Physics-aware Machine Learning to Estimate Ice Thickness of Glaciers in West Svalbard

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Glacier ice thickness is a fundamental variable required for modelling flow and mass balance. However, direct measurements of ice thickness are scarce. Physics-based and data-driven approaches aim to reconstruct glacier ice thicknesses from the limited in-situ data. Farinotti et al. compared 17 models and found that their ice thickness estimates differ considerably on test glaciers.[1] Following these results, Farinotti et al. created an ensemble of models to develop the so-called consensus estimate of the ice thickness for the world’s glaciers in 2019.[2] Later, Millan et al. derived ice thickness estimates for the world’s glaciers using ice motion as the primary constraint. However, these results differ considerably from existing estimates and the 2019 consensus estimates.[3] It is evident, therefore, that significant uncertainty remains in ice thickness estimates.

Deep learning approaches are flexible and adapt well to complex structures and non-linear behaviour. However, they do not guarantee physical correctness of the predicted quantities. Therefore, we employ a physics-informed neural network (PINN), which integrates physical laws into their training process and is not purely data-driven. We include, for example, the conservation of mass in the loss function and estimate the depth-averaged flow velocity. Teisberg et al. also employed a mass-conserving PINN to interpolate the ice thickness of the well-studied Byrd glacier in Antarctica.[4] In this work, we extend the methodology by integrating the ratio between slope and surface flow velocities in estimating the depth-averaged flow velocity and mapping the coordinate variables to higher dimensional Fourier Features.[5] This allows to encompass glaciers in western Svalbard, addressing challenges posed by basal sliding, surface melting, and complex glacier geometries. Using surface velocity data from Millan et al. and topographical data from Copernicus DEM GLO-90[6] gathered through OGGM[7], the model predicts ice thickness on glaciers with limited measurements. We are extending it to perform as a predictor of thickness for glaciers with no observations. Here, we present the machine learning pipeline, including the physical constraints employed and preliminary results for glaciers in western Svalbard.


