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Data-Driven Inference of the Mechanics of Slip Along Glacier Beds Using Physics-Informed Neural Networks

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Reliable projections of sea level rise depend on accurate representations of how fast-flowing glaciers slip along their beds. Specifically, ice sheet models require a quantitative sliding law that relates basal drag to sliding velocity and glacier geometry, yet the proper form of the law remains uncertain. Here, we present a novel deep learning-based framework for learning the time evolution of basal drag from time-dependent ice surface velocity and elevation observations. We train a pair of probabilistic neural networks through a combination of time-dependent surface observations, governing equations for ice flow, and known physical constraints. Neural network outputs are stochastic predictions of time-varying basal drag that do not require any prior assumptions on the form of the sliding law. This training strategy is well-suited to large volumes of remote sensing data while providing a natural way to integrate our existing understanding of the physics of ice flow into the learning process.

We test this framework on 1D and 2D ice flow simulations and demonstrate that, under certain stress conditions, recovery of the underlying sliding law parameters and their uncertainties can be derived from the stochastic predictions of time-varying basal drag. We also apply these methods to Rutford Ice Stream and Pine Island Glacier in Antarctica to investigate subglacial hydrological effects for the former and evidence for regularized Coulomb sliding for the latter.