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Learning to filter: Snow data assimilation using a Long Short-Term Memory network

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In snow-dominated regions, today's snow is tomorrow's water, making reliable estimates of snow water equivalent (SWE) and snow depth crucial for water resource management. In this context, data assimilation is a powerful tool to optimally combine models and measurements, enhancing accuracy and reliability. Ensemble-based techniques like the Ensemble Kalman Filter (EnKF) and Particle Filter (PF) are often used but their deployment in real-time applications can make it challenging to ensure timely and accurate results. To address these challenges, we propose an innovative data assimilation framework for snow hydrology that leverages Long Short-Term Memory (LSTM) networks. Using data from seven diverse study sites across the Northern Hemisphere, our framework is trained on the outputs of an EnKF, persuing a balance between computational efficiency and model complexity to advance data assimilation applications in snow hydrology. This LSTM-based framework achieves performance comparable to the EnKF in improving open-loop estimates, with only minor increases in root-mean-square error (RMSE): +6 mm for SWE and +6 cm for snow depth on average. Adding a memory component enhances stability and accuracy, especially under sparse data conditions. When trained on long-term datasets spanning 25 years, the LSTM framework demonstrated promising spatial transferability, with accuracy reductions of less than 20% for snow water equivalent and snow depth estimation. After training, the LSTM approach significantly outperformed a parallelized EnKF in computational efficiency, reducing runtime by 70% while maintaining comparable accuracy. Training on multi-site data further ensured robust performance across diverse climate regimes and during both dry and average water years, with a modest RMSE increase compared to the EnKF (+6 mm for SWE and +18 cm for snow depth). By combining the strengths of traditional ensemble methods and modern machine learning, this framework offers a scalable, computationally efficient, and reliable alternative for operational snow hydrology data assimilation.