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Integrating physical constraints into neural networks for piezometric time series modeling: application to the Beauce limestone aquiferAbstract:

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Accurate simulation of groundwater level dynamics remains a major challenge due to the complex interplay between climatic forcing, subsurface properties, and hydrological processes. In this study, we propose a hybrid modeling approach that combines data-driven neural networks with physically based constraints to reproduce piezometric time series of the Beauce limestone aquifer, located in the Centre–Val de Loire region (France). This aquifer has been monitored for several decades and benefits from an extensive observation network. Twelve piezometers were selected to represent the diversity of groundwater responses, including systems characterized by strong inertial behavior.

The neural network is trained by minimizing a cost function measuring the mismatch between observed and simulated groundwater levels. To enhance training convergence and predictive skill, the cost function is augmented with a term derived from physical processes governing groundwater evolution. These processes are based on the inter-reservoir drainage laws implemented in the global hydrological model Gardenia (©BRGM). Gardenia conceptualizes the transfer of water from precipitation to the aquifer through three reservoirs: soil, unsaturated zone, and saturated zone. Infiltration is controlled by the square of soil saturation, effective rainfall is partitioned between runoff and percolation following an exponential law defined by a half-life parameter and a partitioning factor, and groundwater discharge to the river is described by an exponential recession law governed by a distinct half-life.

The proposed architecture combines a Long Short-Term Memory (LSTM) network with a Multi-Layer Perceptron (MLP), allowing the model to exploit both the temporal dependency structure of hydrological time series and the nonlinear representation capacity of feedforward neural networks. Results show that incorporating physical constraints into the learning process significantly improves both training stability and predictive performance compared to a purely data-driven approach. Finally, the hybrid model performances are compared with those of the Gardenia model, highlighting the added value of combining physical understanding with machine learning for groundwater level simulation.