A Spatially Consistent Bias Correction Technique for Distributed Streamflow Modeling

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Background

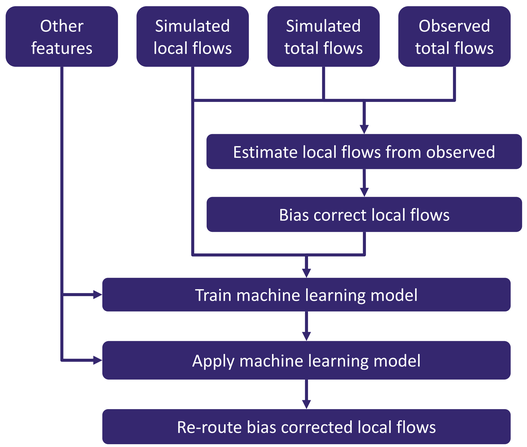
Streamflow bias correction is needed to plan for hydropower, resource management, and climate adaptation

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

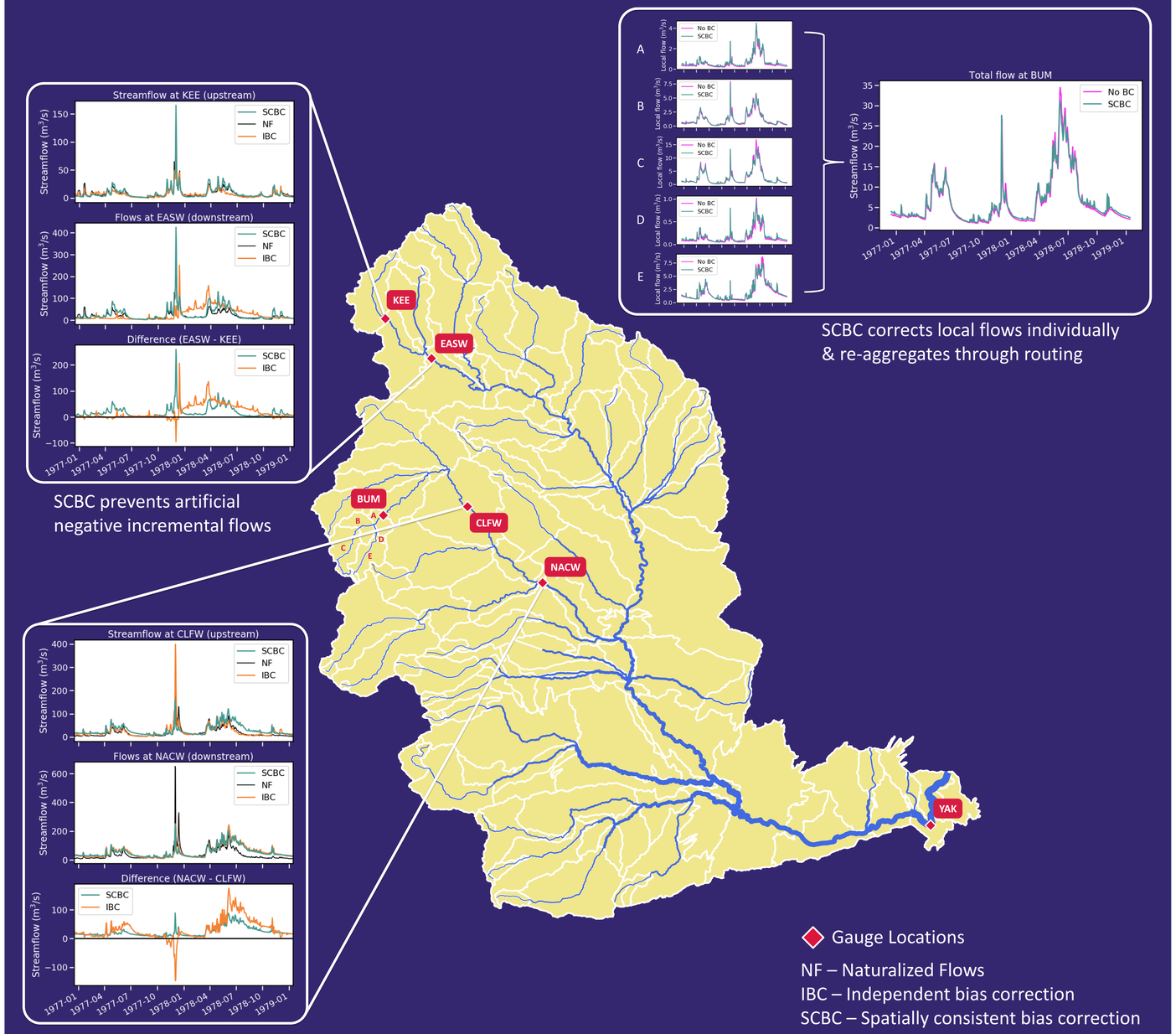
Using quantile mapping based approach for BC

Using LSTM network for regionalization

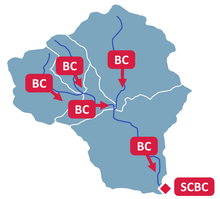
Features currently used in training LSTM network:

- air temperature
- precipitation
- basin area
- local flow

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



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 re-aggregated 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

Acknowledgements

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