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Post-processing Hydrologic Model Output for Water Resources Studies: A Spatially-consistent, Process-based Correction Method

Andrew Bennett[1], Bart Nijssen[1], Yifan Cheng[1], Adi Stein[1], and Marketa McGuire[2]
[1]University of Washington, Seattle, United States of America (andrbenn@uw.edu)
[2]Bureau of Reclamation, Denver, United States of America

Water resources studies often rely on simulated streamflow from hydrologic models. Model-based streamflow estimates are often not directly usable in water resources studies because all models, no matter how well-calibrated, contain systematic errors. Water resources studies rely on simulated streamflow as inputs to compute reservoir releases and diversions and do not function well if those inputs are significantly biased in time and/or space. Post-processing is therefore used to reduce these systematic errors in model outputs. This post-processing step to remove model errors is typically referred to as bias-correction, and often impacts the entire distribution of flows rather than just the mean.

Existing post-processing techniques typically have three short-comings. First, simulated streamflow at unique locations are often bias-corrected independently, disregarding the connection between locations that is imposed by the river network. This destroys the spatial consistency of the streamflow across a river network. Second, bias-correction methods often rely on simple, time-invariant mappings between observed and simulated streamflow, without regard for the different hydrological processes that drive streamflow. For example, a hydrological model may have different systematic errors in representing snowmelt than in representing soil drainage, necessitating different corrections. Third, the application of a bias-correction method is often restricted to locations where observed and simulated streamflow exist, even though these locations represent only a small subset of streamflow input locations to a water resources model.

We present a post-processing method for streamflow that addresses all three of these shortcomings of existing streamflow bias-correction methods. The method accounts for the spatial relations imposed by the river network, allows for the incorporation of process-information, and applies the bias-correction for all reaches in a stream network. We develop a mapping from the modeled output at the gages with flow observations, which we use as the basis for training a machine learning (ML) model to perform the site-specific bias-correction. We then apply the ML model to local streamflow contributions for each river segment, including river segments without flow observations. Finally, we combine the local bias-corrections across the stream network, to create accumulated bias-corrected streamflow time series that are spatially-consistent across the stream network. We demonstrate our method for daily streamflow in a river basin in the western United States.