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Glacier point mass balance modeling using machine learning

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Estimations of glacier mass balance are commonly made using field techniques, empirical or physically based models, and remote sensing. More recently, data-driven tools like machine learning have become powerful complements to these conventional techniques. This study explores the potential of using machine learning to simulate the individual point mass balance of 30 sites from 13 glaciers in Switzerland spanning over 60 years, sourced from the Glacier Monitoring Switzerland (GLAMOS) network. To this end, we use two machine-learning models: LASSO regression, a linear regression model with L1-regularisation, and eXtreme Gradient Boosting (XGBoost), a gradient-boosted ensemble of decision trees. The models are driven by temperature and precipitation data at 1 km grid resolution from the Federal Office of Meteorology and Climatology (MeteoSwiss). The seasonal point mass balance data are used to train and test the models for each site individually. A comparative analysis is performed in which the performance of the LASSO regression and XGBoost are compared to a standard approach of calculating mass balance from a temperature-index model. In this analysis, we also explore how different temporal frequencies of climate variables, ranging from annual to monthly, affect the performance of the machine learning methods. Beyond their computational efficiency, these machine learning models are particularly suited to provide valuable insights into feature importance. Harnessing this, we study which months' temperature and precipitation most significantly contribute to explaining individual stake mass balances and compare these findings with commonly assumed drivers of mass balance.