coupled ocean–ice-sheet models currently remain rare and computationally too expensive to run circum-Antarctic or global simulations at a sufficiently high resolution over centennial to millennial timescales.

Instead, ice-sheet modellers rely on simpler models to provide basal melt forcing to Antarctic ice-sheet models (e.g. Jourdain et al., 2020). In recent decades, a variety of such dedicated basal melt models has been developed, ranging from simple parameterisations, assuming a linear or quadratic dependency on the difference between the ocean temperature and the local freezing point (e.g. Jourdain et al., 2020), to simple models emulating the circulation in the cavity, assuming plume dynamics (e.g. Lazeroms et al., 2018), an overturning circulation (Reese et al., 2018a), or both (Pelle et al., 2019), to more complex models resolving the horizontal circulation component (Lambert et al., 2023) or relying on machine learning techniques (e.g. Burgard et al., 2023).

For their initial development, all basal melt models were calibrated and assessed based on present-day observations or simulations close to present-day conditions and, thus, were applied to force numerous ice-sheet models. However, the evaluation of a subset of models against a common reference revealed a large spread in the resulting melt rates and melt patterns (Burgard et al., 2022, 2023). An idealised ice-sheet modelling study also revealed the choice of basal melt model

to dominate the uncertainty in mass loss and grounding-line retreat (Berends et al., 2023). In addition, the application of several models of ocean properties simulated by a coupled ocean–ice-sheet model showed large discrepancies in the melt resulting from ocean conditions warmer than at present (Burgard et al., 2023), raising the question of how the basal melt models differ in terms of their sensitivity to ocean warming.

To assess the intermodel spread in basal melt sensitivity to ocean warming, here, we compare a subset of five dedicated basal melt models of different levels of complexity. First, we calibrate the basal melt models based on an idealised ocean forcing mimicking present-day conditions and on satellite-derived estimates of present-day melt. Second, we apply two different ocean forcings representing a sub-thermocline warming of 1 and 2 °C and quantify the change in melt rates and melt patterns. With this study, we highlight and interpret key differences in the behaviour of the various basal melt models for present-day and warm ocean conditions and provide an intermodel range of basal melt sensitivities for the 40 largest Antarctic ice shelves. As no observational dataset is available to evaluate the sensitivities, we cannot provide a recommendation regarding the best- or worst-performing model. Instead, we aim to provide users with an overview of the behaviour of the different basal melt models in terms of patterns and sensitivity to ocean warming.

2 Data and methods

To simulate a basal melt pattern, each model requires information on ice shelf cavity geometries, as well as an ocean forcing in the form of a vertical profile of temperature and salinity in front of each ice shelf. In the following, we describe the input data (Sect. 2.1), the five basal melt models (Sect. 2.2), the experimental setup (Sect. 2.3), and our calibration approach for the free parameters (Sect. 2.4).

2.1 Data

The ice shelf geometries are based on the most recent version of the BedMachine dataset (BedMachine v3, Morlighem et al., 2020), which we regrid to a 2 km × 2 km horizontal grid. We define the ice shelf domains based on masks from the Ice sheet Mass Balance Intercomparison Exercise (IM-BIE) community (Rignot et al., 2019). In order to allow the representation of meltwater exchange within shared cavities of neighbouring ice shelves, we merge ice shelves that have no clear distinction from an oceanic point of view (such as Filchner–Ronne and Crosson–Dotson) into one. Throughout this study, we focus on the 40 largest ice shelves of the remaining ensemble, containing all ice shelves with an area of at least 1000 km².

The observational estimates of basal melt used for the present-day calibration are taken from Paolo et al. (2023).

These are based on 26 years (1992–2017) of satellite altimetry. In this estimate, the total Antarctic integrated melt is 954 Gtyr^{−1}, which is at the lower end of existing estimates, with others ranging from 1080 Gtyr^{−1} (Davison et al., 2023) to 1325 Gtyr^{−1} (Rignot et al., 2013) and with uncertainties on the order of 200 Gtyr^{−1}. For calibration, we use the melt rates averaged over the whole period.

2.2 Basal melt models

We compare the behaviour of five basal melt models: the quadratic parameterisation, the PICO model, the Plume model, the 2D model LADDIE, and a neural network.

- In the quadratic parameterisation (e.g. Jourdain et al., 2020), basal melting is expressed as a quadratic function of the difference between the local ocean temperature, directly extrapolated from the temperature in front of the ice shelf, and the local freezing point. Here, we adopt the quadratic local formulation, accounting for the local ice shelf slope as described by Burgard et al. (2022).
- PICO (Reese et al., 2018a) is a box model that mimics an overturning circulation in the cavity, known as the ice shelf pump (Lewis and Perkin, 1986). Only the bottom ocean properties in front of the ice shelf are applied at the grounding line and then are modified while being advected along the ice shelf draft, across a number of boxes dependent on the distance from the grounding line, leading to melting and freezing along the way.
- The Plume model (e.g. Lazeroms et al., 2018) is a one-dimensional model of a buoyant meltwater plume formed at the grounding line and rising along the ice shelf draft following prescribed flowlines on the two-dimensional grid. We use the implementation by Burgard et al. (2022) but include an improved method to identify the originating grounding-line depth by propagating plume paths from the grounding line to the rest of the ice shelf.
- The two-dimensional model LADDIE (Lambert et al., 2023) solves the vertically integrated Navier–Stokes equations in the upper mixed layer of the ice shelf cavity. Melt rates are computed using the commonly adopted “three-equation parameterisation”, and the overturning is represented by a parameterised entrainment. The model can be seen as an extension of the one-dimensional Plume model, accounting for the horizontal flow under the influence of geometric steering and Coriolis deflection.
- The neural network (Burgard et al., 2023) is a simple multilayer perceptron trained to emulate a cavity-resolving version of the ocean model NEMO at

1/4° horizontal resolution (details can be found in Burgard et al., 2022). Compared to Burgard et al. (2023), the training dataset has been expanded with several projections, including those from Mathiot and Jourdain (2023), to account for warmer ocean conditions.

2.3 Experiments

For each model and ice shelf, three experiments are performed: a reference (REF) and two warming experiments (+1 and +2 °C). The REF experiment is designed to represent present-day conditions in an idealised framework. Ocean conditions are divided into six categories (Fig. 1a): Bellingshausen, East Amundsen, West Amundsen, cool, cold, and ISW (i.e. Ice Shelf Water). The first four contain a thermocline separating an upper layer at surface freezing temperature from a warm layer of Circumpolar Deep Water (CDW). The thermocline depth is taken at 500 m (similarly to observations in the Amundsen Sea as in, for example, Dutriex et al., 2014), except for the Bellingshausen Sea, where a shallower thermocline exists; there, a depth of 380 m is taken.

The subsurface warm water mass has a temperature of 1.2 °C (Bellingshausen and East Amundsen), 0.4 °C (West Amundsen), and −1.2 °C (cool). These values are inspired by in situ observations (e.g. Dutriex et al., 2014). The cold ocean conditions are described by a full water column at surface freezing point. Finally, the ISW conditions contain a linear function of temperature of −0.3 °C 1000 m^{−1} to represent the presence of supercooled Ice Shelf Water, producing a temperature of approximately −2.1 °C at 1000 m, comparable to observations in the Filchner Trough (Sallée et al., 2024). Salinities are taken such that a quadratic density stratification arises, again inspired by in situ observations, except for ISW, where a linear stratification is imposed.

Several experimental choices, such as the Bellingshausen thermocline depth, the cool sub-thermocline temperature, and the division of ice shelves between cold and cool forcing, could not be sufficiently constrained by observations. For these choices, to create plausible conditions, we apply a form of inversion in which we optimise the REF forcing using LADDIE to reproduce observed basal melt rates in the associated regions. As a consequence, the agreement between simulated melt rates by LADDIE and observational melt estimates may be slightly exaggerated in comparison to the other four models.

For each ice shelf, we restrict the intrusion of CDW into the cavity if there is a bathymetric obstacle at the ice shelf front. For points within the cavity that are deeper than this bathymetric obstacle, temperature and salinity are extrapolated downwards from the deepest entrance depth.

For the two warming experiments, we add 1 and 2 °C to the temperature below 500 m, which is the depth of our idealised CDW in most regions, and we leave the upper layer unchanged. The applied temperature profiles are visualised in

Fig. 1a. A salinity anomaly is applied to compensate for the temperature anomaly, such that the density profile is identical for all experiments. By assuming a constant density across the experiments, we do not account for the increasing stratification which would result from the increased input of fresh-water into the ocean. As shown by, for example, Lambert et al. (2024), this increased stratification can amplify the sub-surface warming and thereby further increase the sensitivity of ice shelf melt to ocean warming. By ignoring this feedback, our melt sensitivities may be conservative estimates.

From these three experiments, we extract three indicators describing the melt sensitivity of the ice shelves according to the five basal melt models in the range between reference ocean conditions and a 2 °C warming. First, a “melt sensitivity” is defined as follows:

$$\left. \frac{dM}{dT} \right|_{(\text{REF}, +1^\circ\text{C})} = \frac{M_{+1^\circ\text{C}} - M_{\text{REF}}}{T_{+1^\circ\text{C}} - T_{\text{REF}}}. \quad (1)$$

Here, M is the melt rate averaged over a specific region of an ice shelf. In this study, we use the melt averaged over the entire ice shelf $\bar{M}$ or over the deepest 10 % of an ice shelf M_{10} . T is the temperature forcing at the deepest point of this ice shelf. If the cavity is unblocked by bathymetric obstacles and the ice shelf base extends well below the thermocline depth, the temperature difference is 1 °C. Otherwise, the temperature difference is between 0 and 1 °C (Fig. 1a). The second indicator we introduce is the “nonlinearity” of this sensitivity, which is defined as follows:

$$\frac{d^2\bar{M}}{dT^2} = \left(\left. \frac{d\bar{M}}{dT} \right|_{(+1^\circ\text{C}, +2^\circ\text{C})} - \left. \frac{d\bar{M}}{dT} \right|_{(\text{REF}, +1^\circ\text{C})} \right) / (T_{+1.5^\circ\text{C}} - T_{+0.5^\circ\text{C}}). \quad (2)$$

This metric quantifies how the melt sensitivity changes when ocean temperatures increase. Positive values indicate that a +2 °C warming induces more than twice the melt increase of a +1 °C warming. Finally, changes in basal melt in the deep regions of ice shelves may have a larger impact than changes in shallower regions, and melt sensitivities in deep regions may be considerably higher than ice shelf averages (e.g. Jourdain et al., 2020; Reese et al., 2018b). Hence, as a third metric, we define the “deep amplification” DA of the melt sensitivities:

$$\text{DA} = \left. \frac{dM_{10}}{dT} \right|_{(\text{REF}, +1^\circ\text{C})} / \left. \frac{d\bar{M}}{dT} \right|_{(\text{REF}, +1^\circ\text{C})}. \quad (3)$$

Values above 1 indicate that the melt sensitivity in the deep region exceeds the ice shelf average melt sensitivity.

2.4 Calibration

To enable a consistent intercomparison between the different basal melt models, we calibrate them based on the same reference state, which mimics present-day conditions. We use

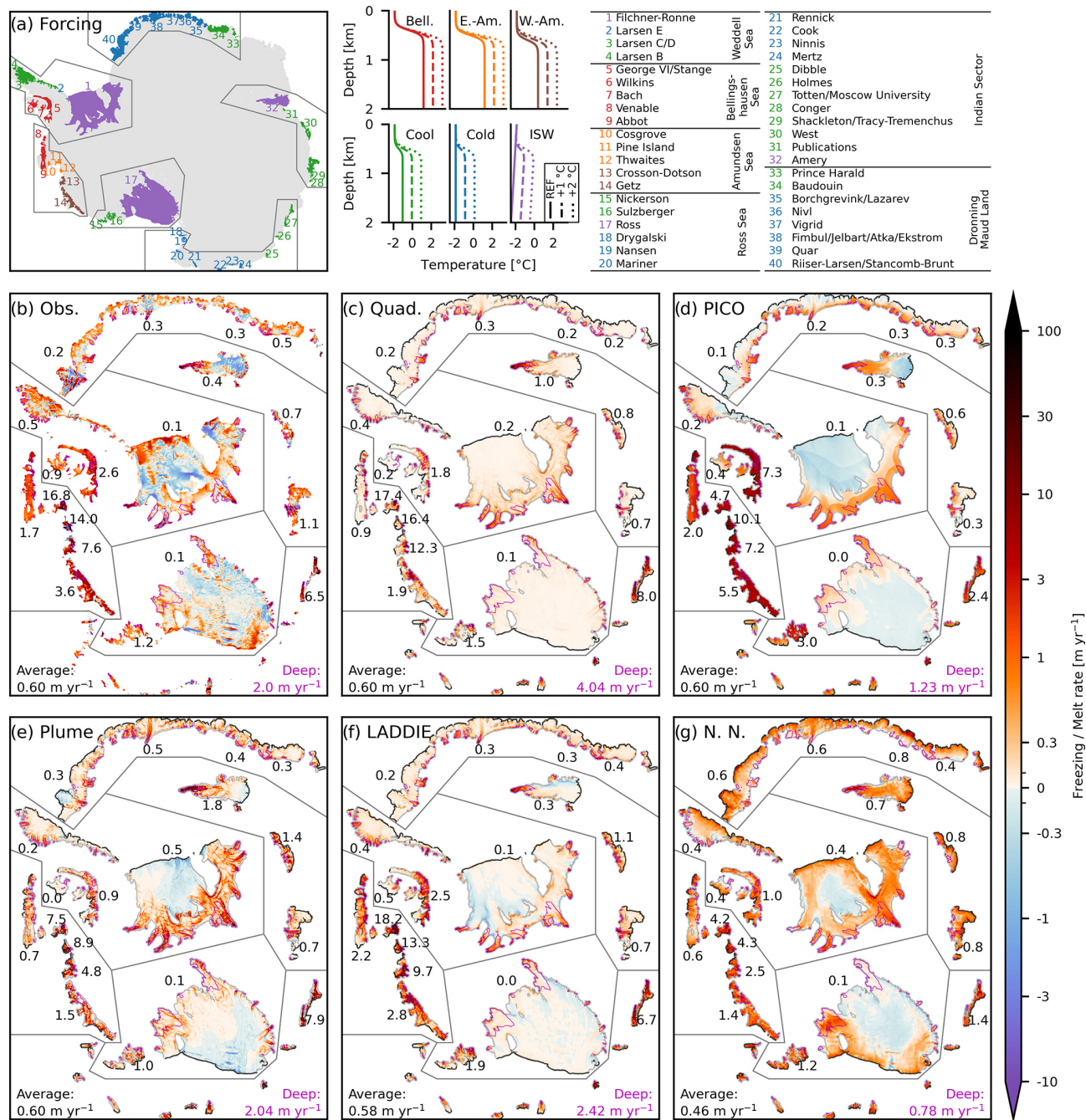


Figure 1. Ocean forcing and reference basal melt patterns. (a) Forcing, denoted by six colours, applied to 40 major ice shelves and corresponding ice shelf names. Temperature profiles applied in the reference (REF) and warming experiments. The map also displays the contours of the “puzzle pieces” shown in panels (b) to (g). Basal melt patterns (m yr⁻¹) for (b) present-day observational estimates (Paolo et al., 2023) and (c) the quadratic parameterisation, (d) PICO, (e) the Plume model, (f) LADDIE, and (g) the neural network (N.N.), forced with REF forcing. Grey (black) contours surrounding ice shelves denote the grounding line (calving front). The numbers shown along a selection of ice shelves are average melt rates in m yr⁻¹. The spatial average over the 40 ice shelves is shown in the bottom left; the average in the deepest 10 % of each ice shelf (marked by magenta lines) is shown in the bottom right (magenta numbers).

the temperature and salinity profiles from the REF experiment as forcing and calibrate the models to minimise the absolute difference to the observed ice shelf melt (Paolo et al., 2023) averaged over the 40 ice shelves (0.60 m yr^{-1}). Note that melt rates throughout this paper are defined as metres of water equivalent per year. For the quadratic parameterisation, this leads to a dimensionless turbulent exchange coefficient parameter K of 7.8×10^{-5} .

Both PICO and the Plume model have two tuning parameters, and a trial-and-error method indicates that the empirical functions between the parameters derived by Burgard et al. (2022) cause an underestimation of the melt. Instead, for PICO, we probe a plausible range of effective turbulent temperature exchange velocities γ_T^* and select the one leading to the maximum melt when using the empirical function given by Burgard et al. (2022), linking the overturning coefficient C to γ_T^* . We then infer the corresponding C needed to reach the target melt, resulting in a turbulent temperature exchange velocity γ_T^* of $0.85 \times 10^{-5} \text{ m s}^{-1}$ and an overturning coefficient C of $7.4 \times 10^6 \text{ m}^6 \text{ s}^{-1} \text{ kg}^{-1}$. For the Plume model, we probe the plausible parameter space (shown in Fig. 9a of Burgard et al., 2022) and find a minimum absolute difference for a Stanton number of 3.2×10^{-4} and an entrainment coefficient E_0 of 11.9×10^{-2} .

As the REF profiles were partly designed based on an inversion-like method with LADDIE, no recalibration of LADDIE is needed. The main tuning parameters are the top drag coefficient $C_{d,\text{top}}$ of 1.1 and the minimum layer thickness D_{min} of 6.6 m (Lambert et al., 2023). For the neural network, the 40 data points are insufficient for a robust new training. Hence, we use the version where training has been extended to projections and use it as a NEMO emulator, accepting potential biases in the reference state.

3 Results and discussion

3.1 Reference melt patterns

Overall, the consistent calibration to the circum-Antarctic ice shelf melt yields similar average melt rates of between 0.58 and 0.60 m yr^{-1} for four out of five basal melt models (Fig. 1c–f). The neural network, which could not be recalibrated, produces slightly lower average melt rates of 0.46 m yr^{-1} (Fig. 1g), which is likely to be the consequence of a warm bias in the training dataset. In addition to average melt rates, all basal melt models reproduce the comparably higher melt rates for the ice shelves in the Amundsen Sea and for the Totten/Moscow University ice shelves (nos. 10–14 and 27 in Fig. 1a). This illustrates that the contrast between warm and cold ocean conditions is appropriately translated to a contrast between high and low melt rates by all models. A comparison of the melt rates between the Amundsen Sea (observed: $0(10 \text{ m yr}^{-1})$) and Filchner–Ronne (observed: $0(0.1 \text{ m yr}^{-1})$) reveals that this contrast is

well captured in the quadratic, PICO, and LADDIE models, while the Plume model and the neural network underestimate this contrast by an order of magnitude ($0(5 \text{ m yr}^{-1})$ vs. $0(0.5 \text{ m yr}^{-1})$, respectively).

In terms of patterns of melting and freezing, the quadratic parameterisation stands out in several ways (Fig. 1c). First, the patterns are purely governed by the depth of the ice shelf draft and by the local slope. Second, the model does not reproduce refreezing as this requires a representation of the advection of meltwater. The purely depth-dependent pattern and explicit slope dependence combine into a strong deep amplification. For the quadratic parameterisation, this value (6.7) is twice the value derived from observations (3.3).

The spatial patterns of PICO are strongly constrained by the box pattern (Fig. 1d). The inherent assumption of the highest melt in the first box closest to the grounding line leads to wide bands of relatively uniform melting along the grounding lines and, in the case of cold cavities, relatively uniform refreezing in the centre and close to the ice shelf fronts. As the melt rates are, by design, weakly dependent on depth and independent from the draft slope, the deep amplification is relatively low (2.1) compared to observations.

The melt patterns of the Plume model (Fig. 1e) display a stronger heterogeneity than the quadratic and PICO models. In this model, the local slope angle relative to the imposed meltwater pathway induces small-scale variations in melting and refreezing. Similarly to PICO, the transition from melting to refreezing in the cold ice shelves occurs further away from the grounding line than in the observations. However, the deep amplification is nearly identical to the observed value, indicating that the depth and slope dependence of melt rates are well represented by this model.

In comparison to the prescribed meltwater flowlines in the Plume model, the resolved meltwater circulation of LADDIE (Fig. 1f) allows for a number of additional features. In particular, the impact of Coriolis deflection leads to an asymmetry in melting and refreezing rates which are concentrated near the western boundaries, in qualitative agreement with the observed patterns. In addition, the resolved circulation leads to a better positioning of the transition from melting to refreezing, closer to the grounding line, than PICO and the Plume model. The deep amplification (4.2) is higher than observed, possibly relating to the imposed minimum layer thickness, which can lead to an overestimation of the heat transport to the deepest grounding lines. Detailed tuning of this parameter, as done by Lambert et al. (2023), can constrain melting in the deep regions.

The melting and freezing patterns simulated by the neural network (Fig. 1g) also reflect the Coriolis-deflected meltwater circulation as simulated by NEMO. This allows for a generally well-distributed pattern of melting and refreezing on the Filchner–Ronne and Ross ice shelves. In addition, the neural network simulates “mode-3” melting close to the ice shelf front, most visible along Dronning Maud Land and the Filchner–Ronne and Ross ice shelves. This melting is caused

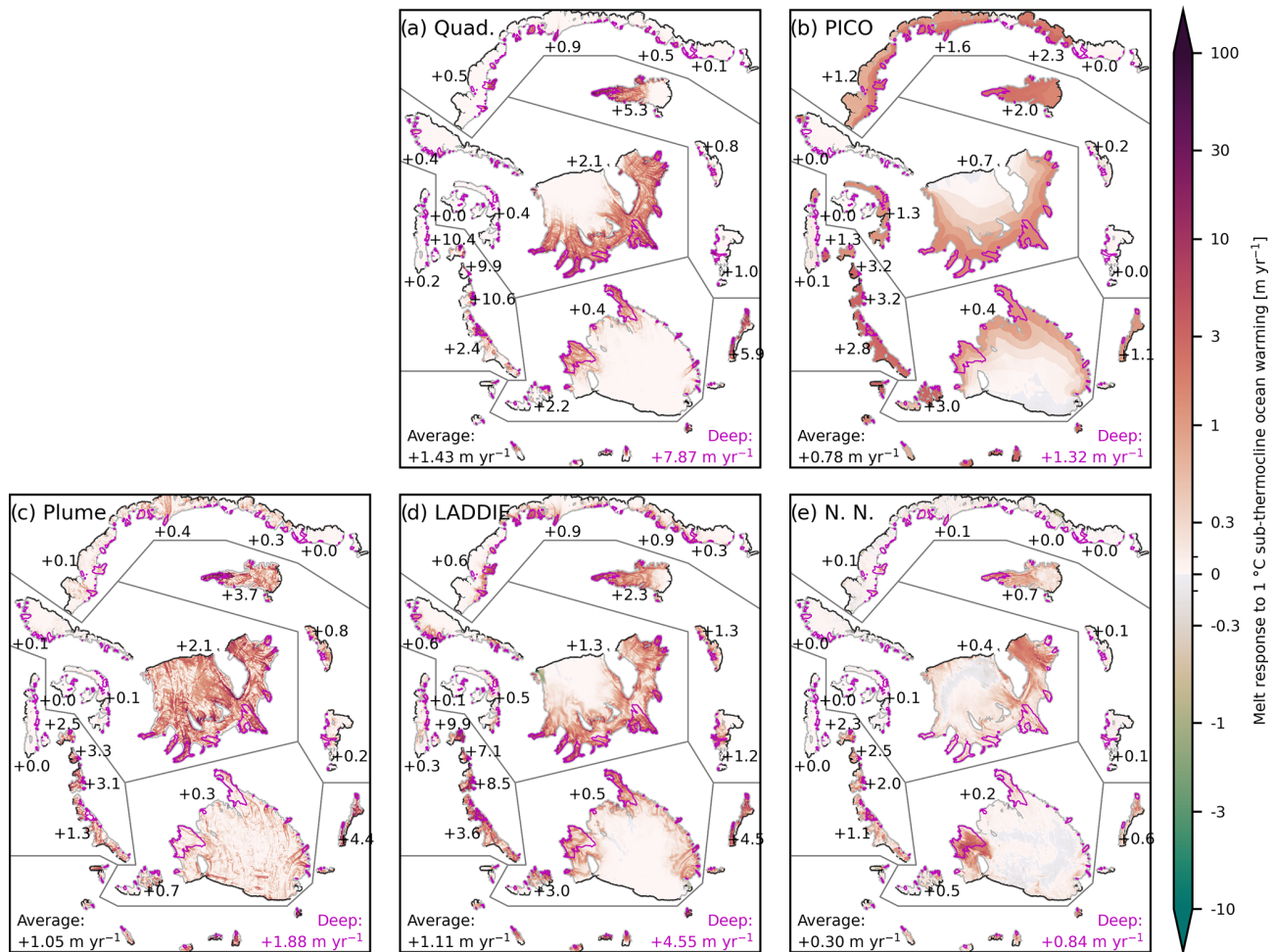


Figure 2. Spatial melt response to a 1 °C sub-thermocline warming expressed as the increase in melt relative to the reference (shown in Fig. 1) for (a) the quadratic parameterisation, (b) PICO, (c) the Plume model, (d) LADDIE, and (e) the neural network (N.N.). Grey (black) contours surrounding ice shelves denote the grounding line (calving front). The numbers indicate the average response for selected ice shelves. The numbers at the bottom denote the Antarctic-wide average response (left) and the Antarctic-wide response averaged over the deepest 10 % of all ice shelves (bottom right in magenta).

by the presence of Antarctic Summer Water (AASW) and cannot be explained by our forcing (hence, this melting is not simulated by the other models). Instead, it is an intrinsic feature learned from the NEMO training dataset. The NEMO training dataset is based on annual averages, which intrinsically incorporate months in which AASW intrudes under the ice shelf, leading to melt near the front. Thus, the neural network will reproduce this pattern with any forcing. The neural network shows the lowest deep amplification (1.7), which is a reflection of lower melting at depth in NEMO due to a lower resolution and, therefore, a smoother and shallower ice draft.

3.2 Melt sensitivity

All ice shelves show an increase in basal melting in response to a sub-thermocline ocean warming of 1 °C (Fig. 2), ranging from 67 % for the neural network to 240 % for the quadratic

parameterisation, with a median of 175 %. In all models, the melt sensitivity is stronger at depth, though the intermodel spread in terms of sensitivities in the deep regions is an order of magnitude, ranging from 0.8 m yr⁻¹ (neural network) to 8 m yr⁻¹ (quadratic). These sensitivities in the deep regions are a factor of 1.7 (PICO) to 5.5 (quadratic) higher than the ice shelf average values. Average values of the melt rates for both +1 and +2 °C are summarised in Table S1 in the Supplement, alongside Fig. S1 in the Supplement, which shows a reproduction of Fig. 2 for the +2 °C experiment.

The patterns of the melt response show distinct features related to the underlying model assumptions. The quadratic parameterisation shows zero melt increase in the shallowest regions as it does not account for advection from the deeper regions where warming is applied. PICO shows a relatively uniform melt response which is strongly constrained by the box structure. Plume shows a scattered melt response, mainly

driven by the local slopes. LADDIE shows melt patterns reflecting the advective pathway of the simulated meltwater plumes. The neural network shows a melt response concentrated in specific regions, possibly reflecting a sensitivity in the cavity circulation in NEMO.

The melt sensitivities according to the different models can vary by an order of magnitude. In Fig. 3a and b, we show the melt sensitivity $\frac{dM}{dT}$ based on the $+1^\circ\text{C}$ warming experiment. The unweighted distribution of the 40 ice shelves indicates that the neural network produces the lowest melt sensitivities, whereas the quadratic parameterisation and LADDIE produce, on average, the highest sensitivities. Notably, both average and median sensitivities of all models fall below the uncertainty ranges of previous estimates of bulk sensitivities, derived from idealised modelling (LARMIP-2, Levermann et al., 2020) or from a calibration based on subsurface ocean warming and observed Antarctic ice discharge (van der Linden et al., 2023).

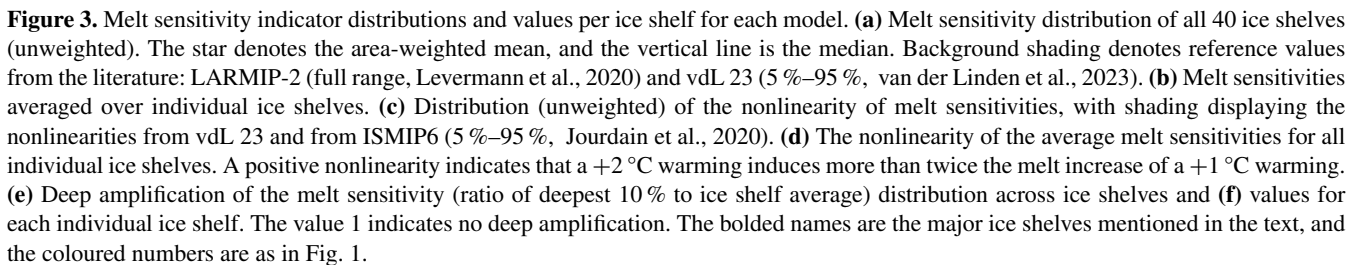
We have three explanations for this discrepancy. First, the models are calibrated on remote sensing estimates which are slightly lower than other estimates. This may result in a low bias in our modelled sensitivities. Second, as explained in Sect. 2.3, our experimental design with constant stratifications may lead to a further low bias in modelled sensitivities. An increased stratification would strengthen the buoyancy forcing in models that account for this (all except the quadratic parameterisation); however, accounting for this melt–stratification feedback is a remaining challenge for stand-alone basal melt models. Third, as shown by Lambert et al. (2024), the calibration method of van der Linden et al. (2023) leads to an overestimation of melt sensitivities when ignoring the positive feedback between meltwater and subsurface ocean warming. Taking into account these causes of discrepancy can lead to a better agreement between our melt sensitivities and other estimates.

On the individual ice shelf level, some consensus on the melt sensitivity is found between the models despite the overall strong intermodel disagreement. All models agree on a general classification of the major ice shelves, denoted by bolded names in Fig. 3, into three categories: those with comparably weak, moderate, or strong melt sensitivities. For the Larsen C/D (no. 3), George VI/Stange (5), Abbot (9), Ross (17), and Shackleton/Tracy–Tremenchus (29) ice shelves, all models produce a weak sensitivity (below $1.5\text{ myr}^{-1}\text{ }^\circ\text{C}^{-1}$) of the ice shelf average melt. In addition, all models agree, to some extent, on a moderate sensitivity for the Filchner–Ronne (1), Getz (14), and Amery (32) ice shelves. Although the current literature provides limited material for comparison, Reese et al. (2023) derived melt sensitivities for Filchner–Ronne ranging from 0.7 to $1.5\text{ myr}^{-1}\text{ }^\circ\text{C}^{-1}$ based on three-dimensional ocean simulations. Compared to these estimates, the melt sensitivity of LADDIE ($1.3\text{ myr}^{-1}\text{ }^\circ\text{C}^{-1}$) is closest, whereas that of PICO agrees with the lower bound of this estimate ($0.7\text{ myr}^{-1}\text{ }^\circ\text{C}^{-1}$).

The third class on which all models qualitatively agree contains the presently fast-melting ice shelves which display above-average melt sensitivities. These are the ice shelves located in the Amundsen Sea, except for the Getz ice shelf (nos. 10–13) and the Totten/Moscow University ice shelf (27). Quantitatively, however, the intermodel spread is considerably large. For the Crosson–Dotson, Thwaites, and Pine Island ice shelves in the Amundsen Sea, the melt sensitivities of the quadratic parameterisation and LADDIE are approximately a factor 3 higher than those of the other three models (PICO, Plume, and neural network). Again, Reese et al. (2023) provide comparison melt sensitivities based on in situ observations at the fast-melting Dotson ice shelf ranging from 11 to $20\text{ myr}^{-1}\text{ }^\circ\text{C}^{-1}$. The high sensitivities of the quadratic and LADDIE models agree best with these estimates, indicating that the melt sensitivity in the Amundsen Sea may be underestimated by the latter three models. For Totten/Moscow University, the sensitivities of the quadratic parameterisation, Plume, and LADDIE are approximately a factor 5 to 6 higher than those of PICO and the neural network. More generally, the melt sensitivity of these presently fast-melting ice shelves is most dependent on the choice of the basal melt model.

To the first order, the nonlinearity is correlated with the melt sensitivity (Fig. 3b and d). Both sensitivity and nonlinearity are strongest for LADDIE and the quadratic parameterisation and weakest for PICO and the neural network. Notably, PICO shows a perfectly linear melt sensitivity (zero nonlinearity) for approximately half of the ice shelves, with a marked exception for the ISW ice shelves (Filchner–Ronne (1), Ross (17), and Amery (32)). For the neural network, 4 out of 40 ice shelves show a negative nonlinearity, reflecting a decrease in the melt sensitivity when the ocean warms up; this subset includes the Ross ice shelf (17). In comparison to previous estimates from the calibration of the quadratic parameterisation in relation to reference melt rates (ISMIP 6; Jourdain et al., 2020) or the calibration of a quadratic relationship between ocean temperatures and ice discharge (van der Linden et al., 2023), the nonlinearities in our estimates are relatively low. Based on the clear correlation between melt sensitivities (Fig. 3b) and nonlinearities (Fig. 3d), the causes of this discrepancy are likely to be the same as the causes of the discrepancy in melt sensitivities which were suggested previously. In addition, we find that the nonlinearity in the quadratic parameterisation is strongest among the five models, indicating that the calibration by Jourdain et al. (2020) may lead to strong nonlinearity.

Considering the ice-shelf-specific nonlinearities (Fig. 3d), again, some consensus arises. All models agree that the melt sensitivities of George VI/Stange (5) and Abbot (9) are perfectly linear. Similarly, all models agree on a weak nonlinearity in the melt sensitivities of Larsen C/D (3), Ross (17), and Shackleton/Tracy–Tremenchus (29). In contrast, for all models, the nonlinearity of Totten/Moscow University (27) ranks among the highest values. Estimates of the



The deep amplification of melt sensitivities shows a particularly large intermodel spread which exceeds the spread between individual ice shelves (Fig. 3e and f). The quadratic parameterisation gives the highest values, with amplifications above a factor of 5 for 30 out of 40 ice shelves. This high amplification can be attributed to the strong depth and slope dependence and the omission of meltwater advection, similarly to the discrepancy between deep and shallower re-

The large intermodel spread in terms of both melt sensitivity and deep amplification results in extreme differences in terms of melt sensitivities in the deep regions. For example,

the melt sensitivity in the deepest 10 % of the Pine Island ice shelf ranges from $1.3 \text{ myr}^{-1} \text{ }^{\circ}\text{C}^{-1}$ (PICO) to $81 \text{ myr}^{-1} \text{ }^{\circ}\text{C}^{-1}$ (quadratic). For Totten/Moscow University, this sensitivity in the deep regions ranges from $0.3 \text{ myr}^{-1} \text{ }^{\circ}\text{C}^{-1}$ (neural network) to $50 \text{ myr}^{-1} \text{ }^{\circ}\text{C}^{-1}$ (quadratic). As melt in the deep regions most strongly impacts buttressing, we identify this intermodel spread in deep melt sensitivities – which can exceed 2 orders of magnitude in presently fast-melting ice shelves – as one critical source of model uncertainty in basal melt forcing. Further unravelling this intermodel spread should be a primary research focus to put into context the uncertainties in future projections of ice-sheet mass loss and sea level rise and, ultimately, to reduce them. The quantitative comparison of ice-shelf-specific melt sensitivities and derivatives thereof, based on five dedicated melt models, can function as a starting point to address this issue.

4 Conclusions

For five basal melt models of varying complexity, an idealised sub-thermocline $1 \text{ }^{\circ}\text{C}$ warming scenario induces an increase of 67 % to 240 % in Antarctic-wide basal melting, depending on the model, with a median increase of 175 %. For a $2 \text{ }^{\circ}\text{C}$ warming, the increase ranges from 141 % to 680 %, with a median of 415 %. This large intermodel spread highlights the challenge in reducing uncertainties induced by basal melt in projections of Antarctic ice mass loss. We calibrated the five models to simulate a common reference state, resulting in comparable average melt rates for present-like conditions. However, already, in these reference conditions, different model assumptions lead to large differences in the melt patterns. The intermodel disagreement is enhanced in the melt sensitivities to ocean warming for both patterns and integrated metrics. Hence, a consistent calibration based on present-day melt rates is no guarantee of consistency in melt sensitivities. The intermodel disagreement applies, in particular, to melt sensitivities of individual ice shelves and their spatial patterns.

Within the assessed ensemble of five basal melt models, the quadratic parameterisation has the highest melt sensitivity, the strongest nonlinearity in terms of the sensitivity, and the strongest amplification in the deeper regions. PICO displays an overall moderate melt sensitivity which is particularly uniform within each ice shelf and generally remains constant under further warming. The Plume model has an intermediate average melt sensitivity, which is suppressed (below-average) at depth for most ice shelves and moderately nonlinear. LADDIE has an intermediate but strongly nonlinear melt sensitivity and an intermediate amplification at depth. Finally, the neural network has the lowest melt sensitivity, exhibiting a moderate nonlinearity and an intermediate amplification at depth.

Our results can provide context to more carefully interpret simulations by ice-sheet models using one of these basal melt

models. Each model has its advantages and disadvantages in terms of its ease of use, its ability to represent present-day melt patterns, and its potential realism in terms of melt sensitivities to ocean warming. Hence, the models could not be ranked in terms of overall quality despite the large intermodel spread. Rather, these results can provide guidance for further development of the models or alternative calibration approaches. Moreover, we conclude that future ensemble-based studies – such as the next phase of the Ice-Sheet Model Intercomparison Project (ISMIP7) – should retain diversity in their basal melt forcing to prevent underestimation of uncertainties.

Code and data availability. The multimelt Python package (<https://doi.org/10.5281/zenodo.15837949>; Burgard, 2025) was used for the quadratic, PICO, and Plume parameterisations. All code and data are available on Zenodo (<https://doi.org/10.5281/zenodo.14523963>, Lambert and Burgard, 2024).

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Author contributions. EL prepared the temperature and salinity profiles and performed simulations with LADDIE. CB prepared the input geometry and calibrated and performed simulations with the other four models. Both of the authors contributed equally to the analysis and writing.

Competing interests. The contact author has declared that neither of the authors has any competing interests.

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