Effect of Subshelf Melt Variability on Sea Level Rise Contribution From Thwaites Glacier, Antarctica

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Abstract Modeling and observations suggest that Thwaites Glacier, West Antarctica, has begun unstable retreat. Concurrently, oceanographic observations have revealed substantial multiyear variability in the temperature of the ocean water driving retreat through melting of the ice shelf that restrains inland glacier flow. Using an ensemble of 72 ice-sheet model simulations that include an idealized representation of ocean temperature variability, we find that variable ice-shelf melting causes delays in grounding line retreat, mass loss, and sea level contribution relative to steady forcing. Modeled delays are up to 43 years after 500 years of simulation, corresponding to a 10% reduction in glacier mass loss. Delays are primarily caused by asymmetric melt forcing in the presence of variability. For the “warm cavity” conditions beneath Thwaites Ice Shelf, increases in access of warm, deeper water are unable to raise water temperatures in the cavity by much, whereas increases in access of significantly colder, shallow water reduce cavity water temperatures substantially. This leads to lowered mean melt rates under variable ocean temperature forcing. Additionally, about one quarter of the mass loss delay is caused by a nonlinear ice dynamic response to varying ice-shelf thinning rate, which is amplified during the initial phases of unstable, bed-topography-driven retreat. Mass loss rates under variability differ by up to 50% from ensemble mean values at any given time. Our results underscore the need for taking climate variability into account when modeling ice sheet evolution and for continued efforts toward the coupling of ice sheet models to ocean and climate models.

Plain Language Summary Warm ocean water melts the floating extensions of the Antarctic Ice Sheet called ice shelves. The thinning of the ice shelves reduces their ability to hold back the flow of the grounded glaciers behind them. This causes faster ice flow to the ocean and sea level rise. Recent ocean measurements around Antarctica have shown that the ocean temperature near West Antarctica varies by a few degrees over years or decades, which may be unrelated to climate change. However, modeling studies of how much Antarctic glaciers will contribute to sea level rise have largely ignored these short-term fluctuations. We ran an ice sheet model of Thwaites Glacier, one of the largest glaciers in the region, that includes these short-term fluctuations in ocean temperature dozens of times to investigate if they affect how quickly the glacier retreats. The model simulations that included the fluctuations always retreated more slowly than a run that ignored them. Depending on the strength and frequency of the fluctuations, the delay in glacier retreat and sea level rise was up to 10%. This delay occurs primarily because the ocean temperatures near Thwaites Glacier are already relatively warm for Antarctic conditions, and it is easier for temperature fluctuations to bring colder water to the ice shelf than it is to bring warmer water. Our results show that short-term fluctuations due to climate variability can matter to glaciers in Antarctica and that ice sheet and climate models need to take them into account when projecting future sea level rise.

1. Introduction

The retreat of marine glaciers in Antarctica is the greatest single source of uncertainty in future sea level rise projections (Stocker et al., 2013). The glaciers in the Amundsen Sea sector of West Antarctica are particularly vulnerable to rapid, unstable retreat due to the presence of bed topography that deepens inland from the ocean and therefore may be subject to the so-called “marine ice sheet instability” (Schoof, 2007; Weertman, 1974). However, floating ice shelves that fringe the ice sheet act to restrain the flow of inland, grounded ice, preventing or forestalling unstable retreat (Dupont & Alley, 2005; Goldberg et al., 2009; Gagliardini et al., 2010; Gudmundsson, 2013; Fürst et al., 2016). Recent rapid retreat of these glaciers has been tied to
incursions of deep, warm modified Circumpolar Deep Water (mCDW) onto the continental shelf and into the cavities beneath the region's ice shelves, leading to enhanced subshelf melting and a reduction in their ability to buttress the adjacent grounded ice (Jacobs et al., 1996; Jenkins, Dutrieux, et al., 2010, 2016; Joughin et al., 2010; Rignot & Jacobs, 2002; Shepherd et al., 2004). Complicating this understanding further are recent observations that show the access of warm water has not been uniformly increasing but instead has been episodic in nature, with decadal-scale variability in ocean temperatures near the ice shelves (Christianson et al., 2016; Dutrieux et al., 2014; Jacobs et al., 2013; Jenkins et al., 2016, 2018).

Thwaites Glacier holds enough ice to raise global sea level by 65 cm (Rignot et al., 2019) and may be susceptible to marine ice sheet instability due to a strongly overdeepened interior bed topography and few lateral topographic constraints (Cornford et al., 2015; Joughin et al., 2014). Indeed, recent observations (Rignot et al., 2014) and modeling (Arthern & Williams, 2017; Cornford et al., 2015; Joughin et al., 2014; Seroussi et al., 2017; Waibel et al., 2018; Yu et al., 2018) suggest that unstable retreat has already begun, likely driven by changes in sub-ice-shelf melting. However, existing modeling studies that attempt to predict future Thwaites evolution have largely ignored the observed short-term ocean variability.

Available Amundsen Sea oceanographic observations have clearly demonstrated that annual-to-decadal variability in the depth of mCDW on the continental shelf is a dominant ocean driver of ice-shelf melting in the region, obscuring any long-term trend that might exist there (Christianson et al., 2016; Dutrieux et al., 2014; Jacobs et al., 2013; Jenkins et al., 2016, 2018). Variability in the depth of the thermocline (the sharp gradient in temperature separating warmer, deep water and cooler, shallow water) is closely regulated by atmospheric conditions, particularly wind stress magnitude, which affects downwelling and sea-ice driven ocean stratification (Jenkins et al., 2016; Holland et al., 2019). This variability in the vertical ocean temperature profile and the associated ice-shelf melt response has been directly linked to the El Niño/Southern Oscillation (ENSO) (Jenkins et al., 2016; Holland et al., 2019; Steig et al., 2012; Paolo et al., 2018). Subshelf melting in the region is also affected by the strength and position of the Amundsen Sea Low (ASL) (Paolo et al., 2018). Furthermore, other climate modes modulate the ENSO teleconnection to the Pacific sector of the Southern Ocean and the strength of the ASL, including the Southern Annular Mode, the Pacific Decadal Oscillation, and the Atlantic Multidecadal Oscillation (Goodwin et al., 2016; Fogt & Bromwich, 2006; Fogt et al., 2011; Li et al., 2014; Meehl et al., 2016; Schneider et al., 2012). While the exact impact of these various modes of climate variability on ice shelf basal melting is not fully understood, there has been little investigation of their impacts on Amundsen Sea sector glaciers, despite ocean temperature-driven basal melting being a primary control on ice sheet dynamics via ice shelf buttressing.

Here, motivated to better understand the effects of ocean variability on ice sheet dynamics and associated sea level changes, we force an ice sheet model of Thwaites Glacier with variable ocean temperature that is reflective of variability in regional Amundsen Sea observations. We find that when variability is taken into account, Thwaites Glacier mass loss and the associated sea level rise are reduced by up to 10% due to delays in grounding line retreat and mass loss. The slowed retreat is primarily due to the inability of variability in the depth of the thermocline to warm the subshelf cavity much beyond the already warm state that exists beneath Thwaites Ice Shelf. A smaller fraction of the delay in glacier retreat appears to be driven by a nonlinear ice dynamic response to ice-shelf thinning. The results indicate that climate variability can be important for driving variability in ice sheet dynamics.

2. Methods
2.1. Ice Sheet Model Configuration and Simulations
We model the evolution of Thwaites Glacier using the MPAS-Albany Land Ice (MALI) model (Hoffman et al., 2018). MALI solves a first-order, three-dimensional approximation to the nonlinear Stokes equations for ice velocity (also referred to as the “Blatter-Pattyn” model; Blatter, 1995; Pattyn, 2003; Schoof & Hewitt, 2013) using the finite element method (Tezaur et al., 2015). The model solves the following system of PDEs:

\[
\begin{align*}
-\nabla \cdot (2\mu \hat{e}_s) + \rho g \frac{\partial s}{\partial z} &= 0, \\
-\nabla \cdot (2\mu \hat{e}_s) + \rho g \frac{\partial s}{\partial y} &= 0,
\end{align*}
\]

(1)

where \(\nabla\cdot\) is the divergence operator, \(s \equiv s(x, y)\) represents the ice sheet upper surface, and the vectors \(\hat{e}_s\) and \(\hat{e}_z\) are given by

\[
\hat{e}_s = \begin{pmatrix} 2\hat{e}_{xx} + \hat{e}_{yy}, \hat{e}_{xy}, \hat{e}_{xz} \end{pmatrix},
\]

(2)
Figure 1. (a) Location map and model domain setup. Thwaites Glacier model domain area is colored by modeled ice surface speed in the initial condition, with gray shading indicating ice-free regions of the model domain. Black line is grounding line position. Gray line indicates ice shelf extent outside of the model domain. Thin white lines are contours of model mesh resolution. The two points in the corners of the map identify the model domain location in a Polar Stereographic projection with true scale at 71° S and WGS84 ellipsoid. Inset map shows location of model domain in red within Antarctica. (b) Ice sheet surface speed observed by satellite from Rignot et al. (2011). (c) Optimized basal friction parameter, $\beta$, used to minimize the misfit between modeled and observed surface velocity. (d) Bed topography in the vicinity of present-day Thwaites Ice Shelf. Purple line is the grounding line position in the original geometry data set derived from BEDMAP2. Blue line is the grounding line position after the 5-year relaxation procedure and is the initial condition for all simulations presented. White lines are the grounding line positions observed by InSAR for the period 1994–2000, and the black line is the observed grounding line position from 2011 (Rignot et al., 2014). Yellow line is the fixed calving front position in our simulations. Black dot identifies the deepest depth of the sill.

The effective viscosity, $\mu_e$, is given by

$$\mu_e = A \left( \frac{1}{\bar{\mu}} \right)^{1/n}.$$

and

$$\dot{\varepsilon}_2 = \left( \dot{\varepsilon}_{xy}, \dot{\varepsilon}_{xx} + 2\dot{\varepsilon}_{yy}, \dot{\varepsilon}_{yz} \right)^T.$$
In equation (4), $A$ is a temperature-dependent rate factor, and $n$ is an exponent taken as three for polycrystalline glacier ice. The effective strain rate $\dot{e}_e$ is given by the second invariant of the strain-rate tensor. The rate-factor $A$ follows an Arrhenius relationship using the form and parameter values described by Paterson (1982). Ice thickness evolution is performed using an upwind finite volume scheme. For a given grid resolution, increased accuracy at the grounding line is achieved through a subgrid parameterization of stresses. Additional details of the model formulation can be found in Hoffman et al. (2018) and Tezaur et al. (2015). In this application, we use a linear basal friction law.

Ice thickness and bed elevation are interpolated onto the model mesh from the BEDMAP2 data set (Fretwell et al., 2013) but with the addition of a pinning point near the tip of the eastern portion of Thwaites Ice Shelf required to match ice velocity and aerogravity observations as described by Cornford et al. (2015) (Figure 1d). We prescribe a constant internal ice temperature from Van Liefferinge and Pattyn (2013) interpolated onto our model mesh. Ice shelf stiffness is calculated entirely from ice temperature, rather than through optimization, to avoid development of rheological discontinuities as the grounding line retreats. The ice shelf calving front position is fixed in time at the approximate 1995 position that is represented in the BEDMAP2 data set (Figure 1d); a fixed calving front position eliminates the need to explicitly model iceberg calving and also eliminates changing ice shelf front position as a complicating factor when comparing different model ensemble members. Surface mass balance is fixed in time and comes from the 1979–2010 average climatology of RACMO2.1 as described by Lenaerts et al. (2012). Ice shelf basal mass balance forcing is described below.

We perform our simulations on a variable resolution mesh with 1-km cell spacing throughout the region of bedrock overdeepening (Figure 1a). In the upper catchment, mesh resolution gradually coarsens to a maximum of 8 km. The lateral boundary conditions along the edges of the domain are Dirichlet boundary conditions for velocity with a value of zero. For the MISMIP3d experiments (Pattyn et al., 2013), MALI required kilometer-scale resolution to fully resolve grounding line migration due to the use of a subgrid parameterization of grounding line position (Hoffman et al., 2018). To ensure this resolution is adequate for the model configuration used here, we performed a grid convergence study using a subset of the Thwaites glacier domain, running a control simulation for 25 years at uniform 0.5-, 1-, 2-, 4-, and 8-km resolutions. Flux across the grounding line and change in grounded area during the simulation was nearly identical for the 0.5- and 1-km resolution runs (<3% difference) but differed increasingly at coarser resolutions. Thus, we consider 1-km resolution to be adequately resolved without unnecessarily increasing model cost.

We initialize the model to produce an initial condition with a transient that is similar to observations, rather than a steady-state initial condition. We optimize the basal friction parameter at each model grid cell to minimize the misfit between modeled and measured ice surface velocity (see Hoffman et al., 2018; Perego et al., 2014) (Figures 1a–1c). Satellite-derived ice surface velocity data for the optimization was measured in 2007–2009 (Rignot et al., 2011). While this approach generates a modeled ice surface velocity field very similar to observations, it leads to initially large, transient, flux divergence anomalies due primarily to inconsistencies between the true bedrock topography and that used in the model (e.g., Perego et al., 2014). To adjust for this, we conduct a 5-year, forward model "relaxation," which allows the majority of the large, fast transients to dissipate from the optimized initial condition. We use the end state after the 5-year relaxation as the initial condition for all experiments. In this state, the modeled flux across the grounding line is 125 Gt year$^{-1}$, which compares favorably with measured fluxes of 115–132 Gt year$^{-1}$ in the 2006–2010 time period (Mouginot et al., 2014). Similarly, the modeled grounding line position is everywhere within 15 km of the 2011 grounding line position mapped by Rignot et al. (2014) (Figure 1d).

A series of 500-year model simulations of Thwaites Glacier were performed to compare the effect of fixed versus variable ocean temperatures. A control run used a fixed ocean temperature profile for the duration of the 500-year simulations to force the ice-shelf basal-melt parameterization described in section 2.2. Note that in the parameterization, subshelf melt rates change as the ice shelf geometry changes and follow the grounding line in a realistic way, as described below.

In addition to the control run, six ensembles were conducted that include sinusoidal variations in the ocean temperature profile forcing the ice-shelf basal-melt parameterization. The six ensembles were composed of combinations of two values of amplitude of thermocline depth variation (150 and 300 m) and three values of variability period (5, 20, and 70 years). These variability parameters and their chosen values are described in section 2.3. Each of the six ensembles was composed of 12 simulations evenly sampling phase offset across
Figure 2. Parameterization for ice shelf basal melting. Application for Thwaites Glacier initial condition is shown. (a) Temperature profiles used in melt calculation: $T_R$ is the regional temperature profile that is the input to the parameterization. $T_C$ represents temperature in the subshelf cavity by adjusting $T_R$ for the sill depth ($Z_{sill}$). $T_f$ is the freezing temperature. $T_\infty$ is the temperature at infinite distance along a melt plume. The temperature in the plume, $T$, is calculated from the parameterization as an exponential decay from $T_C$ to $T_\infty$. (b) Thermal driving calculated from (a). The local thermal driving, $(T - T_f)$, is calculated as the difference between the plume temperature and freezing temperature at each depth. The regional thermal driving, $\langle T - T_f \rangle$, is the mean of $(T - T_f)$ between the grounding line depth ($Z_{GL}$) and the calving front depth ($Z_{CF}$). (c) Modeled melt rate is proportional to the product of $(T - T_f)$ and $\langle T - T_f \rangle$. The parameterization was loosely calibrated to observed melt rates from Rignot et al. (2013), which are shown here separated for the eastern (blue) and western (orange) sections of Thwaites Ice Shelf.

one sinusoidal cycle. This resulted in a total of 72 simulations for sampling the effects of ocean temperature variability on Thwaites Glacier evolution. An animation of a run with variability is provided as supporting information Movie 1.

Importantly, in each run with variability, variations in time were applied relative to the ocean temperature profile used in the control run. This ensured that the time-mean ocean temperature profile is the same in all simulations, allowing us to isolate ocean temperature variability as the only driver of intersimulation differences in long-term ice sheet change. In all scenarios, there was no secular trend in ocean temperature; the simulations represent projections of committed mass change from Thwaites Glacier under sustained current conditions and do not include any additional effects related to future anthropogenic forcing. Individual simulations were conducted on 240 processors each using NERSC's Edison supercomputer (https://www.nersc.gov/users/computational-systems/edison/). The full set of 73 (control run plus 72-member ensemble), 500-year simulations used 3.1 million core hours.

2.2. Ice Shelf Basal Melting Parameterization
To investigate the role of subshelf melt variability, we implemented a subshelf-melt parameterization that borrows aspects from buoyant plume theory rather than being purely empirical and reproduces the following key features of observed subshelf-melt rates in the Amundsen Sea region (Figure 2):

- Melt rates are proportional to the product of local ocean thermal driving (ocean temperature minus freezing temperature) and the velocity of the overturning flow;
- Melt rates are higher at deeper ice shelf drafts where warm, mCDW meets the ice shelf through density-driven flow;
- Entrainment of meltwater and cooler ambient water into the buoyant melt plume causes decreasing melt rates at shallower depths; and
- The presence of a bathymetric sill blocks access of deeper water masses from entering the subshelf cavity and affecting melt rates.

To capture these features, we derived a simple, depth-dependent melt parameterization that allows the grounding line to retreat into deeper water without creating unrealistic melt rates at depth. While retaining the simplicity of depth dependence, the parameterization borrows from plume theory the concept that both meltwater and ambient water are entrained unto a buoyant plume as it ascends the ice-shelf base. Thus, melting at a given depth is not just determined by the properties at that depth but also retains some “memory” of the plume flow from the grounding line up to that depth. Melt rates are a function of the ocean temperature profile in the ice-shelf cavity, but unlike many previous depth-dependent melt parameterizations, we take into account not only the local ocean properties but also an approximation of the “history” of the plume as it traveled from the grounding line. The parameterization also makes use of modeling (Holland et al., 2008; Jourdain et al., 2017) and observations (Jenkins et al., 2018) that suggest that mean melt...
rates are a quadratic function of mean thermal forcing (ambient ocean temperature minus freezing temperature) because the velocity of the overturning flow is proportional to the mean thermal forcing. Details of the parameterization and its derivation can be found in Appendix A.

A desirable property of the parameterization is that it is straightforward to see how melt rates are affected by ocean temperature variability, since melt rates are a direct function of the profile of ocean temperature in the cavity. To force the subshelf melt parameterization, we apply the idealized ocean temperature profile used by De Rydt et al. (2014) and De Rydt and Gudmundsson (2016), which is based on observations (Christianson et al., 2016; Dutrieux et al., 2014) from Pine Island Bay (Figure 2). This profile represents a shallow layer of cold Winter Water (the cold surface water mass formed from brine rejection during sea-ice formation) at −1 °C from the surface to 300-m depth and a deep layer of warm mCDW at 1.2 °C below 700-m depth. Temperature varies linearly between these two regions in a transitional thermocline zone (Figure 2a). While De Rydt et al. (2014) and De Rydt and Gudmundsson (2016) used this profile to force their explicit model of ocean circulation within an ice shelf cavity, we use it as the far-field input for our melt parameterization.

While this parameterization has a theoretical basis and produces a number of desirable features as described above, its relatively simple form does require addressing several notable caveats and limitations. Importantly, although the parameterization adopts some aspects of plume theory, the resulting melt rates should not be mistaken for a solution of the full 1-D plume equations. Given that it is not clear that the 1-D plume equations result in melt rates that compare well with observations (Lazéroms et al., 2018) or coupled ice sheet-ocean models (Favier et al., 2019), this was not our aim. Additionally, the simple depth dependence results in the largest melt rates occurring exactly at the grounding line. This is contrary to the fact that high-resolution ocean modeling shows that the highest melt rates occur near the grounding line, but that very close to the grounding line, melt rates decrease toward zero (Asay-Davis et al., 2016; De Rydt & Gudmundsson, 2016; Favier et al., 2019). This will likely result in a positive bias in mass loss and associated grounding line retreat in our model. However, as the goal of our study is comparing the inclusion of ocean variability to simulations without variability rather than absolute sea level projections, we accept the trade-off for ease of implementation.

Among the various free parameters of the parameterization (see Appendix A), we choose to treat the plume thickness, $D$, and the melt factor, $K$, as calibration parameters. Using observationally derived estimates of present-day ice shelf basal melt rates from Rignot et al. (2013), we adjust the two parameters to allow the parameterization to approximate the depth distribution of melt rates (Figure 2). The magnitude of maximum melting ($\sim 55$ m year$^{-1}$) is controlled by $K$, while the melt rate at the shallowest depths of the ice shelf ($\sim 15$ m year$^{-1}$ at $\sim 200$-m depth) is controlled by $D$ for a given $K$. The sill depth, $z_{\text{sill}}$, is set to a depth of 663 m, which is the deepest depth of the shallowest ridge in the bed topography in our modeling domain (Figure 1d). This happens to be the ridge on which the initial grounding line is located, so that the presence of a sill applies throughout the entire simulations (i.e., the grounding line is never advanced seaward of the sill). To approximate present-day melt rates, we set $K = 8.5$ kg m$^{-2}$ s$^{-1}$ °C$^{-2}$ and $D = 30$ m. Within MALI, the melt parameterization is applied only to grid cells classified as floating. This is determined in MALI by evaluating the hydrostatic ice floatation criterion at the center of each grid cell. Note that because of the dual grid implementation used in MALI (Hoffman et al., 2018), this convention leads to treatment of melting near the grounding line in a fashion similar to, but not identical to, the SEM1 melt parameterization described by Seroussi and Morlighem (2018).

While the parameterization is tuned to present-day estimates of Thwaites Ice Shelf melt rates (Figures 3a and 3b), we constructed the parameterization such that melt rates remain physically reasonable as the subshelf cavity shape evolves during the simulation: (1) Melt rates remain a function of ocean temperature as opposed to simply ice shelf draft, which increases dramatically during these simulations; (2) maximum melt rates follow the grounding line as it retreats; and (3) melt rates decrease toward an “ambient” value at shallow ice shelf draft (Figures 3c and 3d).

For the ice sheet model initial condition, our parameterization yields total melt for Thwaites Ice Shelf of $98.8$ Gt year$^{-1}$, close to the observationally derived estimate of $97.5 \pm 7$ Gt year$^{-1}$ (Rignot et al., 2013). While we are unable to validate the parameterization for an evolving ice shelf due to lack of observations and thus cannot have high confidence in its use for projecting future sea level rise, its physically based features allow us to use it confidently to assess the sensitivity of ice sheet evolution to ocean temperature variability.
Figure 3. (a) Observationally derived basal melt rate for Thwaites Ice Shelf from Rignot et al. (2013). (b) Modeled basal melt rate from parameterization described in section 2.2 for the initial ice geometry. (c) Modeled basal melt rate from parameterization for Year 175 of the control run. (d) Modeled basal melt rate from parameterization for Year 350 of the control run.
2.3. Subshelf-Melt Forcing Variability

To add variability to the melt forcing, we apply sinusoidal variations in the depth of the ocean temperature profile, keeping the shape of the profile fixed (Figure 4). This is motivated by observations of shoaling and deepening of mCDW in the Amundsen Sea as a dominant aspect of oceanic temperature variability, at Pine Island Bay (about 100 km from Thwaites Ice Shelf; Christianson et al., 2016; Dutrieux et al., 2014), at Dotson Ice Shelf (about 350 km to the west; Jenkins et al., 2018), and at Getz Ice Shelf (about 500 km to the west; Jacobs et al., 2013). These observations show depth variations of the thermocline of over 200 m occurring (up to 500 m at Getz Ice Shelf Jacobs et al., 2013) over a 20-year period, with large fluctuations over 2-year periods. It is reasonable to hypothesize, however, that the roughly 20-year observational record does not fully sample the possible range of mCDW variability.

Motivated to understand the impacts of these observed variations on ice sheet evolution, we perform ensembles of ice sheet simulations that include different values of the amplitude and period for the variability imposed on the depth of the ocean temperature profile. Changes in ocean salinity are not included. Our model ensembles include an amplitude of 150 m, which approximates the observed vertical thermocline variability in Pine Island Bay, and a second, larger amplitude of 300 m that is moderately larger than the largest changes observed at Getz Ice Shelf. We choose periods of 5, 20, and 70 years, roughly corresponding to periods for commonly studied modes of climate variability. The ENSO has most power at 2–7 years (D’Arrigo et al., 2005; Li et al., 2011), and assessments of the Pacific Decadal Oscillation suggest a spectral peak at 15–25 years (Mantua & Hare, 2002). Additional spectral power may exist at even longer periods, for example, the ENSO includes a cycle of 50–90 years (Li et al., 2011), the Pacific Decadal Oscillation may have an additional spectral peak at 50–70 years (Mantua & Hare, 2002), the ASL may exhibit 60- to 140-year periodicity (Kreutz et al., 2000), and the Atlantic Multidecadal Oscillation includes periodicities of 50–90 years (Knudsen et al., 2011; Schlesinger & Ramankutty, 1994).

These modes of climate variability have varying and poorly understood effects on conditions in the Southern Ocean and complex interactions with one another. While we do not intend the sinusoidal variability we impose to be directly reflective of specific modes, our idealized 5-, 20-, and 70-year forcing periods aim to represent a realistic range of variability. We do not consider shorter periods of variability, because ocean temperature variations with shorter than 5-year periods are likely too short to support an equilibrium response in ice shelf melting for a small, warm ice shelf such as Thwaites, due to incomplete flushing of the subshelf cavity (Holland, 2017). Representing such complex behavior is beyond the ability of our melt parameterization, which assumes instantaneous adjustment of melt rates to far-field ocean temperature.

As described above in section 2.1, six ensembles including ocean temperature variability were conducted for each combination of amplitude (150 and 300 m) and period (5, 20, and 70 years).
Figure 5. Summary of model results. In each panel, black represents the control run, and colors summarize ensembles with ocean temperature variability. For each ensemble, the thick line is the ensemble mean, and the dashed lines are the ensemble minimum and maximum. (a) Spatially averaged melt rate applied by subshelf melt parameterization. (b) Volume above floatation. Corresponding sea level rise contribution is shown on the right axis. (c) Mass loss rate. (d) Difference in sea level rise contribution for each ensemble relative to control run. All ensemble members with ocean temperature variability exhibit less contribution to sea level rise than the control run. (e) Delay in grounded area relative to control run for each ensemble.

3. Results

Thwaites Glacier exhibited sustained retreat during the control run without ocean temperature variability, reaching 158,500-Gt mass loss in volume above floatation (437.9-mm sea level equivalent) after 500 years (Figure 5b). Loss in volume above floatation was 9,375 Gt (25.9 mm sea level equivalent) at Year 100 and 58,540 Gt (161.7-mm sea level equivalent) at Year 300. The rate of mass loss, calculated as decreasing volume above floatation to reflect sea level contribution potential, increases from about 50 to 100 Gt year$^{-1}$ over the first century of the simulation (Figure 5c). Between Years 100 and 160, the mass loss rate rapidly increases to over 200 Gt year$^{-1}$. This occurs as the grounding line migrates across a last set of bathymetric highs (approximately $-600$-m depth) and subsequently retreats unstably into deeper terrain (less than $-1,000$-m depth). Around Year 280, the grounding line again begins retreating past a range of restraining bathymetric highs into deeper terrain (less than $-1,400$-m depth). Mass loss rates again increase, reaching 600 Gt year$^{-1}$ over the following 100 years. After the grounding line has retreated through the deepest parts of the basin and encountered bathymetry shallower than $-1,000$ m, mass loss rates reduce to $\sim400$ Gt year$^{-1}$—still substantially greater than mass loss rates during the first 300 years of the simulation.

During the control simulation, mean ice shelf melt rates range between $\sim10$ and 20 m year$^{-1}$ (Figure 5a), similar to current observational estimates of 17.7 m year$^{-1}$ (Rignot et al., 2013). Changes in area-mean melt rate over time are largely driven by the changing hypsometry of the ice shelf draft; when larger fractions of the ice shelf’s lower surface occur at deeper depths where melt rates are larger, the area-mean melt rate
Figure 6. Distribution of mass loss delay within each ensemble at different times. Each dot is one of the 12 runs within each ensemble. The ensemble mean is shown with an x and the median with a circle. (a) Averaged over Years 50–100. (b) Averaged over Years 200–250. (c) Averaged over Years 450–500. Note the y axis range differs in each plot.

increases. Note that because the minimum sill depth occurs at a similar depth to the initial grounding line position, the ocean temperature controlling maximum melt rates at the grounding line changes little from the initial values during the control run; thus, maximum melt rates near the grounding line change only modestly from initial values during the simulations (range of 53–68 m year$^{-1}$ over simulation). Area-mean melt rates decrease as the grounding line retreats due to the fixed calving front position and a growing fraction of the ice shelf existing at relatively shallow draft. In contrast, melt rates increase when a greater proportion of the grounding line retreats from bathymetric highs into deeper bathymetry and is therefore exposed to warmer ocean water at depth.

When variability is included in the simulations, all model runs result in less mass loss at a given time than in the control run. This effect varies from 8.6- to 40.0-mm cumulative sea level contribution (2.0% to 9.1%) at Year 500 (Figure 5d) and is larger for variability with larger amplitudes and/or longer periods. Additionally, for a given amplitude and period, there is significant variability introduced due to the initial phase offset, highlighting the need for ensembles (Figures 5d and 6). A notable finding is that the variability in the rate of mass loss for a single model realization, relative to the ensemble mean, is up to 50% at a given point in time. This provides an estimate for the uncertainty introduced when relying on a single simulation to estimate rates of mass loss (or equivalently, the rates of eustatic sea level rise) in the presence of variable forcing.

We do not assess the impact of variability on equilibrium glacier mass. However, model results show that the pathways of grounding line position and mass loss remain very similar when variability is included—but occur at later times relative to the control (Figures 5b and 5c). The decrease in sea level contribution at a given point in time reflects a variability-induced delay in the transient evolution of the glacier. We define a delay as the additional time required for the grounded area in an ensemble member to retreat to the same value simulated in the control run at a given time (Figure 5e).

The delay in mass loss induced by the presence of variability ranges from 9 to 43 years at Year 500 for the modes of variability explored (Figures 5e and 6). For variability comparable to recent observations in Pine Island Bay (150 m), the mass loss delay after 500 years is 9–18 years depending on the forcing period. While the longer periods of variability induce longer delays, the effect is relatively modest with the smaller amplitude of variability. However, for the large amplitude variability (300 m), there is more than a doubling in the induced mass loss delay. Variations in mass loss delay due to the phase of the imposed variability also become substantially larger for the large amplitude and longer period ensembles; for the case with variability of 300-m amplitude and 70-year period, ensemble range in mass loss delay at 500 years is 35% of the ensemble mean, while variability with 150-m amplitude and 5-year period exhibits ensemble spread of only 10% (Figure 5c). For our extreme variability scenario at Year 350, ensemble spread in mass loss rate is over half the ensemble mean.
Figure 7. Model results shifted in time to account for variability-induced delay to provide a more direct comparison with control simulation. Colors are as in Figure 5. Solid lines represent mean of each ensemble. (a) Delay-adjusted mass loss rate. (b) Delay-adjusted melt rate. Dashed lines indicate range of ensemble. (c) Difference between delay-adjusted melt rate in ensembles from melt rate in the control run. Dashed lines refer to times references in (e). (d) Delay-adjusted delay rate (i.e., the slope of the delay-adjusted curves in Figure 5e). (e) Maps of modeled grounding line positions for key periods of mCDW temperature-limitation effect. The limits of the period of high melt rate difference between control and ensembles with variability (c) is shown by maroon lines at Years 250 (thick line) to 390 (thin line). Period of rapid delay accumulation in ensembles with variability (d) is shown by light gray lines corresponding to Years 260 (thick line) to 280 (thin line). Second period of rapid delay accumulation shown in dark gray lines corresponding to Years 290 (thick line) to 310 (thin line). All grounding line positions are from control run. Grounding line position at Year 0 is shown with blue line for reference. Fixed calving front position is shown in yellow.

4. Discussion
4.1. Comparison to Previous Modeling of Thwaites Glacier
Our control simulation generates mass loss that fits within the range described by previous studies. Compared to a similar melt forcing used by Joughin et al. (2014) (their “m=3” simulation), our simulation loses mass faster in the first 100 years (maximum mass loss rate of 136 Gt year$^{-1}$ compared to about 80 Gt year$^{-1}$), but both models initiate a sudden phase of rapid mass loss around Year 100 when the grounding line first retreats into substantially deeper terrain. Our results are similar to that of Joughin et al. (2014) for their case with weakened ice shelf margins, with our results reaching a maximum rate of sea level contribution of 1.85
mm year\(^{-1}\) in Year 325. Similarly, our control run generates mass loss rates in the first (96 Gt year\(^{-1}\)) and second (212 Gt year\(^{-1}\)) centuries comparable to those reported by Cornford et al. (2015) (75 and 320 Gt year\(^{-1}\), respectively). Our control run yields a 10.1-mm contribution to sea level rise at Year 50, which is slightly less than the range of 12.1 to 13.3 mm modeled by Seroussi et al. (2017). This is despite our melt parameterization yielding a somewhat larger melt rate at Year 50 (141 Gt year\(^{-1}\)) than the coupled ocean-ice sheet model used by Seroussi et al. (2017) (up to \(\sim\)130 Gt year\(^{-1}\)). The difference is likely due to our use of an interpolated bed topography data set, which is known to be artificially rough and hence leads to reduced rates of retreat relative to more realistic mass-conserving bed topography (Nias et al., 2018). Yu et al. (2018) report a range of 14- to 42-mm sea level contribution from Thwaites Glacier in the next 100 years for a range of ice flow models, basal friction laws, and melting scenarios, which spans the projection from our control run of 25.9 mm. Our control run falls within the range of previous mass loss projections for Thwaites Glacier and thus serves as a reasonable basis for comparing with simulations that include variability in ocean temperature and submarine melt forcing. Note however that, because our model configuration does not include any changes to the mean forcing relative to the initial time, it does not represent a projection of ice sheet conditions under future climate.

### 4.2. Reduced Melt Rate Under Ocean Temperature Variability

In all variability scenarios, the delay in mass loss for the ensemble mean increases monotonically over time as the glacier retreats. However, the rate of increase in delay varies as the simulations progress (Figure 5e). It is difficult to identify the causal mechanism for changes in the rate of increase of the delay, such as differences in mean melt rate between runs or interactions with specific bed topographic features. This is because different runs can exhibit very different ice-sheet and ice-shelf state (e.g., grounding line position) at any given model time due to the delay itself. To account for this, we shift model results in time to account for the variability-induced delay to allow for direct comparison of the ensemble states with the control run (Figure 7). Specifically, at each point in time for a run with variability, we find the time from the control run at which ice sheet grounded area is the most similar. We then define the difference between these times as the “delay,” with a negative value indicating that the run with variability is retreating more slowly than the control. We choose grounded area as the metric for aligning the model runs, instead of, say, volume above floatation, because comparing runs with a common grounded area leads to grounding line positions and, by association, ice-shelf shape that are the most similar between different runs. This allows a more direct assessment across all runs of interactions of the grounding line with bed topographic features and how ice-shelf hypsometry affects melt.

This shift of the time coordinate accounts for the majority of the discrepancy in the mass loss rate between the control run and the ensembles (cf. Figure 5c and Figure 7a), as well as the melt rate (cf. Figure 5a and Figure 7b). With this shift, it becomes apparent that the mean melt rate experienced by the ensembles is less than in the control run (Figure 7c) and that the timing of lowered mean melt rate in the ensembles matches many of the periods of increased rate of delay (e.g., Year 150 and Years 250–400 in Figures 7c and 7d). Despite symmetric variations in the ocean temperature profile about the control state, the total mass loss due to melting over the entire 500 years is 2–4% smaller in runs with variability relative to the control run.
Figure 9. Area-mean melt rate as a function of depth to top of mCDW calculated for ice shelf geometry in control run at Years 430 (open black circles) and 285 (filled gray circles). Depth to top of mCDW in control run is shown with large symbols.

The lower mean melt rate in the ensembles with ocean variability can be explained by a nonlinear sensitivity of subshelf-melt rate to ocean temperature changes in the melt parameterization (Figures 8a and 8b). This occurs because of the specific interactions of the ocean temperature profile with the sill depth at Thwaites Glacier. The reference depth of the top of the near-isothermal mCDW layer (~700 m) is very close to the depth of the sill (~688 m) that prevents access of deeper water masses into the subshelf cavity. As a result, when the mCDW shoals, the temperature of the deepest, and therefore warmest, water entering the cavity remains close to its original temperature due to uniform temperature within the mCDW layer. It is this deepest water within the cavity that reaches the grounding line, and we use its temperature in calculating melt at the grounding line in our parameterization. In contrast, when the mCDW deepens, the grounding line is exposed to increasingly colder ocean temperatures higher in the oceanographic temperature profile. The result is that mCDW shoaling results in a smaller magnitude of melt rate increase than the magnitude of melt rate decrease associated with mCDW deepening (Figure 8b). Note that this effect applies even during the initial phases of the simulation when the grounding line depth is above that of the sill, because the initial grounding line depth (~693 m) is similar to that of the sill.

In other words, an upper limit on temperature increase in the subshelf cavity due to the approximately isothermal nature of mCDW limits the extent to which melt rate can increase. While this is a result of the specific oceanographic and bathymetric conditions near Thwaites Glacier, we expect it to be common among so-called “warm-shelf” situations. For example, neighboring Pine Island Glacier has a similar sill depth of approximately ~750 m (Christianson et al., 2016; Jenkins, Dutrieux, et al., 2010). The effect is similar to the “warm-shelf” phase described by Hellmer et al. (2017) where ice-shelf melt rates cease to increase after mCDW floods the continental shelf.

A main conclusion of this study is that deviations in ice-shelf melt rate are asymmetric about the mean state under variable ocean temperature conditions. As discussed, this occurs because of the relation between the sill in front of Thwaites Glacier and the depths of the ambient ocean water masses. The asymmetry in the melt rate under variability is strongly affected by the fact that the sill depth is quite close to the depth at the top of the mCDW layer below which temperature no longer changes. A shallower sill depth would cause the ice-shelf cavity to not be exposed to mCDW at all, even under changes to the depth of the temperature profile, and therefore, the ice shelf would be predominantly affected by temperatures changes within the thermocline. In that case, changes in melt rate would be more symmetric. In the case of an extremely shallow sill depth or grounding line, a melt asymmetry in the other direction would occur where “cold” excursions of variability would have less impact than warmer excursions due to the approximately isothermal nature of cold and shallow Winter Water. Thus, the existence of “warm cavity” conditions under Thwaites Ice Shelf and a sill at a similar depth to the top of mCDW are necessary features for the asymmetric ice-shelf melt rate under variability. While our melt parameterization distinctly exhibits this behavior, we believe this to be a physical effect that would be seen in more complete ocean models and the real world and not just an artifact of our parameterization. Thus, while other ice shelves with similar conditions (e.g., Pine Island Glacier) would be subject to similar effects, this result is not general to all ice shelves.

The limited increase in melt rate with mCDW shoaling counteracts the quadratic temperature dependence of subshelf melt rate (Holland et al., 2008; Jenkins et al., 2018) that generates increasingly larger melt rates as ocean temperature increases (Figure 9). Over the range of temperature variations observed in the Amundsen Sea, this nonlinearity is fairly weak (Jenkins et al., 2018), allowing the mCDW temperature-limitation effect to dominate in our simulations. While the magnitude of the mCDW temperature-limitation effect is related to the form of our melt parameterization, there remains a strong physically based, qualitative argument for this process limiting melt rates. That is, melt sensitivity to mCDW shoaling is expected to be significantly lower in the presence of a blocking, submarine sill, as demonstrated here with our subshelf melt parameterization and previously in explicit modeling of subshelf cavity circulation by De Rydt et al. (2014). Of note is that the impact of mCDW temperature limitation within the subshelf cavity only results in significantly decreased melt rates relative to the control at certain times (Figure 7c). This can be explained...
as a consequence of ice shelf hypsometry. The asymmetry in melt rate under variable forcing is more pronounced where ice shelf draft is deep (Figure 8b), so the effect is only important to shelf-averaged melt rate when a substantial fraction of the ice shelf draft exists at depths close to the sill depth. This can be seen by comparing ice shelf geometry (as indicated by the hypsometry distributions shown in Figure 8c) at Years 285 and 430 of the control run, which have similar grounding line and calving front depths, but are representative of periods where delay and associated melt reduction in the runs with variability (adjusted for delay) are high and low, respectively (Figures 7c and 7d). The ice shelf draft in Year 285 has a relatively large area below −600 m (Figure 8c) where the melt response to changes in thermocline depth are strongly nonlinear in our parameterization. Conversely, the ice shelf draft in Year 430 predominantly has area at moderate depths where the melt response is close to linear. The impact of the mCDW temperature limit at depth is significant to the area-integrated melt rate in Year 285 but not in Year 430 (Figure 9).

The presence of significant fractions of the ice-shelf draft deep in the water column is more likely to occur when the grounding line, and thus the deepest parts of the ice shelf, lies in deep bathymetry. The extended period of time from Years 250 to 390 when the runs with variability experience lower melt rates than the control run (Figure 7c) corresponds to the period when the grounding line is traversing the large, deep basin in the center of the domain (Figure 7e).

However, the difference in melt rate affects the accumulation of mass delay more when the grounding line begins unstable retreat into an overdeepened basin. The highest melt rate differences occur around Year 330, but the periods of highest delay rate occur during Years 260–280 and Years 290–310 (Figure 7d), which are both times when the grounding line retreats through smooth, overdeepened basins (Figure 7e). This suggests that marine ice sheet instability may be amplifying differences in melt forcing.

4.3. Ice Dynamic Response to Variable Melting

To quantify the delay in glacier retreat as a function of lowered melt rates, as opposed to other possible mechanisms, we conducted one additional ensemble that controls for melt rate. In this ensemble, we imposed
Figure 11. Delay-adjusted model results comparing an ensemble with linearly varying ocean temperature profile depth (amplitude 300 m, period 20 years; orange) and an ensemble with linearly varying subshelf-melt rate (cyan). Plots are as in Figure 7. (e) Maps of modeled grounding line positions for key periods of nonlinear ice dynamics effect. Periods of rapid delay accumulation in scaled-melt variability ensemble (d) are shown with three sets of gray lines: light gray lines bracket Years 95 (thick line) and 130 (thin line), medium gray lines bracket Years 245 (thick line) and 285 (thin line), and dark gray lines bracket Years 295 (thick line) and 315 (thin line). All grounding line positions are from control run. Grounding line position at Year 0 is shown with blue line for reference. Fixed calving front position is shown in yellow.
variability directly on the melt rate magnitude in order to ensure symmetry to either side of the melt rates used for the control (i.e., higher or lower melt rates). For this melt forcing, the ocean temperature profile was held fixed (as in the control), and the melt magnitude at a given depth was scaled sinusoidally by a linear factor (applied to $K$ in equation (A1)). This scaling factor was set to $\pm 60\%$ to match the magnitude of melt variations in the previous ensemble with period 20 years and amplitude 300 m. The new ensemble used a period of 20 years with six ensemble members of differing phase offset and is compared to the results of the previous ensemble with period 20 years and amplitude 300 m (Figures 10 and 11).

The results show that the scaled-melt ensemble has a similar range of melt variability as the previously described scaled-depth ensemble (Figure 11b), but the difference in ensemble-mean melt is much closer to the control run; the cumulative mass lost to melting for the ensemble mean is within 0.1% of that in the control run (Figure 11c), whereas the cumulative melt for the scaled-depth ensemble mean was 3.3% less than the control run. At Year 500, the delay in the scaled-melt ensemble is 6.5 years, compared with 26.7 years for the scaled-depth ensemble (Figure 10d), suggesting that \(~75\% of the delay in our ensembles is due to the mCDW temperature-limitation effect described above.

In the scaled-melt ensemble, the delay rate is close to zero over most of the simulation (Figure 11d), consistent with small differences in melt rate from the control run (Figure 11c). However, there are a few periods where the scaled-melt ensemble exhibits nonzero delay rate, despite the absence of a difference in melt rate from the control—notably Years 95–130 and Years 245–285 (Figure 11e). This is evidence for an additional delay mechanism, which as we discuss further below, is related to a nonlinear ice dynamical response to varying ice shelf thickness and its associated buttressing.

At these times, as subshelf melt rate increases and ice shelf buttressing is consequently reduced (via decreasing ice thickness), the flux across the grounding line increases at a progressively smaller rate. This is demonstrated in Figure 12, which shows simulations of the mass loss rate when the subshelf melt field used in the control run is scaled uniformly over a range of values and applied for 10 years. At low melt rates, mass loss rate increases linearly with increasing basal melting. However, the increase in mass loss rate for a given increase in melt rate becomes progressively smaller so that at large melt rates, further melt rate increases have relatively little additional effect on mass loss rate.

We can quantify the asymmetry in dynamic response by comparing the mass loss rate resulting from steady melt forcing to the mean mass loss rate over the range of melt rates occurring in the 300-m amplitude ensembles. For Year 200, a time when mass loss rate is steady (Figure 7a), the asymmetric dynamic response to melting causes a 1.2% difference in mass loss rate. However, for Year 272 (Figure 12b), when the rate of grounding line retreat begins to accelerate rapidly (Figure 7a), there is a much larger 8.5% difference. A similar nonlinear ice dynamic response to ice shelf thinning was demonstrated by Reese et al. (2018, see supplemental material).

### 4.4. Role of Variability Period

While we find that longer-period variability increases the delay in glacier mass loss, the shortest period considered (5 years) still exhibits a small but measurable difference in retreat rate relative to the control
run. As the period of variability decreases below 5 years, we expect delays to become increasingly trivial. This expectation is consistent with Holland (2017), who showed that for small, warm ice shelves (similar to Thwaites Ice Shelf), ocean temperature variability below 5-year periodicity has a complex interaction with subshelf melting that tends to cancel out the effects of warm and cold phases of variability, at least for idealized model configurations. This is because water mass residence times are long enough relative to the period of variability to preclude complete cavity flushing between alternating warm and cold phases.

The ability of the ice geometry to adjust to varying melt rates with long period variability also propagates inland to grounded ice. Short-duration perturbations to ice shelf geometry cause ice velocity changes due to membrane stresses that are instantaneous but propagates tens of kilometers at most (Williams et al., 2012), while longer-period forcing can also induce changes to driving stress (mostly ice sheet surface slope) that propagate farther inland and have lasting effects (Williams et al., 2012; Waibel et al., 2018). Williams et al. (2012) estimated the transition between these two modes of response for Thwaites Glacier to be at about 18 years, so longer-period melt-induced variability may cause an interior ice response via both mechanisms. It is this increasing adjustment from inland grounded ice that results in larger variations in grounded glacier mass loss at longer periods of ocean forcing variability (Snow et al., 2017).

4.5. Comparison to Other Studies of Ice-Sheet Response to Climate Variability

In this study we have identified two nonlinearities in ice-sheet response to climate forcing that lead to asymmetric responses to variable forcing. The first is that excursions of equal size in shoaling and deepening of the ocean temperature profile result in different magnitudes of increase or decrease in the melt rate beneath Thwaites Ice Shelf. The second is that ice flux and grounding line retreat are more sensitive to decreases in ice-shelf thinning due to basal melting than they are to increases. Both of these effects lead to decreased mass loss and decreased glacier retreat under variable ocean forcing than for constant forcing with the mean of the variable ocean state.

Previous studies of the Greenland Ice Sheet forced by variable climate forcing have found a similar nonlinearity (Mikkelsen et al., 2018; Tsai et al., 2017). In that case, curvature in the shape of the function relating air temperature to surface mass balance lead to a larger ice sheet under constant climate forcing relative to climate with variability, the opposite net effect to what we see due to opposite sign of the curvature of the relevant forcing-response function. Additionally, simpler models have clearly shown that variability in climate forcing can cause shifts in ice sheet equilibrium states and rates of change and can induce dynamic behaviors not exhibited by deterministic forcing (Mantelli et al., 2016; Roe & Baker, 2016; Robel et al., 2018, 2019).

Of particular relevance is the recent study by Robel et al. (2019) that also applied variations in subshelf melt rate to ensembles of a model of Thwaites Glacier. Additionally, through a simple glacier model and stochastic perturbation theory, Robel et al. (2019) show that marine ice sheet instability amplifies the uncertainty of glacier mass loss with a rate that is proportional to the bed slope (and to a lesser extent the nonlinearity...
in the grounding line flux. The spread of the ensemble is also proportional to the timescale of the variability in the forcing, a relationship we also see. Robel et al. (2019) use 500-member ensembles of an ice sheet model of Thwaites Glacier with many similarities to ours (fixed ice temperature, calving front, and basal friction; linear viscous basal friction law; basal friction optimized to present-day ice surface velocity; and 1-km mesh resolution) and a few notable differences (mass-conserving bed topography instead of BEDMAP2; two-dimensional shelfy-stream approximation instead of three-dimensional Blatter-Pattyn; a simpler depth-based melt-parameterization; different treatment of melt near the grounding line; and variability applied directly to the magnitude of melt rate at the grounding line instead of to ocean temperatures). They find that over the course of their 850-year simulation, ocean variability causes uncertainty of up to nearly 50% of the total ice loss at the end of the simulation.

In Figure 13a, we plot "fractional uncertainty," defined by Robel et al. (2019) as $4\sigma_{\text{vol}}/\mu_{\text{loss}}$, where $\sigma_{\text{vol}}$ is the standard deviation of ice volume across the ensemble over the course of the simulation and $\mu_{\text{loss}}$ is the total ice loss at the end of the simulation averaged over the ensemble. Our ensembles exhibit a similar general shape, with slowly growing fractional uncertainty that increases substantially when the grounding line retreats through large overdeepened basin in the interior of Thwaites basin (at Years 300–500 in our simulations and Years 550–750 in their simulations) and then decreases. Additionally, we see that variability with longer timescales yields greater uncertainty, which is a feature of their theory. However, the spread in our simulations is substantially smaller (peak of ∼0.5–5% for our six ensembles) than in theirs (close to 50% for variability with a 30-year timescale).

While the significant differences between the two models make it difficult to explain the difference in model spread, we hypothesize that the different bed topography data sets and the different melt parameterizations may be responsible for the difference in model spread. The theoretical framework of Robel et al. (2019) identifies bed slope as the most important control on amplification of model spread. The mass-conserving bed methodology yields substantially smoother bed topography than standard interpolation methods (Morlighem et al., 2011), and smoother, more spatially coherent bed slopes may be required for the amplification mechanism to operate effectively in two-dimensional models. If this hypothesis is correct, it would suggest that bed roughness is important not only for rates of glacier mass loss (Nias et al., 2018) but also for uncertainty in mass loss. Additionally, we see a greater fractional uncertainty when we apply variability to the maximum melt rate, as Robel et al. (2019) did, than when we apply variability to the ocean temperature profile, despite the two ensembles providing very similar variations in the area-averaged melt rate (Figure 10a). The likely explanation is that the ensemble fractional uncertainty is most sensitive to melt rates at or near the grounding line, and those vary more strongly when modifying the maximum melt rate directly than when modifying the ocean temperature profile. Thus, the details of how ocean variability affects variability in melt rates may have an important control on glacier mass uncertainty caused by climate variability. Finally, our ensembles include only a single periodicity in ocean forcing, Robel et al. (2019) employ stochastic variability. The spectrum of variability that their method includes may induce more uncertainty. Further studies should focus on using melt rates and their variability determined directly from ocean models.

4.6. Study Limitations

In configuring our study, we made a number of choices about model implementation that affect the realism and generalizability of the results and conclusions. While we employ a higher-order approximation to the equations of ice motion, our model excludes a number of physical processes that may be important for Thwaites Glacier over the timescales considered: These limitations include using a fixed calving front (as well as ignoring the potential for ice cliff failure), ignoring evolution of the ice temperature field and mechanical weakening of shear margins, using a fixed basal friction field (and ignoring evolving basal processes), and ignoring isostatic rebound and evolving sea level. Though these missing physical processes reduce the realism of the simulations, excluding them helps to isolate the differences in model runs with and without ocean variability, without the potential for confounding feedbacks. In particular, processes affecting the ice shelf (calving, ice-cliff failure, and shear margin damage) could lead to divergent threshold behavior that would complicate the primary goal of the study. An additional reason for keeping the model simpler was to reduce model cost to allow many ensembles to be run. The recent study by Robel et al. (2019) also investigating the impact of ocean variability on evolution of Thwaites Glacier included the same modeling limitations listed above, presumably for similar reasons. Future studies should explore what interactions these other effects may have with variability-induced delay and uncertainty.
In addition to choices about what physical processes to include, there were additional modeling choices that affected the simulations. We chose to use a model domain that follows the present-day boundaries of Thwaites Glacier to keep model cost low enough to allow simulation of many ensemble members. However, previous studies have shown that the boundaries of Thwaites Glacier are likely to expand significantly in the future due to interactions with neighboring basins, particularly Pine Island Glacier (Arthern & Williams, 2017; Cornford et al., 2015). While ignoring this effect will affect the projections of total mass loss from the model, we expect it to have a secondary effect on quantifying the impacts of including or excluding ocean variability. Another important modeling choice is the use of a linear basal friction law. Theory (Schoof, 2007; Tsai et al., 2015) and modeling (Brondex et al., 2017; Gillet-Chaulet et al., 2016; Joughin et al., 2009) indicate that grounding line retreat through regions where the bed is reverse sloped occurs more rapidly when the form of the basal friction law is increasingly nonlinear. Model inversion studies suggest a fairly high exponent on the nonlinear basal friction relation is appropriate for Thwaites and neighboring Pine Island glaciers (Gillet-Chaulet et al., 2016; Joughin et al., 2009). Thus, our use of a linear bed may result in an underestimate of Thwaites Glacier retreat. The ice dynamic feedback we identify in this study appears to be strongest through overdeepened basins, and therefore, using a nonlinear basal friction law may result in longer delays under variable ocean forcing than we demonstrate here. Robel et al. (2019) demonstrate that use of a more nonlinear basal friction law will skew distributions toward greater mass loss under variable ocean forcing. However, their theory does not assess how the skew relates to the case of steady forcing, so it is unclear how it relates to our conclusions here.

6. Summary and Broader Context

By comparing ensembles of simulations of glacier evolution that include ocean temperature variability against a control where variability is absent, we demonstrated that multicentury-scale glacier mass loss and associated sea level rise can be reduced by up to 10% due to delays in grounding line retreat when variability is present. Notably, however, while the existence of ocean variability can delay glacier retreat, the effect is not large enough to halt retreat of Thwaites Glacier under idealized, present-day forcing, even under extreme modes of variability and ignoring climatic changes.

We identify the primary mechanism causing this delay as the inability for deep water column temperatures to increase further once near-isothermal mCDW floods the lower depths of the subshelf cavity. This causes decreased sensitivity of melt rate to mCDW shoaling and a lowered mean melt rate when the depth to mCDW varies. This decreased sensitivity is strongest at depth and therefore has a greater effect when the ice shelf geometry includes a larger area deep in the water column. In turn, this primarily occurs when the grounding line is rapidly retreating across a reverse-sloped bed and the progressively increasing flux of ice across the grounding line is sufficient to overwhelm the ability of melting to thin the shelf to shallower depths. This effect is a consequence of the depth of the sill in front of Thwaites Glacier being similar to the depth of the top of mCDW.

We also identify a nonlinear ice dynamic sensitivity associated with ice shelf thinning, presumably through reduced buttressing, and we estimate it accounts for about 25% of the delayed retreat when variability is present. This mechanism leads to slower mean glacier retreat under variable melting than retreat for steady melting. In our simulations, the magnitude of this effect is only important during the onset of rapid grounding line retreat through overdeepened bedrock topography.

While our ice shelf basal melt parameterization simplifies the complexities of ice shelf-ocean interactions and is forced by idealized sinusoidal ocean variability, we suggest that our primary finding of delayed ice sheet retreat under variability is robust. We expect that similar behavior will manifest in an emerging class of coupled ice-sheet/Earth system models that include complex climate variability modes. Furthermore, existing observations of Amundsen Sea mCDW depth variability span less than two decades, which is small relative to estimated periods of important Southern Ocean variability modes. This suggests a potential for larger magnitudes of variability than we have modeled here, particularly if extreme El Niño events increase with climate warming (Cai et al., 2014). This could be confirmed using coupled ice-sheet/Earth system modeling. Finally, replication of our study with a coupled climate model could confirm the full net mass balance and dynamical effect of correlated variability in subshelf melt and snow accumulation, as demonstrated by Paolo et al. (2018) in response to ENSO variability.
Appendix A: Details of the Ice Shelf Basal Melting Parameterization

The melt parameterization used in this study is a variant of the quadratic, local/nonlocal parameterization described in Favier et al. (2019, see their Equation (5)):

$$\dot{m} = K(T - T_f)(T - T_f), \quad (A1)$$

where \(T - T_f\) is the local thermal driving at a given depth and \(\langle T - T_f \rangle\) is the thermal driving averaged vertically from the nominal grounding-line depth \(z_{GL}\) to the nominal calving-front depth \(z_{CF}\):

$$\langle T - T_f \rangle = \frac{\int_{z_{GL}}^{z_{CF}} (T - T_f) \, dz}{z_{CF} - z_{GL}}. \quad (A2)$$

In two horizontal dimensions, we calculate \(z_{GL}\) as the mean depth of the deepest 25% of the grounding line. This was chosen to ensure that a relatively small fraction of locations along the grounding line are deeper than \(z_{GL}\), while also ensuring \(z_{GL}\) varies smoothly as the grounding line position evolves and is not unduly affected by the grounding line depth at any single location (e.g., the absolute deepest point). \(z_{CF}\) is calculated as the mean depth of the entire calving front. The \(\langle T - T_f \rangle\) “nonlocal” term is intended to encompass the response of the buoyant overturning circulation to changes in thermal driving. In contrast to plume theory, observations and modeling suggest a nonlocal response because of the overturning circulation induced by the buoyant flow. Mass continuity requires that flow out at the calving front must be supplied by inflow, which occurs close to the sea floor. This large-scale circulation results from the cumulative effects of melting over large portions of the cavity, rather than from the local ambient conditions. \(z_{GL}\) and \(z_{CF}\) evolve during the simulation and are recalculated on each time step. We note that our version of the parameterization differs from that of Favier et al. (2019) in both the use of the “plume” temperature \(T\) in the thermal driving (as opposed to the ambient temperature in the cavity \(T_c\)) and in that we average the thermal driving over depth, while they average over the area of the ice shelf. We use a mean thermal driving averaged between \(z_{GL}\) and \(z_{CF}\) to simplify the implementation in MALI.

In order to determine the depth- and time-dependent temperature \(T(z, t)\) of the melt plume in (A1), we began with the mass- and heat-conservation equations from a plume model, equations (1) and (3) from Jenkins (1991):

$$\frac{\partial (UD)}{\partial x} = \dot{e} + \dot{m}, \quad (A3)$$

$$\frac{\partial (UDT)}{\partial x} = \dot{e}T_c + \dot{m}T - \gamma_T(T - T_f), \quad (A4)$$

where \(U, D,\) and \(T\) are the velocity, thickness, and temperature within the melt plume; \(x\) is the tangential direction to the ice draft along the plume flow; \(\dot{e}\) is the entrainment rate; \(\dot{m}\) is the melt rate; \(\gamma_T\) is the exchange velocity for heat; \(T_c\) is the ambient temperature in the cavity, and \(T_f\) is the depth-dependent freezing temperature (defined below).

It should be noted that subsequent literature on 1-D plume models (e.g., Jenkins & Bombosch, 1995; Jenkins, 2011; Lazeroms et al., 2018) have \(\dot{m}T_f\) rather than \(\dot{m}T\) for the second term on the right-hand side of (A4). By making use of the boundary condition at the ice-ocean interface (Asay-Davis et al., 2016)

$$\rho_{fw}\dot{m}L = \rho_{fw}\gamma_T c_p(T - T_f), \quad (A5)$$

where we have neglected the sensible heat flux into the ice, it can be shown that

$$\frac{\dot{m}}{\gamma_T} = \frac{\rho_{fw} c_p}{\rho_{fw} L} \frac{T - T_f}{T_f}. \quad (A6)$$
The first fraction on the right-hand side is of order one and the second fraction is of order 4% even for a relatively large thermal driving \( T - T_f \) of 4 °C. Thus, the error in (A4) by using the Jenkins (1991) formulation, \( \dot{m} (T - T_f) \), is a small percentage of the last term in that equation. The Jenkins (1991) formulation is convenient because it leads to a simple elimination of \( \dot{m} \) in what follows.

Applying the chain rule to (A4) and substituting in (A3), we have

\[
UD \frac{dT}{dx} + \dot{e}T = \dot{e}T_C - \gamma_T (T - T_f). \tag{A7}
\]

The usual form for \( \dot{e} \) is (see Jenkins, 1991)

\[
\dot{e} = E_o U \sin(\alpha), \tag{A8}
\]

where \( E_o = 0.036 \) is a constant from laboratory observations, modified to compensate for the missing Coriolis effects in the 1-D plume model (Jenkins, 1991), \( \sin(\alpha) \) is the slope of the ice-shelf base, and \( \alpha \) is the slope angle. The thermal exchange velocity can be expressed, for a so-called two-equation boundary condition, as (see Jenkins, Nicholls, et al., 2010; Jenkins, 2011)

\[
\gamma_T = \sqrt{C_p \Gamma_T} U = StU, \tag{A9}
\]

where \( St = 5.910 \times 10^{-4} \) is the Stanton Number. With these substitutions, (A7) becomes

\[
D \frac{dT}{dx} = \sin(\alpha) D \frac{dT}{dx} = E_o \sin(\alpha) (T_C - T) - St (T - T_f). \tag{A10}
\]

For the purposes of the parameterization, we assume that \( T_C, \alpha, D, \) and \( T_f \) vary slowly enough with \( z \) that they can be approximated as constants. A faithful solution of the 1-D plume equations would mean that these terms, particularly \( D \), vary in nonnegligible ways along the plume. While some 3-D ocean simulations (e.g., Asay-Davis et al., 2016; Holland et al., 2008) suggests that much of the sub-ice-shelf plume may have a relatively constant thickness, this assumption should be taken as a significant simplification in the parameterization. We reiterate that we are not attempting to produce a faithful solution to the 1-D plume equations. Short of numerically solving the full set of 1-D plume equations, we do not have a compelling way to determine the functional form of \( D \) as a function of depth or distance from the grounding line, and any such nonconstant form would add significantly to the complexity of computing the melt rate.

With these caveats in mind, taking these parameters as constant simplifies the model to an ordinary differential equation with constant coefficients. The solutions to this equation have the form \( T = T_\infty + Be^{-\zeta/z} \).

The values of \( T_\infty \) and \( \zeta \) are found by substituting into (A10):

\[
-\frac{\sin(\alpha)DB}{\zeta} e^{-\zeta/z} = E_o \sin(\alpha) (T_C - T_\infty) - Be^{-\zeta/z} - St (T_f - T_\infty) - Be^{-\zeta/z}. \tag{A11}
\]

This can only be true if the constant and exponential terms balance separately, that is

\[
\frac{\sin(\alpha)D}{\zeta} = E_o \sin(\alpha) + St, \tag{A12}
\]

\[
0 = E_o \sin(\alpha) (T_C - T_\infty) + St (T_f - T_\infty). \tag{A13}
\]

These equations require that

\[
\zeta = \frac{\sin(\alpha)}{E_o \sin(\alpha) + St}, \tag{A14}
\]

\[
T_\infty = \frac{E_o \sin(\alpha) T_C + St T_f}{E_o \sin(\alpha) + St}. \tag{A15}
\]

In other words, \( T_\infty \), the limit of the plume temperature over long distances as the initial condition is forgotten, is the weighted average of the ambient temperature (weighted in proportion to the entrainment rate) and the freezing temperature (weighted in proportion to the rate of turbulent heat transport from the ice-ocean to the plume).
interface). For our problem, $E_0 \sin(\alpha) \approx 3.6 \times 10^{-4}$ and $St \approx 5.9 \times 10^{-4}$, so that the far-field plume temperature is a mix of approximately $\frac{5}{6}$ freezing temperature and $\frac{1}{6}$ ambient temperature. The plume temperature decays to this limit over a length scale $\zeta \approx 10D$ to $T_{\infty}$.

To find $B$, we need an initial value at the grounding line, $T(z_{GL}) = T_C(z_{GL}) = T_0$:

$$T_0 = T_{\infty} + B e^{\frac{z_{GL}}{\zeta}}.$$  \hfill (A16)

Putting this all together, we have

$$T = T_{\infty} + (T_0 - T_{\infty}) e^{\frac{z - z_{GL}}{\zeta}},$$  \hfill (A17)

with $\zeta$ and $T_{\infty}$ defined by (A14) and (A15), respectively.

The freezing temperature profile $T_f(z)$ can be approximated by the linear profile with depth from Jenkins (1991):

$$T_f(z) = aS_{ref} + b + cz,$$  \hfill (A18)

with $a = -0.0575 \degree C/PSU$, $b = 0.0901 \degree C$, $c = 7.61 \times 10^{-4} \degree C/m$, and $S_{ref} = 34.4$ PSU. We use a reference salinity for simplicity and because the salinity dependence of the freezing point does not contribute significantly to the thermal driving ($T = T_f$).

To find the melt rate, we need a profile $T_c(z, t)$ of ambient ocean temperature in the cavity, the approximate slope $\sin(\alpha)$ of the ice draft (which, in reality, varies with space but which we hold fixed at a typical value, here chosen to be $1 \times 10^{-2}$), a characteristic thickness $D$ of the plume, and the melt factor $K$. The ambient temperature in the cavity $T_c$ is determined from the regional profile outside the cavity as

$$T_c(z, t) = \begin{cases} T_R(z, t) & z \geq z_{sill} \\ T_R(z_{sill}, t) & z < z_{sill} \end{cases},$$  \hfill (A19)

where $T_R(z, t)$ is the regional ocean temperature profile, discussed in section 2.3.

**Disclaimer**

This paper describes objective technical results and analysis. Any subjective views or opinions that might be expressed in the paper do not necessarily represent the views of the U.S. Department of Energy or the U.S. Government.

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