Early detection and uncertainty quantification of rapid sea-level rise from Antarctica

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1. Focal Areas (i) classification and/or anomaly detection methods applied towards identifying critical climate system thresholds; improved emulator design for (ii) reducing computational costs relative to full-physics models and (iii) improved uncertainty quantification workflows

2. Rationale The evolution of the Antarctic ice sheet in response to climate change remains the single largest uncertainty in projecting future sea-level rise (SLR), with risk-averse projections for 2100 spanning between zero and a half meter[1]. During the past decade, DOE has made substantial investments in new ice sheet and Earth system models needed to improve both understanding and predictive capability in this area. Yet major challenges remain, including better understanding when and under what circumstances significant increases in SLR from Antarctica may be initiated and better quantifying uncertainties in model-based SLR projections. Here, we discuss the potential for transformative advances in these areas through the application of machine learning and artificial intelligence (ML and AI, respectively).

Much of the Antarctic ice sheet rests on bedrock depressed below sea level. This geometry, whereby the bedrock slopes downwards as the ice sheet thickens inland, is unstable to retreat along much of its margin. Where the ice sheet thins to the point of floatation via buoyancy (the transition from grounded ice sheet to floating ice shelves, or "grounding line"), a small amount of downslope retreat results in thicker ice at the grounding line. This increase in thickness leads to a large increase in ice flux and ice thinning at that same location. Thinning leads to additional floatation and further retreat of the grounding line downslope into still thicker ice. Thus, a small initial perturbation may ultimately lead to irreversible ice sheet collapse. This "marine ice sheet instability" (MISI) is well characterized theoretically[2,3] and is reproduced by current models[4].

Triggers for the MISI are well understood - ice shelf thinning and/or break-up can occur due to interactions with the ocean (below) or the atmosphere (above), followed by grounding line retreat[7,8]. These behaviors are represented by current ice sheet[4,8] and Earth system[9,10] models. While large-scale retreat and collapse of West Antarctica would take many thousands of years, the *initiation* of that retreat (via MISI) could occur in the coming years or decades[a]. Such an occurrence would lead to catastrophic impacts on coastal infrastructure and ecosystems worldwide. A question of critical importance is then how to unequivocally recognize the relevant threshold (ice sheet and climate) behaviors - if and when they occur - from the myriad of other signals within Earth's complex climate system. A related question of extreme practical importance to policymakers and planners is how best to quantify, and if possible reduce, uncertainties in model-based projections of these same processes.

3.1 Narrative: Approach and Motivating Questions We propose using output from ensembles of ice sheet and Earth system model simulations to generate datasets (spatiotemporal time series) for use in ML and AI training (supervised and/or unsupervised methods; classification and/or anomaly detection approaches). This training will be used to identify critical features, behaviors, or thresholds within the ice sheet and climate systems, which can then be targeted in observations. Similarly, these approaches may be used to design improved observational

[a] Observations and modeling[5,6] have been interpreted as indicating that a MISI may already be underway along parts of the West Antarctic ice sheet margin.

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sensors and campaigns for targeting these same features. Critical to this approach is that current models *allow and account for* the relevant features and behaviors of interest. For example, when subject to appropriate forcing, DOE ice sheet models demonstrate MISI up to and including full collapse of specific sectors of the ice sheet[4,11,12]. DOE's Energy Exascale Earth System Model (E3SM)[13] simulates submarine melting beneath ice shelves as well as the relevant local, regional, and distal climate processes[9,10] that impact that melting[b]. These same ensembles can be used with ML and AI approaches to generate computationally cheaper, physically-based, reduced order models ("emulators") for use with existing or new uncertainty quantification workflows. Thus, in addition to better understanding, identifying, and quantifying the conditions under which rapid SLR from Antarctica may occur, we also aim to improve our ability to quantify uncertainties that accompany SLR projections.

With this general approach in mind, we pose the following questions around which we identify (below) several focus areas for ML-and-AI enabled research: (1) What ice sheet observations indicate that a MISI has or may be initiated within the Antarctic ice sheet? (2) What broader Earth system observations point to climate forcing that could initiate an Antarctic MISI? (3) What are the uncertainties associated with SLR projections made using ice sheet & Earth system models? (4) What observations are critical for monitoring relevant threshold behaviors or for reducing uncertainties in SLR projections?

3.2 Narrative: Research Focus Areas We identify three primary areas of research related to ice sheet evolution and sea-level rise that will leverage ML and AI approaches, including: (1) the detection, characterization, and classification of anomalous events; (2) the discovery and design of reduced order models; (3) the design of improved uncertainty quantification workflows. Below, we elaborate primarily on the first, with briefer introductions to the latter two. We further note that, within each of these research areas (or "use cases"), numerous other related problems in Earth system science might be similarly approached.

3.2.1 Detection, characterization, and classification of anomalous events Ensembles of ice sheet model simulations will be used to generate a wide range of potential future ice sheet evolutionary paths, which will then be used with ML/AI approaches to identify critical, observable behaviors associated with the initiation of a MISI. For example, simulations could be binned for training based on whether or not unstable grounding line retreat has initiated within a given time window, based on different rates of grounding line retreat, rates of ice flux, or rates of ice sheet thinning (supervised classification). Alternatively, a given rate of grounding line retreat, grounding line flux, or ice sheet thinning might be used to identify a threshold behavior beyond which a MISI is inevitable (anomaly detection). Supervised approaches will be based on well understood system behaviors (requiring "expert judgement"). Eventually, unsupervised approaches may remove this subjectivity by illuminating new behaviors or thresholds not currently associated with MISI (e.g., combinations of subtle observations). Ensembles of Earth system model simulations will be similarly analyzed to clearly identify features or thresholds in climate forcing that might ultimately initiate a MISI. One example includes increased submarine melting (leading to ice shelf thinning and, subsequently, unstable grounding line retreat) as a result of warm ocean water intrusions into ice shelf cavities following regional changes in wind stress divergence[14].

[b] Here we primarily discuss *known* behaviors of concern and *known* climate processes that lead to these behaviors. Behaviors and processes of additional interest – currently *unknown or uncharacterized*, yet manifest in our models – may also be illuminated through the application of unsupervised learning approaches.

The critical signatures of these regional climate perturbations and their far-field forcings may be "learned" by ML/AI approaches trained on simulations, and thereafter monitored from observations. A specific example relevant to ice shelf thinning and grounding line retreat in West Antarctica is the strength and location of the Amundsen Sea low (ASL) pressure center (impacting regional wind forcing) as influenced by tropical Pacific climate variability (ASL teleconnections to ENSO)[15].

3.2.2 Discovery and design of reduced order models Modern PDE-based ice sheet models[16,17] have been developed, matured and, to some extent, validated over more than a decade. While they are computationally expensive, they are physics based, can efficiently run on DOE HPC platforms, and have gained the trust of the scientific community. For most science applications, we do not expect that these emulators will be able to fully replace traditional computational models. However, emulators can be useful in at least two relevant contexts: (1) to improve complex physics modules (contained within existing multi-physics models) that are poorly understood and/or too expensive to model; (2) to create cheap, reduced order emulators of costly computational models, designed and trained to be used for specific tasks (e.g., predicting sea-level rise and related statistics). Several approaches for generating efficient emulators are being investigated[18]. Recent efforts[19,20] based on operator regression strategies show promising results. Specific examples of (1) include finding emulators for subglacial hydrology or iceberg calving submodels[c]. In this case, significant research needs to be devoted to ensure that these hybrid (PDE+ML) models can be efficiently trained and evaluated.

3.2.3 Improved uncertainty quantification workflows Efforts around uncertainty quantification with ice sheet models have pursued a number of approaches to date. Bayesian inference approaches have been limited to idealized or highly simplified problems[21] or under the significant simplification of a Gaussian posterior distribution[22]. Similarly, forward propagation has been limited to problems that assume unrealistically small parameter spaces[23]. These limitations are related to the computational cost of full-physics forward models (as discussed above) and the "curse of dimensionality". In fact, the initialization of a modern ice sheet model so that it can realistically reproduce present-day observations requires the inference of parameter fields with $>10^6$ unique parameters. One of the primary goals for the improved emulators discussed above would be in applying these towards reducing costs in both the calibration and forward propagation phases of uncertainty quantification workflows (see reference 24 for an example of using an emulator to infer subglacial model parameters).

[c] see related white paper "Hybrid (PDE+ML) models in the context of land ice modeling" (M. Perego et al.)

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