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# **A tool for bias correcting spatially distributed streamflow simulations with process-dependent corrections**

**Science and Technology Program**

**Research and Development Office**

**Final Report No. ST-2018-PROJECT-ID (1895)-REPORT NUMBER  
(ENV-2022-036)**



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The mission of the Bureau of Reclamation is to manage, develop, and protect water and related resources in an environmentally and economically sound manner in the interest of the American public.

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## **Acknowledgements**

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14. ABSTRACT Water resources planning requires statistically unbiased predictions of streamflow. Modeled streamflow is commonly used as input to water resources models to evaluate operational scenarios in Reclamation long-term planning studies, for example Basin Studies under the WaterSMART Program. However, systematic errors (e.g., incorrect process descriptions, errors in observed data, and uncertainties around model parameters) are ever-present in our predictions. These biases in modeled streamflow cascade into issues with water resources model simulations, ultimately making them unusable in some cases. To account for these sources of systematic error post-processing techniques, referred to as bias correction, are used to reduce the effects of these errors. Existing streamflow bias correction techniques have several shortcomings which we address in this work. In this project, we developed a bias correction technique that addresses two issues. First, previous bias-correction techniques generally ignore the relationship of streamflow across the river network, in turn destroying the spatial-temporal consistency of streamflow. Second, previous methods are commonly built on simple mappings between reference and simulated flows without accounting for systematic errors that vary in time. This new approach preserves spatial consistency and provides options for process-dependent corrections. Further, this new approach was tested for future climate change scenarios, acknowledging the likelihood of non-stationarity in streamflow biases.					
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# **A tool for bias correcting spatially distributed streamflow simulations with process-dependent corrections**

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# Peer Review

## Bureau of Reclamation Research and Development Office Science and Technology Program

**Final Report ST-2018 -Project ID(1985)- Report Number (ENV-2022-036)**

**A tool for bias correcting spatially distributed streamflow simulations with process-dependent corrections**

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# Executive Summary

## Background

Projections of the hydrologic impacts of climate change rely on a modeling chain that commonly includes estimates of future greenhouse gas emissions, global climate models, and that provides changes in time-varying boundary conditions as input to hydrologic models. The resulting time series of hydrologic model output, such as unregulated streamflow, are regularly used in turn as input for impact studies, for example studies to evaluate reservoir levels and releases under future conditions. While the hydrologic model results can sometimes be used directly in these impact studies, many applications require additional post-processing to remove systematic model biases. Water resources models and impact studies are a prime example application of simulated streamflow. Water resources models rely on specific flow rates or volumes for reservoir releases and diversions and if the unregulated streamflow inputs are significantly biased in time and/or space, modeling can result in inconsistent (or even erroneous) study findings.

This post-processing step to remove model biases is typically referred to as bias-correction, even though the post-processing step often impacts the entire distribution of streamflow rather than only the mean. Various quantile-mapping approaches have been developed that adjust the entire distribution of modeled streamflow to match a reference distribution (commonly from a reconstructed naturalized streamflow dataset) developed over a specified historical period. Simulations of future streamflow are then post-processed using this same mapping to remove hydrologic model errors.

All existing bias-correction methods assume that model biases under future conditions are similar to those in the past and do not vary with time. The methods differ in the selection of the streamflow timeseries that are used to develop the mapping and in the details of the actual mapping. For example, the streamflow bias-correction method that is currently in use by the Bureau of Reclamation (Reclamation) develops a separate quantile-mapping for each month of the year and uses that to correct projected future streamflow for that month. This method results in discontinuities in daily streamflow at month boundaries, but perhaps more importantly, it uses time (month of the year) as the organizing principle for developing the quantile-mapping, even though model biases are process rather than time-related. For example, a model bias in April during the reference period may be snow-melt related rather than April-related. Applying an April-based mapping to future April conditions may result in a correction that is based on model deficiencies in the representation of snowmelt, even when snow may no longer be present in a future April.

## Process-conditioned and Spatially Consistent Bias Correction

A second shortcoming of existing streamflow bias-correction procedures is that they treat all flow locations independently, ignoring the topology of the channel network. As the interest has shifted toward model simulations with shorter time intervals (e.g., daily rather than monthly), this independent treatment of flow locations can result in physically inconsistent artifacts (e.g., flow mass balance) in incremental streamflow between successive downstream locations. The University of Washington (UW) has closely collaborated since 2013 with Bonneville Power Administration (BPA), Reclamation, and U.S. Army Corps of Engineers (USACE) on the River Management Joint Operating Committee Phase 2 (RMJOC-II) project to evaluate the effects of climate change on the hydrology of the Columbia River (RMJOC-II 2018). This project served both as an update to the RMJOC Phase 1 study and as an extension. As part of the update, RMJOC-II uses newer global climate model simulations (Coupled Model Intercomparison Project Phase 5 (CMIP5) rather than CMIP Phase 3 (CMIP3)). The extension focuses on an evaluation of methodological choices on the spread in streamflow projections. To that end, the RMJOC-II project uses multiple emission scenarios, global climate models, downscaling methods, hydrologic models, and model parameter data sets, resulting in 172 different projections of climate change impacts on Columbia River streamflow.

Initially the project used the same bias-correction method that has been broadly used across Reclamation projects, that is, a monthly quantile mapping approach with rescaling of daily values. However, the method resulted in multiple artifacts— for example, discontinuities at month boundaries and in some cases a substantial reshaping of the seasonal hydrographs. As part of the RMJOC-II project, the UW team developed an alternative bias-correction method which is based on the method of preservation of ratio (PresRat; Pierce et al. 2015). This method, titled *bmorph* (<https://github.com/UW-Hydro/bmorph>), operates on a daily time step, does not result in monthly discontinuities and maintains the ratio between future and historical streamflow volumes in the bias-corrected time series. In addition, *bmorph* ensures that timing shifts in the streamflow hydrograph are not affected by the bias-correction method itself but are the direct result of changes in timing in the raw model time series. However, in spite of these improvements, neither the original bias correction technique nor *bmorph* resolves all challenges. At least two major challenges remain to be addressed. Since *bmorph* adopts the timing of the original model output, it does not reproduce the timing of the reference streamflow (and thereby maintains bias in the timing of streamflow) for the historical period, which makes it difficult for use the resulting time series in water resources management studies, which is the main interest of the RMJOC-II project. In addition, since both methods correct all locations independently, incremental streamflow can exhibit the artifacts discussed above even after bias-correction.

## Research Outcomes and Work Products

Reclamation partnered with UW to develop a new bias-correction method that a) uses hydrologic process as the basis for developing the mapping between reference and modeled streamflow; and b) accounts for the spatial connectivity that results from the channel network when processing multiple locations.

Results from implementing two modular and composable streamflow bias-correction techniques show how these techniques, which are designed with streamflow in mind, can be an improvement over existing methods. The simple regionalization technique presented in this work, based on interpolating between gauged locations, provides spatially distributed (and spatially consistent) bias-corrections, while still maintaining performance close to the performance of bias-corrections that are tuned at each individual gauge location independently.

Results also show that correcting on daily minimum temperatures via conditional bias-correction can improve the timing of the bias-corrected streamflow compared with the unconditioned bias-corrections across seasons in the Yakima River basin. The choice of the specific conditioning variable in the conditional bias correction method is flexible and can be based on locally dominant processes. Reducing bias in simulated streamflow is critical when it is used as input to a water resources model for the purpose of evaluating scenarios for long-term water management and planning. Federal agencies, such as the Bureau of Reclamation, rely on these techniques to study how scenarios of future hydrology may impact existing reservoir operations, for example. These studies may inform future investments in infrastructure or modifications to operations. Refinement of bias-correction techniques may help reduce uncertainty in planning scenarios, thereby saving costs in structural or non-structural modifications that may be based on over-conservative planning to compensate for future uncertainty. Currently, water managers rely on ad hoc approaches to developing local inflows based on streamflow simulations and simply live with the concept that bias-correction techniques cannot address changing streamflow timing. Alternative methods, such as the spatially consistent bias correction with conditioning (SCBC\_C) method described here, are critical steps toward reducing uncertainties in planning scenarios.

By demonstrating two approaches to bias-correcting streamflow simulations, we found that improvements can be made to the previously used methods that are generally taken from bias-correcting climate and atmospheric models. By designing correction techniques which target distributed streamflow simulations, we can design new bias-correction methods that perform well. However, these initial implementations were built around the simplest possible method. Improving the way in which interpolation is performed between gauged locations, handling headwaters which flow into the mainstem, and allowing for conditioning on multiple variables may improve these methods further. The results of our bias-correction techniques are based on our initial workflow implementation. The bias correction method is designed in a way that allows it to be modular and extensible, making it easy to build on the initial implementation that is described in B2022.

The work referenced above for the Yakima River basin has been accepted for publication to *Journal of Hydrometeorology* (Bennett et al. *in press*). The final manuscript is attached to this report as Appendix A.

## Process-conditioned and Spatially Consistent Bias Correction

Model codes for the bias correction procedure as well as documentation for the model code are available at the following links:

- <https://github.com/UW-Hydro/bmorph>
- [https://bmorph.readthedocs.io/en/latest/bias\\_correction.html](https://bmorph.readthedocs.io/en/latest/bias_correction.html)

Computer code for the bmorph method, which was written in the Python programming language, and the release that corresponds to the work presented here, is also published with DOI: <https://doi.org/10.5281/zenodo.5348463>. Note that the GitHub code repository includes the source code and text for the model documentation.

A webinar describing the bmorph package was held on September 9, 2021 for Reclamation staff. The webinar included a tutorial that is available online (see under *Presentations, Publications, and Online resources* below). The slides from the webinar are attached to this report as Appendix B.

The development, application, and documentation of bmorph constituted the main part of the research work under the UW cooperative agreement. This work has been completed and resulted in software, documentation, and a journal article that is currently in press.

In the process of completing the bias-correction application in the Yakima River basin, additional research questions were identified and explored as synergistic activities. Two such activities were—(1) experiments to explore non-stationarity in streamflow bias correction; and (2) an application of the new bias-correction—bmorph method (Bennett et al. *in press*) in the upper Rio Grande basin to explore its performance under a very different hydroclimate setting (North American Monsoon and groundwater flow dominated hydrology) than the Yakima River basin (predominantly snow-dominated hydrology). Discussions on these two activities are presented next.

## Experiments to Explore Non-stationarity in Streamflow Bias Correction

In Fall 2021, an additional model experiment was conducted to evaluate the performance of the new bias correction method under a non-stationary climate. Specifically, we examined quantitatively how well a streamflow bias correction method trained on a historical period performs in bias correcting a future period. In this experiment, we used the output from two hydrologic models rather than observed (i.e., reference) and modeled times series. We treated the output from model A as the truth or reference time series and the output from model B as the time series that needs to be corrected. We then used bmorph to develop a mapping between the output from these models for one period and applied this mapping to correct the output from model B for a different (future) period. Finally, we evaluated whether the bias corrected streamflow time series more closely matches the output from model A than the uncorrected

time series. In the remainder of this summary, we refer to the streamflow simulations from model A as the reference time series and the simulations from model B as the simulated time series.

We took advantage of the existing dataset of climate change projections for the Columbia River in the Pacific Northwest region of the United States and Canada (from the RMJOC-II study). This dataset, described in Chegwiddden et al. (2019), was developed to evaluate the effects of methodological choices on the spread of the ensemble of climate change projections and uses CMIP5 climate projections. The full dataset contains 160 projections of future climate, consisting of two emission scenarios, ten climate models, two statistical downscaling methods and four hydrological model configurations. For this experiment, we used hydrologic outputs from two of the hydrologic model configurations, VIC-P1 and PRMS-P1. See Chegwiddden et al. (2019) for more information about the model configurations. VIC refers to output from the Variable Infiltration Capacity (VIC) model (Liang et al. 1994) and PRMS refers to output from the Precipitation Runoff Modeling System (Leavesly et al. 1983), while P1 refers to a specific model configuration. Bias corrections were performed for both emission scenarios and all ten climate models. We limited ourselves to hydrologic variables based on climate model output that was downscaled and bias corrected using the multivariate adaptive constructed analogs (MACA) approach (Abatzoglou and Brown, 2012). In summary, we bias corrected 20 separate climate projections.

We selected four subbasins that represent different hydroclimatic regions within the Columbia River basin. The Flathead River basin in the northeastern part of the Columbia River basin is strongly snow-dominant with a historical streamflow peak at the basin outlet in June. Under climate change the basin is expected to become transient by the 2080s under RCP85, although snow will continue to play an important role. The Yakima River basin is located on the leeward side of the Cascade mountain range and precipitation decreases from the mountainous headwaters to the basin outlet. The Deschutes River basin is located in the south central part of the Columbia River basin and is semi-arid with a large groundwater contribution to streamflow. Unfortunately, neither of the two hydrologic models captured this groundwater contribution particularly well, but because this is a perfect model experiment, we are mostly interested in the basin because it is drier and warmer than the Yakima River basin. Finally, the Willamette River basin is a rain-dominant basin, with streamflow peaks often associated with atmospheric river events during the fall and winter.

We used the *bmorph* software package from B2022 to implement the bias correction workflows. This experiment explored bias corrections in non-stationary climate using the same types of bias corrections as described by B2022. In the first case, termed “independent bias correction” or IBC in B2022, streamflow time series at sites across the network were corrected independently. In the second case, termed “spatially consistent bias correction” or SCBC, bias corrections were applied to local inflows to each stream segment. These bias-corrected local inflows were then rerouted through the channel network. We conditioned on minimum air temperature (SCBC-T) following the example of B2022, who showed that minimum air temperature could act as a proxy for cold season processes, which play an important role in the hydrologic cycle in the study area, and which are expected to change in response to climate change. Conditioning on month-of-year or SCBC-M was motivated by streamflow bias

## Process-conditioned and Spatially Consistent Bias Correction

correction methods that have been used previously in climate change studies. These methods create mappings for each individual month-of-year and then apply these methods to the same months in the future. We trained the bias correction for the period 1950-10-01 to 1980-09-30 (water years 1951 through 1980 or WY 1951-1980) and then bias corrected the flows for three future periods: WY 1981-2010 (1990s), WY 2041-2070 (2050s), and WY 2071-2099 (2080s). The final period was one year shorter because of the available model period. All experiments were run independently, so that the bias correction was retrained for each of the 20 projections, for each of the three experiments (SCBC-U, SCBC-M, and SCBC-T), and for each of the four study basins (see next section). As a result, we performed 240 separate bias corrections for three periods (1990s, 2050s, and 2080s).

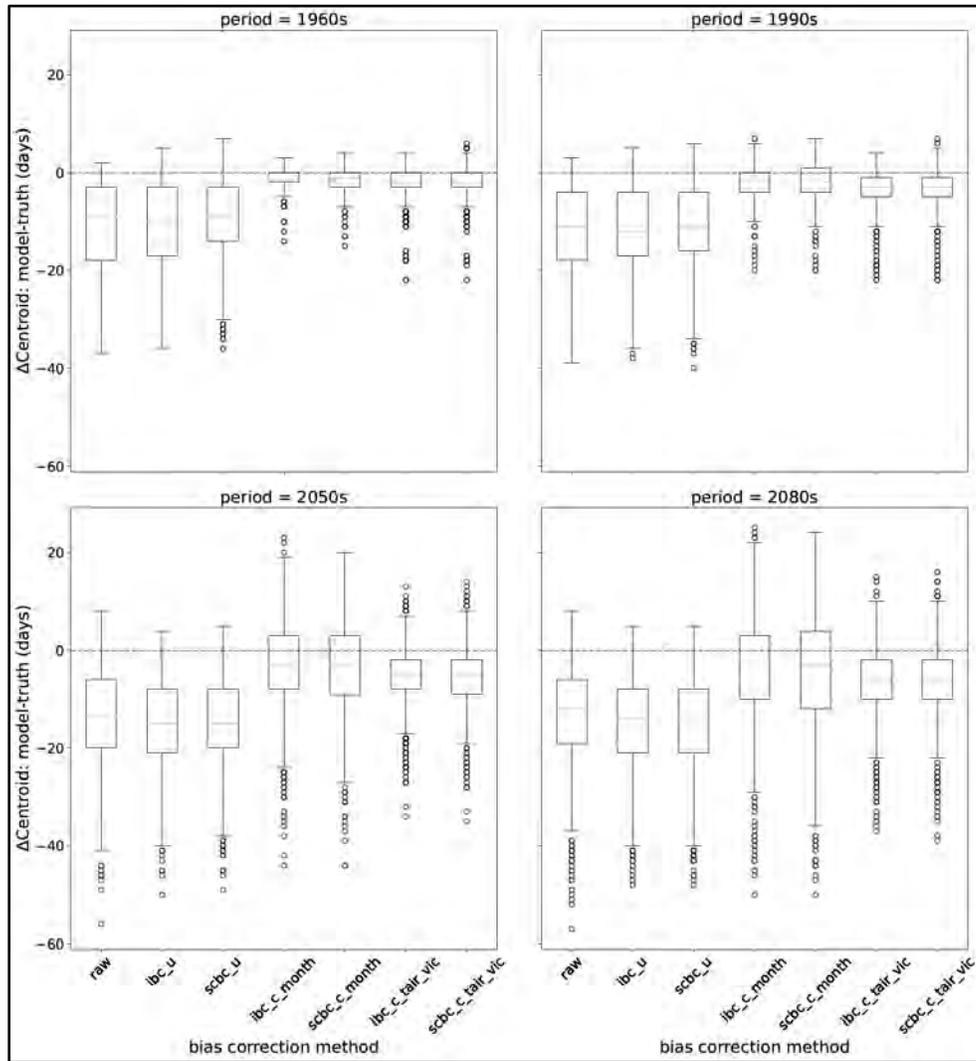
We examined the performance of the bias correction methods, both for the control period and the future periods. The choice of these metrics is motivated by previous studies of climate change in the Columbia River basin. We calculated the metrics for each of the 240 bias corrections described in the previous section and for each of the individual river segments in the four subbasins.

Figure 1 illustrates a sample of preliminary results from the perfect model experiment. The figure conveys the difference in the centroid of timing of streamflow (in days) between the modeled timeseries (model B) and reference (model A). The centroid of timing is calculated as the day of the year when half the annual streamflow (based on water years) has passed the flow location. A value of zero (dashed horizontal line), indicates that the centroid of timing is the same for both the modeled and reference time series. The model time series shows an earlier centroid of timing in all periods. As is expected, the unconditional bias corrections (`_u`) do not change the timing of streamflow and show timing differences that are similar to those in the raw simulations. The conditional bias corrections (`_c_month` and `_c_tair_vic`) reduce the timing differences for all periods, including the future, with a slightly larger bias (but smaller spread) for the bias corrections conditioned on air temperature versus those conditioned on month of year.

For the perfect model experiment in which we explored the implications of bias correction in a non-stationary climate (i.e., resulting from climate change), analysis of results is underway, and will be described in a manuscript that is being prepared for submission.

Nijssen, B., A. Stein, A. Bennett, and M. McGuire, 2022: Stress testing streamflow bias correction methods using a perfect model experiment. *Environmental Research: Climate*, in preparation.

## Process-conditioned and Spatially Consistent Bias Correction



**Figure 1.—**Boxplots of the difference in the timing (days) of the centroid of the flow as a function of the bias correction method. The x-axis labels correspond to the following: raw denotes the uncorrected simulations, ibc denotes the independent bias correction method, scbc denotes the spatially consistent bias correction method, \_u denotes that the bias correction was unconditioned on any other variable, and \_c\_month and \_c\_tair\_vic denote conditioning on the month and on the air temperature, respectively. The boxplots show the values for all four case study basins. The box extends from the first quartile to the third quartile of the data, with a line at the median. The whiskers extend from the box by 1.5 times the inter-quartile range. The open circles show points that are past the end of the whiskers.

## Application of the bmorph Method in the Upper Rio Grande Basin

In addition to development of the new bias-correction techniques and their application in the Yakima River basin, we explored the application of the new bias correction methods in the Rio Grande basin (Figure 2), where losing reaches are known to exist (i.e. upstream streamflow is greater than downstream streamflow) and where conditioning variables may differ.

Figure 3 illustrates preliminary results for bias correction at four locations within the upper Rio Grande basin, whose locations are illustrated in Figure 1. Results are illustrated only for the univariate bias corrections (indicated with labels including \_u), which do not incorporate conditional bias correction. Results illustrate bias corrections using the IBC, “independent bias correction” and SCBC, “spatially consistent bias correction” approaches. As a result, the bias corrections do not show shifts in the timing of the hydrographs. To account for systematic timing shifts, additional exploration into the dominant processes driving, as well as biases in seasonal streamflow timing, would be required; that is, exploration into the appropriate conditioning variable or variables. Figure 1 shows that the SCBC method results in seasonal hydrographs that are generally closer to the reference dataset in the downstream-most locations but may not be an improvement over the IBC method at the “04\_delnorte” location. These results will need further analyses. The new methods show promise for maintaining mass balance of such a river system despite having reaches with a net loss of water. However, additional exploration would be required into how losing reaches may be represented in the river routing model that is part of the bias-correction workflow.

## Process-conditioned and Spatially Consistent Bias Correction

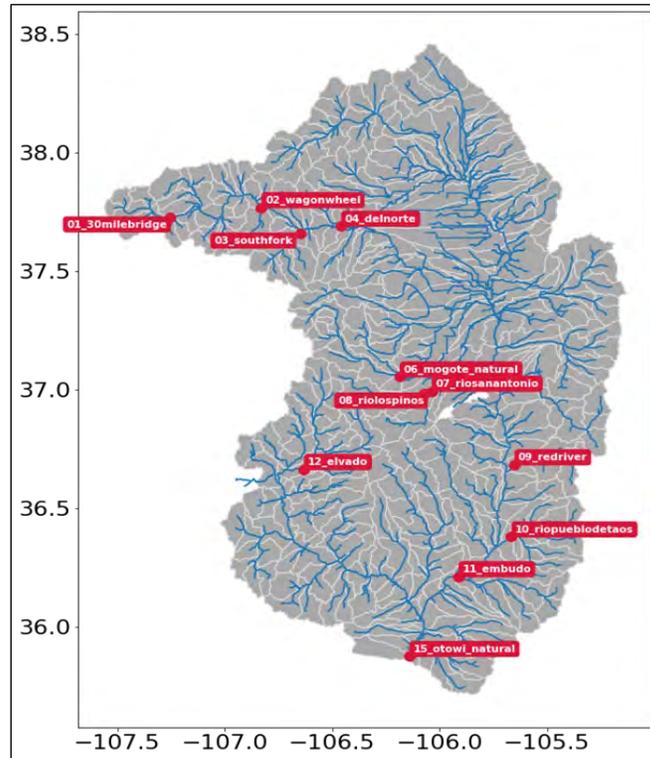


Figure 2.—Schematic of bias correction locations in the upper Rio Grande basin.

### Process-conditioned and Spatially Consistent Bias Correction

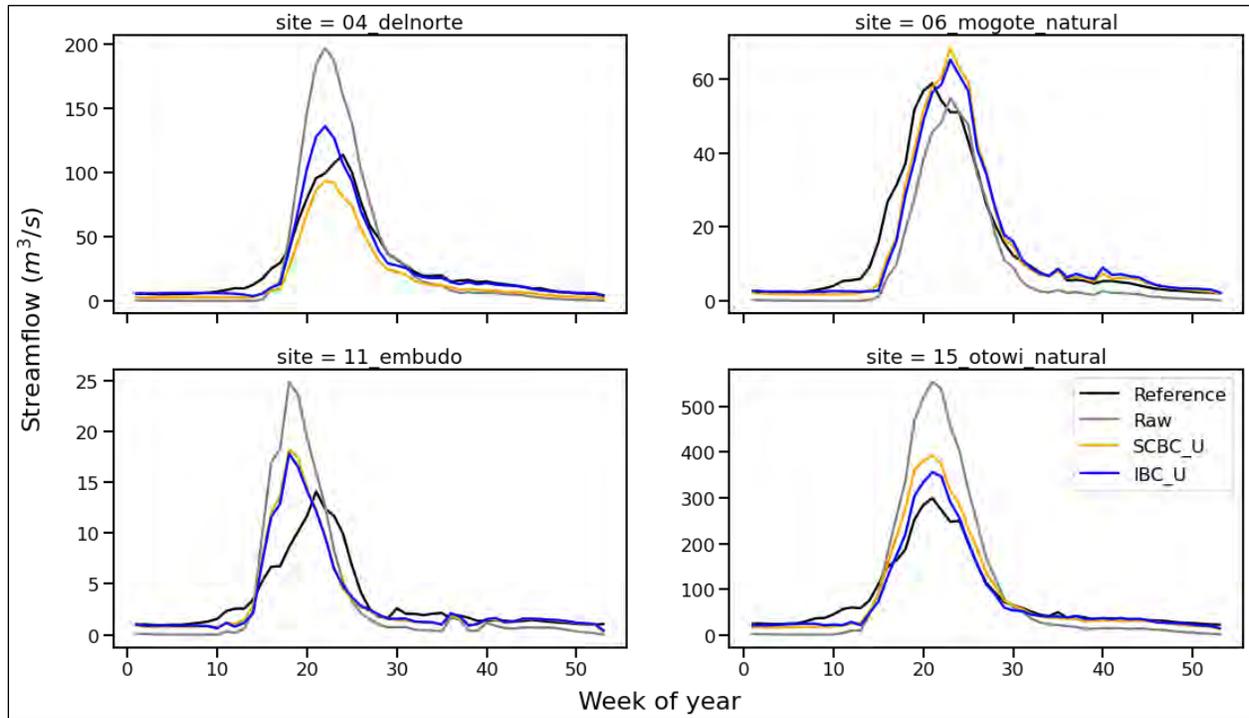


Figure 3.—Preliminary results for bias correction in the upper Rio Grande basin.

## Main Report

The work referenced above for the Yakima River basin has been accepted for publication to *Journal of Hydrometeorology* (Bennett et al. *in press*). The final manuscript is attached to this report as Appendix A.

Further, a webinar describing the bmorph package was held on September 9, 2021 for Reclamation staff. The webinar included a tutorial that is available online (see under *Presentations, Publications, and Online resources* below). The slides for the webinar are attached to this report as Appendix B.



## Presentations, Publications, and Online Resources

### Presentations:

AGU Fall Meeting 2019: Nijssen, B., Bennett, A., and M. McGuire. 2019. *A Spatially Consistent Bias Correction Technique for Distributed Streamflow Modeling*. AGU Fall Meeting, H41N-1897, San Francisco, California.

EGU Meeting 2020: Bennett, A., Nijssen, B., Cheng, Y., Stein, A., and M. McGuire. 2020. *Post-processing Hydrologic Model Output for Water Resources Studies: A Spatially-consistent, Process-based Correction Method*. EGU General Assembly 2020, Online, 4–8 May 2020, EGU2020-6036, <https://doi.org/10.5194/egusphere-egu2020-6036>.

Lunch-time seminar to NASA's Advanced Software Technologies Group (ASTG): Bennett, A., Nijssen, B., Cheng, Y., Stein, A., and M. McGuire. 2020. *Incorporating river network topology and process information into a streamflow post-processing technique*. NASA Brownbag Seminar, Online, June 8, 2020.

AGU Fall Meeting 2020: Stein, A., A. Bennett, B. Nijssen, B., and M. McGuire, M. 2020. *A Spatially Consistent Bias Correction Method for Hydro-climatically Diverse Watersheds*. AGU Fall Meeting 2020, Online, December 7, 2020, H004-0015.

USBR Webinar 2021: Bennett, A., B. Nijssen, A. Stein, and M. McGuire. 2021. *A tool for bias correcting spatially distributed streamflow simulations with process-dependent corrections*. Webinar to US Bureau of Reclamation, Online, September 9, 2021. See appendix B.

### Publications:

Bennett, A., A. Stein, Y. Cheng, B. Nijssen, and M. McGuire. . A process-conditioned and spatially consistent method for reducing systematic biases in modeled streamflow. *Journal of Hydrometeorology*, *in press*. Available online at: <https://doi.org/10.1002/essoar.10507877.3> . See appendix A.

Nijssen, B., A. Stein, A. Bennett, and M. McGuire. 2022. Stress testing streamflow bias correction methods using a perfect model experiment. *Environmental Research: Climate*, in preparation.

### Online resources:

bmorph code repository: <https://github.com/UW-Hydro/bmorph>. Code for this project was released as v1.0.0 and is archived under <https://doi.org/10.5281/zenodo.5348463>.  
bmorph documentation: <https://bmorph.readthedocs.io>. Note that the source code for the documentation is part of bmorph's GitHub repository.

bmorph tutorial: A bmorph tutorial was created for online access using binder in support of the webinar for USBR on September 9, 2021. This tutorial is still available at [https://notebooks.gesis.org/binder/v2/gh/UW-Hydro/bmorph/tutorial?filepath=tutorial%2Fbmorph\\_tutorial.ipynb](https://notebooks.gesis.org/binder/v2/gh/UW-Hydro/bmorph/tutorial?filepath=tutorial%2Fbmorph_tutorial.ipynb) [Last accessed, February 8, 2022], but will not necessarily be maintained. Note that the source code for the documentation is part of bmorph's GitHub repository.

## References

- Abatzoglou, J. T., and Brown, T. J. 2012. A comparison of statistical downscaling methods suited for wildfire applications. *International Journal of Climatology*,. <https://doi.org/10.1002/joc.2312>
- Chegwidden, O. S., and Coauthors. 2019: How Do Modeling Decisions Affect the Spread Among Hydrologic Climate Change Projections? Exploring a Large Ensemble of Simulations Across a Diversity of Hydroclimates. *Earths Future*. <https://doi.org/10.1029/2018EF001047>
- Leavesley, G. H., Lichty, R. W., Troutman, B. M., and Saindon, L. G. 1983. *Precipitation-runoff modeling system—User's manual*. U.S. Geological Survey Water-Resources Investigations Report, 83(4238), 207.
- Liang, X., Lettenmaier, D. P., Wood, E. F., and Burges, S. J. 1994. A simple hydrologically based model of land surface water and energy fluxes for general circulation models. *Journal of Geophysical Research*. <https://doi.org/10.1029/94JD00483>
- Pierce, D. W., D. R. Cayan, E. P. Maurer, J. T. Abatzoglou, and K. C. Hegewisch. 2015. Improved Bias Correction Techniques for Hydrological Simulations of Climate Change. *Journal of Hydrometeorology*. <https://doi.org/10.1175/JHM-D-14-0236.1>.
- RMJOC-II. 2018. Climate and Hydrology Datasets for RMJOC Long-Term Planning Studies: Second Edition (RMJOC-II) Part I: Hydroclimate Projections and Analyses. June 2018. <https://www.bpa.gov/p/Generation/Hydro/hydro/cc/RMJOC-II-Report-Part-I.pdf>.

Taylor, K. E., Stouffer, R. J., and Meehl, G. A. 2012. An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*.  
<https://doi.org/10.1175/BAMS-D-11-00094.1>.



# **Appendix A - A process-conditioned and spatially consistent method for reducing systematic biases in modeled streamflow**

A manuscript containing pertinent data and results pertaining to the development and evaluation of a new streamflow bias correction method is in press in *Journal of Hydrometeorology*.

Bennett, A., A. Stein, Y. Cheng, B. Nijssen, and M. McGuire. 2022. A process-conditioned and spatially consistent method for reducing systematic biases in modeled streamflow. *Journal of Hydrometeorology*, **in press**. Available online at: <https://doi.org/10.1002/essoar.10507877.3>.



# A process-conditioned and spatially consistent method for reducing systematic biases in modeled streamflow



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## ABSTRACT

Water resources planning often uses streamflow predictions made by hydrologic models. These simulated predictions have systematic errors which limit their usefulness as input to water management models. To account for these errors, streamflow predictions are bias-corrected through statistical methods which adjust model predictions based on comparisons to reference datasets (such as observed streamflow). Existing bias-correction methods have several shortcomings when used to correct spatially-distributed streamflow predictions. First, existing bias-correction methods destroy the spatio-temporal consistency of the streamflow predictions, when these methods are applied independently at multiple sites across a river network. Second, bias-correction techniques are usually built on time-invariant mappings between reference and simulated streamflow without accounting for the processes which underpin the systematic errors.

We describe improved bias-correction techniques which account for the river network topology and allow for corrections that account for other processes. Further, we present a workflow that allows the user to select whether to apply these techniques separately or in conjunction. We evaluate four different bias-correction methods implemented with our workflow in the Yakima River Basin in the Northwestern United States. We find that all four methods reduce systematic bias in the simulated streamflow. The spatially-consistent bias-correction methods produce spatially-distributed streamflow as well as bias-corrected incremental streamflow, which is suitable for input to water management models. We demonstrate how the spatially-consistent method avoids creating flows that are inconsistent between upstream and downstream locations, while performing similar to existing methods. We also find that conditioning on daily minimum temperature, which we use as a proxy for snowmelt processes, improves the timing of the corrected streamflow.

## SIGNIFICANCE STATEMENT

To make streamflow predictions from hydrologic models more informative and useful for water resources management they are often post-processed by a statistical procedure known as bias-correction. In this work we develop and demonstrate bias-correction techniques which are specifically tailored to streamflow prediction. These new techniques will make modeled streamflow predictions more useful in complex river systems undergoing climate change.

## 1. Introduction

The use of computational models of hydrologic systems has become a nearly ubiquitous way to forecast streamflow and plan for the allocation of water resources. However, these predictions are often biased, because they are subject to systematic errors in the model inputs, model parameter values, and process representations. Regardless of the source of these errors, which are often difficult to determine, the introduction of such biases in predictions degrades their quality. To address these biases, it is common to “bias-correct” or “post-process” these predictions through some statistical procedure (Chen et al. 2013; Guo et al. 2020; Hashino et al. 2007). These corrections are particularly important when simulated streamflow values are used as input to water resources models, in which specific streamflow and storage thresholds trigger water management decisions. We refer to these correction methods generally as “bias-correction” techniques for simplicity, though they typically correct for the entire range of distributional errors rather than only for an overall bias in the mean.

Bias-corrections are commonly applied at multiple steps and to multiple variables along the modeling chain (e.g. those described by Bosshard et al. 2013 and Wilby and Dessai 2010), most often precipitation and temperature in atmospheric model output and streamflow in hydrologic model output. While these modeling chains are not all exactly alike, they do contain some commonalities that are relevant to this study (Figure 1). Depending on the spatial and/or temporal scale considerations a climate model (either a finer-scaled regional model or a coarser-scale global model) or a weather forecast model is used to generate meteorologic forcing data. This forcing data is often bias-corrected and possibly downscaled to a finer spatiotemporal resolution to drive the hydrologic model. Following running a hydrologic model the predicted streamflow is also commonly bias-corrected before being used in a water management model to make management decisions.

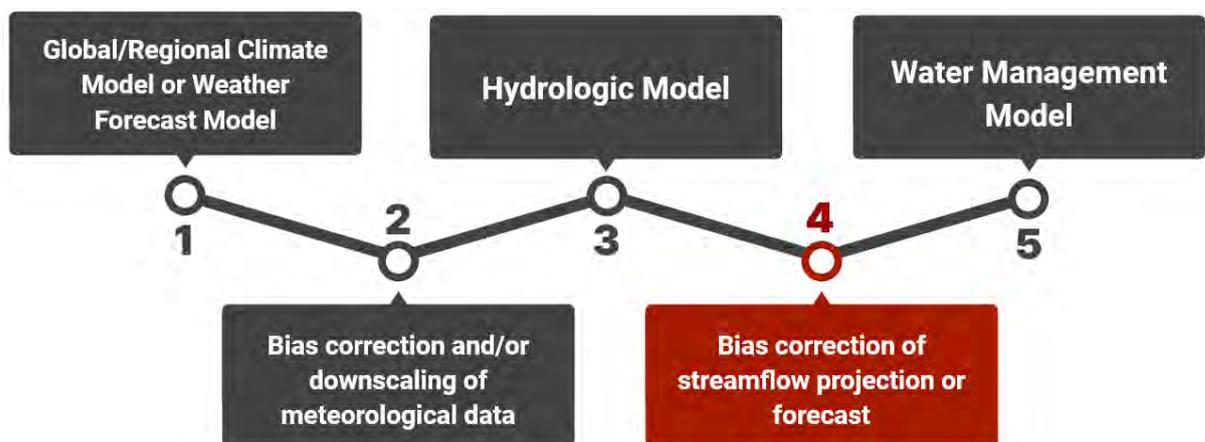


Figure 1. An example of the type of hydrologic modeling chain that we considered when developing our streamflow bias correction methods (step 4, highlighted in red).

Most studies in the bias-correction literature deal with the correction of atmospheric variables (corresponding to step 2 in figure 1), especially in the context of climate change studies (Cannon 2018; Maraun 2013; Pierce et al. 2015; Shi et al. 2008; Wood et al. 2004). Precipitation and temperature in particular are often bias-corrected before they are used as input to hydrologic models. Few studies explicitly discuss streamflow bias-correction (step 4 in figure 1). Hashino et al. (2007) evaluated three bias-correction methods (multiplicative correction, regression method, and quantile mapping) to bias-correct ensemble streamflow forecasts for a single site on the Des Moines River in Iowa, USA. Hamlet et al. (2013) used a quantile mapping procedure to bias-correct streamflow estimates in a study of climate change impacts on the hydrology of the Columbia River basin in the Pacific Northwest. Their bias-correction procedure was based on earlier work by Snover et al. (2003) and Wood et al. (2002) in which a monthly varying correction was calculated based on naturalized historical flows and model simulations for the same period. These same corrections were then applied to simulated flows under different climate scenarios. Farmer et al. (2018) used flow-duration-curves to bias-correct simulated streamflow at ungauged locations. All these examples are concerned with bias-correcting streamflow projections at longer timescales (generally greater than a month, often over many years), which is the general type of application that we considered during our method development as well. There may be other considerations in bias-correcting short-term and real-time streamflow forecasts, which we will explore in the discussion.

We focus on bias-correction methods for streamflow simulations and address two shortcomings found in the existing methods as used in the previously discussed studies. First, streamflow bias-correction methods that originate from the atmospheric science literature tend to assume that bias-corrections can be applied independently at multiple locations on a river network. In doing so, they ignore the upstream-downstream connection imposed by the river network (which we refer to as spatial consistency). Bias-correction at upstream and downstream sites treat the same parcels of water, that originated at the headwaters, in potentially different ways. This alters the relationships between streamflow at upstream and downstream sites and reduces the spatial-consistency of streamflow across a river network. As a result, incremental flows between sites along a river network, which are often used as input to water management models often become physically unrealistic, especially at shorter

time intervals (e.g. daily flows). For example, in the Missouri Headwaters Basin Study (Bureau of Reclamation and Montana Department of Natural Resources and Conservation 2021), bias-corrected streamflow used as input to a water resources model was problematic, because bias-corrections were developed independently for more than 20 sites, many of which had overlapping watershed areas. The methods we propose in this paper address this problem directly.

Second, many existing streamflow bias-correction methods assume stationarity in the underlying processes between the reference period, which is used to train the bias-correction method, and the application period, for example the end of the 21st century. This has been shown to be a particularly important problem in the context of climate change projections (Maraun 2016). Although some methods condition the bias-correction on time-of-year (for example, a different quantile mapping for each month), the underlying assumption is that the same quantile mapping is valid for the same time-of-year in the future. This can be problematic. For example, imagine that a hydrologic model performs poorly in simulating snow melt and that snow melt historically occurs during April. A monthly varying bias-correction procedure would then indicate a large correction in April. However, under a warming climate, snow melt may occur earlier or seasonal snow may disappear altogether (Musselman et al. 2017; Livneh and Badger 2020). In this case, the bias-correction would still result in a large bias-correction in April. This is because, as pointed out by Vrac and Friederichs (2015), many bias-correction techniques are not able to change the timing (that is, for example the “rank-chronology” as determined by the Spearman correlation) of the corrected timeseries. While some multivariate bias-correction techniques do not strictly adhere to this limitation (François et al. 2020; Cannon 2018; Clark et al. 2004), shifts in timing are more of an indirect-effect rather than the primary purpose of the techniques, so they are not suitable for correcting streamflow predictions in a changing climate. These multivariate techniques which allow for shifts in timing usually aim to maintain or correct the covariance structure between locations. However, for bias-correcting streamflow this is not applicable because of the directional and tree-like structure of the river network topology. Correcting for covariance structures on a river network would allow corrections at downstream sites to “propagate” up the river network, which we generally consider unphysical behavior. Similarly, models may have different biases under more extreme conditions which may become more prevalent in the future climate (Slater et al. 2021), thereby altering the cumulative distribution functions (CDFs) of simulated streamflow used

to calculate corrections. Rather than assuming stationarity for the underlying CDFs, we would like to allow for non-stationarity in processes that are primarily responsible for the systematic biases (process-conditioning).

We propose to preserve spatial consistency across the river network by bias-correcting only the independent portions of the flows, that is, we correct the local flow contribution from each individual sub-basin. Then, these locally bias-corrected flows can be re-aggregated by a routing model that integrates surface runoff and upstream flow, as is normally done to produce the total streamflow. Bias-correction of intervening flows automatically ensures spatial consistency of the flows between upstream and downstream sites. This approach requires estimation of local inflows at all locations, including sites for which we do not have reference flows (for example, streamflow measurements).

To allow for non-stationarity in the bias-correction and to allow for process-conditioning, we propose to condition our bias-corrections with respect to another variable on which the simulated errors may depend. This idea was originally proposed by Bellprat et al. (2013) who suggested such a method might be useful for accounting for the role of soil moisture in the correction of air temperatures. However, to our knowledge the idea remains untested for streamflow bias-correction.

We evaluate our implementation of these bias-correction techniques on the Yakima River Basin in the Pacific Northwestern United States and demonstrate their ability to better preserve spatial consistency by comparing them against an independent bias-correction technique. Further, we show how process-conditioning, while accounting for environmental factors such as the air temperature, can improve bias-corrections. In section 2 we describe our methodology, including both a description of the spatially-consistent bias-correction method as well as our method of incorporating process-awareness into bias-correction methods. We also outline details of the Yakima River Basin and data sources in section 2. In section 3 we present the results of each of our test cases. Following the results, we discuss the current state of our workflows and discuss future avenues for development in section 4. Finally, we summarize and provide concluding remarks in section 5.

## **2. Methods**

### *a. Study region and data*

We apply our bias-correction techniques to the Yakima River Basin in the Pacific Northwestern United States (figure 2). The Yakima River Basin is a 16 thousand square kilometer sub-basin of the Columbia River Basin located on the eastern slopes of the Cascade mountains in central Washington state. The Yakima River Basin has a strong gradient in hydroclimate from the headwaters to the outlet. The headwaters are characterized by the humid eastern slopes of the Cascade mountains and receive over 2500 mm of precipitation in an average year. The outlet at the confluence of the Yakima and Columbia Rivers is arid, receiving on average less than 250 mm of precipitation per year. This gradient in precipitation coincides with a large gradient in elevation, with the headwaters exceeding an elevation of 2000 meters and the outlet at just over 120 meters above mean sea level. Due to orographic effects in the headwaters, most of the precipitation falls as snow through the fall and winter months which drives a strong seasonal cycle in streamflow.

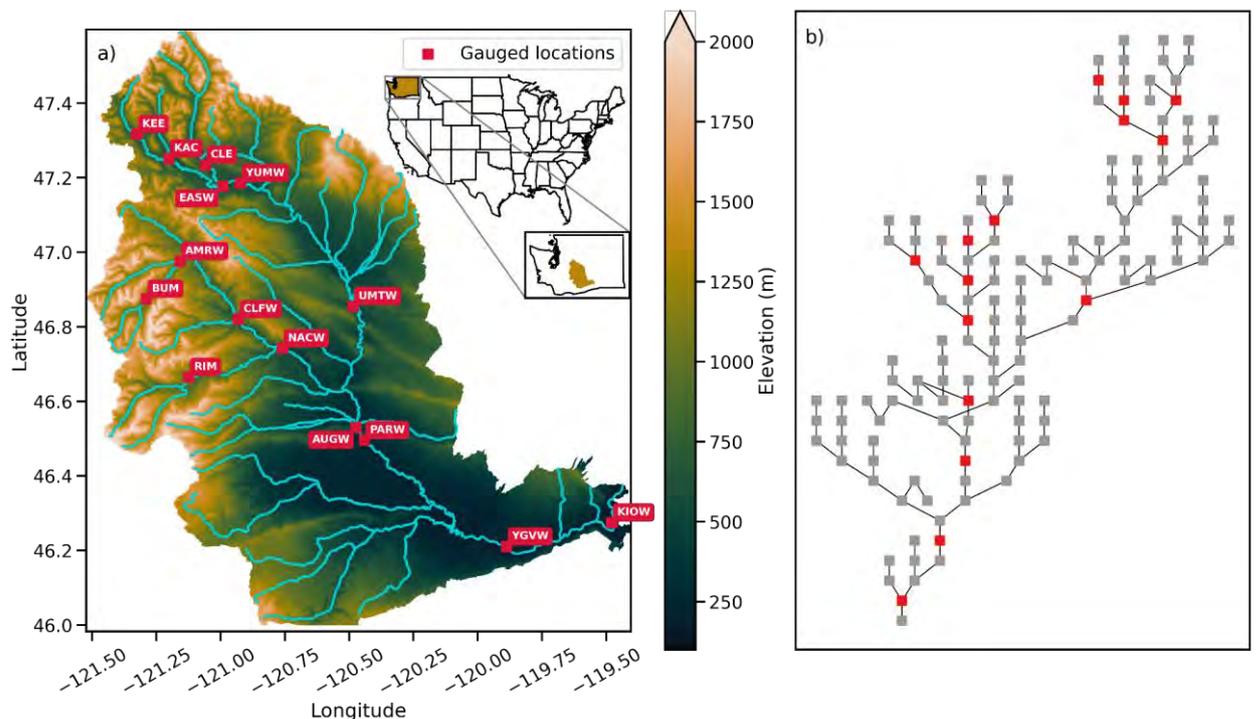


Figure 2. Yakima River Basin map. Gauged sites are shown in red, and are labeled with their stream gauge abbreviations in panel a. The stream network topology, with gauged locations highlighted in red is shown in panel b.

For this study we used simulations covering the entire Columbia river basin as described by Chegwiddden et al. (2019). In particular we use the runoff generated by the simulations at a daily timestep for the historical period covering water years 1980-2009, from the Variable

Infiltration Capacity (VIC; Liang et al. 1994) model with the VIC-P1 parameter set (Chegwidden et al. 2019). The resulting runoff fields from the VIC simulations were arranged on a 1/16° latitude-longitude grid, however the approach we take for streamflow routing is based on a vector, or unstructured, river network mesh. To align the simulated runoff to the river network we then remapped the gridded 1/16° VIC output onto the Geospatial Fabric unstructured mesh (Viger and Bock 2014) using a weighted averaging scheme. The remapped runoff is then routed through the river network using the mizuRoute river routing model (Mizukami et al. 2016) to produce the raw simulated streamflow that is analyzed in this study. We used the impulse response function routing method from mizuRoute in this implementation, though in principle the kinematic wave tracking routing method should also work. Our bias-correction technique can be run on either gridded or unstructured domains, and we chose to use the unstructured domain because we had the mizuRoute setup for the Yakima River available on the unstructured mesh.

Because neither VIC nor mizuRoute incorporates any land use or reservoir regulation components we use no regulation, no irrigation (NRNI) flows as our reference dataset instead of observations, which include the effects of human infrastructure (Pytlak et al. 2018). These NRNI flows were developed by the United States Army Corps of Engineers and the United States Bureau of Reclamation to produce flow estimates that are free of regulation and corrected for water withdrawals for irrigation. We used the NRNI flows to calculate the CDFs which are used to bias-correct the simulated flows. For all bias-corrections we use water years 1980-1991 to train the CDFs and 1992-2009 to apply the bias-corrections. Bias-correction is performed at the daily timestep.

Site	Winter Average Daily Low Temp (°C)	Summer Average Daily High Temp (°C)	Winter Average Precipitation (mm/day)	Summer Average Precipitation (mm/day)	Upstream Area (km <sup>2</sup> )
KEE	-5.7	17.8	11.0	2.1	144
KAC	-4.6	21.1	7.1	0.9	167
EASW	-6.5	20.5	6.8	1.0	679
CLE	-5.3	22.8	4.6	0.5	526

YUMW	-6.5	23.3	4.7	0.7	1304
BUM	-8.2	17.9	6.8	0.9	192
AMRW	-8.2	17.5	6.9	1.0	206
CLFW	-8.3	21.3	5.3	0.8	1228
RIM	-6.5	22.0	4.2	0.6	485
NACW	-7.7	25.2	2.2	0.4	2437
UMTW	-6.9	26.3	1.7	0.4	4135
AUGW	-5.5	28.5	1.4	0.4	525
PARW	-4.3	29.7	0.9	0.3	9592
YGVW	-3.2	30.0	0.8	0.3	13767
KIOW	-3.1	29.6	1.0	0.3	14444

Table 1. Average meteorologic conditions at gauged sites which have reference NRNI streamflow

*b. Description of the bias-correction workflows*

The overall workflow for the bias-correction methods is shown in schematic form in figure 3. The workflow is split into two pieces, a preprocessing step and the bias-correction step. We built a reference implementation of this workflow in the software package, *bmorph*, which is freely available and open source (Bennett et al. 2021). For specifics of the input data requirements and configuration options see the *bmorph* documentation (<https://bmorph.readthedocs.io>).

The preprocessing step depends on whether the chosen bias-correction method should enforce spatial consistency and whether the chosen bias-correction method should consider external variables through conditioning. If a spatially consistent method is selected the locations of the reference gauges must be mapped onto the river network topology, which is then used to locate upstream and downstream gauges for each river reach, along with an interpolation factor which is used to provide regionalized bias-corrections at each river reach. If process conditioning on another variable is used the other variable must also be associated with the underlying river network and gauge sites. For example, the meteorological data used

to force the hydrologic model may not be on the same spatial domain as the river routing model, and so a way of selecting the meteorologic data which is overlapping with each river reach is determined in this step. We expand on the implementation of these bias-correction options in sections 2b and 2c, respectively. If neither of these options are selected, as in most traditional streamflow bias-correction methods, the preprocessing step may be omitted.

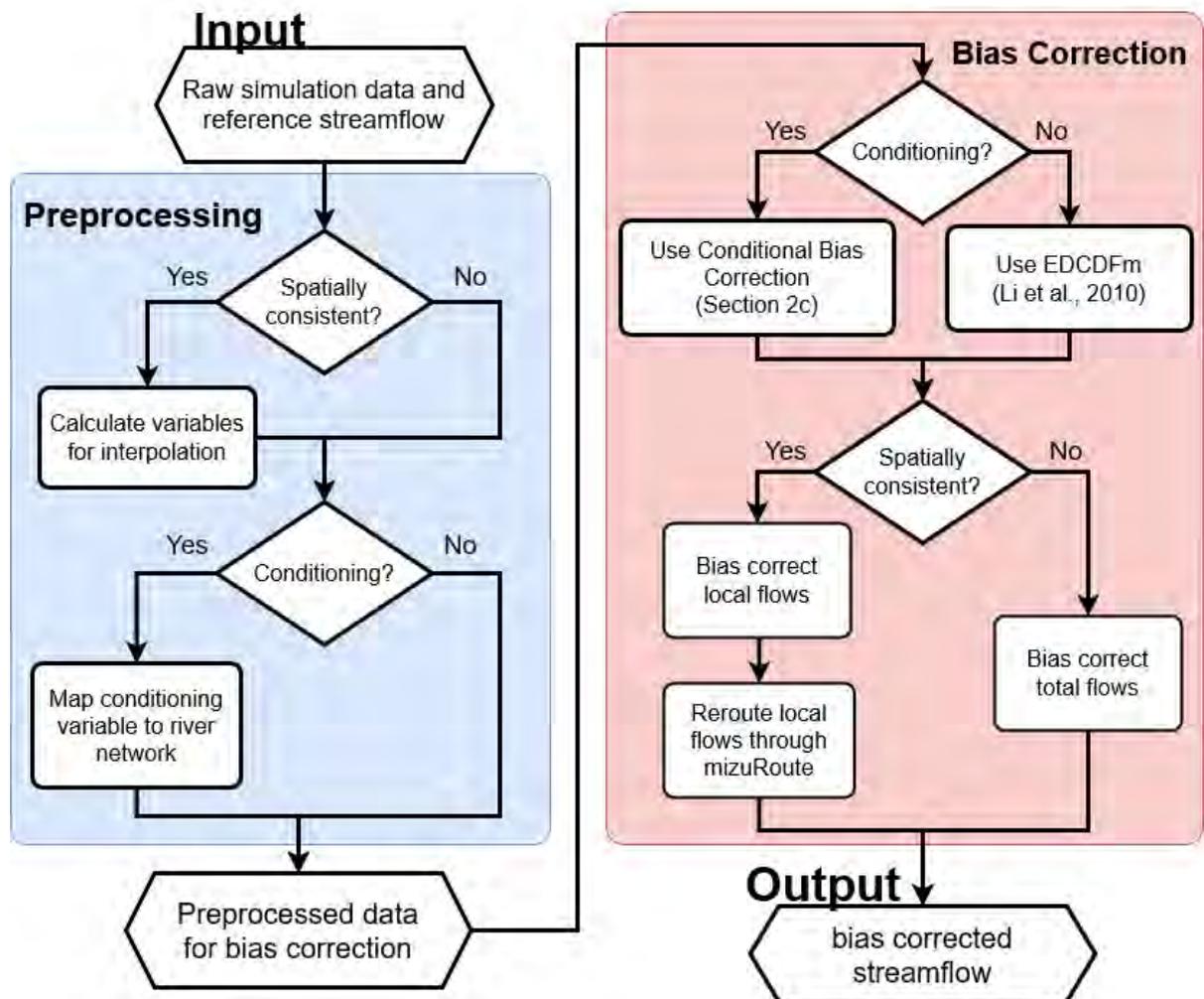


Figure 3. Schematic of the workflow for the bias-correction options implemented in this study.

Once preprocessing is complete, the resulting data can be input into the bias-correction workflow. This workflow also has branches for performing spatially consistent bias-correction and conditional bias-correction. The current implementation allows for these options to be chosen independently, resulting in a flexible workflow that can be extended to add additional steps and/or options. For instance, we provide two underlying bias-correction techniques, the conditional bias-correction that we describe in section 2c and the Equidistant Cumulative Distribution Function method (EDCDFm; Li et al. 2010). In principle any

number of other bias-correction techniques could be implemented independently of whether spatially consistent bias-correction is used.

A post-processing technique similar to the one described in the PresRat method (Pierce et al. 2015) was used to preserve changes in the mean flow between the training period and the application period. Ours differs only in that it uses a rolling window (overlapping periods) of 365 days rather than a strided window (non-overlapping periods). For clarity, because two methods of bias-correction were introduced in Pierce et al. (2015), the bias-correction technique that we mimic for our underlying implementation is applied in the time domain rather than the frequency domain.

### c. Spatially consistent bias-correction

To implement a spatially consistent bias-correction technique for distributed streamflow predictions we have developed a regionalization technique which interpolates the target distribution between reference flow sites. A regionalization technique is required to perform bias-corrections for each local inflow, many of which do not have associated reference flows. The regionalization technique makes use of the topology of the river network by selecting target distributions which are nearby and interpolating between them as a function of some statistical measure (such as the correlation or a mean bias error). A schematic representation of this interpolation is shown in figure 4.

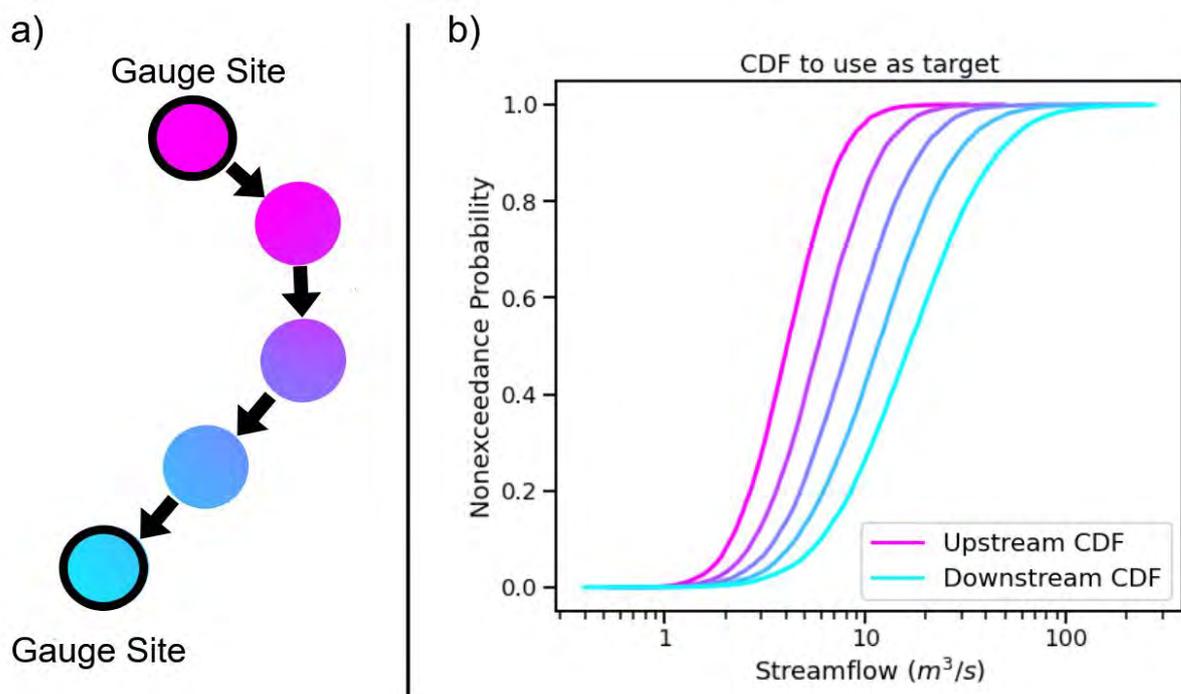


Figure 4. Schematic of interpolated bias-correction. Panel a shows a schematic of stream segments where upstream and downstream gauge sites are highlighted with a black outline. Intermediate stream segments are colored via a linear color gradient. Panel b shows how CDFs are interpolated along the stream network. The color gradient of the CDFs matches the interpolation as you go from the upstream gauge site to the downstream gauge site in panel a.

When interpolating between gauged sites we use the formula:

$$\tilde{Q}_{interp} = \alpha \cdot BC^{up}(Q_{oc}^{up}, Q_{mc}^{up}, Q_{mp}) + (1 - \alpha) \cdot BC^{down}(Q_{oc}^{down}, Q_{mc}^{down}, Q_{mp}) \quad (1)$$

where  $\tilde{Q}_{interp}$  is the bias-corrected streamflow for locations for which no reference flows are available,  $BC^i$  is the bias-correction function at either the upstream ( $i = up$ ) or downstream ( $i = down$ ) location,  $Q_{oc}$  is the observed or reference data,  $Q_{mc}$  represents the simulated streamflow values during the reference period, and  $Q_{mp}$  the simulated streamflow that will be bias-corrected. The values for  $\alpha$  are computed in the preprocessing step, which is also when the locations of the upstream and downstream gauge sites for each river reach are recorded (figure 4).

The calculation of the  $\alpha$  value can be done in a number of ways. For this study, we use the coefficient of determination ( $r^2$ ) between the streamflow at each intermediate site and the up/downstream simulated streamflow to determine the interpolation factor. Given an upstream streamflow,  $Q^{up}$ , and downstream streamflow,  $Q^{down}$ , then the interpolation factor for an intermediate streamflow,  $Q^i$ , is given by:

$$\alpha = \frac{r^2(Q^i, Q^{up})}{r^2(Q^i, Q^{up}) + r^2(Q^i, Q^{down})} \quad (2)$$

Two edge cases for computing the interpolation factor require special handling. When there are no gauge sites to select either up or down stream, we use gauges at other locations in the network that have the highest  $r^2$  value. When a site has multiple upstream gauge sites as tributaries, we similarly choose the site which has the highest  $r^2$  value of the available upstream sites. While we use the coefficient of determination as our method of interpolating between sites, it is possible to implement this approach for a wide array of appropriate measures of similarity. Our reference implementation in *bmorph* also includes options to regionalize based on spatial distance, Kullback-Leibler divergence (Cover and Thomas 2006), and Kling-Gupta efficiency (Gupta et al. 2009), though we have not explored how these choices affect the resulting bias-corrections.

To compute the bias-corrected local flows we take the ratio of the bias-corrected total flow and raw total flow, which results in a multiplier describing the relative change that should be applied to the local inflows. Given that  $Q^i$  is a total uncorrected streamflow,  $\tilde{Q}^i$  is the bias-corrected total streamflow from equation 1, and  $q^i$  is a local simulated streamflow, then we compute the bias-corrected local flow at each river reach as

$$\tilde{q}^i = q^i \cdot \frac{\tilde{Q}^i}{Q^i} \quad (3)$$

These corrected local flows are then re-routed through mizuRoute to produce a spatially-consistent bias-corrected streamflow (SCBC).

#### *d. Conditional bias-correction*

We incorporate process information into the bias-correction scheme by modifying the EDCDFm algorithm (Li et al. 2010). The original EDCDFm equation is given as:

$$\tilde{Q}_{mp} = Q_{mp} + F_{oc}^{-1} \left( F_{mp}(Q_{mp}) \right) - F_{mc}^{-1} \left( F_{mp}(Q_{mp}) \right) \quad (4)$$

where  $Q_{mp}$  is the modeled streamflow,  $F_{oc}^{-1}$  is the inverse of the CDF of the observed or reference data,  $F_{mp}$  is the CDF of the modeled projection,  $F_{mc}$  is the CDF of the modeled data during the reference period, and  $\tilde{Q}_{mp}$  is the corrected modeled projection. This formulation is extended to condition on a two-dimensional (2-D) probability distribution function (PDF):

$$\tilde{Q}_{mp} = Q_{mp} + F_{oc}^{-1} \left( F_{mp}(Q_{mp} | y_{mp}) | y_{oc} \right) - F_{mc}^{-1} \left( F_{mp}(Q_{mp} | y_{mp}) y_{mc} \right) \quad (5)$$

where  $y_i$  is the conditioning variable. To compute  $\tilde{Q}_{mp}$  we first calculate the 2-D PDF via a histogram estimator and then for each timestep at which we wish to correct, we compute the CDF conditioned on the value of  $y_i$  for that timestep (figure 5). We refer to this method as conditional bias-correction (CBC).

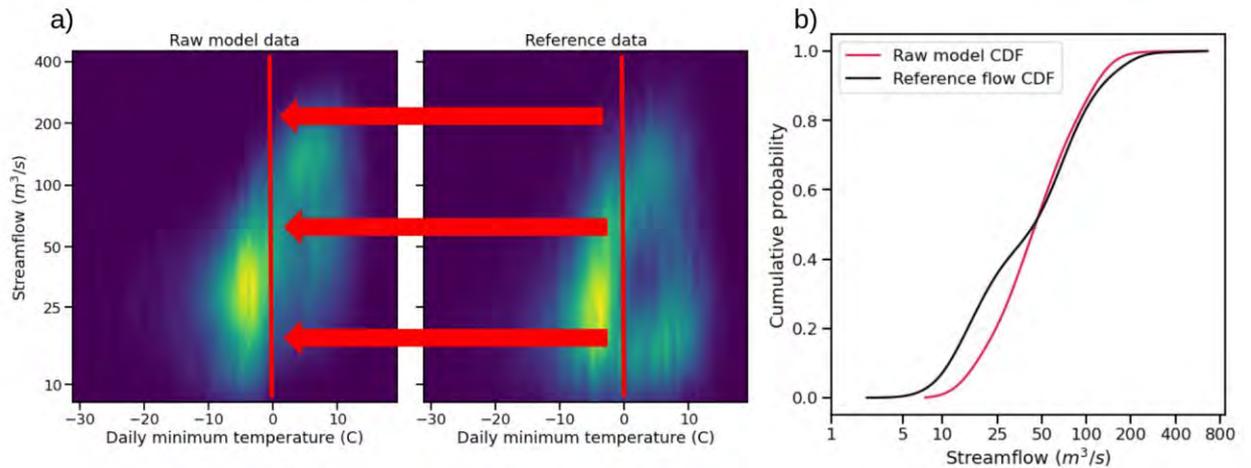


Figure 5. Schematic of conditional bias-correction (CBC). Panel a shows how conditioning on two-dimensional PDFs is computed. First, the PDFs are estimated from the data using histograms. In this example, we show the daily minimum temperature on the x-axis and streamflow on the y-axis. The left sub-plot shows the calculated PDF for the raw model data, while the right sub-plot shows the reference data. Areas of high probability are shown in brighter colors. The line at 0 °C indicates the position of conditioning for the daily minimum temperature. Panel b shows the CDF functions for both the raw and reference data as conditioned at 0 °C.

For this study we use as  $y_i$  the daily minimum temperature given by the forcing data which was used to run the VIC model and set the number of bins in our histogram estimator to be 100 in both dimensions, though these parameters are adjustable by the user. We use the daily minimum temperature because we hypothesize that there are snowmelt related biases in the late-spring and early-summer periods, as will be explored in the results.

#### e. Evaluation Scenarios

To evaluate the spatially consistent and conditional bias-correction methods in the Yakima River Basin, we compare the results of each of the combinations of the two new methods against EDCDFm (Li et al. 2010). The four evaluation scenarios are detailed in Table 2. We refer to methods which use the blending as spatially consistent bias-correction (SCBC) techniques, while those that do not as independent bias-correction (IBC) techniques. Similarly, we denote methods which use the conditional bias-correction with C and those which do not condition as U (for univariate). In this case we refer to EDCDFm as IBC\_U. By comparing each of the methods both independently and in conjunction we are better able to understand their impacts on bias-correction of streamflow.

	Spatially consistent BC (using interpolation)	Independent BC (no interpolation)
Univariate BC	SCBC_U	IBC_U
Conditional BC	SCBC_C	IBC_C

Table 2. Combinations of methods used in the analysis. Both the blending and conditioning can be turned on and off independently, leading to four bias-correction methods.

### 3. Results

Our results are organized into three sections which evaluate different aspects of the bias-correction process. In section 3a, we provide a general evaluation that compares the performance of the bias-correction methods across the Yakima River Basin. We show that all four correction methods can largely reduce the bias of the raw simulated streamflow, though some of their qualitative behaviors differ. In sections 3b and 3c, we further analyze these differences with respect to our two new methods. In section 3b, we show how conditioning on daily minimum temperatures improves the seasonal cycle of the bias-corrected streamflow as well as look at how the underlying probability distributions change with respect to the daily minimum temperature. In section 3c, we show how SCBC eliminates artifacts between river reaches. We also show how our SCBC method allows for finer grained analysis of bias-correction on spatially distributed streamflow simulations.

#### *a. General evaluation*

In figure 6, we show the mean weekly hydrographs for all scenarios (including raw and NRNI flows) for the bias-corrected period at each of the gauged sites. For the northern sub-regions (KEE, KAC, EASW, CLE, YUMW, and BUM), we see general agreement between the raw flows and the NRNI flows. At some of the sites (notably CLE and BUM) we see improvements in timing with the conditional bias-correction methods. In the western portions of the catchment between UMTW and PARW (that is, at AMRW, CLFW, RIM, NACW, and AUGW) we see relative disagreement between methods. Generally, methods which were conditioned on daily minimum temperatures were better able to capture the falling limb of the summer streamflow, indicating resulting flows were corrected to better correspond with

hydrologic processes associated with minimum temperature. At the downstream, mainstem sites (UMTW, YGVW, and KIOW) we see that the conditional bias-corrections were largely better at capturing the patterns of the NRNI streamflow.

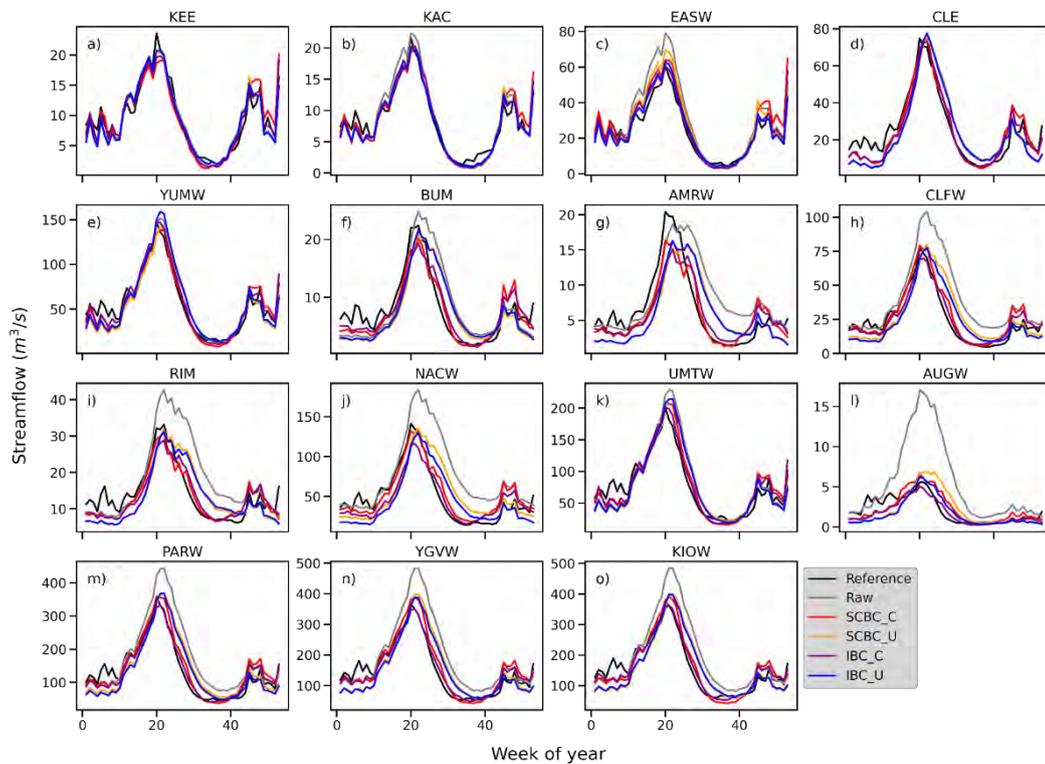


Figure 6. Mean weekly flows over the bias-corrected period for each of the scenarios arranged in approximate stream order (upper left as headwaters, lower right as outlet).

Aggregating this into percent biases across both gauged sites and time (figure 7) we see that all methods are largely able to reduce the bias with respect to the raw simulations. The raw flows have a high bias of, on average, about 25%, while all other methods had biases of less than +/-5%. Additionally, the spread in the mean biases is reduced considerably for all bias-correction techniques. The IBC methods show about twice as much reduction in the spread of biases as the SCBC methods, however the SCBC methods show better mean-bias reductions.

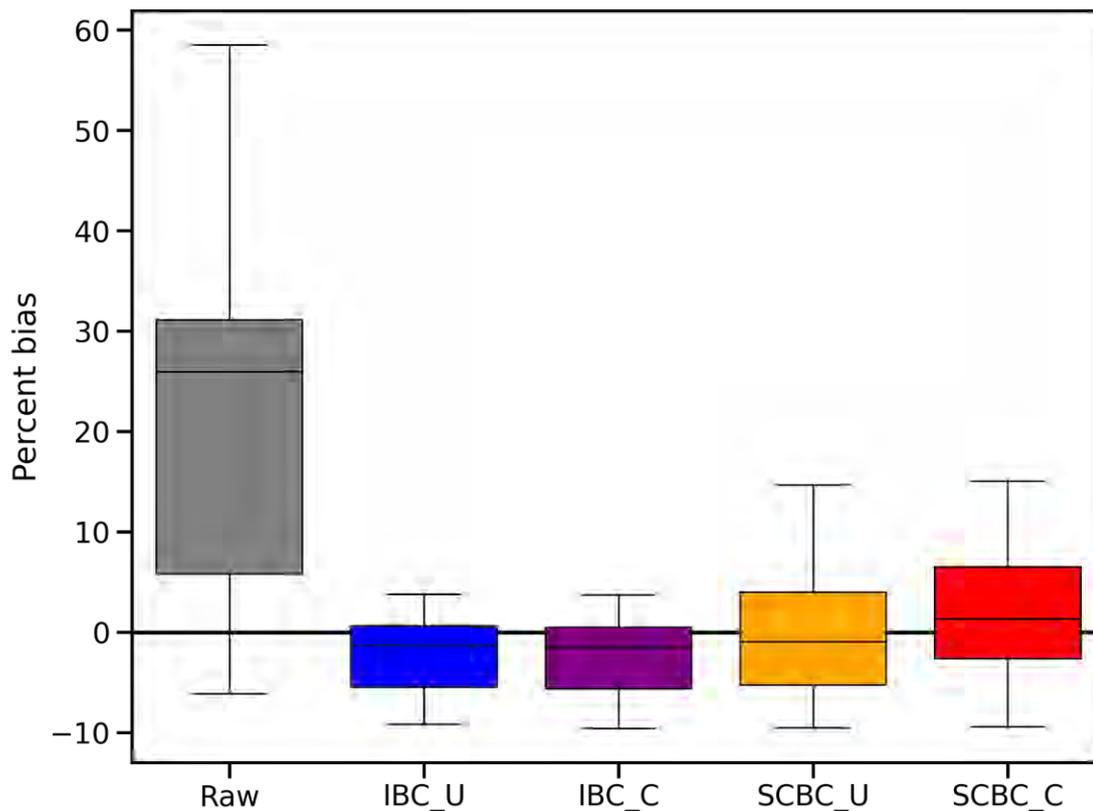


Figure 7. Boxplots of total percent biases across all sites and all time during the bias-correction period. The center marker denotes the median percent bias, the ranges of the boxes denote the interquartile range, and the whiskers extend to 1.5 times the interquartile range. The ideal value of 0 is shown as a black line across the figure.

In addition to just the mean biases, water managers may also be interested in the annual flow volumes throughout the river network. We analyze how these biases are changed at all of the gauged sites for each bias-correction method in figure 8. Generally, we see that all of the bias-correction methods improve the average and spread of the bias in annual flow volumes. Differences between bias-correction methods are most apparent between IBC and SCBC methods in the headwaters. At headwaters sites (e.g. EASW, BUM, and CLFW) we generally see that IBC-based methods are better able to capture the annual flows, though SCBC still provides better volumes than the uncorrected-predictions. We speculate that this is because of the way we select the upstream reference flows in the headwaters, as discussed in section 2c. At the downstream locations (PARW, YGVW, and KIOW) we see that all bias-

correction methods reduce the mean bias effectively, though the SCBC methods show higher variability in their ability to do so.

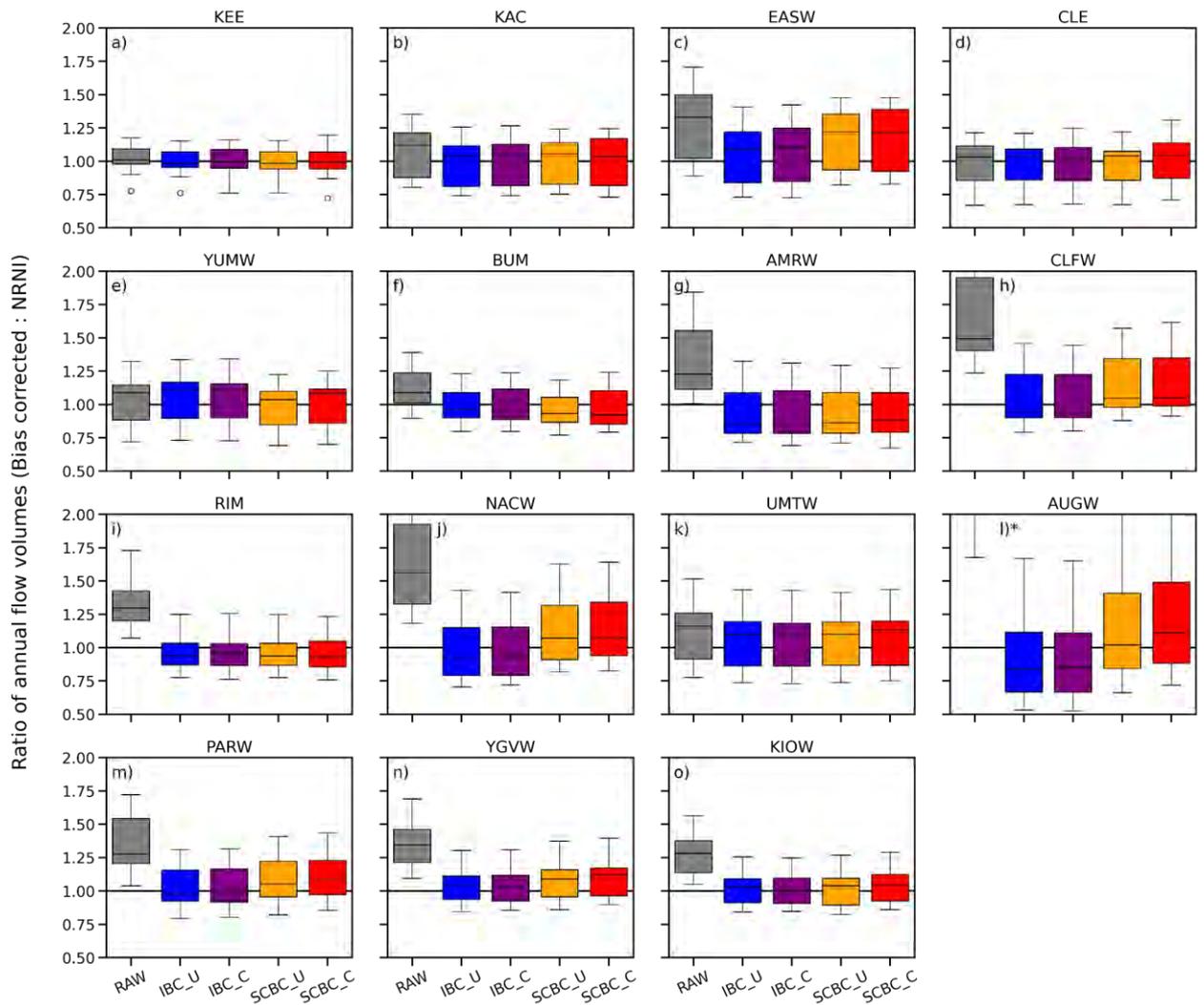


Figure 8. Boxplots of the ratio between each scenario and raw annual flow volumes during the application period (1992-2009, N=18). To calculate data for these boxplots we divided the cumulative annual streamflow for each method (RAW, IBC\_U, etc) by the cumulative annual streamflow from the reference NRNI dataset for each water year. Subplot l) at AUGW is cut off to make the comparison across subplots easier. The center marker of each boxplot denotes the median percent bias, the ranges of the boxes denote the interquartile range, and the whiskers extend to 1.5 times the interquartile range. The ideal value of 1 is highlighted as a black horizontal line across each of the subplots.

### *b. Effect of conditioning on the seasonal cycle*

To understand the effect of introducing a secondary variable to the bias-correction methodology, we analyzed the improvement of simulated streamflow for conditional bias-correction methods (IBC\_C and SCBC\_C). From figure 6 we see that the conditioned bias-correction methods are able to better match the timing of the falling limb of the hydrograph.

To quantify this effect, we calculate the percent biases on a seasonal basis, as shown in figure 9.

Generally, we see that for the winter and summer months (figure 9 panels a and b, respectively) the conditioning on daily minimum temperature results in substantially reduced bias from the raw flows. In the case of the winter season, the unconditioned bias-corrections actually increased the flow biases. During the spring and fall seasons (figure 8 panels c and d, respectively) we see that the conditioned bias-correction methods perform similarly to the unconditioned variants. This is one indication that our choice in using the daily minimum temperature as a proxy for model bias was a reasonable choice. We further explore this choice in section 3c. While we could have chosen any number of other conditioning variables, we chose daily minimum temperatures based on the knowledge of the underlying hydrometeorology of the Yakima River Basin. In the discussion we expand on how we might be able to more systematically understand or derive processes or variables to condition on.

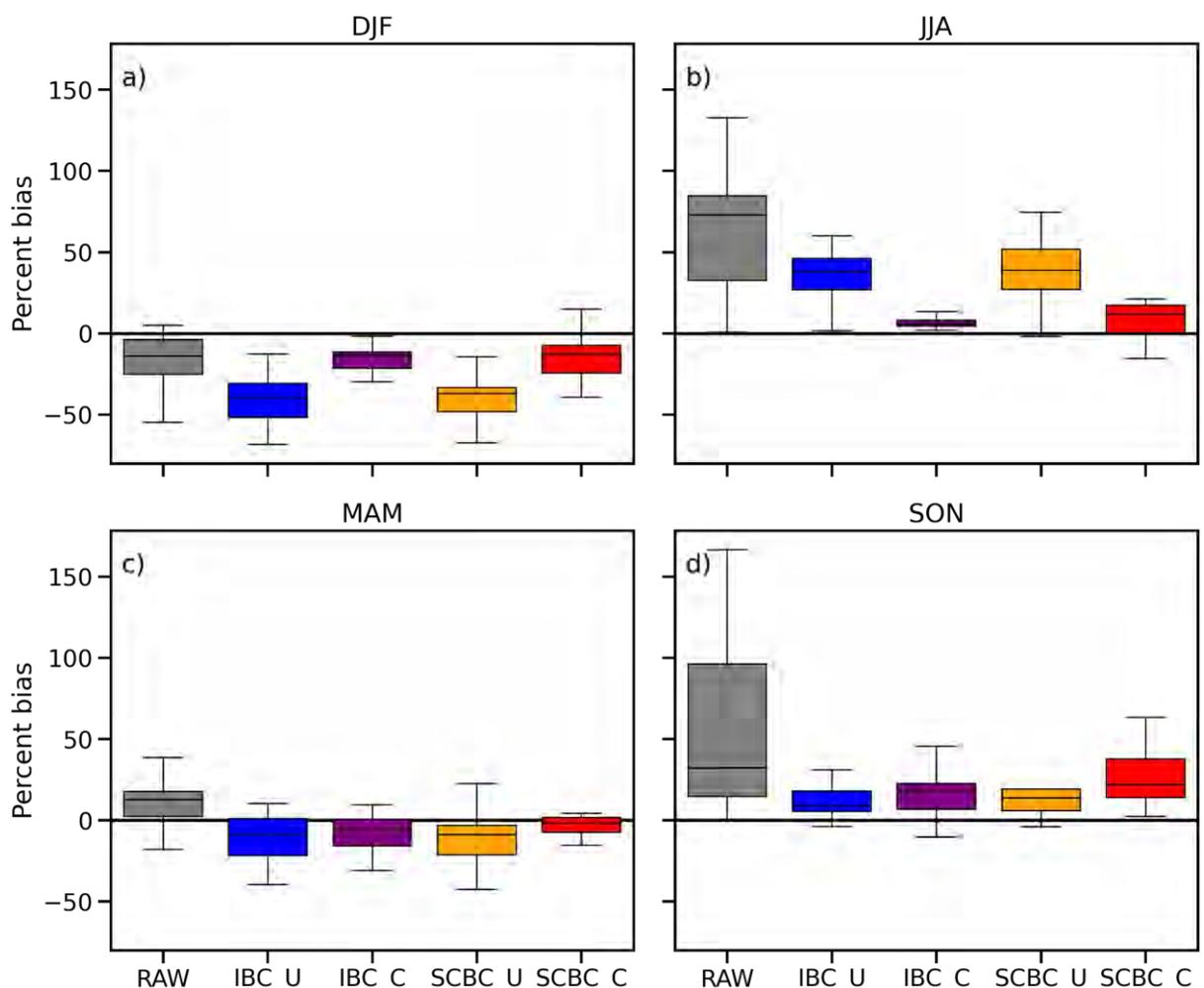


Figure 9. Boxplots of the percent bias for each of the seasons. Panel a shows the biases for all scenarios in winter months (DJF), panel b summer months (JJA), panel c spring months (MAM), and panel d fall months (SON). The center marker of each boxplot denotes the median percent bias, the ranges of the boxes denote the interquartile range, and the whiskers extend to 1.5 times the interquartile range. The ideal value of 0 is highlighted as a black horizontal line across each of the subplots.

To better understand how the conditioning on daily minimum temperature impacted bias-corrections we compute the reference CDFs across a range of values for the conditioning variable, daily minimum temperature, at basins in the headwaters (at EASW) and near the outlet along the mainstem (at YGVW) in figure 10. To do so, we first compute the joint 2-D PDFs and then marginalize on the values of  $T_{min}$  at equally spaced quantiles across the distribution of  $T_{min}$ . For both sites we found that there were substantial differences in the CDFs for different daily minimum temperatures. At EASW all of the CDFs appear to be unimodal, though the steepness and location of the median flow changes with different temperatures.

However, at the downstream site (YGVW; figure 10 panel b), we see that the relative shapes of the CDFs change based on the daily minimum temperature. For both the low and high daily minimum temperatures the CDFs are generally steeper than the univariate equivalent and are still unimodal. However, the CDFs for the curves conditioned at  $T_{min} = 4.7\text{ }^{\circ}\text{C}$  and  $T_{min} = 8.6\text{ }^{\circ}\text{C}$  have a bimodal structure. This is because the daily minimum temperature occurs in an annual cycle and that values corresponds to two different times of year with much different streamflow signatures, for example in spring temperatures are warming and in fall when temperatures are cooling. This is in contrast to the high and low values, which only occur in the summer and winter months, respectively. We further explore this choice of conditioning variable in the supplementary information and discuss the implications of using a conditioning variable with a seasonal cycle in section 4. Figure 10 also gives us a way of anticipating how process-conditioned bias-correction methods will behave in a warming climate. In future conditions where we expect temperatures to be higher, this method would end up using more of the CDFs from the red lines and less from the blue lines.

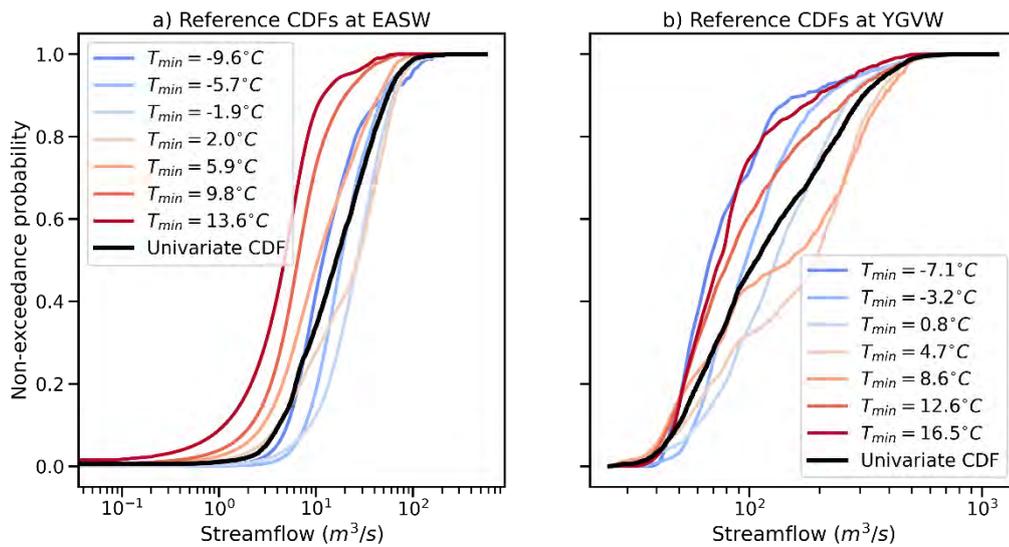


Figure 10. Comparison of cumulative distribution functions (CDFs) for univariate bias-correction (solid black line) and conditional bias-correction at several daily minimum temperatures (shaded blue to red lines). Panel a shows CDFs for a headwaters site (EASW) and panel b shows CDFs for a site on the mainstem of the Yakima River Basin near the outlet (YGVW).

### c. Effect of spatially consistent bias-correction

Thus far we have only looked at the bias-corrections at each gauge location independently, and though we have found that generally the SCBC-based methods are able to reduce systematic bias in the simulated streamflow, they are not quite as performant as the IBC methods. However, as discussed in the introduction, independently bias-corrected streamflow can result in inconsistent behaviors for local inflows while the spatially consistent method was designed to avoid these artifacts.

Figure 11 shows the weekly incremental streamflow at three locations (KEE, NACW, and CLFW) on the Yakima River Basin. We determined the incremental streamflow (or local inflow) by subtracting the flows at the upstream gauged sites. We chose to aggregate to the weekly timescale to eliminate any artifacts of the transit time from upstream to downstream gauged locations for IBC. In all three locations we found periods for which the IBC method shows negative streamflow for at least a week, while SCBC maintains positive streamflow. It is worth noting that in all three cases these are not losing reaches and that the negative streamflow is purely an artifact of the bias-correction technique. This is most noticeable at NACW with the inflows from RIM and CLFW removed, where these artificial negative streamflow happen quite regularly and can be relatively large. While the resulting negative

flows are less at the other two sites shown in figure 11, they are an artifact of the method and may cause errors in water management model simulations.

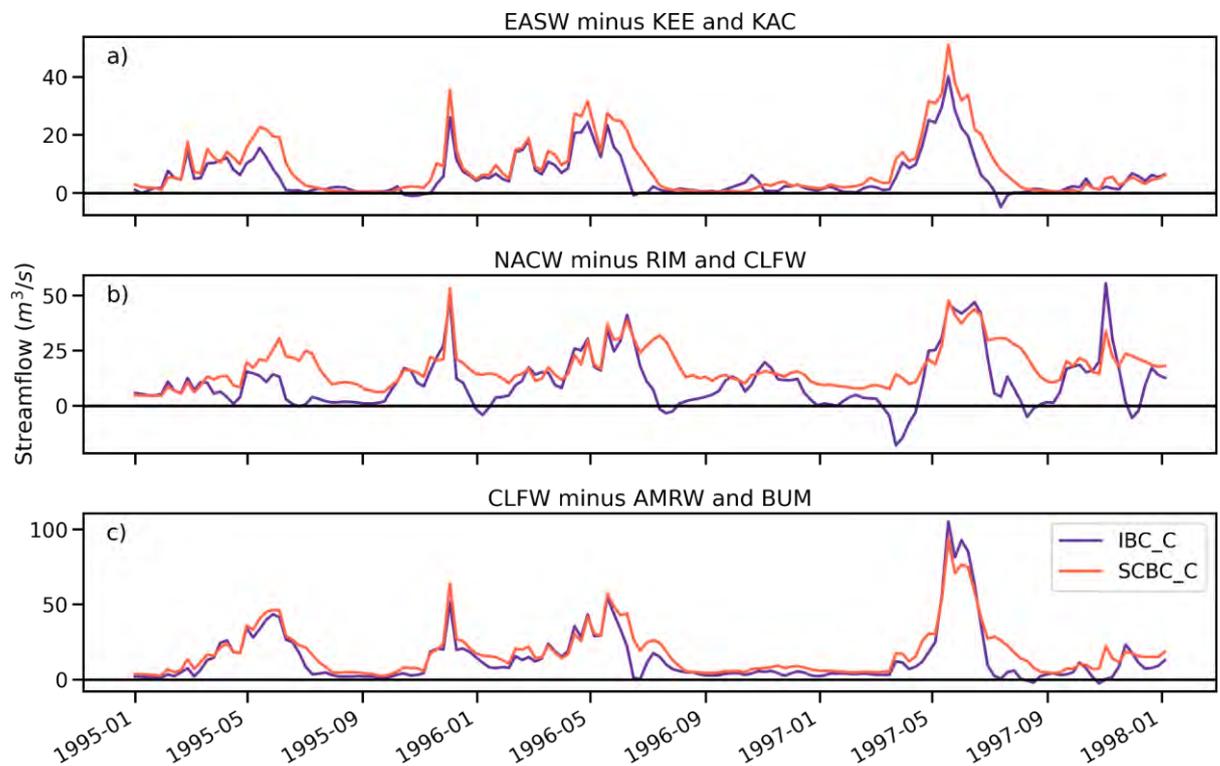


Figure 11. Comparison of streamflow with the streamflow from upstream gauged sites removed.

In addition to providing incremental streamflow at the gauged locations the SCBC method provides bias-corrected streamflow along every river reach in the simulation domain, something that the IBC methods do not provide. We show these as mean changes from the raw streamflow in figures 12 (winter streamflow) and 13 (summer streamflow). These figures show the spatial structure of the bias-corrections across the network. For both periods we see large, spatially coherent differences between unconditional corrections (SCBC\_U) and conditional corrections (SCBC\_C). During the winter period (figure 12) we see that unconditional bias-correction (SCBC\_U) (figure 12a) largely works to decrease streamflow, except in the furthest headwaters. For conditional corrections (SCBC\_C, figure 12b) we see that the bias-correction tended to increase streamflow, particularly along the upper portion of the basin. There are some decreases in the tributaries which flow into the mainstem further downstream, though not as drastic as the unconditional corrections (SCBC\_U).

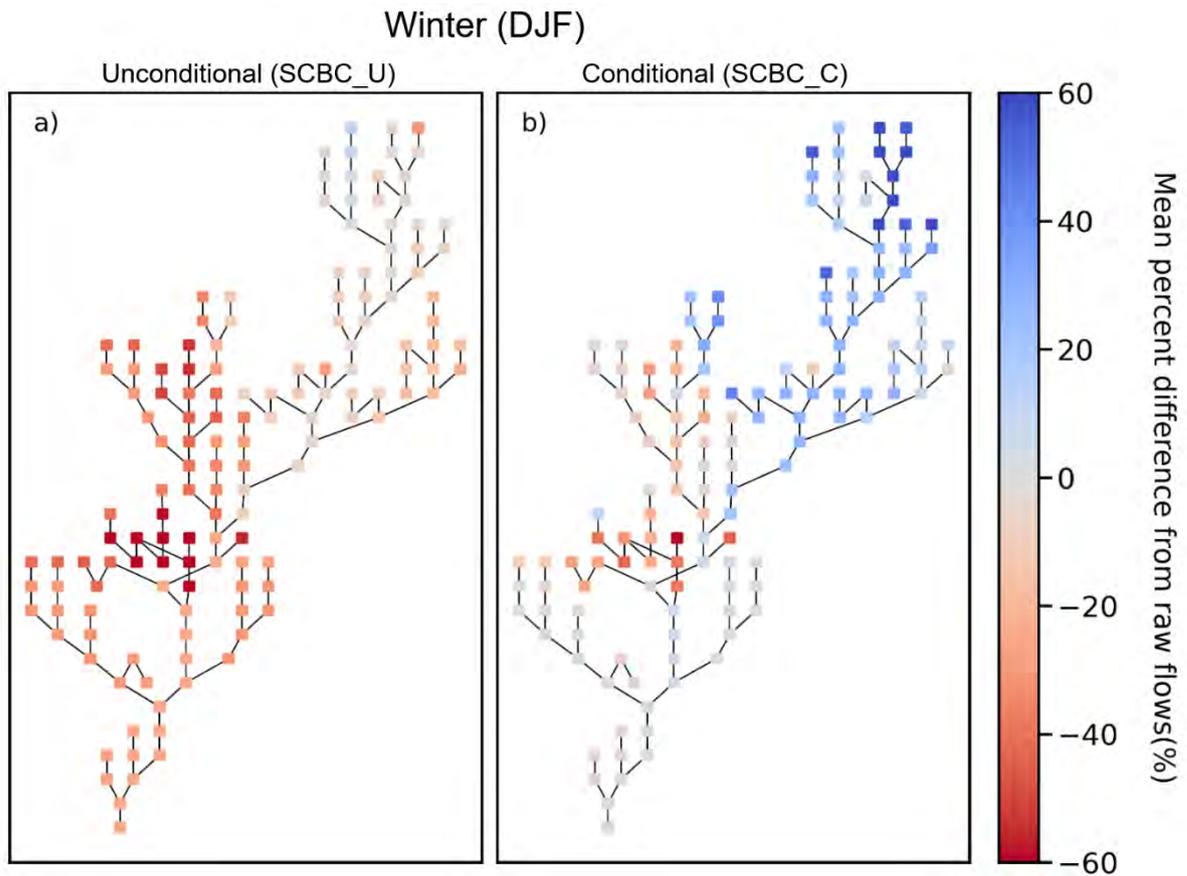


Figure 12. Change in the streamflow at each river reach in the Yakima River Basin for both spatially consistent configurations during winter (DJF).

The summer unconditional corrections (SCBC\_U) (figure 13a) look similar to those in the winter (figure 12a), because the unconditional bias-correction is not able to modify the timing of the corrected streamflow. This can be seen in the annual corrections as well (figure S3, in the supplemental information). However, for conditional (SCBC\_C) corrections in the summer (figure 13b) we see that there are drastic changes from the corrections of winter (figure 13b). During the summer SCBC\_C almost universally decreases streamflow, with the exception of a few locations in the upper headwaters. The reduction in streamflow during the summer and increase in the winter from SCBC\_C, particularly in the snowy headwaters, further demonstrates that conditionally bias-correcting on daily minimum temperatures can be a good proxy for errors in snow representation of the hydrologic model.

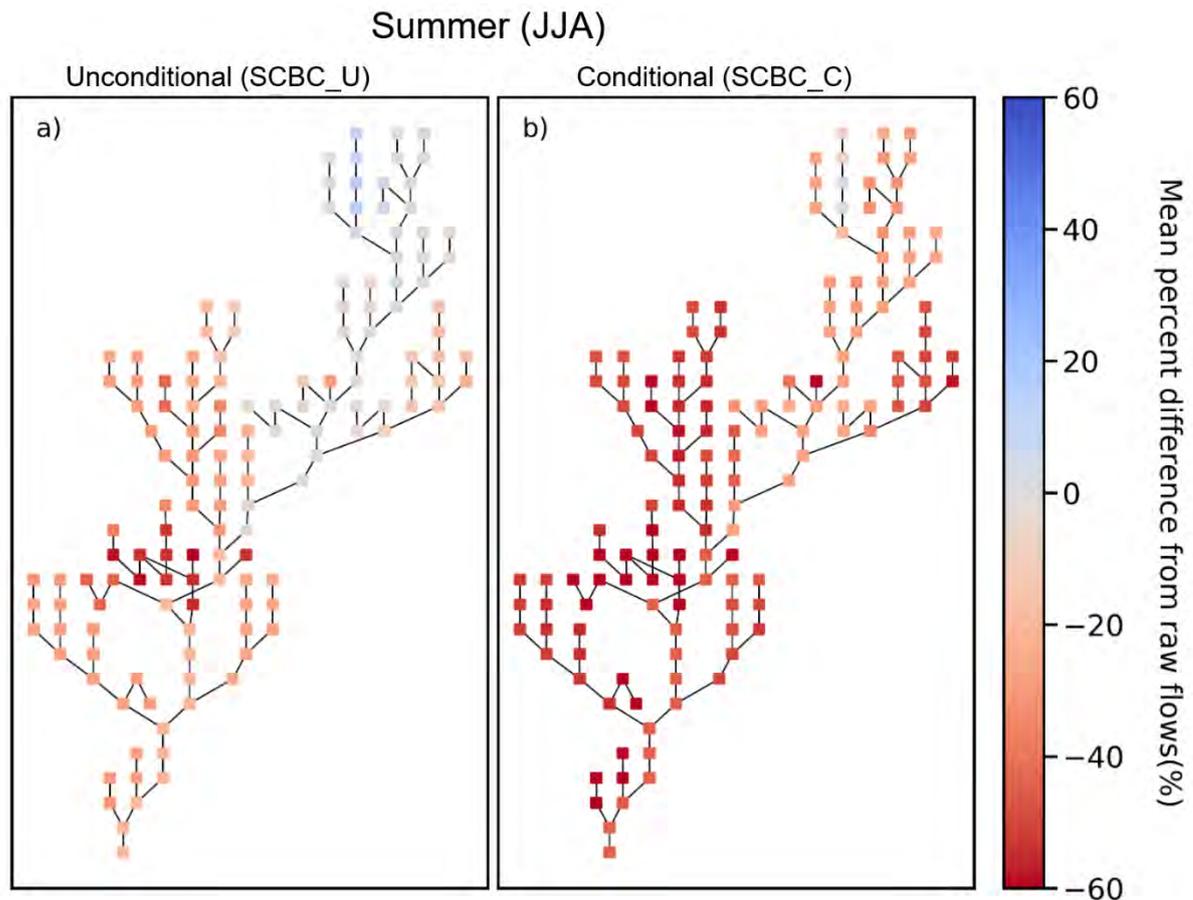


Figure 13. Change in the streamflow at each river reach in the Yakima River Basin for both spatially consistent configurations during summer (JJA).

#### 4. Discussion

We have implemented and demonstrated two new techniques for bias-correcting distributed streamflow simulations. The first technique, spatially consistent bias-correction, allows for bias-correcting spatially distributed streamflow simulations explicitly, which maintains the relationships between gauged locations. The second technique, conditional bias-correction, allows for considering other variables during the bias-correction process by conditioning on a multidimensional probability distribution built on the streamflow as well as the other variables to be considered. We have shown that these methods can be developed in a modular and composable way (that is, we can arbitrarily choose to use spatially consistent methods and conditional methods independently) and have demonstrated their effects when applied separately as well as in conjunction.

The spatially consistent bias-correction method is built on a regionalization technique which interpolates between gauged locations where reference streamflow is available. The current implementation is based on interpolating between gauged locations based on the correlation coefficient, though other methods of interpolation could, in principle, be implemented in our framework. This method maintains spatial consistency by bias-correcting the local flows at each stream segment, and then aggregating them through a river routing model.

Our implementation of spatially consistent bias-correction in the Yakima River Basin showed that correcting local streamflow directly and then rerouting it to recover the total bias-corrected streamflow has similar performance in reducing bias as independent bias-correction. Further, it produces bias-corrected streamflow at every river reach in the domain, which can be used for other purposes, such as inputs into water management or other operational models (Bureau of Reclamation and Montana Department of Natural Resources and Conservation 2021). In addition to the benefits of producing bias-corrected local and total streamflow at all river reaches, this approach eliminates artifacts in the relationship between gauged locations that independent bias-correction can introduce.

The conditional bias-correction method is currently built by computing discretized PDFs on streamflow and an additional conditioning variable via the histogram method. In this study, we chose to use the daily minimum temperature as the conditioning variable, as a proxy for snowmelt processes. We showed that conditioning on the daily minimum temperature was able to improve the timing of the bias-corrected streamflow in the Yakima River Basin. However, it remains an open question of how to choose the conditioning variable in general. While it is theoretically possible to include more variables to condition on, this becomes impractical quickly due to the curse of dimensionality, where the number of possible variable combinations grows exponentially faster than the amount of data, ultimately leading to empirically estimated PDFs which are very sparse, and thus noisy (Bellman 2010). We anticipate that additional pre-bias-correction analysis will need to be done on a region-by-region basis to determine which dominant processes to correct for.

In this study we were primarily interested in bias-correcting streamflow values over multiple years. However, streamflow bias correction is also routinely applied over shorter (hourly to monthly) timescales, for example as part of real-time forecasting operations.. While we have not evaluated the performance of our methods at these shorter timescales, we

note that quantile mapping based techniques are used in these applications as well. Because of this, we hypothesize that the process-conditioned bias-correction technique could translate well to shorter-scale applications, particularly by conditioning on the initial state of the hydrologic model, which is often a large source of error in the forecasts. However, we anticipate that modifications would be needed to ensure that these approaches could be transferred without unanticipated consequences.

## 5. Conclusions

Our results from implementing two modular and composable streamflow bias-correction techniques show how bias-correction techniques, which are designed with streamflow in mind, can make improvements over existing methods. Our simple regionalization technique based on interpolating between gauged locations provides spatially distributed (and spatially consistent) bias-corrections, while still maintaining performance close to the performance of bias-corrections that are tuned at each individual gauge location independently. We also show that correcting on daily minimum temperatures via conditional bias-correction can improve the timing of the bias-corrected streamflow over the unconditioned bias-corrections across seasons in the Yakima River Basin. The choice of the specific conditioning variable in the conditional bias correction method is flexible and can be based on locally dominant processes.

Reducing bias in simulated streamflow is critical when it is used as input to a water resources model for the purpose of evaluating scenarios for long-term water management and planning. Federal agencies such as the Bureau of Reclamation rely on these techniques to study how scenarios of future hydrology may impact existing reservoir operations, for example. These studies may inform future investments in infrastructure or modifications to operations. Refinement of bias-correction techniques may help reduce uncertainty in planning scenarios, thereby saving costs in structural or non-structural modifications that may be based on over-conservative planning to compensate for future uncertainty. Currently, water managers rely on ad hoc approaches to developing local inflows based on streamflow simulations and simply live with the concept that bias-correction techniques cannot address changing streamflow timing. Alternative methods, such as the SCBC\_C method described here are critical steps toward reducing uncertainties in planning scenarios.

By demonstrating two approaches to bias-correcting streamflow simulations we find that improvements can be made to the previously used methods that are generally taken from bias-correcting climate and atmospheric models. By designing correction techniques which target distributed streamflow simulations we can design new bias-correction methods which perform well. However, these initial implementations were often built around the simplest possible method. Improving the way which interpolation between gauged locations, handling headwaters which flow into the mainstem, and allowing for conditioning on multiple variables may improve these methods further.

The results of our bias-correction techniques are based on our initial workflow implementation. We have developed a python package, *bmorph*, which includes the implementation that was used for this analysis (Bennett et al. 2021). It also includes the setup for the Yakima River Basin as analyzed here as a tutorial dataset. The code and data for running this analysis is also available at [doi:10.5281/zenodo.5348461](https://doi.org/10.5281/zenodo.5348461). We have designed *bmorph* in a way that allows it to be modular and extensible, making it easy to build on the initial implementations that we have described here.

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#### *Data Availability Statement.*

The data and analysis for this study is available at [doi.org/10.5281/zenodo.5348461](https://doi.org/10.5281/zenodo.5348461). We have released the *bmorph* package as a freely available and open-source python package at [doi.org/10.5281/zenodo.5348463](https://doi.org/10.5281/zenodo.5348463).

## REFERENCES

- Bellman, R., 2010: *Dynamic Programming*. Princeton University Press, 392 pp.
- Bellprat, O., S. Kotlarski, D. Lüthi, and C. Schär, 2013: Physical constraints for temperature biases in climate models. *Geophys. Res. Lett.*, **40**, 4042–4047, <https://doi.org/10.1002/grl.50737>.
- Bennett, A., B. Nijssen, A. Stein, B. Lounsbury, and O. Chegwidden, 2021: UW-Hydro/*bmorph*: v1.0.0. <https://doi.org/10.5281/zenodo.5348463>.

Bosshard, T., M. Carambia, K. Goergen, S. Kotlarski, P. Krahe, M. Zappa, and C. Schär, 2013: Quantifying uncertainty sources in an ensemble of hydrological climate-impact projections. *Water Resour. Res.*, **49**, 1523–1536, <https://doi.org/10.1029/2011WR011533>.

Bureau of Reclamation, and Montana Department of Natural Resources and Conservation, 2021: Missouri Headwaters Basin Study. 149.

Cannon, A. J., 2018: Multivariate quantile mapping bias correction: an N-dimensional probability density function transform for climate model simulations of multiple variables. *Clim. Dyn.*, **50**, 31–49, <https://doi.org/10.1007/s00382-017-3580-6>.

Chegwidden, O. S., and Coauthors, 2019: How Do Modeling Decisions Affect the Spread Among Hydrologic Climate Change Projections? Exploring a Large Ensemble of Simulations Across a Diversity of Hydroclimates. *Earths Future*, **7**, 623–637, <https://doi.org/10.1029/2018EF001047>.

Chen, J., F. P. Brissette, D. Chaumont, and M. Braun, 2013: Finding appropriate bias correction methods in downscaling precipitation for hydrologic impact studies over North America. *Water Resour. Res.*, **49**, 4187–4205, <https://doi.org/10.1002/wrcr.20331>.

Clark, M., S. Gangopadhyay, L. Hay, B. Rajagopalan, and R. Wilby, 2004: The Schaake Shuffle: A Method for Reconstructing Space–Time Variability in Forecasted Precipitation and Temperature Fields. *J. Hydrometeorol.*, **5**, 243–262, [https://doi.org/10.1175/1525-7541\(2004\)005<0243:TSSAMF>2.0.CO;2](https://doi.org/10.1175/1525-7541(2004)005<0243:TSSAMF>2.0.CO;2).

Cover, T. M., and J. A. Thomas, 2006: *Elements of Information Theory (Wiley Series in Telecommunications and Signal Processing)*. Wiley-Interscience,.

Farmer, W. H., T. M. Over, and J. E. Kiang, 2018: Bias correction of simulated historical daily streamflow at ungauged locations by using independently estimated flow duration curves. *Hydrol. Earth Syst. Sci.*, **22**, 5741–5758, <https://doi.org/10.5194/hess-22-5741-2018>.

François, B., M. Vrac, A. J. Cannon, Y. Robin, and D. Allard, 2020: Multivariate bias corrections of climate simulations: which benefits for which losses? *Earth Syst. Dyn.*, **11**, 537–562, <https://doi.org/10.5194/esd-11-537-2020>.

Guo, Q., J. Chen, X. J. Zhang, C.-Y. Xu, and H. Chen, 2020: Impacts of Using State-of-the-Art Multivariate Bias Correction Methods on Hydrological Modeling Over North America. *Water Resour. Res.*, **56**, e2019WR026659, <https://doi.org/10.1029/2019WR026659>.

Gupta, H. V., H. Kling, K. K. Yilmaz, and G. F. Martinez, 2009: Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *J. Hydrol.*, **377**, 80–91, <https://doi.org/10.1016/j.jhydrol.2009.08.003>.

Hamlet, A. F., M. M. Elsner, G. S. Mauger, S.-Y. Lee, I. Tohver, and R. A. Norheim, 2013: An Overview of the Columbia Basin Climate Change Scenarios Project: Approach, Methods, and Summary of Key Results. *Atmosphere-Ocean*, **51**, 392–415, <https://doi.org/10.1080/07055900.2013.819555>.

Hashino, T., A. A. Bradley, and S. S. Schwartz, 2007: Evaluation of bias-correction methods for ensemble streamflow volume forecasts. *Hydrol Earth Syst Sci*, **12**.

Li, H., J. Sheffield, and E. F. Wood, 2010: Bias correction of monthly precipitation and temperature fields from Intergovernmental Panel on Climate Change AR4 models using equidistant quantile matching. *J. Geophys. Res. Atmospheres*, **115**, <https://doi.org/10.1029/2009JD012882>.

Liang, X., D. P. Lettenmaier, E. F. Wood, and S. J. Burges, 1994: A simple hydrologically based model of land surface water and energy fluxes for general circulation models. *J. Geophys. Res. Atmospheres*, **99**, 14415–14428, <https://doi.org/10.1029/94JD00483>.

Livneh, B., and A. M. Badger, 2020: Drought less predictable under declining future snowpack. *Nat. Clim. Change*, **10**, 452–458, <https://doi.org/10.1038/s41558-020-0754-8>.

Maraun, D., 2013: Bias Correction, Quantile Mapping, and Downscaling: Revisiting the Inflation Issue. *J. Clim.*, **26**, 2137–2143, <https://doi.org/10.1175/JCLI-D-12-00821.1>.

———, 2016: Bias Correcting Climate Change Simulations - a Critical Review. *Curr. Clim. Change Rep.*, **2**, 211–220, <https://doi.org/10.1007/s40641-016-0050-x>.

Mizukami, N., and Coauthors, 2016: mizuRoute version 1: a river network routing tool for a continental domain water resources applications. *Geosci. Model Dev.*, **9**, 2223–2238, <https://doi.org/10.5194/gmd-9-2223-2016>.

Musselman, K. N., M. P. Clark, C. Liu, K. Ikeda, and R. Rasmussen, 2017: Slower snowmelt in a warmer world. *Nat. Clim. Change*, **7**, 214–219, <https://doi.org/10.1038/nclimate3225>.

Pierce, D. W., D. R. Cayan, E. P. Maurer, J. T. Abatzoglou, and K. C. Hegewisch, 2015: Improved Bias Correction Techniques for Hydrological Simulations of Climate Change. *J. Hydrometeorol.*, **16**, 2421–2442, <https://doi.org/10.1175/JHM-D-14-0236.1>.

Pytlak, E., C. Frans, K. Duffy, J. Johnson, B. Nijssen, O. Chegwidan, and D. Rupp, 2018: *Climate and Hydrology Datasets for RMJOC Long-Term Planning Studies: Second Edition*. <https://www.bpa.gov/p/Generation/Hydro/hydro/cc/RMJOC-II-Report-Part-I.pdf> (Accessed August 24, 2021).

Shi, X., A. W. Wood, and D. P. Lettenmaier, 2008: How Essential is Hydrologic Model Calibration to Seasonal Streamflow Forecasting? *J. Hydrometeorol.*, **9**, 1350–1363, <https://doi.org/10.1175/2008JHM1001.1>.

Slater, L. J., and Coauthors, 2021: Nonstationary weather and water extremes: a review of methods for their detection, attribution, and management. *Hydrol. Earth Syst. Sci.*, **25**, 3897–3935, <https://doi.org/10.5194/hess-25-3897-2021>.

Snover, A. K., A. F. Hamlet, and D. P. Lettenmaier, 2003: Climate-Change Scenarios for Water Planning Studies. 6.

Viger, R., and A. Bock, 2014: GIS Features of the Geospatial Fabric for National Hydrologic Modeling. <https://doi.org/10.5066/F7542KMD>.

Vrac, M., and P. Friederichs, 2015: Multivariate—Intervariable, Spatial, and Temporal—Bias Correction. *J. Clim.*, **28**, 218–237, <https://doi.org/10.1175/JCLI-D-14-00059.1>.

Wilby, R. L., and S. Dessai, 2010: Robust adaptation to climate change. *Weather*, **65**, 180–185, <https://doi.org/10.1002/wea.543>.

Wood, A. W., E. P. Maurer, A. Kumar, and D. P. Lettenmaier, 2002: Long-range experimental hydrologic forecasting for the eastern United States. *J. Geophys. Res. Atmospheres*, **107**, ACL 6-1-ACL 6-15, <https://doi.org/10.1029/2001JD000659>.

Wood, A. W., L. R. Leung, V. Sridhar, and D. P. Lettenmaier, 2004: Hydrologic Implications of Dynamical and Statistical Approaches to Downscaling Climate Model Outputs. *Clim. Change*, **62**, 189–216, <https://doi.org/10.1023/B:CLIM.0000013685.99609.9e>.

# Appendix B – Water Operations and Planning Monthly Seminar Series, September 2021

USBR Webinar 2021: Bennett, A., B. Nijssen, A. Stein, and M. McGuire. 2021. *A tool for bias correcting spatially distributed streamflow simulations with process-dependent corrections*. Webinar to US Bureau of Reclamation, Online, September 9, 2021.

[https://doimspp.sharepoint.com/sites/bor-Water-Operations-and-Planning/videos/Forms/AllItems.aspx?id=%2Fsites%2Fbor-Water-Operations-and-Planning%2Fvideos%2FSeptember 2021 Water Operations Planning Seminar pt2%20Emp4&parent=%2Fsites%2Fbor-Water-Operations-and-Planning%2Fvideos](https://doimspp.sharepoint.com/sites/bor-Water-Operations-and-Planning/videos/Forms/AllItems.aspx?id=%2Fsites%2Fbor-Water-Operations-and-Planning%2Fvideos%2FSeptember%2021%20Water%20Operations%20Planning%20Seminar%20pt2%20Emp4&parent=%2Fsites%2Fbor-Water-Operations-and-Planning%2Fvideos)