G-RUN ENSEMBLE: A multi-forcing observation-based global runoff reanalysis

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Although river flow is the best-monitored variable of the terrestrial water cycle, the scarcity of available in situ observations in large portions of the world has until now hindered the development of consistent observational estimates with global coverage. Recently, fusing sparse in situ river discharge observations with gridded precipitation and temperature using machine learning has shown great potential for developing global monthly runoff estimates (Ghiggi et al., 2019). However, the accuracy of the utilised gridded precipitation and temperature products is variable and the corresponding uncertainty in the resulting runoff and river flow estimates was not yet quantified.

Global-RUNoff ENSEMBLE (G-RUN ENSEMBLE) (Ghiggi et al., in review) provides a multi-forcing global reanalysis of monthly runoff rates at a 0.5° resolution, composed of up to 525 runoff simulations. The G-RUN ENSEMBLE is based on 21 different atmospheric forcing datasets, overall spanning the period 1901-2019. The reconstructions are benchmarked against a comprehensive set of global-scale hydrological models (GHMs) simulations, using a large database of river discharge observations that were not used for model training as a reference.

Overall, the G-RUN ENSEMBLE shows good accuracy compared to the set of GHMs evaluated, especially with respect to the reproduction of the dynamics and seasonality of monthly runoff rates. We found that the spread imposed by the atmospheric forcing data in the G-RUN ENSEMBLE is small compared to the spread observed within the ensemble of GHMs simulations driven with a subset of such forcings. This might occur because GHMs are more impacted by biases in the input meteorological forcing and are more susceptible to accumulate errors over the simulation time than the adopted machine learning approach.

In summary, the multi-forcing nature of the G-RUN ENSEMBLE allows to quantify the uncertainty associated with the currently available atmospheric forcings, thereby paving the way for more robust and reliable water resources assessments, climate change attribution studies, hydroclimatic process studies as well as evaluation, calibration and refinement of GHMs.

References