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A Unified Framework for Forward and Inverse Modeling of Ice Sheet Flow using Physics Informed Neural Networks

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Predicting the future contribution of the ice sheets to sea level presents several challenges due to the lack of observations of critical boundary conditions, such as basal sliding. Traditional numerical models often rely on data assimilation methods to determine spatially variable friction coefficients by solving an inverse problem, given an empirical friction law. However, these approaches are not versatile, as they demand sometimes extensive code development efforts when integrating new physics into the model. Furthermore, the requirement for comprehensive data alignment on the computational grid hampers their adaptability, especially in handling sparse data effectively. To tackle these challenges, we propose a transformative approach utilizing Physics-Informed Neural Networks (PINNs) to seamlessly integrate observational data and underlying physical laws into a unified loss function, facilitating the solution of both forward and inverse problems within the same framework. We illustrate the versatility of PINNs by applying the framework to two-dimensional problems on Helheim Glacier in southeast Greenland. By systematically concealing one component within the system, we showcase the ability of PINNs to accurately predict and reconstruct hidden information, emphasizing their adaptability to handle scenarios marked by missing or incomplete datasets. Furthermore, we extend the application to address a challenging mixed inversion problem. We show how PINNs are capable of inferring the basal friction coefficient while simultaneously filling gaps in sparsely observed ice thickness. This mixed inversion problem represents a class of scenarios beyond the reach of conventional numerical methods. Our unified framework offers a promising avenue to enhance the predictive capabilities of ice sheet models, reducing uncertainties and advancing our understanding of intricate ice dynamics.