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Key Points:
- Improvements in Last Interglacial Antarctic mass loss estimates could appreciably reduce future sea-level rise uncertainties
- Last Interglacial sea-level constraints are increasingly informative with respect to Antarctic mass loss over 2060–2150
- If Last Interglacial sea levels were known precisely, projected 2100 Antarctic mass loss could still have up to 50 cm uncertainties

Supporting Information:
- Supporting Information S1

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Could the Last Interglacial Constrain Projections of Future Antarctic Ice Mass Loss and Sea-Level Rise?

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Abstract Previous studies have interpreted Last Interglacial (LIG; ~129–116 ka) sea-level estimates in multiple different ways to calibrate projections of future Antarctic ice-sheet (AIS) mass loss and associated sea-level rise. This study systematically explores the extent to which LIG constraints could inform future Antarctic contributions to sea-level rise. We develop a Gaussian process emulator of an ice-sheet model to produce continuous probabilistic projections of Antarctic sea-level contributions over the LIG and a future high-emissions scenario. We use a Bayesian approach conditioning emulator projections on a set of LIG constraints to find associated likelihoods of model parameterizations. LIG estimates inform both the probability of past and future ice-sheet instabilities and projections of future sea-level rise through 2150. Although best-available LIG estimates do not meaningfully constrain Antarctic mass loss projections or physical processes until 2060, they become increasingly informative over the next 130 years. Uncertainties of up to 50 cm remain in future projections even if LIG Antarctic mass loss is precisely known (±5 cm), indicating that there is a limit to how informative the LIG could be for ice-sheet model future projections. The efficacy of LIG constraints on Antarctic mass loss also depends on assumptions about the Greenland ice sheet and LIG sea-level chronology. However, improved field measurements and understanding of LIG sea levels still have potential to improve future sea-level projections, highlighting the importance of continued observational efforts.

1. Introduction

Coastal communities are facing increasing threats from sea-level rise, creating a growing need for comprehensive probabilistic projections (Horton et al., 2018; Kopp, DeConto, et al., 2017; Kopp et al., 2014) to inform coastal risks and adaptation practices (Buchanan et al., 2016, 2017; Kopp et al., 2019; D. J. Rasmussen et al., 2018). The single largest source of uncertainty in 21st century global mean sea-level rise is the Antarctic ice sheet (AIS). Projected AIS mass loss depends on the ice-sheet physics considered, modeling and statistical methodologies, and observational constraints (e.g., Kopp, DeConto, et al., 2017).

There is deep uncertainty in future AIS sea-level contributions, meaning that their full probability distribution is unknown and cannot be estimated or agreed upon by experts (Lempert & Collins, 2007). The lack of expert agreement on AIS mass loss projections is partially related to unresolved challenges in modeling ice-sheet processes (Bakker, Louchard, et al., 2017; Bakker, Wong, et al., 2017; Bamber et al., 2019; Fuller et al., 2017). There is growing consensus that the AIS is threatened by marine ice-sheet instability (MISI; Schoof, 2007; Weertman, 1974), which would lead to accelerated mass loss irreversible on millennial timescales (Bulthuis et al., 2019; Golledge et al., 2015) and skew probability distributions toward fat upper tails in sea-level projections (Robel et al., 2019). There is some evidence that MISI is already underway in the Thwaites/Pine Island Glacier basins (Favier et al., 2014; Joughin et al., 2014), and western AIS ice discharge has accelerated in recent years (Gardner et al., 2018; Rignot et al., 2019). Even more uncertain is the role of marine ice-cliff instability (MICI), which has recently been proposed and incorporated as a primary loss mechanism in an ice-sheet model for sea-level rise projections (Bassis & Jacobs, 2013; Bassis & Walker, 2012; DeConto & Pollard, 2016; Pollard et al., 2015).

MICI is not well understood and is difficult to parameterize. While it has not yet been observed in Antarctica, there is some modern evidence consistent with cliff instability, such as the documented calving events of Greenland glaciers (DeConto & Pollard, 2016; Parizek et al., 2019). Newly discovered iceberg-keel plough marks also provide evidence for MICI in Pine Island Bay in the early Holocene, ~12 ka (Wise et al., 2017). However, a recent reanalysis of DeConto and Pollard (2016) showed that MICI is not well constrained and is unnecessary for ice-sheet model projections to be consistent with modern and paleoclimate estimates of AIS mass loss (Edwards et al., 2019). Clerc et al. (2019) examined how ice cliffs deform following removal of their buttressing ice shelves. They found that ~90-m-tall ice cliffs would have to be lost near instantaneously after shelf collapse to trigger MICI—on longer timescales viscous relaxation dominates the response. Furthermore, Olsen and Nettles (2019) found that seismic measurements of the aforementioned Greenland glaciers were not indicative of subaerial ice-cliff failure expected with MICI. These findings cannot preclude MICI as a primary mass loss mechanism in Antarctica, but they demonstrate the paucity of observations to constrain this process.

Whether or not major AIS discharge will occur through MISI and/or MICI is critical for future impacts on human systems (Oppenheimer & Alley, 2016; Stammer et al., 2019; Wong et al., 2017). But correlations between observed trends and future large-scale mass losses are weak and insignificant (Kopp, DeConto, et al., 2017), signaling that modern observations are inadequate for constraining potentially nonlinear AIS contributions to sea-level rise. Instead, the information gap must be filled with analogs from the paleo sea-level record. The Last Interglacial (LIG) period has previously been invoked to inform ice-sheet instabilities and model projections (DeConto & Pollard, 2016; Steig & Neff, 2018), but it may currently be an ineffective constraint (Edwards et al., 2019). In this study we investigate how improved estimates or different interpretations of LIG AIS mass loss may be combined with ice-sheet model ensembles to constrain probabilistic projections of future sea-level rise. We specifically choose ice-sheet model simulations which consider the MICI process to complement recent studies using similar statistical and modeling methods (DeConto & Pollard, 2016; Edwards et al., 2019).

The LIG (~129 to 116 ka) was a period of higher orbital eccentricity, slightly warmer than present global mean temperatures, and substantially warmer polar atmospheric temperatures (>3 K warmer than present) and high-latitude ocean temperatures (1 K warmer than present) (Capron et al., 2017, and references therein). Accompanying were estimated global mean sea levels (GMSL) about 6–9 m higher than present (Dutton, Carlson, et al., 2015), driven by a combination of mountain glacial melt, Greenland ice-sheet and AIS mass loss, and thermosteric effects. While the proportional mix of these contributions is uncertain, previous studies determined that some portions of the AIS retreated during the LIG (e.g., Dutton, Carlson, et al., 2015; Dutton, Webster, et al., 2015; Scherer et al., 1998). The LIG has historically been considered an analog for AIS contributions to sea-level rise in warm climates (Hansen et al., 1981; Mercer, 1968), but it may not be ideal for examining future climate change, as LIG and modern external forcing mechanisms are fundamentally different (Capron et al., 2019).

Different interpretations and applications of paleo sea-level estimates have led to divergent conclusions about what instability processes could drive future sea-level rise (cf. DeConto & Pollard, 2016; Edwards et al., 2019). The goal of this study is to develop a framework for analyzing the extent to which the LIG could inform ice-sheet model projections of future AIS mass loss and sea-level rise. We quantify ice-sheet model projections conditioned on multiple LIG estimate distributions and assess how narrower LIG uncertainties could improve understanding of both ice-sheet instabilities and future sea levels. We also investigate how different assumptions about LIG sea-level evolution influence ice-sheet modeling of future sea-level changes. These analyses provide useful targets and research directions for the paleo sea-level observational and ice-sheet modeling communities.

Ice-sheet models are computationally expensive to run at high resolutions necessary for sufficient accuracy. The number of simulations computationally tractable over a model's parameter space is therefore limited, making it difficult to construct an ensemble large enough to perform comprehensive statistical analyses (which are necessary for robust probabilistic projections of sea-level rise and coastal risk, e.g., Kopp, DeConto, et al., 2017; D. J. Rasmussen et al., 2020). In this study we develop a statistical "emulator" designed to mimic the behavior of the ice-sheet model (the "simulator") to fill intermediate solutions that have not been simulated over the ice-sheet model parameter space (Bastos & O'Hagan, 2009; Kennedy & O'Hagan, 2001; C. E. Rasmussen & Williams, 2006). Similar to Edwards et al. (2019), we emulate ice-sheet simulations of the LIG and the future under a high-emissions scenario. The emulator provides continuous estimates of AIS sea-level contributions over two model parameters directly related to ice-sheet instability processes. We perform Bayesian statistical analyses with the emulator output to determine how the LIG constrains future Antarctic sea-level contribution projections.

Section 2 provides a detailed overview of the ice-sheet model ensembles, emulation methodology, the Bayesian approach, and LIG constraints. Our results in section 3 show how current and improved LIG estimates could constrain future Antarctic contributions to sea-level rise. We also demonstrate a specific framework application using paleo sea-level observations and discuss our study's implications for future research directions in the paleo sea-level community. Conclusions are presented in section 4.

2. Models and Methods

2.1. Ice-Sheet Model Simulations

We build ice-sheet model ensembles for the LIG and a future high-emissions scenario (Representative Concentration Pathway 8.5, RCP8.5 Riahi et al., 2011). We run simulations with the PSU ice-sheet model, which has been used in several studies of ice-sheet contributions to past and future sea levels (DeConto & Pollard, 2016; Edwards et al., 2019; Kopp, DeConto, et al., 2017; Pollard et al., 2016; Pollard & DeConto, 2009; Pollard et al., 2017, 2018). The model (Pollard & DeConto, 2012) uses a hybrid combination of the vertically integrated shallow ice and shallow shelf approximations for ice flow (described in Pollard & DeConto, 2012). Ice flux at freely migrating grounding lines is parameterized (Pollard & DeConto, 2009, 2012; Schoof, 2007), while accounting for the buttressing effects of ice shelves. Hydrofracturing from surface melt and structural failure of tall ice cliffs is included (DeConto & Pollard, 2016; Pollard et al., 2015). The model simulates internal ice temperatures, with basal sliding and sediment deformation occurring only where the base is at or near the melt point and no explicit basal hydrology. A Weertman-type basal sliding law over bedrock is used with the norm of the sliding velocity proportional to the squared norm of the basal shear stress and spatially dependent coefficients (Pollard & DeConto, 2012). We run the model on a 10-km-resolution grid over the continental Antarctic.

Model simulations are an improvement on those of DeConto and Pollard (2016) and reanalyzed in Edwards et al. (2019). Model runs use a sub-oceanic melt scheme newly calibrated following a large-ensemble analysis of model performance during the last deglaciation (Pollard et al., 2016). This improvement, developed for DeConto et al. (2020), reduces the need for a subsurface ocean temperature bias correction on the West Antarctic margin by 50% (from 3 to 1.5 K) relative to DeConto and Pollard (2016). Atmospheric climatologies in future simulations are also improved, as discussed below (cf. DeConto et al., 2020).

LIG equilibrium model simulations are forced by representative oceanic and atmospheric conditions from 130 ka constructed from a synthesis of paleoclimate reconstructions and climate modeling (Capron et al., 2014). We run the simulations for 5,000 years to bring them approximately into equilibrium with this fixed climate forcing; we take the final simulation values (year 5000) as representing the peak AIS mass loss response during the LIG. Emulated peak LIG mass losses are later paired with paleo sea-level estimates to assess whether the LIG could constrain future AIS contributions to sea-level rise (sections 2.2–2.4).

Future transient model simulations span 1990–2150 and are reported relative to the year 2000. Following DeConto and Pollard (2016), atmospheric RCP8.5 forcing is time interpolated and log weighted from regional climate model Antarctic snapshots at varying levels of effective CO_2 (1×, 2×, 4×, and 8× preindustrial). Improving on DeConto and Pollard (2016), time-evolving sea-surface temperatures are synchronized in the regional atmospheric model simulations with subsurface temperatures used in the subsurface melt rate calculations, leading to favorable comparisons with an independent NCAR CESM simulation (DeConto et al., 2020, their Extended Data Figure 1).

LIG and future simulation ensembles are constructed by sampling a two-dimensional parameter space on a regularly spaced 14×14 grid. The two parameters, CREVLIQ and CLIFVMAX (Supporting Information Table S1), are detailed in DeConto and Pollard (2016). Briefly, CREVLIQ is the proportional sensitivity of model hydrofracturing to surface liquid, that is, from rain and meltwater ($m/(m/yr)^2$); it is substituted for "100" in Equation B.6 of Pollard et al. (2015). As CREVLIQ increases, ice-sheet crevasses deepen more readily with surface liquid accumulation, which increases the chance of hydrofracturing and removal of buttressing ice shelves. CLIFVMAX is the maximum rate (km/yr) of horizontal cliff wastage once an ice cliff

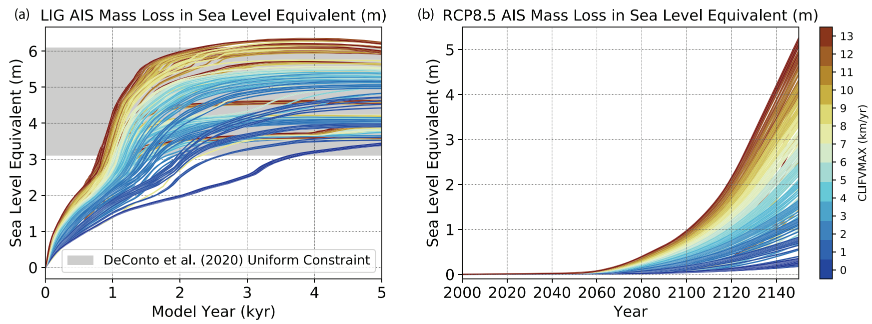

Figure 1. Time series of simulated AIS mass losses in sea-level equivalent (m) under (a) Last Interglacial forcing and (b) RCP8.5 forcing over 2000–2150. Simulated time series are color coded by CLIFVMAX values over 0–13 km/yr. Gray shading in (a) is an illustrative range of estimated LIG AIS sea-level contributions, 3.1–6.1 m, derived in DeConto et al. (2020) and based on the reconstructions of Dutton, Carlson, et al. (2015).

becomes mechanically unstable and collapses (i.e., under MICI); it is substituted for "300" in Equation A.4 of Pollard et al. (2015) (called "VCLIF" in DeConto & Pollard, 2016). Note that when CLIFVMAX = 0 km/yr, ice cliffs cannot retreat even when they would theoretically fail; in this set of simulations MICI is effectively turned off.

Ensembles vary CLIFVMAX and CREVLIQ over ranges of parameter values (0–13 km/yr and 0–195 m/(m/yr)^2, respectively) broader than those of DeConto and Pollard (2016) and Edwards et al. (2019): The CLIFVMAX maximum is 2.6 times larger than in those studies, and the CREVLIQ range 1.3 times larger (Supporting Information Table S1). We expand the parameter value range to explore a greater range of parametric uncertainty, with upper bounds guided by observations (discussed in detail in DeConto et al., 2020) rather than the arbitrarily assigned bounds of DeConto and Pollard (2016).

Figure 1 shows ensemble time series of AIS mass loss in global mean sea-level equivalent from the LIG and RCP8.5 scenario; ensemble member time series are color coded by CLIFVMAX values (time series color coded by CREVLIQ are shown in Supporting Information Figure S1). Figure 1a includes an illustrative range of estimated LIG AIS sea-level contributions (3.1–6.1 m), which was assumed by DeConto et al. (2020) based on reconstructions described in Dutton, Carlson, et al. (2015). This LIG estimate is lower and slightly narrower than that assumed in DeConto and Pollard (2016) and Edwards et al. (2019); this and additional LIG constraints are explored below (section 2.4).

The evolution of LIG simulations (Figure 1a) suggests that there are distinct ice-sheet mass loss events (e.g., the accelerated mass loss in some simulations ~1,000 years into the simulation) in response to constant forcing, depending strongly on model parameter values. This nonlinear behavior results in a multimodal distribution of the ensemble's peak AIS mass loss (section 3). AIS discharge is sensitive to the value of CLIFVMAX on the timescale of centuries, as seen in the first 1,000 years of the LIG ensemble and the entirety of the RCP8.5 simulation (Figure 1b). The nonmonotonic color progression of time series in Figure 1a suggests that CREVLIQ plays a more substantial role in ice-sheet mass loss under LIG forcing and/or on millennial timescales (Supporting Information Figures S1 and S2).

Future simulations of AIS mass loss under RCP8.5 forcing are very similar across the ensemble in the early 21st century; 158 of 196 simulations have loss rates within 1 standard deviation of IMBIE2 observed rates over 1992–2017 (15–46 mm/yr IMBIE-Team, 2018). In ~2060 ice discharge dramatically accelerates among ensemble members with higher CLIFVMAX values, and simulations markedly diverge. Across the simulations ice loss continues to accelerate through 2100 and well into the 22nd century; 86% of the simulated peak loss rates occur after 2130. By 2150, the ensemble's median rate of sea-level equivalent mass loss is 54 mm/yr, and the median AIS sea-level contribution is 2.3 m. Mean RCP8.5 ensemble AIS sea-level contributions are 42 cm in 2100 and 2.3 m in 2150. These values are lower than DeConto and Pollard (2016) large-ensemble projections (without bias corrections and with default model parameters, see their Extended Data Table 1) in both 2100 (77 cm) and 2150 (2.9 m). Differences are largely due to improved model synchronicity in atmospheric forcing, which slows the onset of surface meltwater production and ice-shelf hydrofracturing by ~25 years compared to DeConto and Pollard (2016).

The emulator is trained only on simulations from this single ice-sheet model and with changes only in the parameters discussed above. Other ice-sheet processes or parameters that could lead to ice-sheet and ice-shelf stability or collapse have not been investigated here. Whereas our methodology is developed with a generalizable emulation and calibration framework, quantitative results in section 3 apply only to this specific ice-sheet model. The LIG could inform additional or alternative physical processes (see section 4) not considered here, and the emulation and calibration framework could be extended to include assessments of LIG constraints on the Greenland ice sheet (GrIS), calibration of other ice-sheet models or ensembles (e.g., ISMIP6; Goelzer et al., 2018; Nowicki et al., 2016; Seroussi et al., 2020), calibration of different parameters or regions of parameter space, or calibration with different paleo sea-level constraints (e.g., the Pliocene).

2.2. Emulation

We train the emulator separately on LIG and RCP8.5 ensembles (z_{LIG} and z_{RCP}, respectively) using Gaussian process (GP) regression (e.g., Dubourg, 2011; C. E. Rasmussen & Williams, 2006; Santner et al., 2003). We model the total AIS contributions to GMSL, $f(\theta_1, \theta_2, t)$, as the sum of two terms, each with a zero-mean GP prior distribution:

$$f(\theta_1, \theta_2, t) = f_1(\theta_1, \theta_2) + f_2(\theta_1, \theta_2, t). \quad (1)$$

The first term, $f_1(\theta_1, \theta_2)$, represents a time-independent function on the parameter space (θ_1, θ_2), and the second term, $f_2(\theta_1, \theta_2, t)$, represents the temporal evolution. We specify the prior distributions of each term as

$$f_1(\theta_1, \theta_2) \sim \mathcal{GP}(0, \alpha_1^2 K_1(\theta_1, \theta_2, \theta_1', \theta_2'; \ell_1)), \quad (2)$$

$$f_2(\theta_1, \theta_2, t) \sim \mathcal{GP}(0, \alpha_2^2 K_2(\theta_1, \theta_2, \theta_1', \theta_2'; \ell_2) \cdot K_t(t, t'; \tau)), \quad (3)$$

where θ_1 and θ_2 are values of CLIFVMAX and CREVLIQ normalized by their respective maximum values in the simulator ensemble parameter space (Supporting Information Table S1), α_i are standard deviations, ℓ_i are characteristic length scales in the normalized parameter space, τ is a characteristic timescale, and K_i are specified covariance functions. Because the LIG training data are evaluated at a single time point, there is no temporal term and f_2 is excluded from LIG GP construction. K_i are defined to be Matérn covariance functions with a specified smoothness (shape) parameter, ν, which governs how responsive the function and its realizations are to sharp changes in the training data (C. E. Rasmussen & Williams, 2006). The choice of a Matérn covariance function allows for nonparametric nonlinear behavior in time and parameter space. For the RCP8.5 scenario we set ν to $\frac{5}{2}$ because transient sea-level contributions vary smoothly over the model parameter space and time; for the LIG scenario we set ν to $\frac{1}{2}$ because peak LIG sea-level contributions vary more sharply over the model parameter space. The model form and covariance functions are chosen for a balance of simplicity, minimizing absolute errors and variance (i.e., model accuracy and precision), and maximizing the likelihood of the training data. Other covariance function and model forms were explored but are not presented for brevity (Supporting Information Text S2).

Optimal hyperparameters (α_i, ℓ_i, and τ) of the GP models are found by maximizing the likelihoods of the training simulations (Supporting Information Table S2, C. E. Rasmussen & Williams, 2006). To ensure numerical stability we specify a "nugget" for the optimized GP representing the small-scale variability of the training data. Because the simulator is deterministic we set the nugget variance to 10^{-6} m^2, to ensure that the modeled mean approximately matches the training ensemble data across the parameter space and time. We then condition (train) the optimized GP model on the simulator ensembles ($f|\mathbf{z}$) to arrive at optimized posterior GP models for LIG and RCP8.5 which predict continuous sea-level contributions at parameter values and times between discrete training simulations. We refer the optimized posterior GPs for the LIG (f_{LIG}) and RCP8.5 (f_{RCP}) as "emulators". We perform leave-one-out analyses to validate the emulators following Bastos and O'Hagan (2009) and find they accurately mimic the behavior of the ice-sheet simulator ensembles over the LIG and RCP8.5 scenario (Supporting Information Text S1 and Figures S3 and S4).

Figure 2 shows the emulator mean functions (contours) for the LIG and RCP8.5 in 2100 over the parameter space and the corresponding training simulations (circles). There are natural similarities between the emulated sea levels during the LIG and those projected in 2100 under RCP8.5. Ice-cliff collapse and/or hydrofracturing are clearly relevant drivers of both paleo estimates and future projections by this ice-sheet

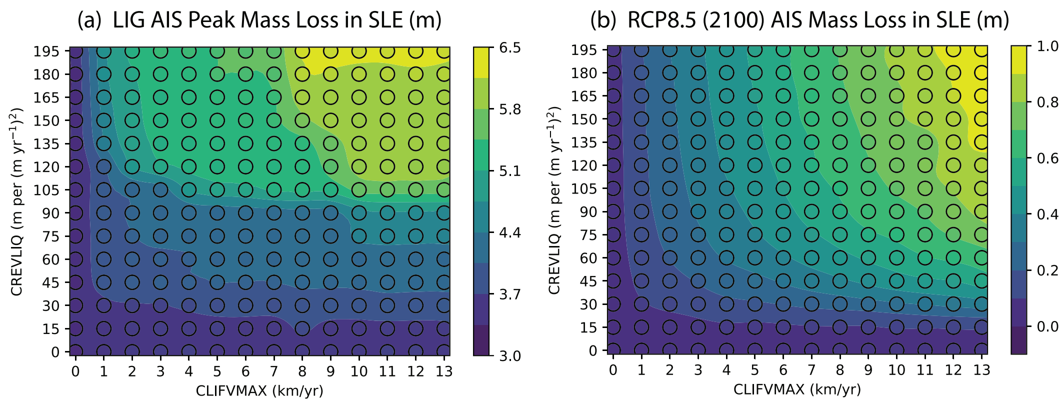

Figure 2. Simulated (filled circles) and mean emulated (contours) AIS mass losses in sea-level equivalent (m) across ice-sheet model parameter space (a) during the Last Interglacial and (b) projected under an RCP8.5 scenario in 2100.

model (see section 2.3): For relatively large values of CREVLIQ and CLIFVMAX, emulated AIS mass loss is relatively high. Sea-level contributions are also substantially lower when either CREVLIQ or CLIFVMAX are near zero, indicating that emulated sea levels with these parameter values are not appreciably influenced by either hydrofracturing from surface liquid or mechanically unstable ice-cliff retreat.

There are also differences between LIG and RCP8.5 emulator mean functions (Figure 2 and Supporting Information Figure S2). Future projected AIS mass loss is more sensitive to CLIFVMAX than CREVLIQ (cf. Figure 1b), which becomes more pronounced throughout the early 22nd century (not shown). Under strong RCP8.5 forcing, MICI triggers quickly, and the modern ice sheet readily loses mass at rates up to the CLIFVMAX bound. In contrast, LIG AIS sea-level contributions are more sensitive to both CREVLIQ and CLIFVMAX in some regions of the parameter space but are nearly constant in other regions (e.g., where CREVLIQ > 120 and $2 <$ CLIFVMAX < 7, Figure 2a). Some LIG simulations (under weaker and prolonged forcing) have discrete mass loss events that are constrained by meltwater-driven hydrofracturing (bound by CREVLIQ, cf. Supporting Information Figure S1), making the LIG simulations generally more sensitive to CREVLIQ than the RCP8.5 simulations. Under prolonged LIG fixed forcing, different AIS sectors can be completely lost regardless of the specific parameter value in these regions of parameter space, resulting in very similar sea-level contributions. This clustering behavior is much less pronounced over the modern period of transient and increasing forcing except along fixed values of CLIFVMAX, as shown by its smoothly varying sea-level contributions (Figures 1b and 2b). These differences across the parameter space have important implications for model calibration. In particular, they imply that even if the LIG contributions were known precisely, there may be a limit to their ability to constrain future projections. For example, the region of the parameter space with LIG contributions of ~5.2 m (CREVLIQ > 120, $2 <$ CLIFVMAX < 7) corresponds to AIS sea-level contributions of ~35–65 cm in 2100 under RCP8.5 forcing (Figure 2b). This limitation is explored in detail in section 3.

Having developed emulators trained on the LIG and RCP8.5 scenario ensembles, we generate 10,000 realizations of emulator output (mean and variance, i.e., the full GP emulator) with a two-dimensional Latin-hypercube design over the parameter space. The time-dependent median and credibility intervals of the RCP8.5 emulated distribution are shown in Figure 3.

2.3. Bayesian Updating

We use a Bayesian updating approach to determine the influence of LIG constraints on projections of future Antarctic contributions to sea-level rise (e.g., Ashe et al., 2019); a glossary of relevant statistical terms is provided in Supporting Information Table S3.

There are two steps in our approach. First, we update the probability distribution of model parameters (θ_1, θ_2) based on a specified LIG constraint distribution. Applying Bayes' theorem,

$$p(\theta_1, \theta_2 | f_{\mathrm{LIG}}) \propto p(f_{\mathrm{LIG}} | \theta_1, \theta_2) p(\theta_1, \theta_2), \tag{4}$$

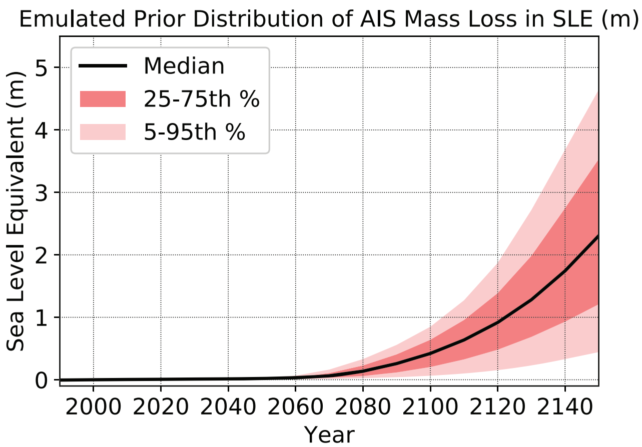

Figure 3. Emulator prior probability distribution of AIS mass loss in sea-level equivalent (m) projected under RCP8.5 forcing over 2000–2150. Shown are the median (solid black line), 25th to 75th (dark red shading), and 5th to 95th percentiles (light red shading) of the distribution.

where $p(\theta_1, \theta_2 \,|\, f_{\mathrm{LIG}})$ is the posterior probability of the parameters conditioned on a LIG constraint distribution, $p(f_{\mathrm{LIG}} \,|\, \theta_1, \theta_2)$. This is implemented by sampling the LIG emulator with parameter values weighted by specified LIG constraints (section 2.4). $p(\theta_1, \theta_2)$ is a uniform prior probability over the input parameter space (Supporting Information Table S1). When the LIG emulator is uniformly sampled with equal likelihood across each parameter set, the emulator is not informed by any LIG constraint, and the posterior distribution mimics the underlying training simulations. We refer to this distribution of AIS mass loss as "unconstrained".

Next, to constrain future projections, we use $p(\theta_1, \theta_2 \,|\, f_{\mathrm{LIG}})$ as the likelihood function of the parameters in the RCP8.5 emulator. This is represented as

$$p(f_{\mathrm{RCP}}|f_{\mathrm{LIG}}) = p(f_{\mathrm{RCP}}|\theta_1, \theta_2)p(\theta_1, \theta_2|f_{\mathrm{LIG}}), \quad (5)$$

such that the probability distribution of the constrained RCP8.5 emulator, $p(f_{\mathrm{RCP}} \,|\, f_{\mathrm{LIG}})$, is equal to the RCP8.5 emulator sampled with a uniform prior, $p(f_{\mathrm{RCP}} \,|\, \theta_1, \theta_2)$ (we refer to this as the "prior" distribution), times the likelihood of the parameter values updated with a specified LIG constraint.

We demonstrate the utility of this approach in three ways. First, we explore how future projections are constrained when peak LIG AIS mass loss, x, is assumed to be precisely known (e.g., to within a 10-cm uncertainty interval). In Equation 4 we define the LIG constraint with a uniform distribution, $p(f_{\mathrm{LIG}}|\theta_1, \theta_2) = p_x$, discretized with 10-cm-wide bins across the range of the underlying LIG simulations:

$$p_x = \mathcal{U}(x - 5\,\mathrm{cm}, x + 5\,\mathrm{cm}],$$

where $x = \{2.0\,\mathrm{m}, 2.1\,\mathrm{m}, \ldots, 6.9\,\mathrm{m}, 7.0\,\mathrm{m}\}$. The associated posteriors of RCP8.5 AIS contributions to sea-level rise, $p(f_{\mathrm{RCP}} \,|\, f_{\mathrm{LIG}})$, are a set of comprehensive time-dependent conditional probability distributions given as a function of LIG AIS mass loss. The conditional probability distributions may be integrated over a range of x values with any specified weightings, resulting in an associated constrained probability distribution of future AIS contributions to sea-level rise.

Second, we examine particular posteriors of RCP8.5 AIS contributions to sea-level rise as a function of several specific LIG constraint distributions, drawn or adapted from the literature. Third, we analyze how the ice-sheet model projections of future AIS mass loss would be influenced through hypothetical improvements in LIG constraint distributions, either by (1) narrowing the range of uncertainty on LIG estimates or by (2) learning that the LIG AIS sea-level contributions were relatively high (>6 m) or relatively low (<3.5 m). Each LIG constraint distribution is detailed in the following section.

2.4. LIG Constraint Distributions

We prescribe a set of LIG constraint distributions, $p(f_{\mathrm{LIG}} \,|\, \theta_1, \theta_2)$, to determine the associated posterior probability distributions of future AIS contributions to sea-level rise (Equations 4 and 5). Differences between these example constraints illustrate how alternative specifications and interpretations of LIG AIS mass loss can influence projections of future sea-level rise. Figure 4a shows the probability density of each constraint distribution, along with the unconstrained LIG emulator distribution (derived by uniformly sampling the model parameter space, as discussed above).

DeConto et al. (2020) *uniform distribution* (D20-U): The uniform constraint of DeConto et al. (2020), $\mathcal{U}(3.1\,\mathrm{m}, 6.1\,\mathrm{m})$, is narrower and lower than that of DeConto and Pollard (2016). The primary difference is that the timing of the LIG AIS mass loss peak is assumed to peak earlier, which affects the constraint derivation; we discuss the implications of LIG sea-level chronology in detail in section 3.3. The D20-U constraint distribution is derived assuming AIS mass loss peaked in the early LIG, concurrent with global mean sea-level estimates of $6 \pm 1.5\,\mathrm{m}$ from Dutton, Webster, et al. (2015). Subtracting off a small Greenland ice-sheet contribution in the early LIG (1 m, Dahl-Jensen et al., 2013; Goelzer et al., 2016;

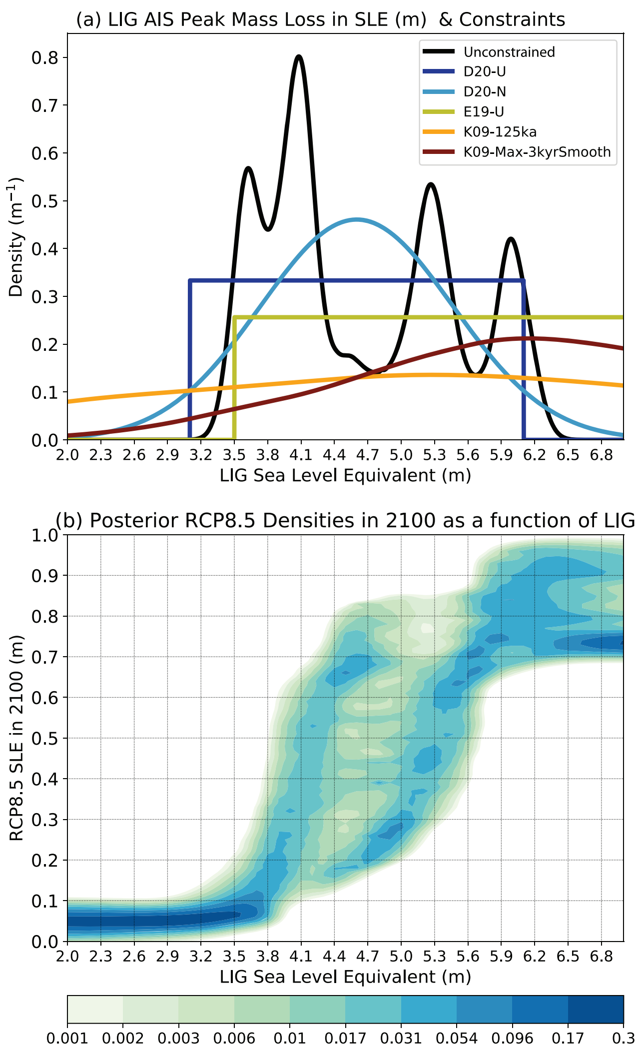

Figure 4. (a) Last Interglacial emulated unconstrained (black curve) and specified constraint (blue, yellow, orange, and red lines curves) probability distributions of Antarctic mass loss in sea-level equivalent (m). (b) Conditional posterior probability densities of Antarctic mass loss in 2100 projected under RCP8.5 forcing (in sea-level equivalent), normalized and plotted as a function of Last Interglacial AIS mass loss in sea-level equivalent (discretized with 10-cm-wide bins, see text).

Helsen et al., 2013) and a thermosteric rise of 0.4 m (McKay et al., 2011), and neglecting early-LIG mountain glacier melt, the residual AIS contribution is estimated as 3.1–6.1 m. Complementing the pass/fail calibration of both DeConto and Pollard (2016) and DeConto et al. (2020), we impose an analogous uniform distribution over 3.1–6.1 m, such that emulated LIG output falling within the constraint is taken as equally likely; emulator output falling outside the constraint is ascribed a probability of zero.

DeConto et al. (2020) *normal distribution* (D20-N): Whereas the uniform distribution assumes fixed limits on the LIG constraint but equal probabilities of LIG contributions between 3.1 and 6.1 m, it is practical to explore the implications of the central value of the estimated LIG distribution being more likely than the bounds. D20-N replaces D20-U with a Gaussian distribution—taking the central value as the mean and the bounds representing 2 standard deviations from the mean—to develop a constraint distribution following $\mathcal{N}(4.6\,\text{m}, (0.75\,\text{m})^2)$.

Edwards et al. (2019) *uniform distribution* (E19-U): The uniform distribution used to constrain the LIG Antarctic contributions in the reanalyses of Edwards et al. (2019) is identical to the calibration of DeConto and Pollard (2016) given by $\mathcal{U}(3.5\,\text{m}, 7.4\,\text{m})$. We include this constraint to specifically compare our Bayesian calibrated ensembles with the results of Edwards et al. (2019), which used a similar emulation method but employed history matching rather than Bayesian calibration of the original DeConto and Pollard (2016) ice-sheet model ensemble.

Kopp et al. (2009) *time slice at 125 ka* (K09-125ka): Kopp et al. (2009) compiled a probability distribution of AIS contributions to sea-level rise (extended by Kopp et al., 2013) by combining a comprehensive database of proxy observations of LIG sea levels, an age model, and GP regression. Posterior probability distributions of AIS LIG sea levels were estimated over time by conditioning on local sea-level and age measurements. To generate a simple constraint distribution consistent with the LIG ensemble, we take a time slice at 125 ka (5,000 years after the initial time period of forcing, 130 ka, section 2.1). This is an overly simplified interpretation of the link between the ice-sheet emulator and the posterior LIG AIS mass loss distributions, because it assumes that emulated peak LIG contributions are representative of the synthesized observational record precisely at 125 ka.

Kopp et al. (2009) *maximum Antarctic contributions during the LIG* (K09-Max-3KyrSmooth): To examine an alternative link between the ice-sheet model simulations and Kopp et al. (2009) constraints, we generate 2,500 samples from the posterior probability distribution of mean global sea level conditioned upon sea-level observations and sampled ages from Kopp et al. (2009). This represents an estimate of the distribution of the global mean sea-level maximum from the model in Kopp et al. (2009). Each sample is a realization of the evolution of AIS sea-level contributions during the LIG (between 129 and 114 ka). Because these samples can be noisy in time, we smooth each sample with a 3-Kyr-window boxcar filter (other smoothing windows were explored, but here we focus on 3 Kyr for brevity). The constraint distribution is then constructed from the peak (global maximum) Antarctic sea-level contribution of each smoothed sample (assuming that each is equally likely), so that it shares an interpretation with the ice-sheet emulator (section 2.1).

We also explore two sets of hypothetical LIG constraints.

High and low distributions (LIG AIS > 6 m and LIG AIS < 3.5 m): We prescribe a set of hypothetical relatively high and relatively low constraints, given by $\mathcal{U}(6.0\,\text{m}, +\infty)$ and $\mathcal{U}(-\infty, 3.5\,\text{m})$, respectively. The resulting

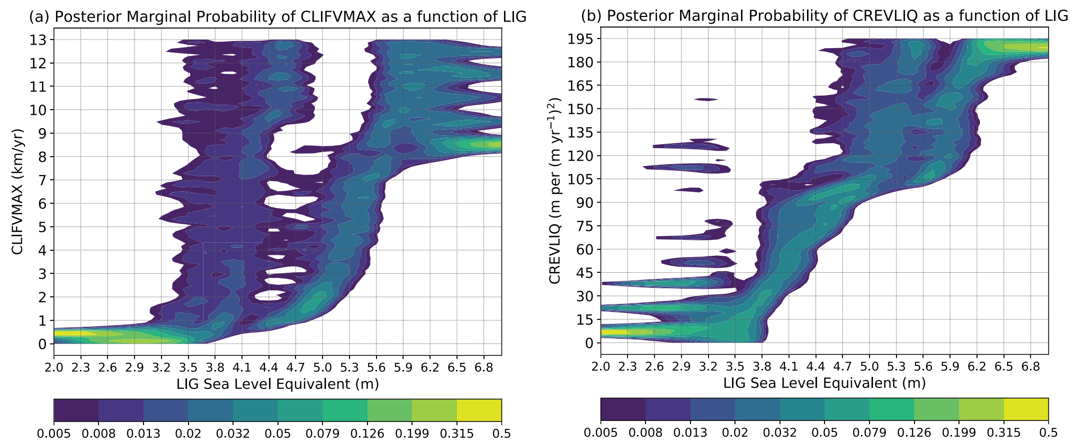

Figure 5. Posterior marginal probability distributions of (a) CLIFVMAX and (b) CREVLIQ, normalized and plotted as a function of Last Interglacial AIS mass loss in sea-level equivalent (discretized with 10-cm-wide bins, see text).

posteriors show how projections of future AIS mass loss could improve if there were a reliable upper or lower bound on LIG AIS mass loss estimates at the margins of the unconstrained LIG distribution.

Sensitivity to reduced uncertainties in LIG estimates (Narrower D20-U): To ascertain how future projections of AIS mass loss could be affected by reduced uncertainties in LIG constraint distributions or improved LIG estimates, we gradually reduce the range of the D20-U constraint by 10%, 25%, 50%, 75%, and 90% and assess the resulting posterior distributions; the central value (4.7 m) of each constraint is identical to that of D20-U. Physically based observational constraints, following a similar narrowing method, are the focus of section 3.3.

For each LIG constraint distribution, we find the associated likelihoods of the model parameters and the posterior probability distributions of projected future AIS contributions to sea-level rise following Equations 4 and 5.

An advantage of the Bayesian framework is that any specified constraint may be assessed. These constraints are not intended to be exhaustive, but rather illustrative of a range of current or potentially improved LIG constraints and their usefulness for informing future projections.

3. Results

3.1. Conditional Probability Distributions

Figure 4b shows the conditional posterior probability densities of RCP8.5 scenario AIS mass loss in 2100 (contoured on a log scale), assuming that the LIG peak AIS sea-level contributions were known to within 10 cm. Along each column of the horizontal axis (x values), the densities sum to one, representing the probability distributions of future AIS mass loss, $p(f_{\mathrm{RCP}} \mid f_{\mathrm{LIG}})$, in 2100 as a function of the associated 10-cm-wide uniform LIG constraint distributions, p_x (section 2.4). Conditional posterior probability densities in 2150 (Supporting Information Figure S6) have a similar structure. Figure 4b summarizes the efficacy of the LIG for informing this ice-sheet model's projections of future sea-level rise.

The posterior marginal probability distributions of CLIFVMAX and CREVLIQ show the related dependencies of model parameter likelihoods as a function of LIG constraints (Figure 5). The marginal probabilities $p(\theta_1 \mid \theta_2, f_{\mathrm{LIG}})$ and $p(\theta_2 \mid \theta_1, f_{\mathrm{LIG}})$ are computed by finding the density of each model parameter as a function of the LIG constraint integrating over the other model parameter, and normalizing such that along each column of x densities sum to one. Comparison between Figures 4b and 5 demonstrates how each LIG estimate informs projections of future AIS mass loss by constraining ice-sheet model parameters.

LIG contributions are relatively more informative on the extreme margins of the emulated probability distribution than in the interior (Figure 4, cf. black curve of Figure 4a). At relatively high and low ends of the unconstrained distribution, there are fewer combinations of ice-sheet model parameter values that produce these sea levels than in the interior (Figure 5), leading to narrower posteriors in future projections. At the high end of LIG AIS mass loss (>6 m), CLIFVMAX values always exceed 7.5 km/yr and CREVLIQ

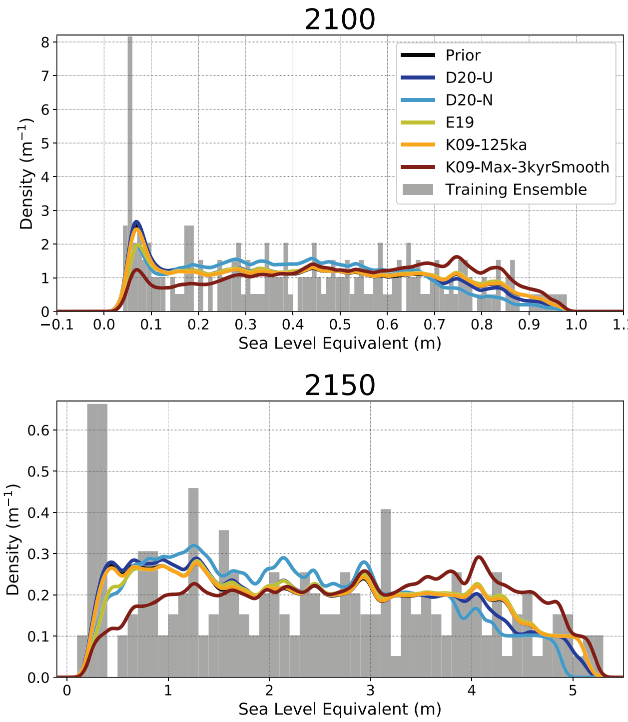

Figure 6. Projected probability distributions of Antarctic ice-sheet mass loss in sea-level equivalent (m) in (a) 2100 and (b) 2150, under RCP8.5 forcing. Distributions are from 10,000 emulator samples and smoothed with kernel density estimation. Shown are the prior RCP8.5 distribution with no constraints (black curves), and distributions under specified Last Interglacial constraints (blue, yellow, orange, and red curves, cf. Figure 4). The ice-sheet model training ensemble is plotted as a histogram scaled for comparison.

values are likewise relatively high (Figure 5), suggesting that MICI—driven by substantial meltwater-driven hydrofracturing and removal of buttressing ice shelves—is important for reaching high LIG losses in this model. Narrow posteriors at the low end of LIG AIS mass loss (<3.5 m) are associated emulator outputs which have little or no mass loss from MICI in this model, that is, CLIFVMAX < 1 km/yr (Figure 5). We further explore specific future projection posterior distributions associated with these relatively high and low LIG constraints in section 3.2.

Conditional RCP8.5 posterior distributions in 2100 associated with intermediate values of LIG AIS mass loss are more broad than at the margins. Even if LIG AIS mass loss was known precisely to within 10 cm, if that value was between 4 and 5.5 m, then there would remain a ∼50-cm range in 2100 projections. For instance, when the LIG contribution is 4.2 m, the associated posterior 95% credible interval in 2100 is 15–65 cm. This broad range in future projections after applying a precise LIG constraint results from the contrasting sensitivities of the LIG and RCP8.5 to parameter configurations (Supporting Information Figure S2). The unconstrained LIG AIS mass loss distribution is multimodal (Figure 4a) indicating that different sectors of the AIS have been completely lost; total mass losses in these individual modes are then insensitive to small changes in parameter values, as seen in the regions of the parameter space which have nearly constant sea-level contributions (Figure 2a). Comparing with Figure 5a shows that there is a wide range of CLIFVMAX values which result in LIG sea-level contributions between 4 and 6 m. But RCP8.5 future AIS mass losses are most sensitive to the CLIFVMAX value when CREVLIQ > 15 m/(m/yr)^2 (Figure 2) and thus have broad posterior distributions when LIG sea-level contributions are between 4 and 6 m. LIG contributions scale gradually with CREVLIQ values until CREVLIQ > 105 m/(m/yr)^2, and then similar LIG contributions are associated with broader ranges of CREVLIQ over 105–195 m/(m/yr)^2 (Figure 5b); future AIS mass losses are relatively insensitive to CREVLIQ in this region of model parameter space (Figure 2).

These varying responses to model parameter configurations most clearly affect RCP8.5 projections when the median in 2100 *drops* from 63 to 32 cm as LIG contributions *increase* from 4.6 to 4.8 m (Figure 4b). This non-intuitive result suggests that in some regions of the parameter space, the model-simulated equilibrium

Table 1
Quantiles of Projected Antarctic Ice-Sheet Mass Loss in Sea-Level Equivalent (m) in 2100 and 2150

2100 Quantiles	Prior	D20-U	D20-N	E19-U	K09-125ka	K09-Max-3KyrSmooth
5	0.07	0.07	0.07	0.07	0.07	0.09
25	0.20	0.20	0.23	0.23	0.21	0.31
50	0.42	0.40	0.40	0.44	0.43	0.52
75	0.64	0.61	0.58	0.65	0.64	0.72
95	0.85	0.83	0.78	0.85	0.85	0.88
2150 Quantiles	Prior	D20-U	D20-N	E19-U	K09-125ka	K09-Max-3KyrSmooth
5	0.44	0.44	0.51	0.52	0.46	0.63
25	1.21	1.17	1.23	1.30	1.24	1.63
50	2.31	2.21	2.18	2.39	2.32	2.81
75	3.54	3.38	3.22	3.58	3.53	3.88
95	4.65	4.56	4.38	4.66	4.64	4.79

Note. Each emulated distribution other than the prior is constrained using a specified Last Interglacial probability distribution (section 2.4).

LIG AIS mass loss is influenced by a different physical process than transient RCP8.5 losses. By 2100, RCP8.5 air temperature anomalies are ~2 K warmer than the applied LIG forcing and are still increasing, leading to accelerating AIS mass loss through MICI that is strongly influenced by CLIFVMAX. In contrast, the applied LIG forcing is cooler and fixed, and the LIG ice sheet equilibrates by losing mass more gradually over a 5,000 period. The slower equilibrium response permits CREVLIQ to play a larger role in LIG AIS mass loss, directing which sectors of ice eventually become unstable through shelf hydrofracturing over a prolonged period of anomalously warm temperatures (Figure 1).

Conditional posterior distributions (Figure 4b) are a powerful and novel tool for illustrating the links between ice-sheet model projections and paleo observational records. If, for instance, a field measurement showed that LIG AIS contributions were >5 m, then the densities in Figure 4b may be integrated across $5\,\mathrm{m} \leq x \leq +\infty$ to show that the range of projected RCP8.5 AIS mass loss in 2100 is ~0.2–1.0 m, with a median of 65 cm. We discuss how conditional distributions may be used in the context of particular paleo sea-level observations in section 3.3.

3.2. Future Projections Given Specific LIG Constraint Distributions

Posterior probability distributions of AIS sea-level contributions in 2100 and 2150 conditional on each LIG constraint distribution, following Equation 5, are shown in Figure 6, along with the emulated prior RCP8.5 distribution and histograms of the training simulations. Distributions are produced with kernel density estimation assuming a Silverman bandwidth (Silverman, 1986) reduced by 80% to prevent over-smoothing. Distribution quantiles are presented in Table 1. For reference, the likelihoods of model parameter sets—$p(\theta_1, \theta_2 \,|\, f_{\mathrm{LIG}})$—associated with each LIG constraint distribution are shown in Supporting Information Figure S5.

From 1990 to 2100, specific LIG constraints (section 2.4) do not very effectively narrow uncertainties in future projections. Quantiles of the prior, D20-U, E19-U, and K09-125ka distributions in 2100 are all within 5 cm (Table 1). D20-N weights the distribution toward the lower end of the projections, dropping the 95th percentile (relative to the prior) by 7 cm. The K09-Max-3KyrSmooth distribution reweights the projection distribution toward the upper tail (cf. Figure 4a), raising the median and 75th percentile by 8–10 cm.

CREVLIQ/CLIFVMAX likelihood functions (Supporting Information Figure S5) show that there is no set of parameter values which are consistently unlikely across all LIG constraints. Thus, interpretations of which regions of model parameters space are viable (and hence, deductions about the related physical processes) will depend entirely on the specific LIG constraint applied. For instance, the E19-U constraint indicates that the least likely parameter sets are where CLIFVMAX values are small (Figure S5d): About 2.6% of the posterior density is associated with CLIFVMAX ≤ 0.5 km/yr, compared with 3.8% if the probabilities were uniformly likely in this region. This result implies that MICI is not ruled out by this constraint, in contrast to the interpretation of Edwards et al. (2019), because under E19-U CLIFVMAX ≤ 0.5 km/yr is only a little

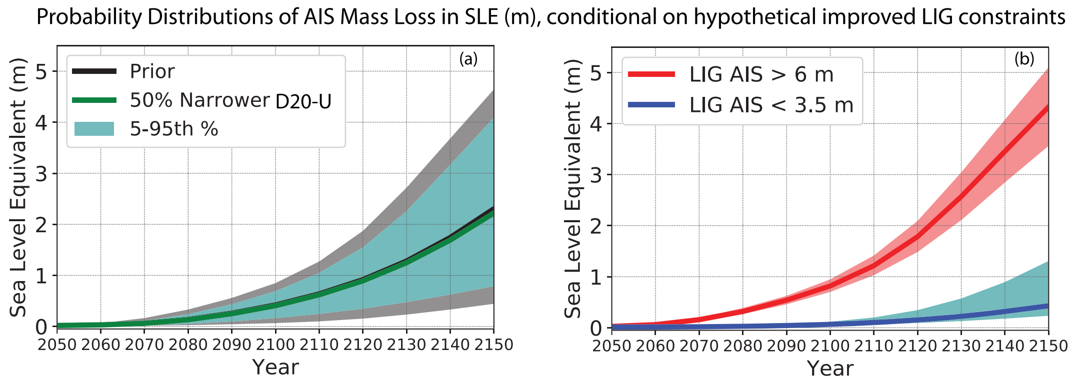

Figure 7. Posterior probability distribution medians (solid lines) and 5th to 95th percentiles (shading) of AIS mass loss in sea-level equivalent (m) projected under RCP8.5 forcing over 2050–2150. (a) Posterior constrained assuming that the D20-U constraint was 50% narrower (green curve/shading) alongside the prior distribution reproduced from Figure 3 (black curve/shading). (b) Posteriors constrained assuming that LIG AIS sea-level contributions were <3.5 m (blue curve/shading) or >6 m (red curve/shading).

more likely than not. As we drop to even lower values of CLIFVMAX (e.g., 0.1 km/yr), the emulated outputs conditioned on E19-U become less and less likely (not shown). However, there remain parameter sets with nonzero likelihoods near CLIFVMAX = 0, especially at higher CREVLIQ values (Figure S5d), such that a no-MICI solution also cannot be excluded. The main differences between this study and Edwards et al. (2019) are the ensemble structure, as well as enhanced atmospheric climatologies and a reduced ocean bias correction in the training simulations (section 2.1). Overall, none of the existing LIG constraints can exclude MICI as a primary loss mechanism (Figure S5), which requires an estimated LIG AIS mass loss of less than ~3.5 m.

The unconstrained LIG emulated distribution nearly coincides with (or in some cases is narrower than) the existing LIG constraint distributions. Whereas this indicates that the ice-sheet model is able to faithfully reproduce peak LIG AIS mass losses, it also confirms an existing challenge found by Edwards et al. (2019): Current LIG estimates are not strong constraints on this ice-sheet model's parameter likelihoods and future projections.

In light of this finding, we investigate how LIG constraints *could* inform future projections of AIS mass loss and sea-level rise if they were improved, using the sensitivity test constraints outlined in section 2.4; the resulting posteriors are presented in Figure 7. In particular, LIG constraints with gradually reduced ranges have a limit to how effective they can be for informing future projections of Antarctic contributions to sea-level rise (Supporting Information Figure S10).

Narrowing the D20-U constraint by 50% results in a posterior distribution highlighting an important property of LIG constraints: They become more effective over time (Figure 7a). Until ~2050 the prior and constrained distribution are nearly identical, then their distributions begin to diverge. AIS mass loss projected by this model becomes increasingly driven by cliff collapse (or the lack thereof) around 2060, and the LIG estimate begins effectively constraining both the most unstable parts of the distribution (which have the highest CLIFVMAX values, cf. Figure 1b) and the least. Figure 7a shows that because these solutions diverge over time, the LIG constraint becomes more informative on the absolute values of sea-level contributions over time. In 2100, the 95% credible interval of the posterior from the 50% narrower D20-U constraint is 14–68 cm, compared to the 7–85 cm interval of the prior (Table 1). In 2150 the constrained 95% credible interval is 0.71–4.07 m, compared with 0.44–4.65 m from the prior. Thus, even if observation-based LIG constraints are of little utility for reducing sea-level projection uncertainties in the near term, they become more meaningful as projections diverge.

We also investigate how projected AIS mass loss could change if there were a known upper or lower bound on the LIG estimate. Figure 7b shows how hypothetical estimates of relatively low (<3.5 m) or relatively high (>6 m) LIG AIS mass loss could strongly influence future projections. If the LIG contributions were known to be <3.5 m, the median and associated 95% credible interval of RCP8.5 projections in 2100 would be 7 and 4–15 cm, respectively. Likewise, if the LIG contributions were known to be >6 m, the associated median and 95% credible intervals of 2100 projections would be 81 and 68–95 cm, respectively.

A striking feature of the posterior distribution associated with LIG AIS mass loss <3.5 m constraint (blue curve/shading in Figure 7b) is the positive skew emerging over time. Simulated ice sheets that become unstable on a reverse-sloping bed have a loss rate proportional to their grounding line thickness, and hence proportional to the amount of ice they have already lost: simulations which have lost more mass retreat faster than those which have lost less mass (Robel et al., 2019). This behavior positively skews the mass loss distribution (similarly shown by Nias et al., 2019).

Notably, interpreting the total AIS mass loss distribution is complicated by different sectors losing mass at different times and rates. As sectors of the ice sheet lose all of their mass, the positive skew disappears (Robel et al., 2019), as seen in the multiple modes of the unconstrained LIG emulated distribution (Figure 4). A bimodal positively skewed posterior distribution associated with the 90% narrowed D20-U constraint (Figure S10) and the weakly skewed prior distribution of RCP8.5 mass loss in 2100 (skew of +0.18, Figure 6) also depict this complex behavior.

In contrast, the posterior distribution associated with LIG AIS <3.5 m well illustrates how different sensitivities to instability can drive skew across an ensemble (Figure 7b). In 2080 the emulated samples associated with higher model parameter values become unstable, and the skew increases from near zero to +1.8 by 2110; after this initial period of instability, the skew remains strongly positive (>+1.3). This behavior also explains how different sensitivities to instability lead to posteriors diverging over time.

3.3. Relevance for Paleo Sea-Level Observations

We have used conditional posterior probability distributions (Figures 4b and 5) to show how the LIG informs this model's projections of AIS mass loss. Our results also show how ice-sheet model parameters are linked to estimates of LIG AIS sea-level contributions. Concurrently, any improvements in understanding physical processes in the ice sheet will also indicate which LIG contributions are most likely. A main benefit of our approach is that it may inform future research and observational efforts to understand LIG sea levels. Here we apply our emulation and Bayesian updating framework to particular paleo sea-level observations, to investigate how assumptions about LIG ice-sheet chronology or improved LIG observations could influence future projections.

Determining sea levels during the LIG and closing its peak sea-level budget are challenging problems. Field observations have large uncertainties, related to measurement error or confounding processes such as glacial isostatic adjustment (GIA) or mantle dynamic topography (DT) (Austermann et al., 2017; Capron et al., 2019; Dendy et al., 2017; Hibbert et al., 2016; Rohling et al., 2017). Still under debate is whether the LIG exhibited variability with multiple global sea-level peaks (Barlow et al., 2018; Kopp, Dutton, et al., 2017), indicating short-term fluctuations (e.g., Rohling et al., 2008), or distinct out-of-phase mass losses between the GrIS and AIS (Dutton, Carlson, et al., 2015). Lacking sufficient near-field evidence, the AIS is typically invoked as an uncertain residual contributor. Yet estimated Greenland ice-sheet mass losses during the LIG also have a wide range of interpretations and central estimates (Dutton, Carlson, et al., 2015, their Figure 3), so it is difficult to disentangle the relative roles of Greenland and Antarctica.

Our method is able to show how these uncertainties in proxy-based reconstructions of LIG sea levels reflect on uncertainties in future AIS contributions to sea-level rise. Here we calculate the 95% credible intervals of AIS sea-level contributions under RCP8.5 forcing in 2100, varying the LIG AIS uncertainty according to three different scenarios for GMSL. Scenarios are derived from a milestone study by Dutton, Webster, et al. (2015), who used sea-level proxies in the Seychelles to constrain polar ice sheet mass losses during the LIG. Scenarios are developed to illustrate how individual components of uncertainty in LIG estimates contribute to projection uncertainties; thus, they are not directly related to any of the holistic projections in section 2.4 (though they are most closely related to the proxy-driven estimates of the K09-Max-3KyrSmooth constraint). We note that this is a close-to-ideal case study, because Seychelles GIA and DT predictions have relatively small uncertainties. All uncertainties are 1σ and assumed to follow a normal distribution. The scenarios are as follows:

1. Relative sea level coinciding with the highest in situ coral measured by Dutton, Webster, et al. (2015) with high-accuracy surveying techniques. The coral assemblage is interpreted as “likely intertidal”, and its elevation is 8 ± 0.2 m above modern sea level.

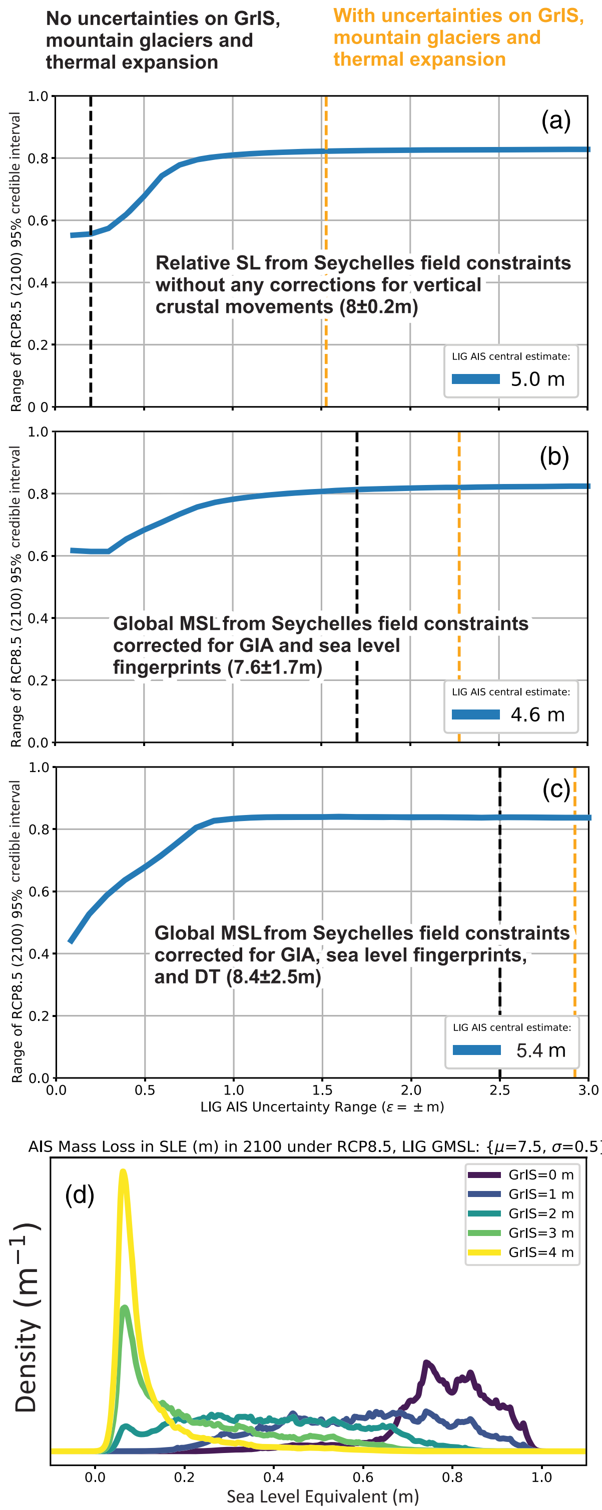

Figure 8. (a–c) Range of 95% credible intervals of future AIS sea-level contributions in 2100 under RCP8.5 forcing (m) conditional on three scenarios of LIG AIS contributions with a central estimate (blue curves) and Gaussian 1σ uncertainties (see text); combined total GrIS and thermosteric mean contributions are taken to be 3 m. Black dashed curves show the total field uncertainties excluding those from GrIS and thermosteric contributions; orange dashed curves include GrIS and thermosteric uncertainties. (d) Probability density functions of AIS contributions in 2100 under RCP8.5 forcing, conditional on LIG GMSL of 7.5 ± 0.5 m, and mean GrIS sea-level contributions varying over 0–4 m.

2. While Scenario 1 is illustrative of very small uncertainties in LIG sea-level estimates, it is also incomplete because it does not account for departures from eustasy due to GIA and sea-level fingerprints. These were calculated by Dutton, Webster, et al. (2015) using model results from Dutton and Lambeck (2012) and Hay et al. (2014). Using these estimates, Dutton, Webster, et al. (2015) calculated LIG GMSL rise was 7.6 ± 1.7 m.
3. Austermann et al. (2017) showed that mantle DT and ocean subsidence effects must be accounted for (each with large uncertainties), before GMSL can be calculated from field data. Here we use their model results for the Seychelles to illustrate how accounting for DT and ocean subsidence influences paleo GMSL estimates and their uncertainties. Subtracting ocean subsidence (-1.4 m) and DT as modeled in Austermann et al. (2017) (-0.8 ± 1.8 m) from Scenario 2, we calculate LIG GMSL rise was 9.2 ± 2.5 m.

For each scenario, we calculate LIG AIS sea-level contributions by subtracting the contributions of the GrIS, mountain glaciers, and thermal expansion following the budgetary approach of Dutton, Carlson, et al. (2015). First, we assume that the GrIS and thermosteric contributions to LIG sea level are known (2 and 1 m, respectively), with no error. We compare with the assumption that, instead, GrIS contributed 2 ± 1.5 m to LIG GMSL, as shown in Dutton, Carlson, et al. (2015, Figure 3). We set the contributions from mountain glaciers and thermosteric expansion to 1 m (Dutton, Carlson, et al., 2015), with arbitrary uncertainties of ± 0.2 m.

This exercise (Figures 8a–8c) shows that, regardless of AIS mass loss during the LIG, any LIG constraint can only substantially reduce uncertainties in this ice-sheet model's projected AIS sea-level contributions if the following two conditions are met: (1) Sea-level data and departures from eustasy are known with $\pm 1\sigma$ uncertainties of a few decimeters, and (2) GrIS and thermal expansion uncertainties are small (<1 m). Constraints on other models could be stronger or weaker, depending on the particular relationship between their parameters and ice-sheet evolution. This could be considered discouraging for the communities working on these topics; that is, the large intrinsic uncertainties that characterize GrIS and proxy-based ESL estimates may seem insurmountable. We instead note that this knowledge gap provides a unique opportunity to do innovative, timely, and important research that feeds directly into the open research questions in the paleo sea-level and ice-sheet communities (Capron et al., 2019).

Results further suggest that the storyline of LIG sea-level evolution has a strong influence on whether the LIG is able to constrain future sea-level changes. Greenland and Antarctic sea-level contributions are inextricably linked during the LIG: Knowledge or evidence about one will inform the other, as shown by assuming LIG total GMSL estimates of 7.5 ± 0.5 m in Figure 8d. Resulting relatively high or low AIS estimates are similar to the hypothetical constraint posteriors in Figure 7b. The links between the ice sheets imply that (1) efforts to improve estimates of GrIS can directly inform future AIS sea-level projections and that (2) the timing of LIG GrIS loss compared with LIG AIS loss is pivotal (Kopp, Dutton, et al., 2017). Storylines where GrIS and AIS mass losses peak simultaneously have a very different interpretation from those where ice-sheet losses peak several thousand years apart (Rohling et al., 2019) and imply different AIS projected contributions to future sea-level rise.

The mismatch between transient future ice-sheet mass loss and peak LIG mass loss limits the effectiveness of the LIG as a constraint. Historically, studies of the LIG have focused primarily on gathering geological evidence of peak LIG GMSL, in part because these are less challenging measurements to make in the field. But comparing the modeled LIG and future time series in Figure 1 shows that the transient onset of LIG losses most closely mirrors future losses, with similar dependencies on model physics and parameters. Both improved transient (rather than equilibrium) ice-sheet model runs and quality estimates of the LIG onset period are highly desirable for constraining AIS changes and future sea-level rise. Sampling biases and the requirement for precise chronologies have to this point thwarted these efforts. But as a coherent picture of LIG sea levels emerges, combining LIG constraints with probabilistic distributions from ice-sheet models—as this study has done—will improve the precision of future sea-level projections.

4. Summary and Conclusions

This study applied Bayesian methods to emulate and calibrate an ice-sheet model to evaluate the ability of LIG AIS mass loss to constrain sea-level rise projections under RCP8.5 forcing. Ice-sheet model training ensembles were developed considering the MICI process, with ensembles spanning over a broader range of model parameter values than previously explored (DeConto & Pollard, 2016). A set of proposed specific

LIG constraint distributions (several of which have been previously used to calibrate ice-sheet model projections) were also employed to explore their effectiveness for constraining future AIS mass loss. The emulator was combined with LIG paleo sea-level field measurements to illustrate how improved LIG observational estimates could potentially narrow uncertainties in future AIS projections.

Results explicitly show how estimates of LIG AIS mass loss could inform which parameter values are most likely in this ice-sheet model, which in turn informs future projections (2000–2150). However, LIG AIS sea-level contributions themselves are not well constrained (e.g., Düsterhus et al., 2016), and not all LIG estimates inform future projections equally. For instance, if LIG contributions were known to be <4 m, then MICI is very unlikely to be a primary loss mechanism in the future Antarctic mass loss projected by this ice-sheet model. Likewise, if LIG contributions were known to be >6 m, the ice-sheet model emulator projects that substantial future mass losses associated with MICI are likely. In either case, uncertainties in future projections from this model would narrow considerably, but some uncertainty would remain because peak LIG Antarctic mass losses have somewhat different sensitivities to ice-sheet model parameters than future changes do. LIG observations which inform the upper and lower limits of the unconstrained probability distribution would be valuable for improving future projections (in the context of this specific model and ensemble). Because ice-sheet model parameter likelihoods and LIG sea-level estimates are closely linked, evidence of constraints on one informs the other. For instance, if there are indications that MICI is not a viable loss mechanism, results here indicate that peak LIG Antarctic sea-level contributions were likely <4 m.

Consistent with the findings of Edwards et al. (2019), posterior distributions calibrated with a Bayesian approach show that currently best-available LIG constraints (which have previously used to calibrate ice-sheet model projections, e.g., DeConto & Pollard, 2016; Edwards et al., 2019) are inadequate to restrict a wide range of model parameter values. Consequently, this study can neither confirm nor exclude MICI as a primary driver of AIS mass loss. However, because the ice-sheet model projections of future AIS mass loss diverge over time—especially after 2060 when MICI begins strongly accelerating mass loss—LIG constraints which are uninformative in the near term become more informative on longer timescales (through 2150).

Conditioning future AIS mass losses on peak LIG sea level exposes direct links between paleo sea-level reconstructions and future sea-level rise. Improvements in field measurements, reductions in uncertainties from GIA or DT, and better chronologies of Antarctic and Greenland ice-sheet retreat during the LIG could all reduce uncertainties in future projections. These results provide strong motivation and support for continued collaborations between the paleo sea-level and ice-sheet communities.

Past studies of LIG sea level have focused primarily on peak GMSL, as they are more readily and reliably measurable, and because it is difficult to establish accurate and precise sea-level chronologies (Dutton, Carlson, et al., 2015). But peak LIG AIS mass losses are not necessarily representative of the transient changes the AIS may experience in the coming decades and centuries. This mismatch between the future and the past limits the applicability of LIG constraints on future Antarctic mass loss. Even if LIG Antarctic contributions were known precisely (±5 cm), there would still be decimeter-scale uncertainties in projections of future Antarctic contributions to sea-level rise. An alternative approach could be to pursue additional field observations detailing or inferring Antarctic changes during the LIG onset, to provide improved constraints on projections of future AIS contributions to sea-level rise. Improved LIG chronologies and observations of LIG Greenland ice-sheet changes could also reduce future projection uncertainties.

This study considered a single ice-sheet model and explored the MICI process. Other parameterized processes (such as the oceanic melt factor or the timescale of isostatic rebound; e.g., Chang et al., 2016; Pollard et al., 2016) are well suited for exploration with the methodological approach developed here. It should be noted that expanding on the number or range of parameters is limited by the computational efficiency of GP modeling, which scales with n samples as $\mathcal{O}(n^3)$ (C. E. Rasmussen & Williams, 2006). Alternative sampling techniques (such as a Latin Hypercube or Sobol sequence) could be utilized to improve efficiency on our factorial scheme. Other considerations—such as the LIG forcing applied, future emissions scenarios, or underlying stochastic processes like basal sliding—also contribute to uncertainties which are beyond the scope of this work, but with simplifications or extensions could be explored with an approach similar to this study.

There is a maximum possible constraint that the LIG can provide to inform ice-sheet model sensitivities to climate warming and future sea-level rise (e.g., Capron et al., 2019, and references therein). Uncertainties in ice-sheet physics and observational evidence currently limit the capability of the LIG to meaningfully constrain sea-level rise projections over the coming century. Despite these limitations, this study has specifically illustrated how models, emulation, and Bayesian calibration may be combined to interpret and guide paleo sea-level observational constraints. A major ongoing research objective is to continue strategically gathering field observations, in order to improve understanding and estimates of LIG sea levels. Such improvements, along with continued integration with modeling and statistical methods, will increase confidence in the physics and projections of Antarctic contributions to sea-level rise over the coming centuries.

Data Availability Statement

Model simulations used in this study are freely available online (at https://doi.org/10.5281/zenodo.3478486). Code to perform emulation and analyses is archived and freely available at https://zenodo.org/record/4058832 (Gilford, 2020). GP regression was performed with GPflow version 1.3.0 (Matthews et al., 2017); some colormaps provided by Crameri (2018).

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