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Towards global hybrid hydrological modeling by fusing deep learning and a conceptual model

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Deep (recurrent) neural networks have proven very useful to model multivariate sequential data streams of complex dynamic natural systems and have already been successfully applied to model hydrological processes. Compared to physically based models, however, the internal representation of a neural network is not directly interpretable and model predictions often lack physical consistency. Hybrid modeling is a promising approach that synergizes the advantage of process-based modeling (interpretability, theoretical foundations) and deep learning (data adaptivity, less prior knowledge required): By combining these two approaches, flexible and partially interpretable models can be created that have the potential to advance the understanding and predictability of environmental systems.

Here, we implement such a hybrid hydrological model on a global scale. The model consists of three main blocks: 1) A Long-Short-Term Memory (LSTM) model, which extracts temporal features from the meteorological forcing time-series. 2) A multi-branch neural network comprising of independent, fully connected layers, taking the LSTM state as input and yielding a set of latent, interpretable variables (e.g. soil moisture recharge). 3) A conceptual model block that implements hydrological balance equations, driven by the above interpretable variables. The model is trained simultaneously on global observation-based products of total water storage, snow water equivalent, evapotranspiration and runoff. To combine the different loss terms, we use self-paced task uncertainty weighing as done in state-of-the-art multi-task learning.

Preliminary results suggest that the hybrid modeling approach captures global patterns of the hydrological cycle's variability that are consistent with observations and our process understanding. The approach opens doors to novel data-driven simulations, attribution and diagnostic assessments of water cycle variations globally. The presented approach is—to our knowledge—the first application of the hybrid approach to model environmental systems.