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Estimating global terrestrial water storage components by a physically constrained recurrent neural network

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While deep learning models are capable of representing complex temporal processes in a data-adaptive way, they lack physical consistency and interpretability. Thus, the combination of machine learning and physically-based approaches in so-called hybrid modeling has been proposed recently [1]. Gathering insights into complex Earth system processes in a *data-driven* way has, arguably, a large potential for hydrology. This is, on the one hand, due to the richness of Earth observations of hydrological quantities, such as terrestrial water storage, runoff, snow cover, or evapotranspiration. On the other hand, the large uncertainties in current global hydrological models across spatial and temporal scales motivate the exploration of alternative, complementary approaches.

In this work [2], we evaluate an experimental approach for the global, data-driven decomposition of terrestrial water storage. Therefore, we developed a dynamic hybrid model which represents the main terrestrial water storage components of groundwater, soil moisture, and snowpack. The model consists of a recurrent neural network that estimates spatiotemporally varying and physically interpretable quantities, which are used as coefficients in a set of hydrological balance equations. The hybrid model is fed with meteorological variables and gridcell-level landscape properties and is optimized end-to-end using gridded evapotranspiration, runoff, terrestrial water storage, and snow water equivalent.

By outsourcing the estimation of coefficients to a neural network, we achieve improved local data adaptivity. The simulated fluxes and storage components are realistic and plausible overall, and our approach yields a larger contribution of soil moisture to the terrestrial water storage variations compared to physically-based hydrological models, especially in tropical savanna regions. The presented approach is a proof of concept of the hybrid modeling approach for the global terrestrial water cycle and we acknowledge uncertainties due to data and physical constraints that can be further improved. The presented work is a first step toward the data-driven yet physically constrained estimation of global water storage components and could find broad application in the Earth sciences.

[1] Reichstein et al. (2019, Nature) <https://www.nature.com/articles/s41586-019-0912-1>

[2] Kraft et al. (2021, HESSD) <https://hess.copernicus.org/preprints/hess-2021-211/>

