Bridging machine learning and physics-based models for **improving snow water equivalent predictions** in the northern hemisphere

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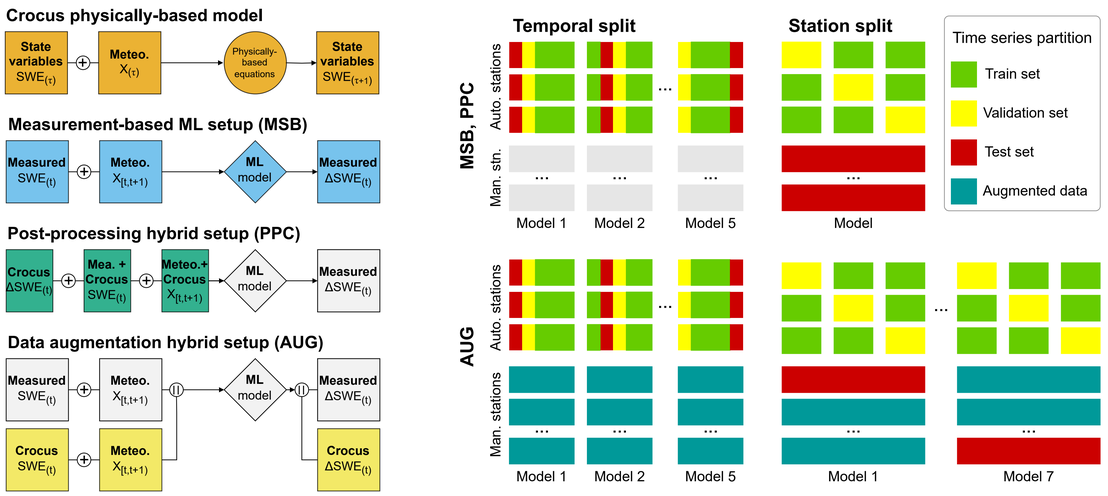
Background: SWE is difficult to quantify due to its high spatiotemporal variability and limited number of available data, because of the difficulty in measuring it.

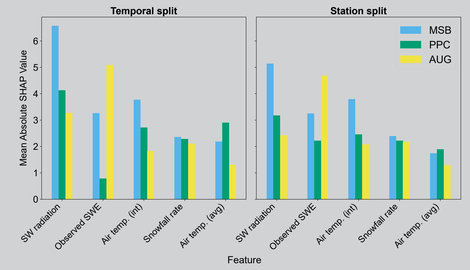
Goal: We want to improve long-term daily SWE simulations for stations or time periods where no snowpack measurements are available.

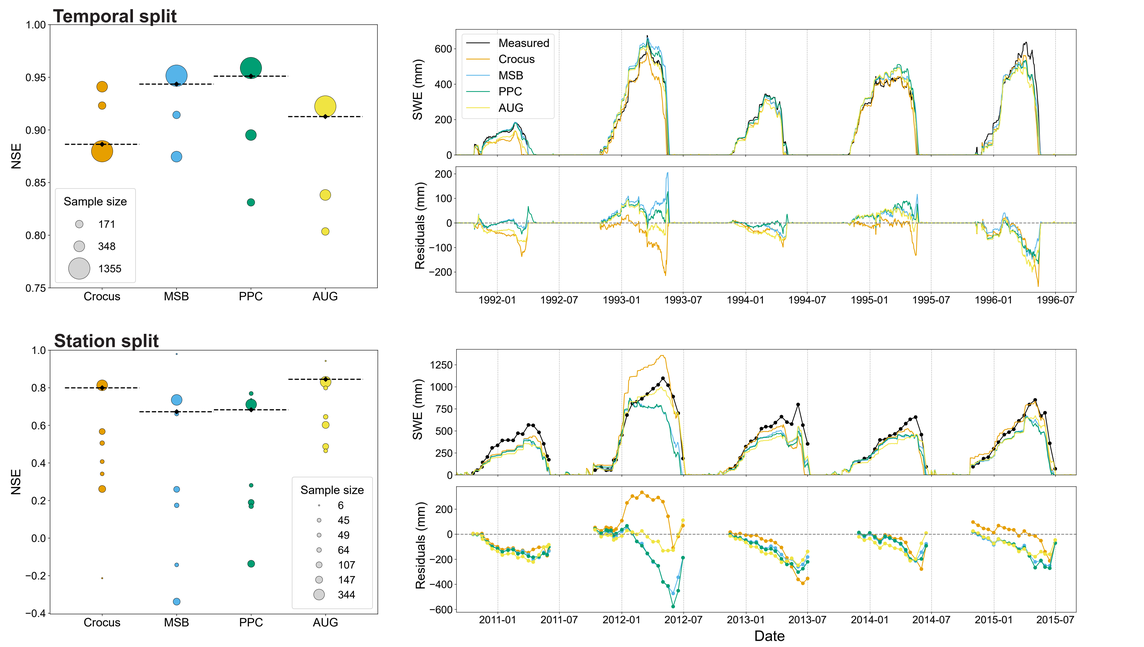
We compare two hybrid setups (PPC and AUG) with a measurement-based ML approach (MSB) and a physically-based model (Crocus) for stations with available historical SWE (station split) and without them (temporal split).



Dataset: *The SWE and meteorological data consisted of 7 to 20 years of in-situ observations at ten stations throughout the northern hemisphere from ESM-SnowMIP, three of which had automatic daily measurements and the rest relied on intermittent manual observations. Crocus simulations ran on the meteorological data from the ten stations were used both in the hybrid models and for benchmarking purposes.*

SHAP analysis: *The feature importances of the ML models are consistent with physical knowledge; temperature and downwards radiation have a negative effect on ΔSWE and snowfall shows a positive linear relationship, despite some deviations at extreme values. Adding lagged variables improves model performance, but are only relevant for some features and up to a week before at most.*





Results: Hybrid models obtain better results than either ML or physically-based models, PPC performs best for temporal extrapolation and AUG for new locations.

The ML-based setups improve the performance of Crocus in the temporal split due to a better snow melt timing, but severly underestimate SWE in the spatial split except for the AUG setup, which obtains 12% lower RMSE than Crocus.

Conclusions: Hybrid models allow fast and accurate SWE predictions based only on meteorological data, enabling forecasts at unprecedented spatio-temporal scales.

Sharing is encouraged

Link to abstract

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