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

Andrew Bennett,[a,b] Adi Stein,[a] Yifan Cheng,[c] Bart Nijssen,[a] Marketa McGuire,[d]

[a] *Department of Civil &Environmental Engineering University of Washington, Seattle, WA*

[b] *Department of Hydrology and Atmospheric Sciences, University of Arizona, Tucson, AZ*

[c] *National Center for Atmospheric Research, Boulder, CO*

[d] *Technical Service Center, US Bureau of Reclamation, Denver, CO*

Corresponding author: Bart Nijssen, nijssen@uw.edu

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 simple, time-invariant mappings between reference and simulated streamflow without accounting for the hydrologic processes which underpin the systematic errors.

We describe improved bias-correction techniques which account for the river network topology and which allow for corrections that are process-conditioned. 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 Pacific 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 also find that the process-conditioning methods improve the timing of the corrected streamflow when conditioned on daily minimum temperature, which we use as a proxy for snowmelt processes.

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, most often precipitation and temperature in atmospheric model output and streamflow in hydrologic model output. Most studies in the bias-correction literature deal with the correction of atmospheric variables, 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. 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.

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. An unrelated problem, which we do not address, was that reference streamflow time series were based on multiple unrelated sources, which is often the case in studies encompassing large watersheds. In the absence of a robust alternative methodology, such as that described here, an ad hoc approach was developed to complete the Missouri Headwaters Basin Study.

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), 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. 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 1). 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.

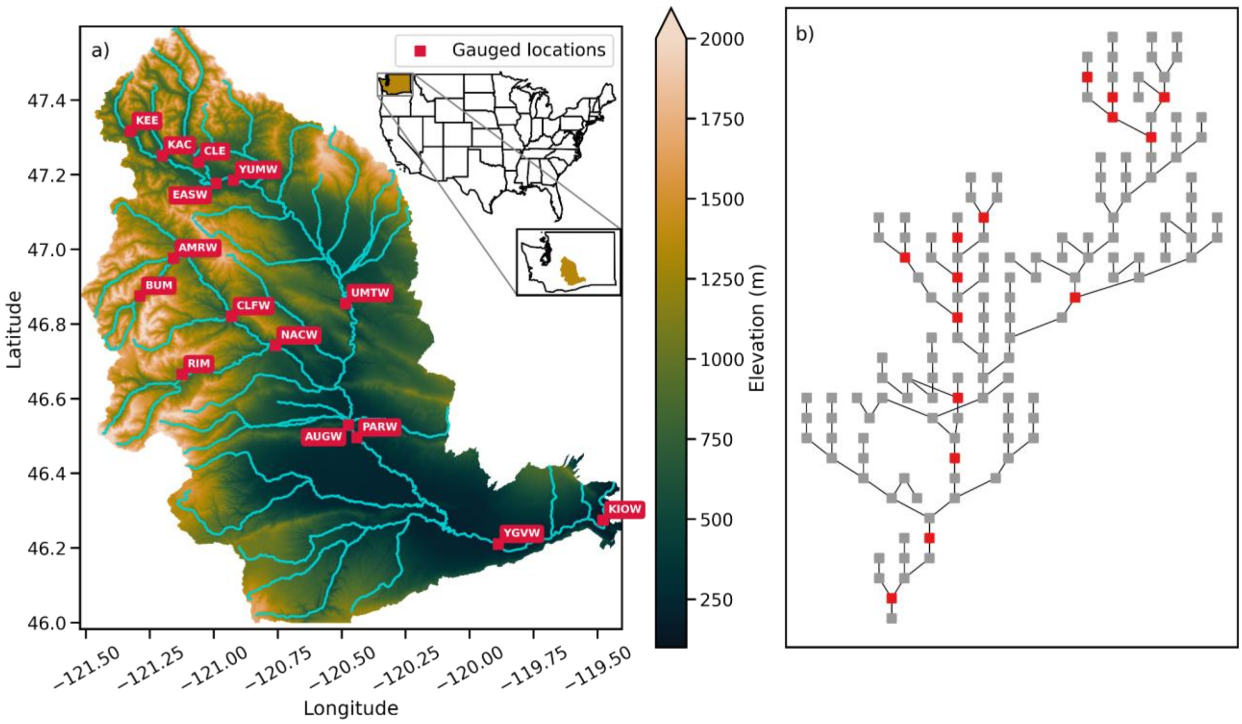

Figure 1. Yakima River Basin map. Gauged sites are shown in red, and are labeled with their stream gauge abbreviations in panel a. The stream network topology, with gauged locations highlighted in red is shown in panel b.

For this study we used simulations covering the entire Columbia river basin as described by Chegwidden et al. (2019). In particular we use the runoff generated by the simulations at a daily timestep for the historical period, 1980-2010, 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 1/16º 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 1/16º 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. 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 reservoir, 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 are used to calculate the CDFs which are used to bias-correct the simulated flows. For all bias-corrections we use the period 1981-1991 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 (ºC)	Summer Average Daily High Temp (ºC)	Winter Average Precipitation (mm/day)	Summer Average Precipitation (mm/day)	Upstream area (km^2)
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 2. 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.

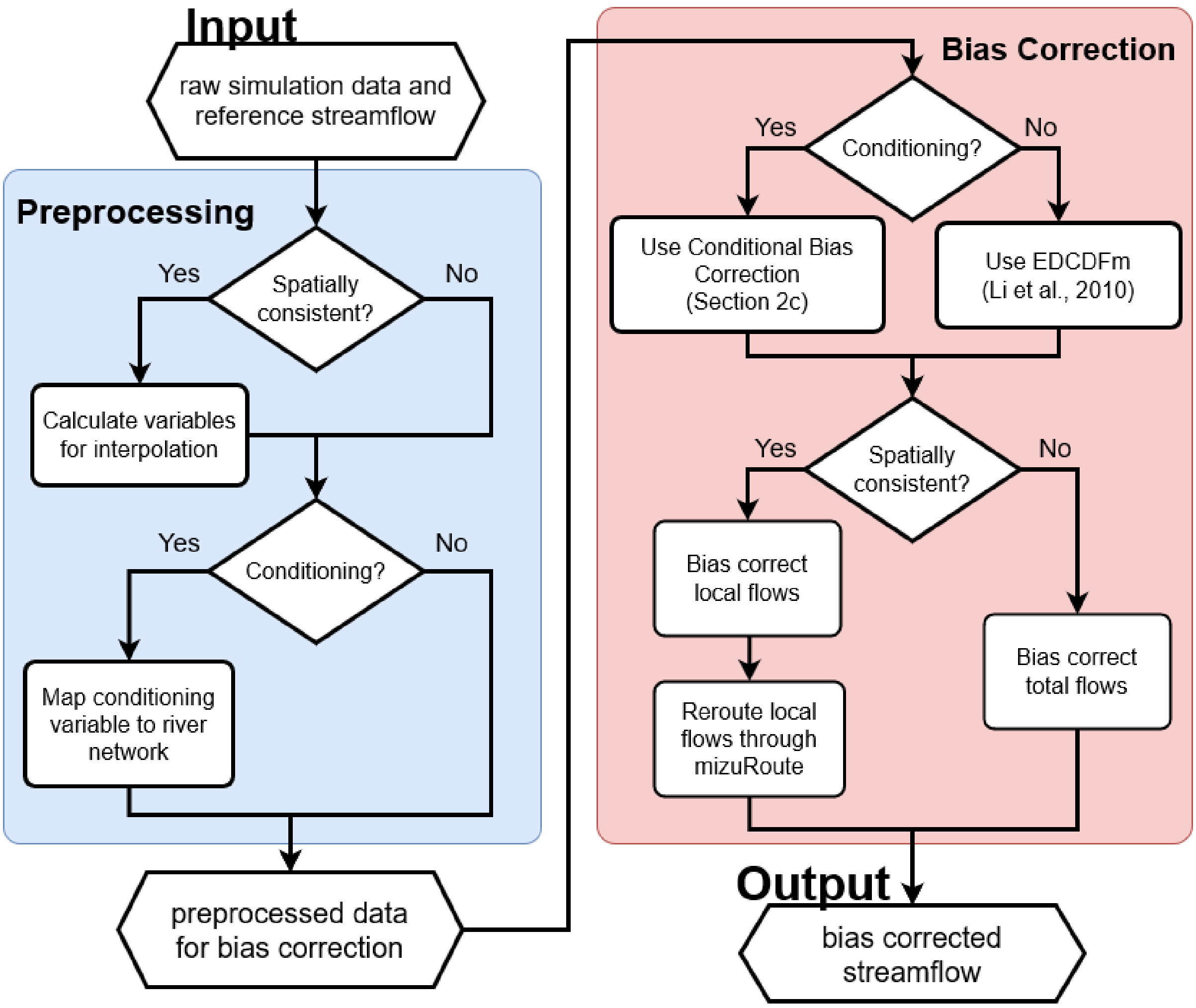

Figure 2. Schematic of the workflow for the bias-correction options implemented in this study.

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 3.

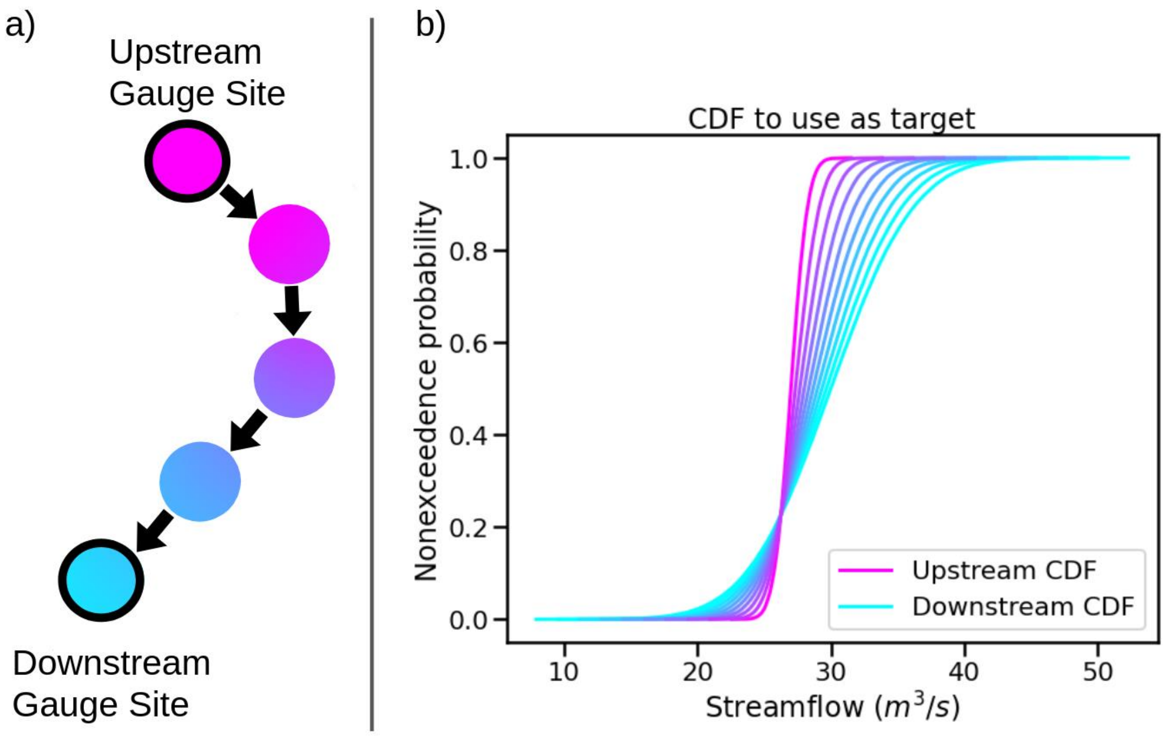

Figure 3. Schematic of interpolated bias-correction. Panel a shows a schematic of stream segments where upstream and downstream gauge sites are highlighted with a black outline. Intermediate stream segments are colored via a linear color gradient. Panel b shows how CDFs are interpolated along the stream 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:

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

where $\tilde{Q}_{interp}$ is the bias-corrected streamflow for locations for which no reference flows are available, BC^{i} is the is the bias-correction function at either the upstream (up) or downstream ($down$) 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 α 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 3).

The calculation of the α 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:

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

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

$$\tilde{q}^i = q^i \cdot \frac{\tilde{Q}^i}{Q^i} \tag{3}$$

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:

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

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):

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

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 4). We refer to this method as conditional bias-correction (CBC).

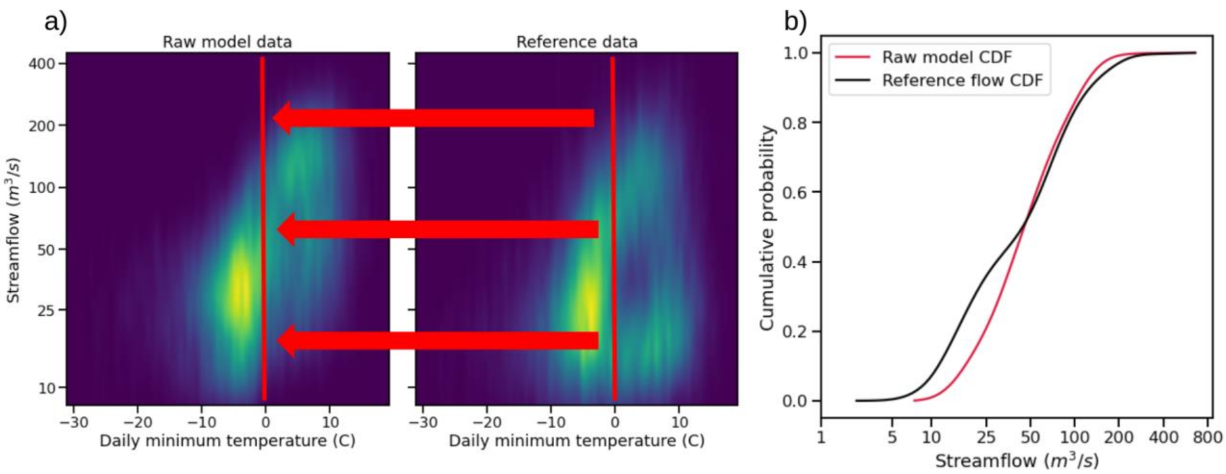

Figure 4. Schematic of conditional bias-correction (CBC). Panel a shows how conditioning on two-dimensional PDFs is computed. First, the PDFs are estimated from the data using histograms. In this example, we show the daily minimum temperature on the x-axis and streamflow on the y-axis. The left sub-plot 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 1. 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 5, 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 subregions (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.

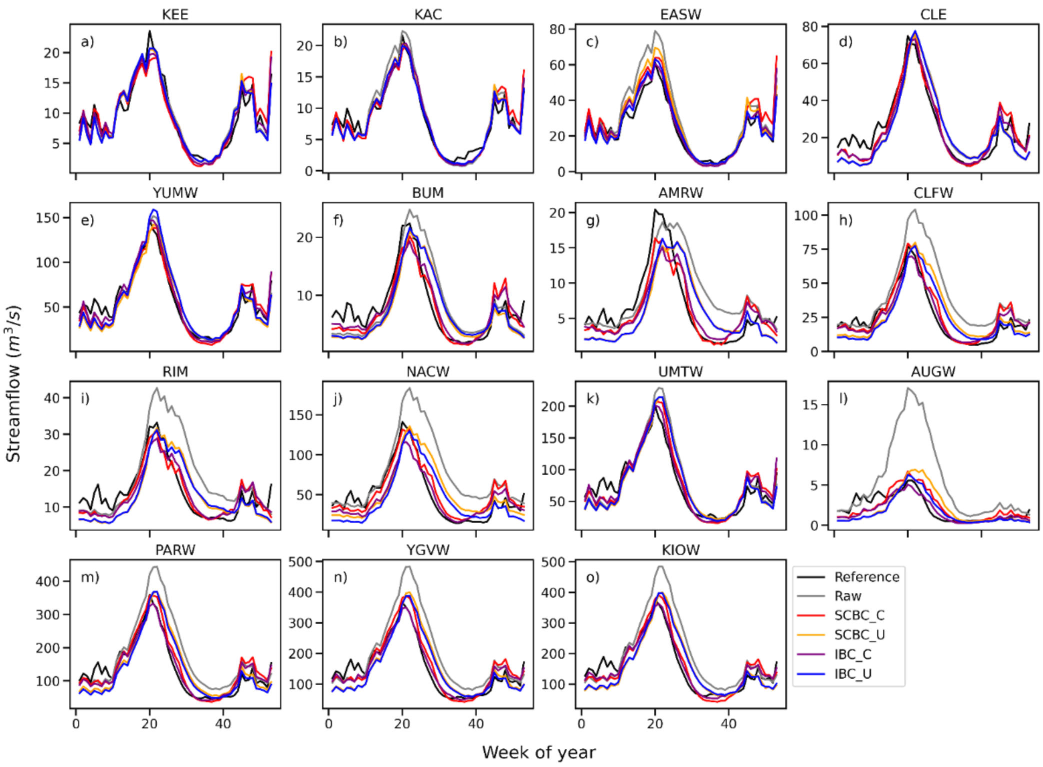

Figure 5. Mean weekly flows over the bias-corrected period for each of the scenarios arranged in approximate stream order (upper left as headwaters, lower right as outlet).

Aggregating this into percent biases across both gauged sites and time (figure 6) 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.

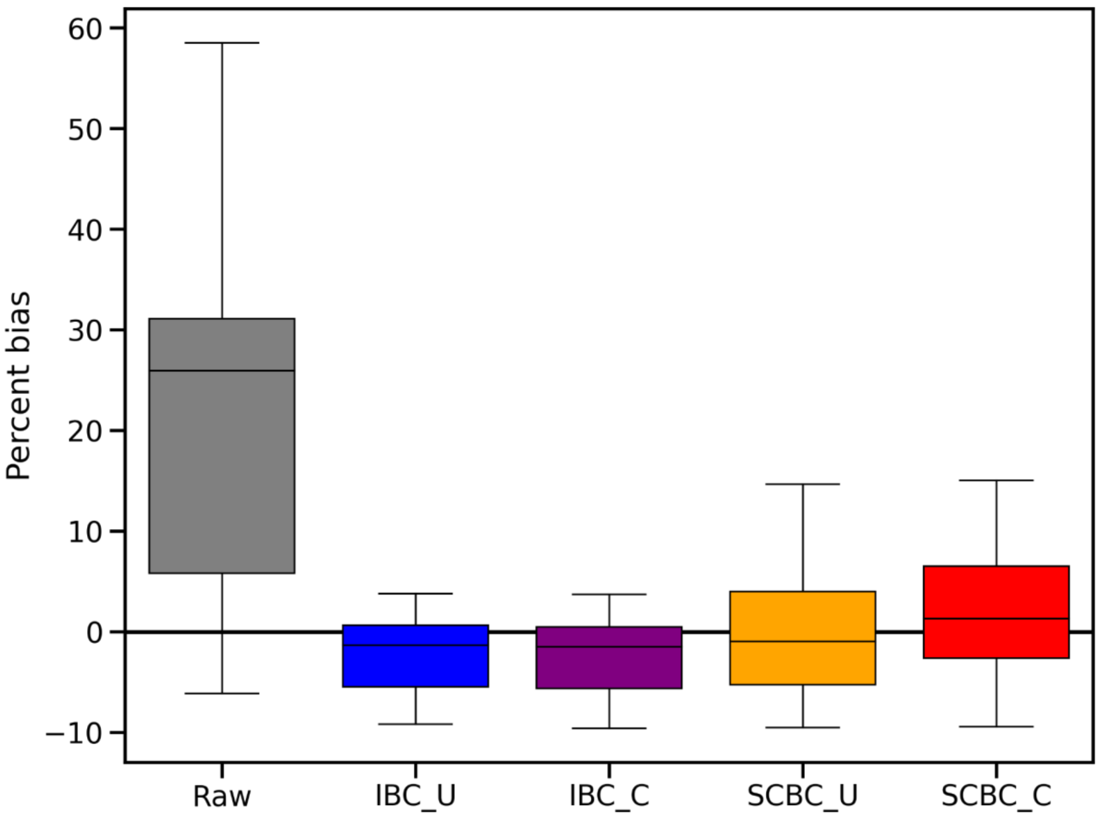

Figure 6. Boxplots of total percent biases across all sites and all time during the bias-correction period.

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 7. 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. 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.

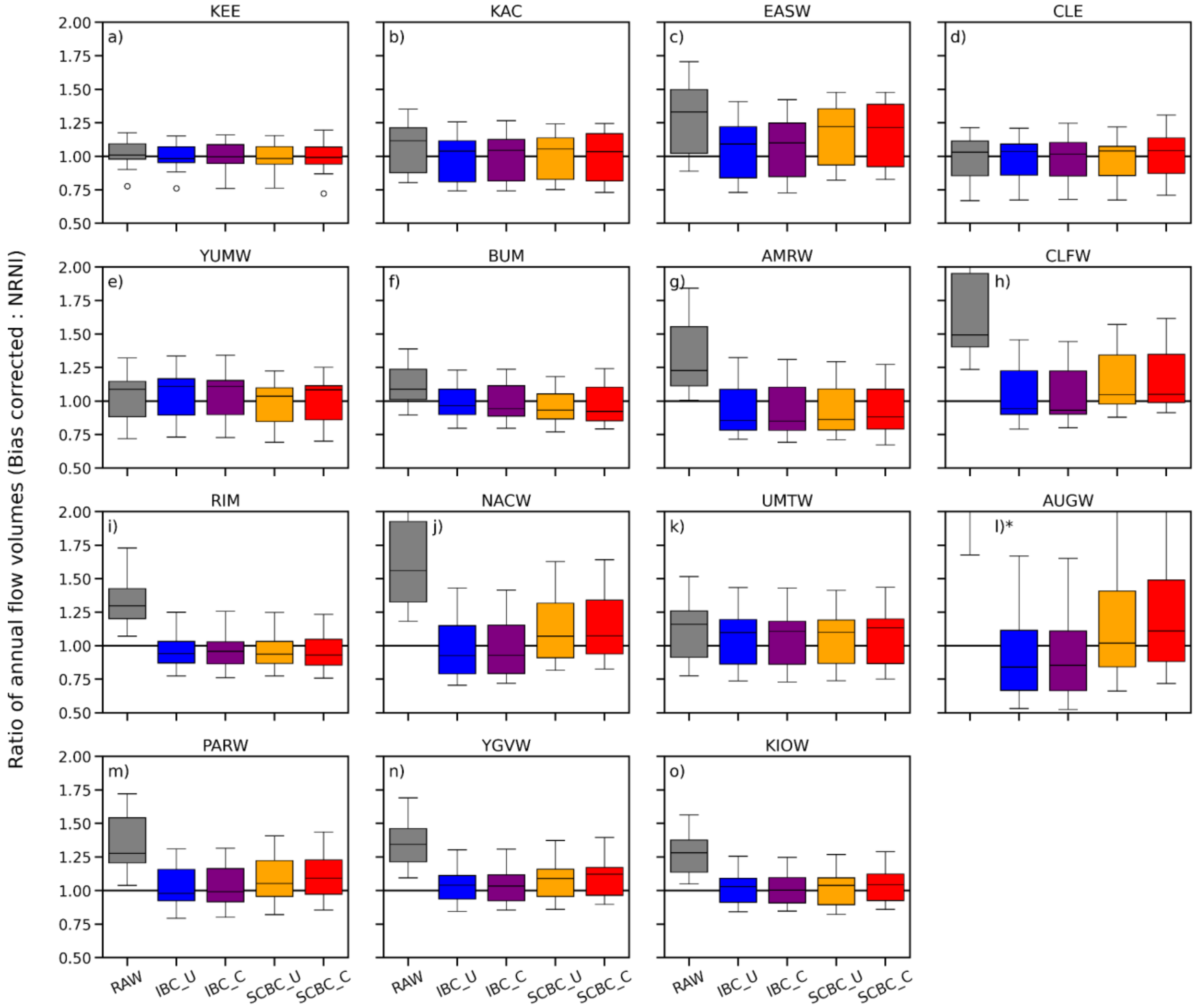

Figure 7. Boxplots of the ratio between each scenario and raw annual flow volumes during the application period (1992-2009, N=19). Subplot l) at AUGW is cut off to make the comparison across subplots easier.

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 5 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 8.

Generally, we see that for the winter and summer months (figure 8 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 7 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.

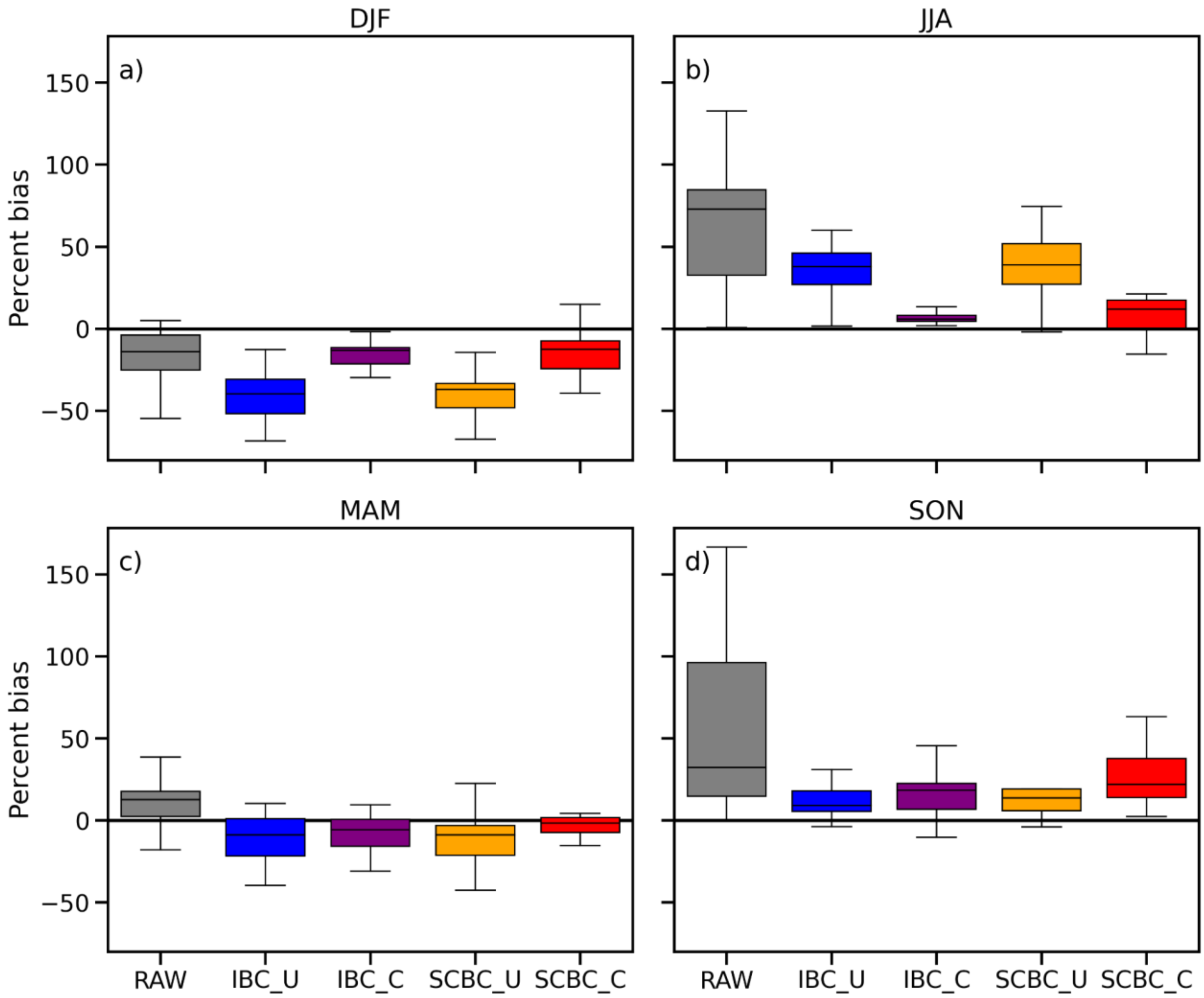

Figure 8. Boxplots of the percent bias for each of the seasons. Panel a shows the biases for all scenarios in winter months, panel b summer months, panel c spring months, and panel d fall months.

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 9. 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 9 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 $T_{min} = 4.7\ ^{\circ}C$ and $T_{min} = 8.6\ ^{\circ}C$ 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.

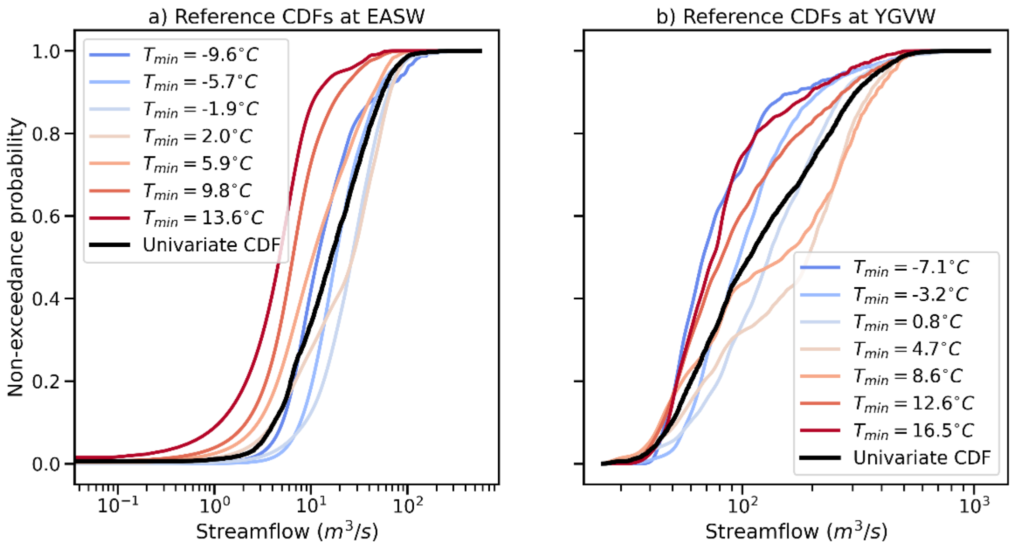

Figure 9. Comparison of cumulative distribution functions (CDFs) for univariate bias-correction (solid black line) and conditional bias-correction at several daily minimum temperatures (shaded blue to red lines). Panel a shows CDFs for a headwaters site (EASW) and panel b shows CDFs for a site on the 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 10 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 10, they are an artifact of the method and may cause errors in water management model simulations.

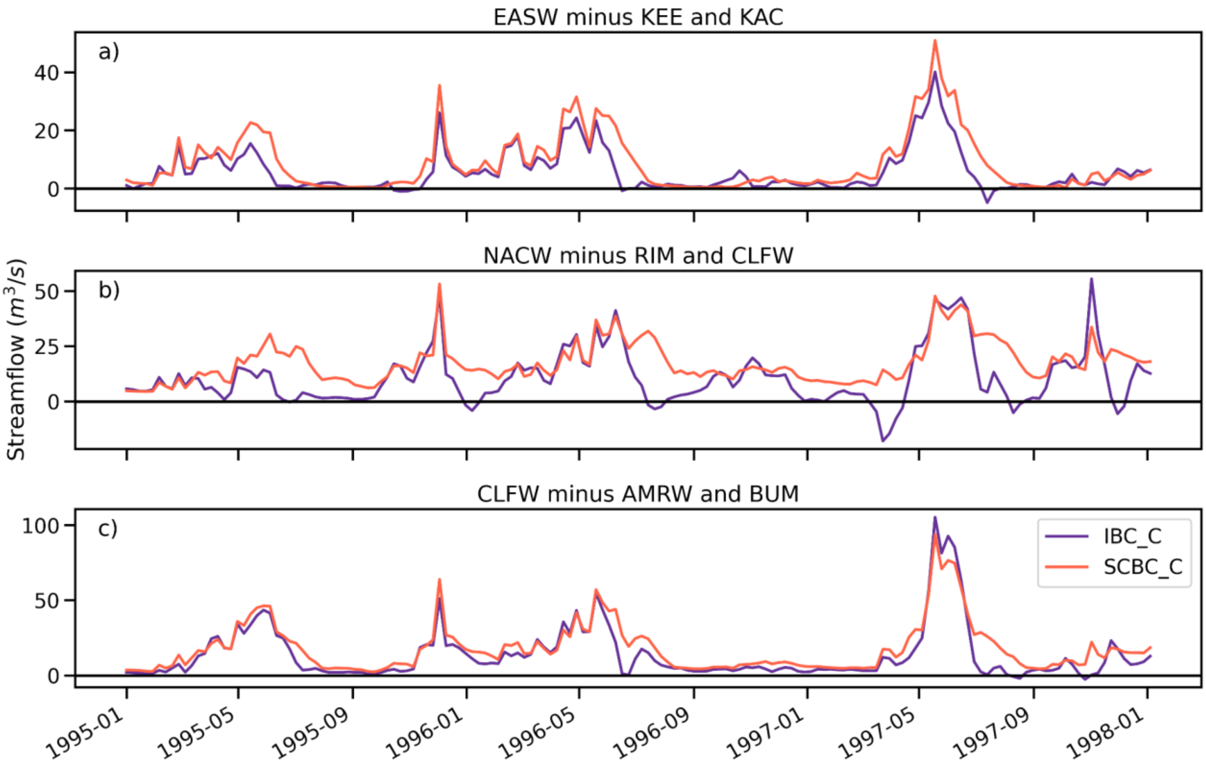

Figure 10. Comparison of streamflow with the streamflow from upstream gauged sites removed.

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 11 (winter streamflow) and 12 (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 11) we see that unconditional bias-correction (SCBC_U) (figure 11a) largely works to decrease streamflow, except in the furthest headwaters. For conditional corrections (SCBC_C, figure 11b) 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).

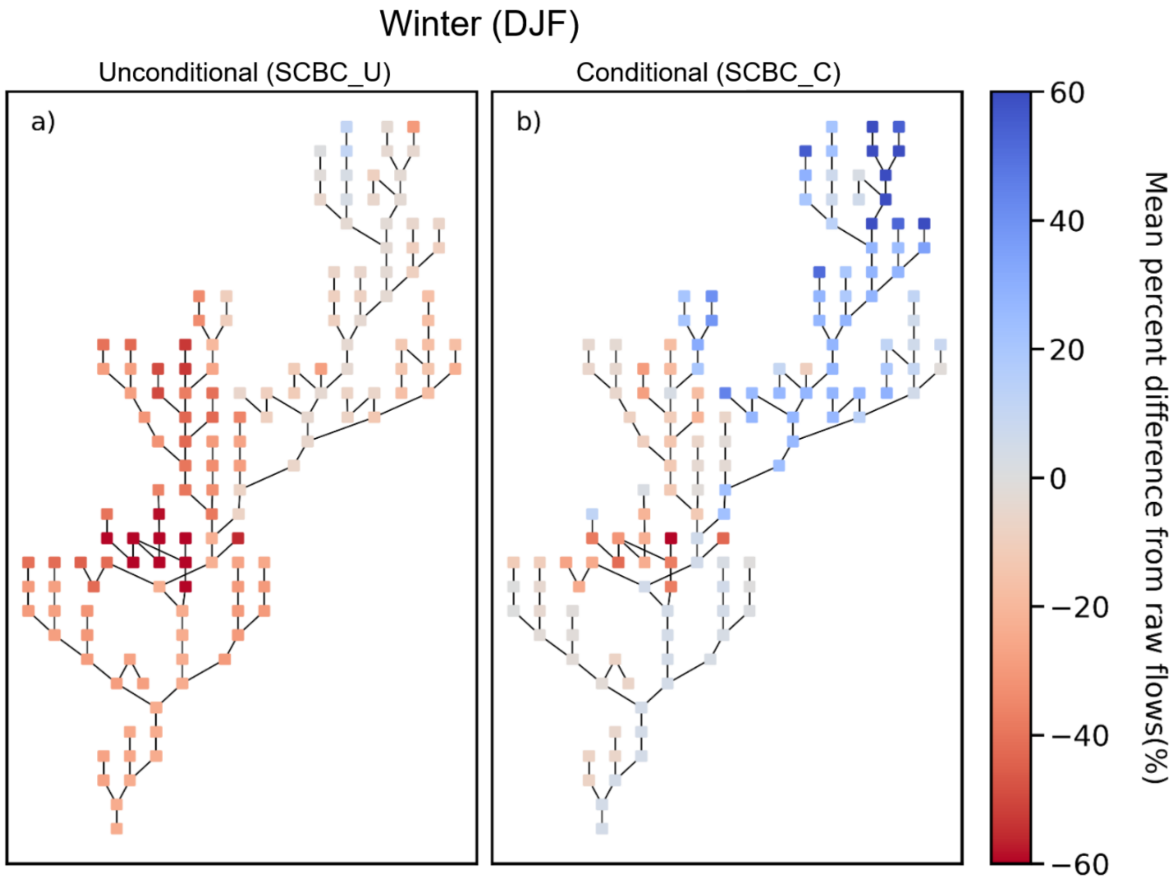

Figure 11. Change in the streamflow at each river reach in the Yakima River Basin for both spatially consistent configurations during winter (DJF).

The summer unconditional corrections (SCBC_U) (figure 12a) look similar to those in the winter (figure 11a), 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 12b) we see that there are drastic changes from the corrections of winter (figure 12b). 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.

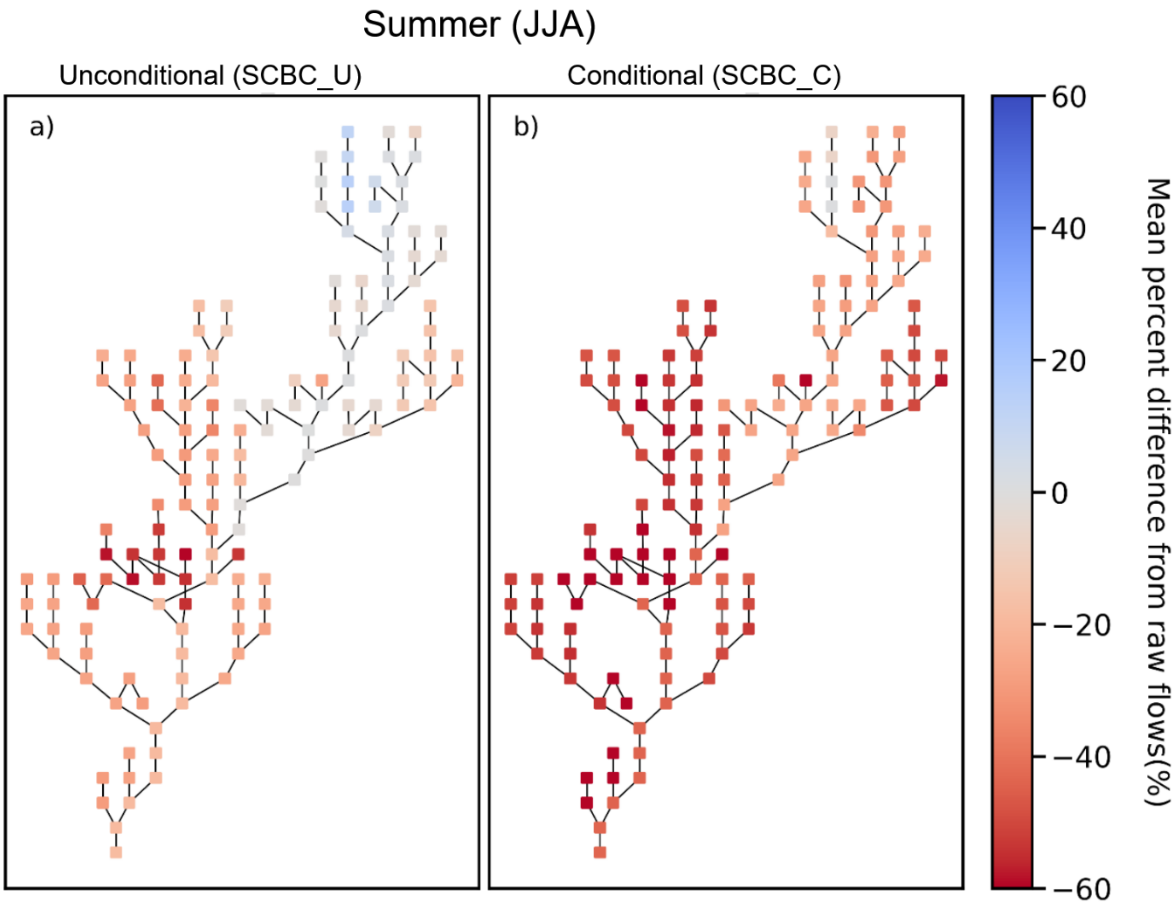

Figure 12. Change in the streamflow at each river reach in the Yakima River Basin for both spatially consistent configurations during summer (JJA).

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.

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. 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. We have released the bmorph package as a freely available and open-source python package at doi.org/10.5281/zenodo.5348463.

APPENDIX

Appendix A: Supplementary Figures

Appendix A contains three supplemental figures which complement the main analysis .

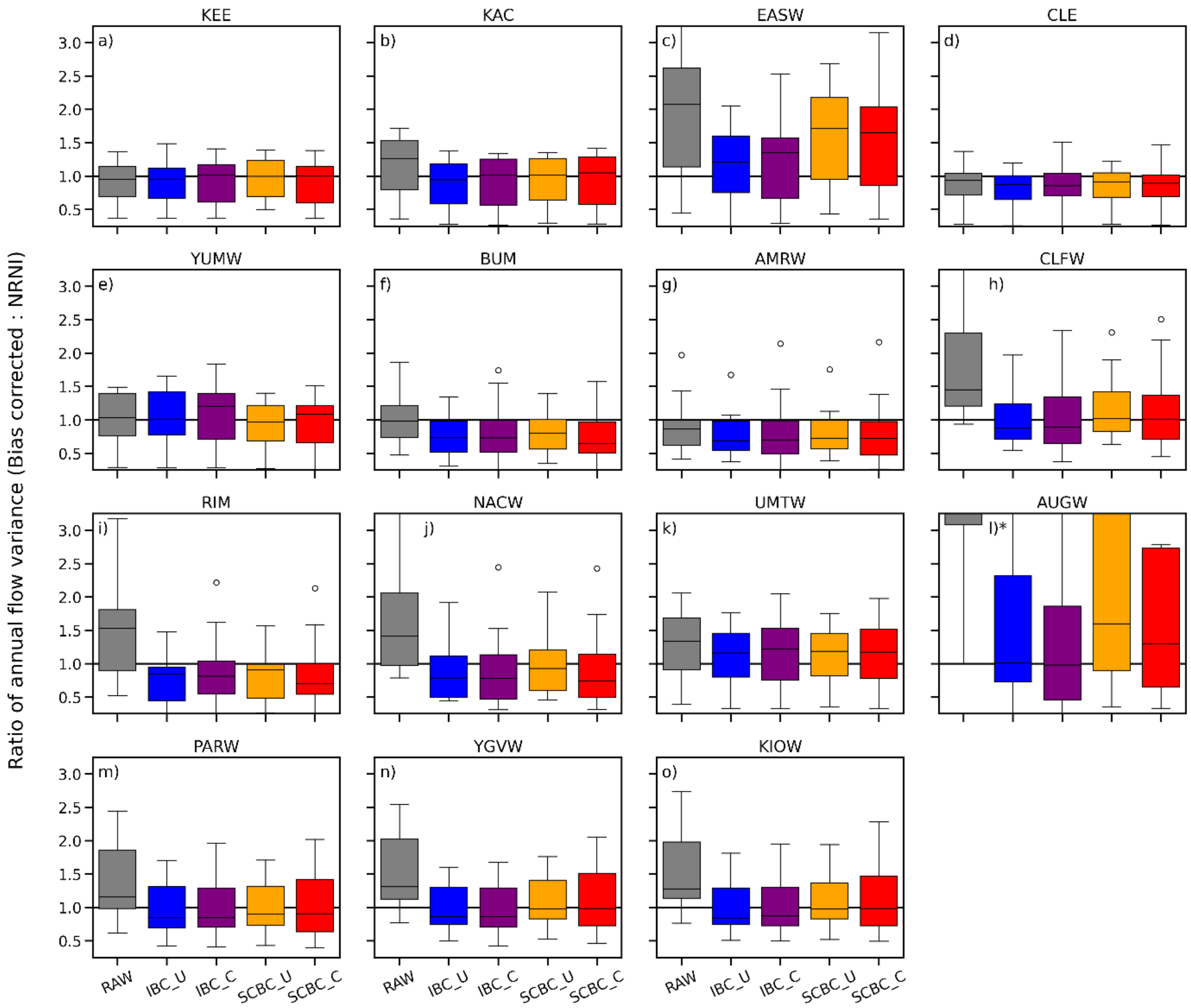

Figure S1. Ratio of the annual variances between the simulated streamflow and reference streamflow.

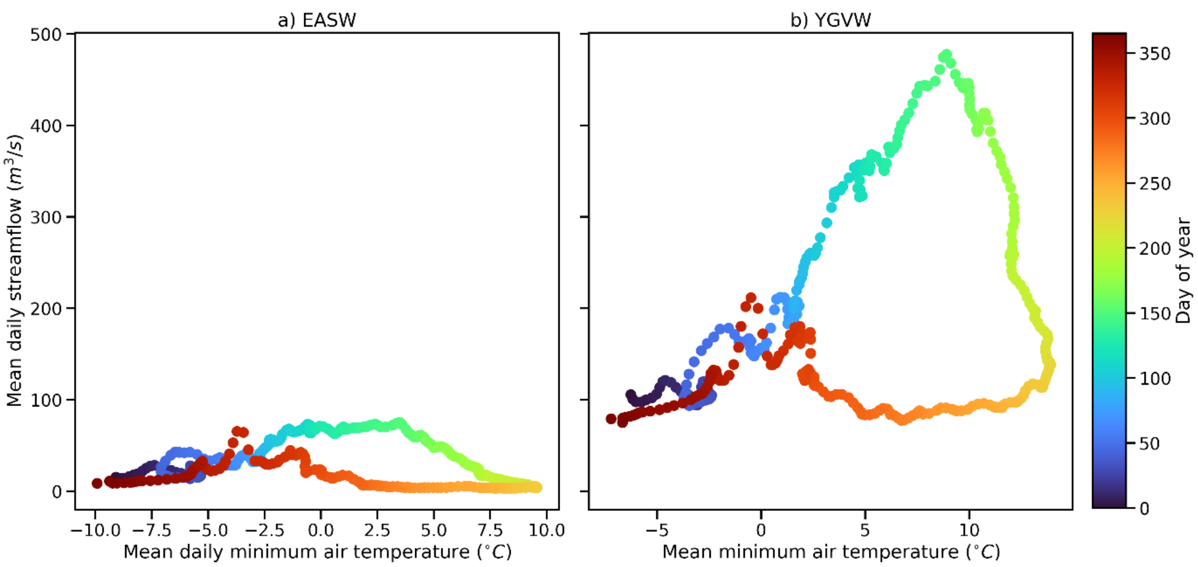

Figure S2. Average seasonal cycle of daily minimum temperature and daily streamflow for EASW (panel a) and YGVW (panel b). Dots are colored by day of year. This figure shows how the bimodal distributions in figure 9 of the main text arise. Bias-corrections conditioned on daily minimum temperature at YGVW with minimum temperatures approximately between 4 and 10 °C have two distinct streamflow regimes with high flow in spring and low flow during fall.

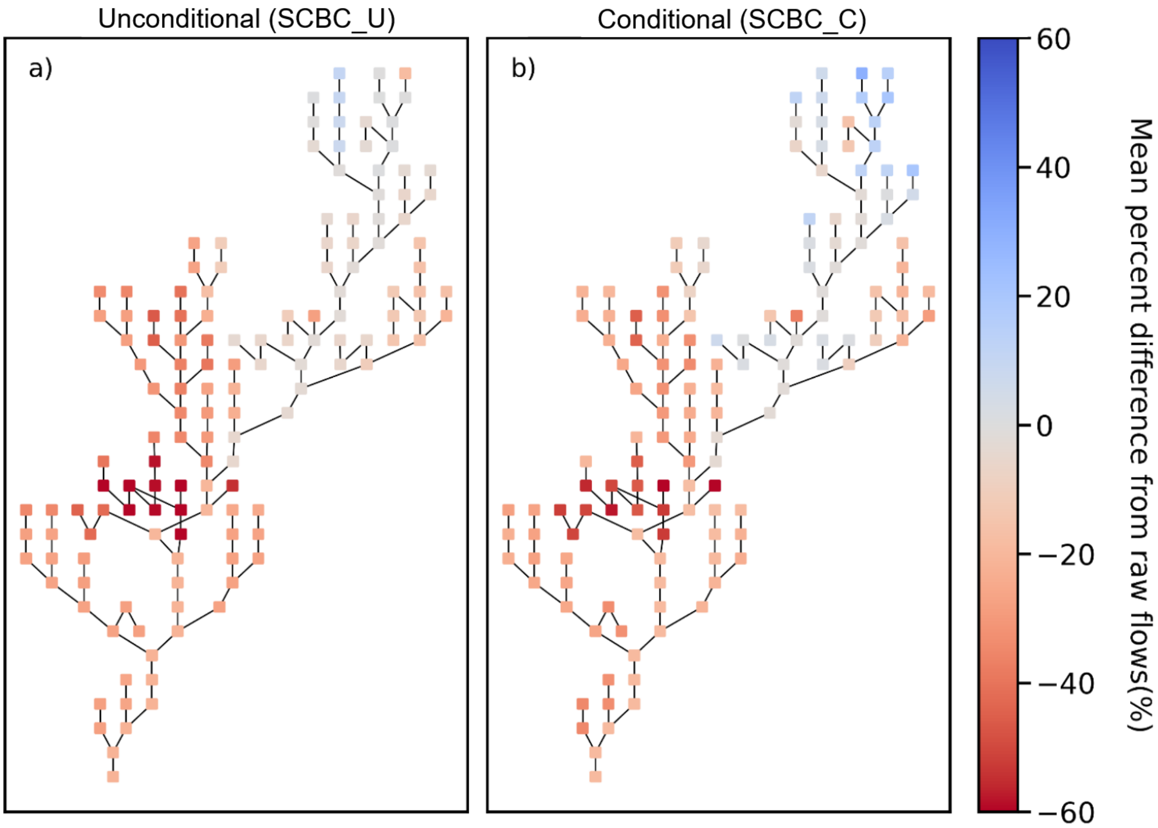

Figure S3. Mean percent difference between the raw simulated streamflow and bias corrected streamflow for every river reach in the Yakima River Basin, over the entire correction period.

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