EGU23-4842, updated on 25 Apr 2024
https://doi.org/10.5194/egusphere-egu23-4842
EGU General Assembly 2023

Introducing DL-GLOBWB: a deep-learning surrogate of a process-based global hydrological model

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Process-based global hydrological models are an important tool for sustainable development and policy making in today's water-scarce world. These models are able to inform national to regional scale water management with basin-scale accounting of water availability and demand and project the impacts of climate change and adaptation on water resources. However, the increasing need for better and higher resolution hydrological information is proving difficult for these state-of-the-art process-based models as the associated computational requirements are significant.

Recently, the deep-learning community has shown that neural networks (in particular the LSTM network) can provide hydrological information with an accuracy that rivals, if not exceeds, that of process-based hydrological models. Although the training of these neural networks takes time, prediction is fast compared to process-based simulations. Nevertheless, training is mostly done on historical observations and thus projections under climate change and adaptation are uncertain.

Inspired by the complementary strengths and weaknesses of the process-based and deep-learning approaches, we present DL-GLOBWB: a deep-learning surrogate of the state-of-the-art PCR-GLOBWB global hydrological model. DL-GLOBWB predicts all water-balance components from the process-based model, including human water demand and abstraction, with a nRSME of 0.05 (range between 0.0001 and 0.32). The DL-GLOBWB surrogate is orders of magnitudes faster than its process-based counterpart, especially as surrogates trained at low resolutions (e.g. 30 arc-minute) can effectively be downscaled to higher resolutions (e.g. 5 arc-minute).

In addition to introducing DL-GLOBWB, our presentation will explore future applications of this deep-learning surrogate, such as (1) improving model calibration and performance by comparing DL-GLOBWB outputs with ins-situ data and satellite observations; (2) training DL-GLOBWB on future model projections to include global change; and (3) the implementation of DL-GLOBWB to dynamically, and at high resolution, visualize the impact of climate change and adaptation to stakeholders.