A Spatially Consistent Bias Correction Technique for Distributed Streamflow Modeling

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Abstract

Planning for hydropower, water resources management, and climate change adaptation requires statistically unbiased hydrologic predictions. However, all hydrologic models contain systematic errors, e.g., incorrect mathematical representations of physical processes and effects of uncertainties in data sources. Statistical post-processing, or bias correction, is often used to reduce the effects of these systematic errors in model outputs. A large number of techniques for performing bias correction has been developed, primarily in the context of correcting statistical properties of independent locations. However, when bias correcting streamflow predictions within the same stream network, this assumption of spatial independence breaks down. Independently bias correcting locations from the headwaters to the mouth of a river system destroys the spatial consistency of the streamflow across a river network. We describe work toward maintaining spatial consistency in streamflow bias correction using a number of locations in the western United States. We simulate the hydrology of the Columbia River in the Pacific Northwestern United States, a river system that spans a number of hydroclimatic and flow regimes that contains a large number of flow gages. 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 compare our method against several commonly used bias correction techniques to evaluate both model performance and spatial consistency.

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Background

Streamflow bias correction is needed to plan for hydropower, resource management, and climate adaptation

Streamflow bias correction typically uses off the shelf methods from atmospheric bias correction

Spatially-independent bias correction of flows destroys the spatial consistency between locations in stream network

We have developed a method for accounting for stream network topology by regionalizing bias corrections on local flows and re-routing the bias corrected flows

Methods & workflow



Workflow consists of individual modules: local flow estimation, bias correction, and regionalization

Using quantile mapping based approach for BC

Using LSTM network for regionalization

Features currently used in training LSTM network:

- air temperature
- precipitation
- basin area
- local flow

We can account for stream network topology by bias correcting local flows





SCBC corrects local flows individually & re-aggregates through routing

Gauge Locations NF – Naturalized Flows IBC – Independent bias correction SCBC – Spatially consistent bias correction

H41N-1897

Flow aggregation



Bias correction is performed on simulated local flows using regionalized model trained on gauged sites then re-routed through a river routing model

Case study

We compare independent bias correction (IBC) to spatially consistent bias correction (SCBC)



SCBC was trained on 150 flow locations in the Pacific northwestern United States over 30 years of daily data and applied to 143 stream segments in the Yakima basin, including 14 gauged sites for comparison to independent bias correction (IBC)

Discussion

IBC still works better on average at individual sites, but SCBC enforces spatial consistency and does not rely on local observations

Re-aggregating bias-corrected local flows maintains spatial consistency and does not introduce artificial negative incremental flows

Areas for further work: estimation of local "observed" flows, machine learning techniques, gathering of more training data

Control of statistical properties of reaggregated bias corrected flows is difficult (e.g. mean, etc.)

What's next?

Future work includes testing of different ML approaches (Random forest, autoregressive models, etc) application of different bias correction methods, and estimation of local flows on observed data

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