A comprehensive calibration framework for the Northwest River Forecast Center

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RESEARCH ARTICLE

A comprehensive calibration framework for the Northwest River Forecast Center

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Abstract
In this paper we present a comprehensive framework developed by the Northwest River Forecast Center (NWRFC) for calibration of arbitrary hydrologic basins. The framework includes hydrology, snow, routing, channel loss, and consumptive use models. Data inputs include a wide range of open access datasets for land use, land cover, and meteorology. The framework can handle basins with diverse hydrologic conditions, including permanently glaciated regions. We also develop a flexible automatic calibration system which can handle numerous unobservable model parameters in a computationally efficient manner such that calibrations can be run on a modern laptop in under 10 minutes. The framework presents a new standard for the quality of calibrations that are possible with lumped conceptual hydrologic models with careful data curation and an objective calibration framework combined with expert local knowledge (human in the loop). In addition we have made wrapper packages available for the entire suite of NSWRFS models including SAC-SMA, SNOW17, and Lagk. We hope these modern interfaces will increase the accessibility of these models and facilitate future research.

KEYWORDS
hydrology, calibration, automatic calibration

1 | INTRODUCTION

The Northwest River Forecast Center (NWRFC) is one of thirteen River Forecast Centers that are part of the United States (US) National Weather Service (NWS), which is in turn part of the National Oceanic and Atmospheric Administration (NOAA). The NWRFC's operational mission includes (1) modeling river basins across the Pacific Northwest in the Columbia River and Coastal Basins in Washington and Oregon (2) providing water resource forecasts and guidance for region, and (3) supporting decision-making while collaborating with NWS core partners (Figure 1). The Pacific Northwest region is composed of a wide range of hydrologic conditions including rain dominated, snow dominated, glaciated, tidally influenced and arid basins, some of which exist in Canada and eventually flow into the US. Forecasts developed by the NWRFC are used across the region to provide timely information about flooding, water supply, drought, recreation, navigation, and environmental flows.

The NWRFC utilizes a suite of models representing soil, snow, routing, channel loss, and consumptive use processes to develop hydrologic river forecasts. The NWS River Forecasting System (NWSRFS) was initial developed in the late 1970's but continues to be utilized today as part of the NWS Community Hydrologic Prediction System (CHPS) (Anderson 2002a and Schaake et al. 2006).

Periodically the NWRFC recalibrates its suite of models as new data and methods become available. In previous iterations, calibration was a mostly manual and labor intensive process. In 2018, the NWRFC began a recalibration effort to modernize its calibration approach by utilizing a new forcing dataset, new zone delineations, improved representation of hydrologic fluxes, transparent model validation, expansion of performance metric evaluated across temporal scales, and an automatic calibration system.

Previous studies have successfully used auto calibration with SAC-SMA and SNOW17. Newman et al. (2015) auto-calibrated 671 headwater basins across the contiguous US spanning a range of hydrologic conditions. They calibrated 11 SAC-SMA parameters, 6 SNOW17 parameters, and 2 for the unit hydrograph with a root mean squared error (RMSE) objective function. RMSE-like objective functions more heavily weight high flows due to the squared term, which can be a benefit for flood applications but can produce biased or low quality simulations during low flow periods. Gupta et al. (1998a) use multiobjective optimization to calibrate 13 SAC-SMA parameters. While multiobjective optimization can provide valuable information about tradeoffs and model limitations, it can be difficult to use in an operational where a single calibrated model is needed. Hogue et al. (2000) developed a multistep automatic calibration scheme which mimics the best aspects of a hand calibration process but cuts down on the overall time spent calibrating. They calibrated 15 parameters overall over a 3 step process. Chouaib et al. (2021) calibrated 13 SAC-SMA parameters in the Eastern US using the Shuffle Complex algorithm (SCE-UA) which which has been shown to work well with smaller parameter sets but may struggle with a larger number of parameters.

In this paper we present a comprehensive approach for hydrologic model calibration used at the NWRFC. The goals were to develop a flexible, reproducible, high performing auto-calibration methodology which can accommodate most NWRFC basins including those with multiple zones, routed upstream flow, channel losses and consumptive use and may have up to 90 parameters. Section 2 discusses the underlying models, Section 3 describes the data, Section 4 discusses specific model enhancements made by the NWRFC during the calibration process, Section 5 describes the auto-calibration process, and Sections 6 and 7 provide detailed results for some basins that have been calibrated and are used operationally by the NWRFC.

2 | EXISTING MODELING SYSTEM

This section describes the general lumped rainfall runoff suite of models used by the River Forecast Centers (RFC) to translate precipitation and snow melt to runoff and route that runoff to basin outlets. A single instance of the following set of models can be used to represent the entire lumped watershed, or alternatively multiple model sets can be used to model discrete portions of the basin, often referred by the RFCs as zones. Each zone (traditionally delineated based on elevation) has its own unique parameter set corresponding to one hydrologic model.

2.1 | Soil and Hillslope Runoff

The Sacramento Soil Moisture Accounting Model (SAC-SMA) is a conceptual lumped soil model (Burnash et al. 1973). The model contains several parameterized buckets, each of which represents a discrete portion of the soil runoff process such as impervious runoff, surface runoff, interflow, and baseflow (Figure 2). It also has a soil moisture accounting function to track water moving in, out, and through the soil moisture column via evapotranspiration, soil-moisture storage, and drainage processes. Ultimately, the SAC-SMA model regulates the timing of water as it travels through the soil column and produces channel inflow (i.e. runoff) which subsequently needs to be routed. The model parameters are not calibrated by sampling the soil profile via field studies, but rather through inference using observations of rainfall and streamflow. A full overview of the SAC-SMA model is provided in the manual (Anderson 2002b).

2.1.1 | Glacial Zones in SAC-SMA

For glacial zones only certain portions of the SAC-SMA are used, primarily those that control the attenuation of water through the system. The following Sacramento model components are turned off; tension water storage, impervious flow, evapotranspiration, and losses from riparian vegetation Anderson (2002a).

2.2 | Snow

The SNOW17 is a temperature indexed snow accumulation and ablation model (Anderson 2006 2002a). The physical process of snow cover is captured by the model but in a simplified form. The model uses air temperature and precipitation rates to inform

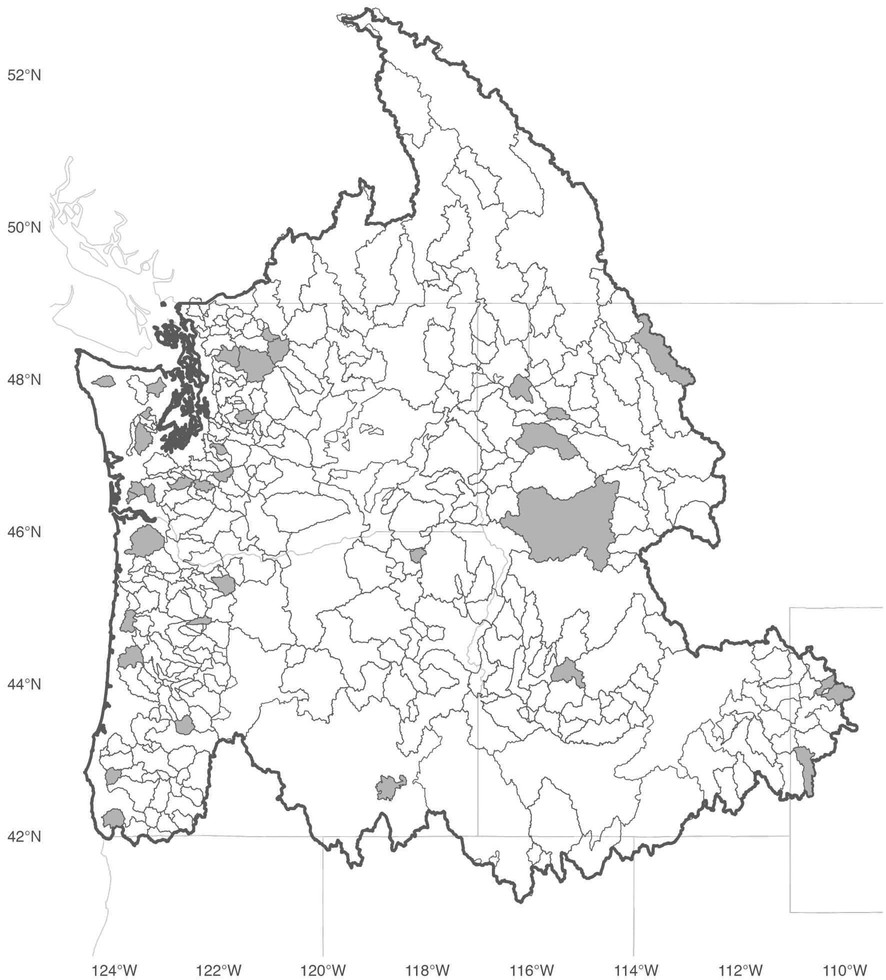

FIGURE 1 Map showing the NWRFC domain (thick black line), CAMELS basins (filled in grey), and other basins modeled by the NWRFC are shown with thin grey lines.

the amount to accumulation of snow melt. The model captures seasonal temperature sensitivity and its impact on the melt rate through the use of a seasonally varying melt factor (Figure 3). There is also an accounting component within the model that tracks the snowpack heat deficit, liquid to water ratio, and snow cover of the area being modeled. The heat deficit needs to rise to 32 °F and the melted water stored in the snowpack has to rise above capacity of the pore space to begin the onset of melt. The model's state of the snow cover controls the amount of melt, where more water is made available as melt when there is more simulated snow cover (Anderson 2006).

2.2.1 | Glacial Zones in SNOW17

Glacial zones are a special case which requires a specific model setup to account for the effectively unlimited available melt. For glacial zones the the initial snow depth is set at an effectively infinite height and the snow is always assumed to cover the entire area (Anderson 2002a).

2.3 | Unit Hydrograph

The unit hydrograph (UH) is a scaled time distribution of a unit depth of excess water over a given area from a rainfall-runoff model (NOAA 2005 and Linsley et al. 1982). Since SAC-SMA handles the timing of runoff through the soil column, the NWS

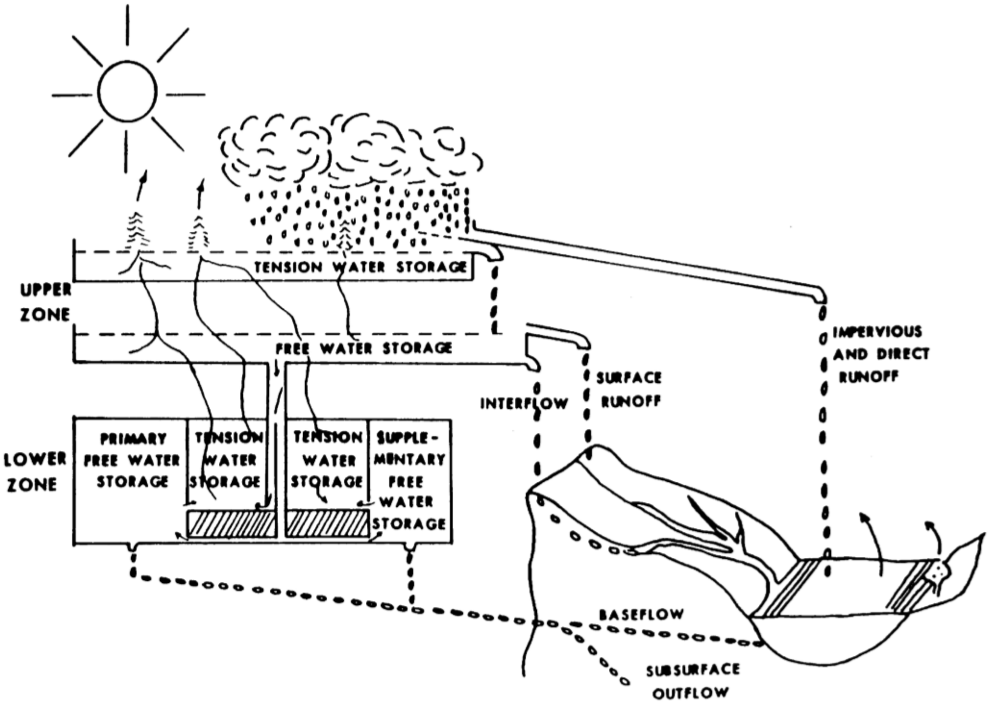

FIGURE 2 SAC-SMA Diagram from Anderson (2002a).

unit hydrograph model does not consider the excess water until it enters the channel system. This is different from traditional unit hydrograph approaches which consider interflow travel paths through the soil column as part of the unit hydrograph shape (Chow et al. 1988). For basins with multiple zones, each zone has a separate UH model and the zone hydrographs are added together to form the outlet hydrograph for the basin.

2.4 | Routing

Typically, the RFCs route a streamflow simulation downstream to the next location being modeled using a hydrologic routing approach to capture lag and attenuation in the hydrograph. If needed, any flow into the stream channel between the two modeling locations (i.e. local channel inflow) is captured by a collection of additional Snow17, SAC-SMA, and UH models to represent that local area. There are multiple hydrologic routing models used by RFCs, but for this approach the Lag and K routing method (lagk) was exclusively used. It is a flexible method of routing since both the Lag and K elements can be either constant or variable by streamflow (Linsley et al. 1982). The lag parameter generates a shift in the hydrograph forward to represent travel time and the K parameter represents the attenuation of the streamflow as it travels downstream.

2.5 | Additional models

There are two additional hydrologic models utilized at the NWRFC; Channel Loss and Consumptive Use. The Channel Loss (CHANLOSS) model accounts for losses or gains of water that occur along a channel reach as a result of interactions with groundwater, anthropogenic impacts, or evaporation from the stream surface. The Consumptive Use (CONS_USE) operation accounts for the impacts of surface water irrigation on streamflow based on crop evapotranspiration demand and irrigation efficiency. The use of these models for particular basin depends on specific local conditions.

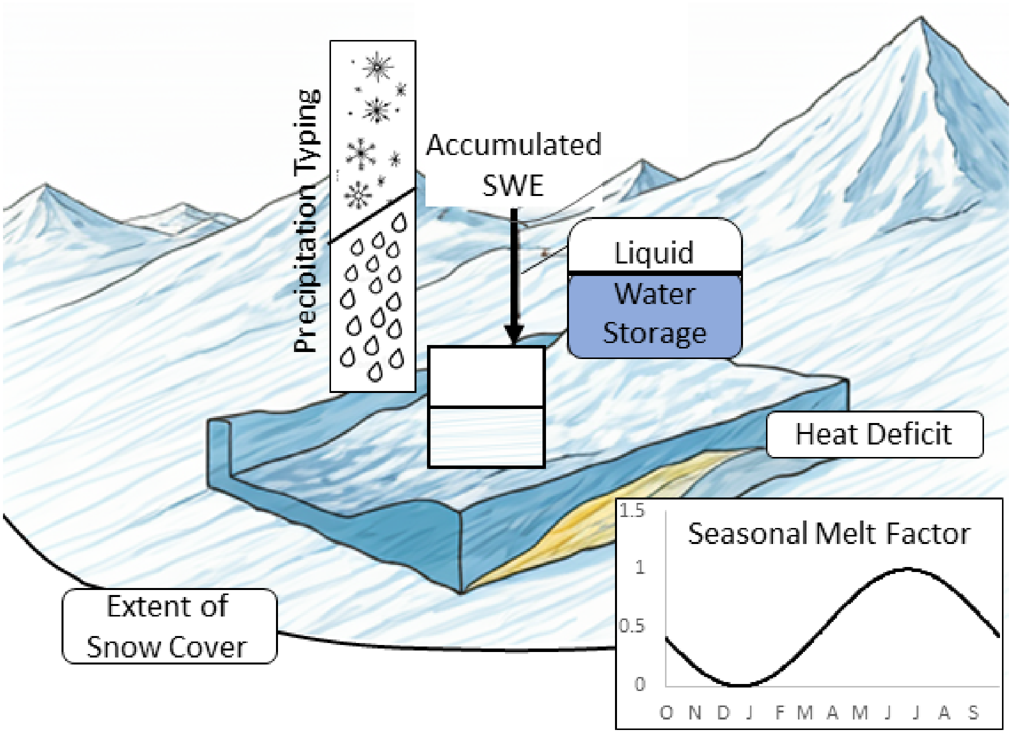

FIGURE 3 Snow17 diagram.

3 | DATA

3.1 | Forcings

The National Weather Service's Analysis of Record for Calibration (AORC), is a multi-decade, high-resolution dataset containing all weather information necessary for forcing land-surface, snow, and hydrologic models has been developed. It includes the period 1979-Present, at a time interval of one hour. Data are stored on a 30" (0.008333°) latitude/longitude grid mesh. The primary motivation for developing this dataset was the need for a climatology-constrained near-surface weather record suitable for calibrating hydrologic models across the U.S. (Fall et al. 2023).

The variables used for this study are 2-meter above ground air temperature, specific humidity, terrain-level pressure, and 1-hour precipitation accumulation. Variables other than precipitation are instantaneous at the start of the hour; precipitation accumulation ends at the given hour. For each time step, zone average values were calculated for all AORC variables used as input into the model.

3.2 | Streamflow data

Hydrologic models developed for operational forecasting by a RFC are typically set at a locations which are also occupied by an established measurement station that is collecting streamflow observations. Prior to beginning a calibration, all subdaily instantaneous and daily average streamflow observations were collected at calibration sites for same period there was AORC data availability. When daily average streamflow were unavailable, for example, the station wasn't established until sometime after the start of AORC availability, the daily average data was imputed.

Imputation of missing daily average streamflow data was conducted using the missRanger R package (Mayer 2024), an implementation of the MissForest algorithm (Stekhoven and Bühlmann 2011). To assess the quality of the imputed data we conducted a cross-validation analysis using available streamflow records by randomly dropping 50% of the data at a time and imputing the rest. The imputed values were compared to observations and performance was assessed using correlation (R^2), NSE, and percent bias. This analysis was conducted 5 times and the results were averaged to asses overall performance of the imputation. Additionally, imputation was conducted using a linear regression model to provide a performance baseline. Performance is generally very favorable with imputed values showing high R^2 and NSE and low bias. On average the random forest imputation algorithm performed 43% better than the linear regression model (average NSE of 0.90 vs. 0.58).

4 | MODEL ENHANCEMENTS

This section describes specific enhancements that were made to the calibration procedure at the NWRFC relative to previous calibrations.

4.1 | Dynamic ET

Evapotranspiration is used as input to SAC-SMA model and interacts with the soil tension water components. Changes to the modeled tension water depends on the evaporation demand and the saturated state of the tension water. The Hargreaves-Samani equation was used to calculate daily potential evapotranspiration (Hargreaves and Samani 1982). The equation is a temperature indexed evaporation approach, but also incorporates solar radiation.

$$PET = C_1(T_a + 17.8)R_e/\lambda(T_x - T_n)^{C_2} \tag{1}$$

Where T_x and T_n are max and min temperatures respectively, and C_1 and C_2 are fitting coefficients. A unique calibrated C_1 coefficient was assigned to the 15th of each calendar month. For days in between the 15th, the coefficient was linearly interpolated using adjacent months. As is common practice, C_2 was set to 0.5.

Although a temperature indexed approach is simple in comparison to a full energy balance method, it is an improvement over legacy NWRFC methods. Previous operational models used a static daily rate regardless of basin conditions. The potential evapotranspiration was converted to evapotranspiration demand by multiplying by a potential evapotranspiration adjustment factor (PETadj). Originally, this factor was recommended to be based on remotely sensed, Normalized Difference Vegetation Index (NDVI) (Koren et al. 1998) and updated with a method described in Kamble et al. (2013). For NDVI, the Vegetation Index and Phenology Vegetation Indices dataset was used to satisfy monthly time-series and spatial resolution coverage (Didan et al. 2015 and Didan and Barreto 2016). An average monthly PETadj factor was calculated for the 15th of each calendar month. For days in between the 15th of each month, the coefficient was linearly interpolated using the adjacent months.

4.2 | Zone Delineation

Part of RFC hydrologic calibration process involves exploring if it is advantageous to split the basin in to multiple discrete modeling zones. In the Western United states, when snow is prevalent in a basin, two zones will be often be used; one zone representing the higher elevations where snowpack persists through the winter and into the spring and another zone where the snowpack is transient. During past calibrations, an elevation would be selected as the line of demarcation and the basin would be split into a upper and lower zone. For certain scenarios, multiple elevations would be used to split it into more than two zones. Glacial regions are typically modeled as their own zone.

As part of this new calibration approach, an unsupervised clustering technique was used to segregate the basin into unique zones. The process requires gridded basin hydrologic characteristics (Table 1). Grids were resampled and regridded to the same one kilometer resolution. Using the hydrologic characteristics for each grid cell within a basin, k-means clustering was used to divide the cells into a specified amount of zones. Due to the role that orographic effects play in many of the hydrologic characteristics utilized, the k-means clustering method often followed elevation contours but with additional nuances such as changes in forest cover, soil type, or basin aspect (Figure 4).

4.3 | Precipitation Typing

Historically, to derive the percentage of precipitation falling as snow, the NWRFC relied on a representative temperature time series assigned to a specific basin elevation, lapse rate, and an area elevation curve. As part of this legacy process a static lapse rate was used, which would often be adequate over long temporal scales but rarely were precise for individual storms.

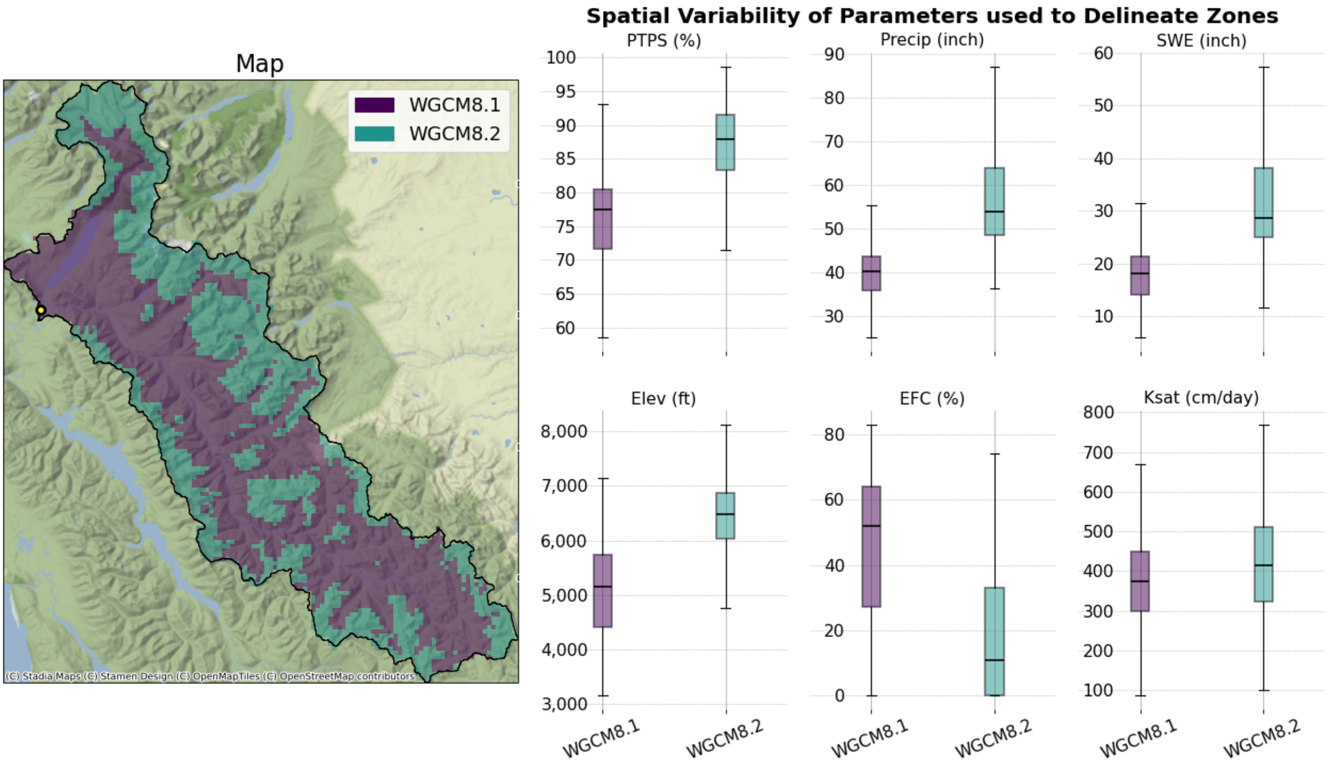

FIGURE 4 Example basin delineation using k-means clustering for the Middle Fork of the Flathead River near West Glacier, Montana. WGCM8.1 and WGCM8.2 indicate the two zones where zone 1 typically corresponds to lower elevations with the shortest travel time to the outlet. The yellow dot indicates the basin outlet.

Dataset	Data Source	Reference
Average PTPS from Nov-Mar	AORC	Fall et al. (2023)
Average Annual Cumulative Precipitation	AORC	Fall et al. (2023)
Topographical Elevation	USGS	USGS (2023)
Effective Forest Cover	NLCD, Canada	Beaudoin et al. (2014)
Saturated Hydraulic Soil Conductivity		Zhang et al. (2018)
30day Avg Max Annual SWE depth	U Arizona	Zeng et al. (2018) Broxton et al. (2019)
30day Avg Max Annual SWE depth, Canada	ERA5-Land	Muñoz-Sabater et al. (2021) CCCS (2019)

TABLE 1 Hydrologic characteristics used for clustering and references for each dataset.

For this recalibration effort, specific humidity and terrain-level pressure from the AORC gridded dataset (Fall et al. 2023) were used to derive surface wet bulb temperatures. The National Weather Service Western Region guidance uses a standardized approach of wet-bulb 0.5 °C being equivalent to rain/snow level (Cleave et al. 2019). Leveraging that guidance, for a given time step, a terrain-level precipitation typing grid was created of binary values using the wetbulb grid's temperature threshold 0.5 °C at each cell (0=above, 1=below). A zone averaged time series of typing was calculated for each time step to be used as input to the model.

5 | AUTOMATIC CALIBRATION

This section describes the procedure used for automatic calibration of a single basin which involves selecting a calibration algorithm, developing calibrated parameters, upper and lower parameter limits for the optimizer, and some special considerations for basins which include snow and routed flow.

The dynamically dimension search (DDS) algorithm Tolson and Shoemaker (2007) was used for optimization of model parameters. DDS has been recognized as robust tool to perform hydrologic model optimizations Arsenault et al. (2014). The DDS algorithm is not designed to find global optimum parameter values but instead find reasonable parameter values within a given computational budget (i.e. iteration limit). Initial testing with the original DDS algorithm by the NWRFC found that when performing a 10,000 iteration run on a single core, the run time and performance was comparable to other statistical optimizers in a comparable total amount of time, such as particle swarm optimization (PSO) which uses multiple cores. This opened up the possibility that each CPU core could run an independent auto-calibration with the DDS optimizer in parallel, with the best result from all the runs used as the final solution. Running the DDS optimizer independently on multiple cores simultaneously is referred to as an embarrassing parallel approach (EP-DDS). Another parallel DDS (P-DDS) implementation approach was explored by B.A. Tolson (2014) that instead of the EP-DDS approach, there is a periodic check in and exchange of information between the runs. B.A. Tolson (2014) found that there is no clear winner between EP-DDS and P-DDS, but each has a distinct advantage depending on how far the algorithm is into the optimization run. They stated that “The next step in parallel DDS algorithm development involves merging the two parallel implementations to develop a parallel DDS implementation that combines the best aspects of EP-DDS and P-DDS.”

Based on the strategies recommended by the author to utilize each strength of EP-DDS and P-DDS, we developed a technique where the check in between independent parallel optimization process progressed as iterations increased. Initially the parallel processes would only exchange information every 1,000 iterations, to closely resemble a DDS-EP run. As the DDS run progresses, the frequency of check-ins increases from 1,000 to 500 to 100 to finally every 10 iterations. As the check in frequency increases, the DDS run more closely resembles the P-DDS process. We call this method the evolving DDS (EDDS) algorithm. The approach resulted in improved run times compared to EP-DDS and P-DDS while still maintaining comparative calibration skill to other optimizers (Arsenault et al. 2014 and Asgari et al. 2023). Calibrations can be run on a modern laptop in about 10 minutes.

5.1 | Objective function

The NWRFC Autocalibration scheme tool only allow for a single objective function construction, is flexible allowing for utilization of multiple metrics including: Nash-Sutcliffe Efficiency (NSE), Kling-Gupta Efficiency (KGE), and Coefficient of Determination (R^2). Metrics can be calculated on either average daily flow data or instantaneous data at the model timestep. Also a combined objective function can be selected which would be the sum of different metric calculated using both daily and instantaneous data. This type of combined objective function is an alternative to multiobjective optimization which can provide detailed information about tradeoffs between objective functions but can be difficult to interpret and use in an operational setting.

Objective function selection is part of the regular calibration work flow. Different constructions of metric combination a combination of time steps are explored to derive a suitable forecasting model for the site unique needs. Generally successful calibration has been found at the NWRFC where metrics have been combined which isolate both location specific high and low flows.

5.2 | Optimized parameters

Generally, parameters were not optimized when a measurable physical value for a specific basin could be observed or derived. Examples of this would be area, mean elevation, effective forest cover, travel time, and latitude. Other parameters were not optimized when they represented the limits of an assumed physical process. These were exclusively SNOW17 parameters and they included: maximum negative melt factor, antecedent snow temperature, base temperature for non-rain melt factor, maximum percent of liquid water held in the snowpack, and daily melt at the snow-soil interface.

However, the majority of parameters associated with the SNOW17, SAC-SMA, and the unit hydrograph derivation cannot be directly linked to measurable basin attributes, and were optimized during the calibration process.

5.3 | Basin clustering for limits

To determine appropriate physically based parameter limits, K-means clustering was performed to group all basins modeled by the NWRFC. Clustering was done using basin averaged hydrologic properties (Table 1) and average cyclical daily hydrograph shape for each modeled basin. For each group of modeled NWRFC basins determined by the clustering algorithm, model

SAC-SMA	SNOW17	Unit Hydrograph	LagK
adimp	areal depletion curve	shape	K
lzfpm	mfmax	scale	lag
lzfsm	mfmin		
lzpk	scf		
lzsk	si		
lztwm	uadj		
pctim			
pfree			
rexp			
riva			
uzfwm			
uzk			
uztwm			
zperc			

TABLE 2 Model parameters that are optimized as part of the auto-calibration procedure.

parameter limits were collectively shared. This is conceptually similar to the idea of hydrologic landscape regions (Leibowitz et al. 2016 and Patil et al. 2013). Parameter limits were informed by prior calibration efforts for each basin in a group, NWSRFS calibration literature Anderson (2002a), and a manual review. We found that appropriate physically realistic parameter ranges are critical for mitigating equifinality (multiple parameter sets with the same objective function value) in conceptual hydrologic models (Her et al. 2019).

5.4 | Calibration of the Unit Hydrograph Model (UNIT-HG)

Each zone within a basin needs its own Unit Hydrograph (UNIT-HG) model to route runoff to the basin outlet. The model is based on a synthetic gamma distribution unit hydrograph (Croley 1980) and so has a shape and scale parameter that need to be calibrated. When using a single zone, the UNIT-HG parameters can be inferred from data using baseflow separation methods. When using multiple zones for a basin, the UNIT-HG parameters are latent and unobservable and so must be calibrated.

The USGS National Hydrologic Dataset (NHD) (U.S. Geological Survey National Geospatial Program 2022) was used to calculate the maximum travel time for excess water to reach a basin's outlet which was used to constrain the UNIT-HG parameters. Using a method proposed by Maidment et al. (1996), an overland flow velocity grid was calculated, assuming a velocity limit of 0.02 to 2 m/sec. The basin velocity information, along with a NHD flow direction gid, was used to calculate the maximum travel time to the basin outlet. The maximum travel time was used to set the total UH length, then during optimization a shape parameter is randomly sampled which, given the UH length, fixes the scale parameter. The UNIT-HG gamma shape and scale parameters were constrained during optimization so that the unit hydrograph shape length was within 25% of the calculated maximum travel time to the basin outlet.

For prior NWRFC calibrations, duplicate unit hydrographs were used for each zone. With the inclusion of automatic calibration, each zone had its own optimized unit hydrograph using the calculated maximum travel time to the basin outlet. In practice this improves calibrations by allowing the model to be more flexible. In some cases this exacerbates the equifinality of the solution space and causes something akin to label switching in hidden markov models (Bracken et al. 2016 2014). We observed in some cases that one zone serves as the baseflow and the other zone serves as the flashy component, and in a second run of the optimizer simply due to randomness, the role of each zone switches. This issue was generally avoided by careful use of parameter limits.

5.5 | Areal Depletion Curve

In order to apply SNOW17 to an area, the model tracks areal extent of the snow cover. That extent is derived by developing a calibrated relationship between the depth of the snow water equivalent and the amount of snow cover. This relationship, known as the areal depletion curve, is expected to be be both physically reasonable and continuous. To ensure these two requirements are met, the following equation was used

$$s_c = s_d^b + (1 - a)s_d^c \tag{2}$$

where s_d is the snow depth, s_c is the areal extent of snow cover, and a, b, and c are parameters that were optimized with limits that ensured a physically reasonable result. In practice, the areal depletion curve is typically discritized into 10 evenly spaced points.

5.6 | LagK Table

Similar to the areal depletion curve, two lookup tables were used to characterize the lag and attenuation within the LagK model. Both the lag and attenuation values were associated with flow of the upstream tributary. Also, like the area depletion curve, the values within the table should be physically realistic and smooth. For lag and k values, the equation was used

$$\text{lag or k table entry} = a(Q-d)^2 + bQ + c \tag{3}$$

where a, b, c, and d were were optimized. For streamflow (Q) associated with the table, the observed historical streamflow observations were used to derived upper and lower limits.

Upper and lower limits of lag were set by calculating a range of possible travel time from the upstream model being routed to the basin outlet. The upper and lower travel time calculation relied on river miles between the two points and assumed river speed could vary from one to seven miles an hour. The lag table was limited so that travel time has to decrease with increasing flow.

5.7 | Forcing Climatological Corrections

Gridded meteorological observations datasets have some accepted level of spatial and temporal error at any particular point due to the necessary interpolation required to derive a complete dataset (Lundquist et al. 2019). The AORC forcing dataset used for this study suffers from this issues (Fall et al. 2023). The errors in these gridded meteorological observations have consequences when running a calibration spanning multiple successive water years, especially with regard to the persistent bias between simulated and observed streamflow.

For the automatic calibration scheme adopted by the NWRFC, it was accepted that the AORC dataset differed from the true precipitation, temperature, evapotranspiration, and precipitation typing within a given basin. To account for this, the optimizer was allowed to apply mid month adjustment factors to each month independently. For example, the same adjustment factor was optimized and applied to the 15th of January in the calibration period of record. For days in between the 15th, the adjustment factor was linearly interpolated using adjacent months. Precipitation, temperature, precipitation typing, and potential evaporation each had their own unique adjustment factor for each month.

The adjustment factors were constrained so that the resulting calibration period of record's (POR) monthly climatology for any of the four forcings had to be within limits of the monthly climatology defined by an external gridded datasets climatology (Table 3). Also constraints were imposed to maintain temporal consistency month to month in the climatology by ranking the AORC monthly climatology and utilizing a parameters which control how equitably to apply the adjustment factor between the months. While it is not standard to adjust forcing data that is used for hydrologic calibrations during calibration, this approach can be used when forcing data has known but complex biases when compared to observations and a high quality calibration is required. This is akin to an on-demand bias correction which is typically performed as a preprocessing step before calibration.

5.8 | Software wrappers

As part of the calibration effort we sought to modernize the NWSRFS Fortran code and provide interfaces through widely used contemporary programming languages. To this end we created two packages in both Python and R which contain and wrap the legacy Fortran code. These packages provide simple interfaces to the SAC-SMA, SNOW17, UH, LAG-K,CHANLOSS, and CONS_USE models used by the the NWRFC in practice. The packages and documentation are available here: https://github.com/nwrfc/nwrfc-hydro-models

Precipitation Datasets	Reference
CHIRPS	(Funk et al. 2015)
ERA	Muñoz-Sabater et al. (2021)
NCAR	Newman et al. (2015)
PRISM	Daly et al. (2008)
Temperature Datasets	Reference
Daymet	Thornton et al. (2022)
ERA	Muñoz-Sabater et al. (2021)
NCAR	Newman et al. (2015)
TopoWX	Oyler et al. (2014)
Evapotranspiration Datasets	Reference
ERA	Muñoz-Sabater et al. (2021)
GLEAM	Miralles et al. (2011)
P-LSH	Zhang et al. (2015)
TerraClimate	Abatzoglou et al. (2018)
Precipitation Typing Datasets	Reference
ERA	Muñoz-Sabater et al. (2021)

TABLE 3 External gridded datasets for forcing climatology adjustment limits.

6 | MANUAL CALIBRATION REVIEW

At the NWRFC, when the calibrations are developed using the objective framework presented here, a final "human in the loop" step is conducted before a calibration is approved for operations. In this step an expert human forecaster reviews all the automatically calibrated parameters and examines the model output for inconsistencies or errors. This step incorporates expert local knowledge and helps to mitigate the equifinality for which conceptual hydrologic models are especially prone (Her et al. 2019).

7 | CALIBRATION RESULTS - CAMELS BASINS

Calibration studies often use a single objective function such as root mean squared error (RMSE) or NSE which is minimized to produce an optimal parameter set (Chouaib et al. 2021 and Arsenault et al. 2014 and Hogue et al. 2000). Both metrics rely on squared deviation between observed and simulated values and so put more weight on high flows. This unequal weighting can misrepresent low flows, which can be just as important to water managers in the Pacific Northwest for hydropower, fish management, navigation and recreation. For these reasons we selected a combined objective function for which balances low and high flows

$$\min \sum_i \mathrm{NSE}(s_i - o_i) + \mathrm{NSE}(\log(s_i) - \log(s_i))$$

where p represets the model parameters, s_i is the simulated flow, and o_i is the observed flow at timestep i. Note that the model was run at a 6 hour timestep but the objective function was computed for daily average values.

The first set of results is shown in Figure 5, a Bydyko diagram (Chen and Sivapalan 2020) for each of 38 CAMELS basins that share contain a NWRFC forecast point. We have added in one additional basin WCHW1 the Sauk River above White Chuck R which is upstream of SAKW1. A Budyko diagram displays the limits (energy or water) of a basin which play a string role in its overall hydrologic behavior. The KGE metric was used to evaluate the calibrations (Gupta et al. 1998b). Any value above -0.41 indicates a calibration better than the mean, and values closer to 1 indicate better alignment with observations (Knoben et al. 2019). Each zone has been colored by its overall performance (KGE) which ranges between 0.75 and 0.98. Basins in the NWRFC domain are typically energy limited due to ample precipitation but some basins particularly on the east side of the Cascade Rnage can be water limited. The calibration framework presented here is able to adequately capture a wide range of hydrologic conditions where dryer basins tend to perform slightly better then wet basins.

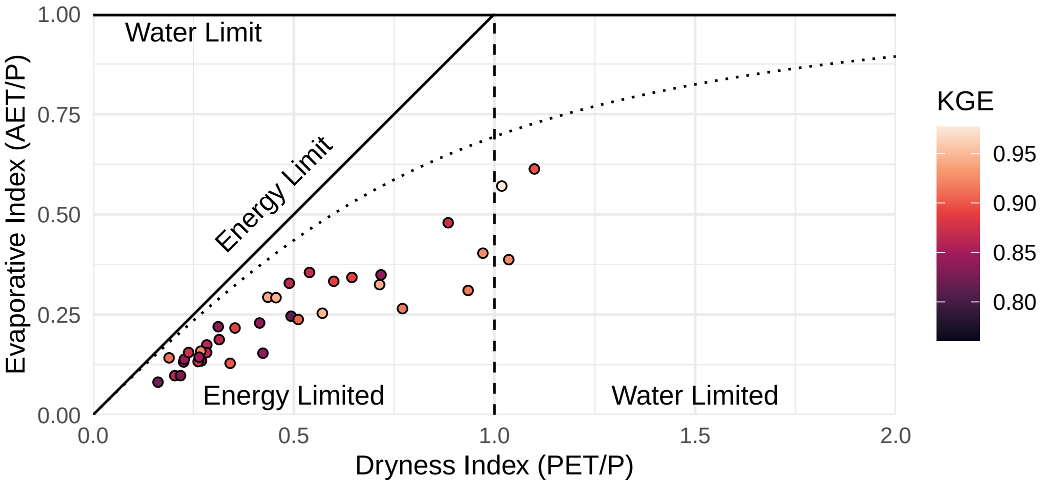

FIGURE 5 Budyko diagram showing long term behavior of the calibrated simulations for each zone of the three test basins.

8 | CALIBRATION RESULTS - CASE STUDIES

In this section we provide a detailed look at the calibration results of three representative basins in the NWRFC domain. The first, Nehalem R near Foss, Oregon (USGS #14301000, NWS ID FSSO3) is a rain dominated basin with a winter peak and limited snowmelt. The second, the middle fork of the Flathead River near West Glacier, Montana (USGS #12358500, NWS ID WGCM8) is a snow dominated basin with a summer peak and limited winter rainfall. The third, the Sauk River Near Sauk, WA (USGS #12189500, NWD ID, SAKW1), which is a basin with routed upstream inflow and both summer snowmelt and winter rain.

Table 1 shows the KGE values for each cross validation period (denoted CV1 through CV4) which drops 1/4 of the data, approximately 10 years, to compute the calibration objective function for the remaining data. A run was also conducted using the entire period of record (POR) for calibration, this represents the calibration that is used operationally. The table also has rows representing the calibration results with forcing adjustments and without. Notably the KGE values are relatively stable across the CV folds and the POR run, which indicates that the auto-calibration is finding similarly optimal solutions. It is especially encouraging that the POR runs results are generally similar in quality to the CV runs which indicates no major data issues. At SAKW1 and WGCM8, the forcing adjustment does little to improve the overall calibrations but at FSSO3, the forcing adjustments dramatically improve the calibration results, indicating a potential issue with the raw AORC forcings in this basin. These results indicate that forcing adjustment is not necessary in all basins but that it does not degrade the performance when used.

basin	Forcing Adjustment	CV1	CV2	CV3	CV4	POR
FSSO3	Yes	0.935	0.947	0.942	0.943	0.945
FSSO3	No	0.710	0.713	0.716	0.680	0.704
SAKW1	Yes	0.853	0.845	0.853	0.841	0.856
SAKW1	No	0.840	0.841	0.838	0.807	0.837
WGCM8	Yes	0.956	0.964	0.963	0.958	0.956
WGCM8	No	0.956	0.960	0.953	0.953	0.957

TABLE 4 KGE values for the three test basins for each cross validation (CV) period and the entire period of record (POR). Also provided are the results with forcing adjustment and without.

To facilitate intermodel comparison at different basins and showcase the flexibility of the calibration framework, we present detailed results from the three basins described in the previous section. Figure 6 shows sample timeseries from continuous simulations from 2019 to 2022 using the POR calibrations. The modeled timeseries (orange) show generally good agreement with the observations (black) with some disagreement on the peak flows and some falling limbs. This is due to the combined objective function which equally weights low and high flows at a daily timestep.

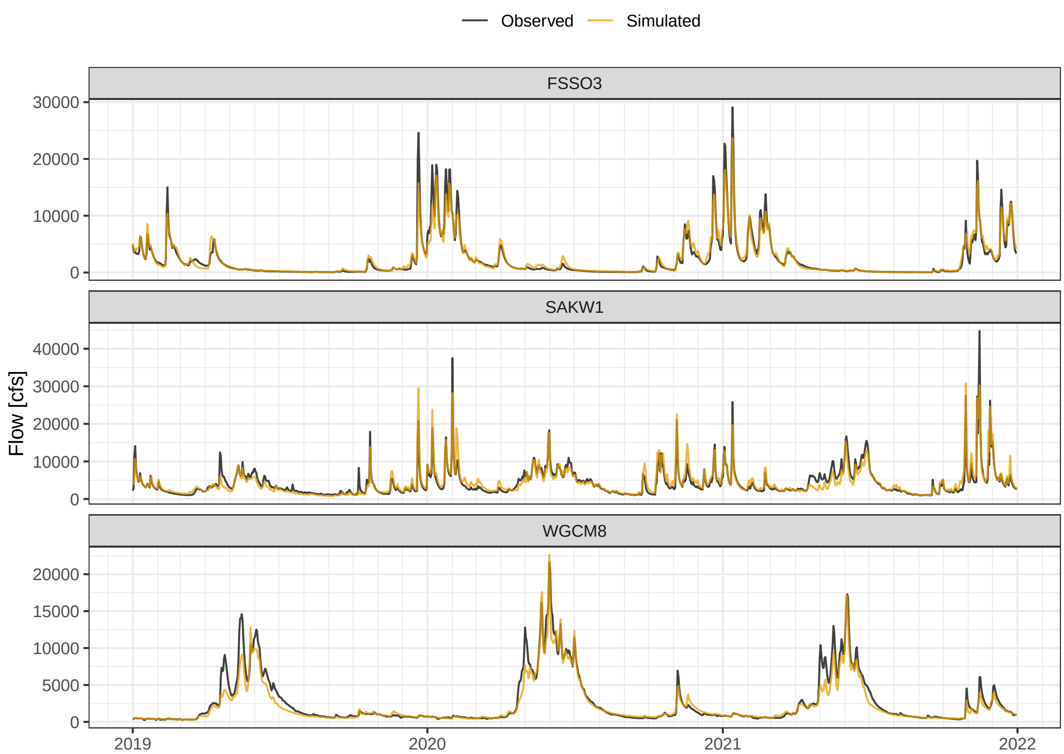

FIGURE 6 Example calibrated continuous simulations from 2019 to 2022.

Figure 7 shows cyclical plots which combine the entire POR continuous simulation. Each year of simulation (1980-2022) is overlayed on the same Julian day and the 10th and 90th percentiles are computed for each day, which is represented by the gray bands. The median of the POR simulations is shown in blue and the median of the historical data is shown in black. Cyclical plots can quickly pinpoint structural errors in hydrologic models. It is desirable to see the median of the observations fall within the simulation band and ideally close to observed median, which is the case in each of these basins.

9 | DISCUSSION

In this paper we have presented a comprehensive framework developed by the RFC for calibration of arbitrary hydrologic basins. The framework includes hydrology, snow, routing, channel loss, and consumptive use models. Data inputs include a wide range of open access datasets for land use, land cover, and meteorology inputs. The framework can handle basins with diverse hydrologic conditions, including permanently glaciated regions. We developed a flexible objective automatic calibration system which can handle numerous unobservable model parameters in a computationally efficient manner such that calibrations can be run on a modern laptop in under 10 minutes. In addition we have made wrapper packages available for the entire suite of NSWRFS models including SAC-SMA and SNOW17. We hope these modern interfaces will increase the accessibility of these models and facilitate future research.

In the results presented here we discussed three basins representing a range of hydrologic conditions present in the NWRFC domain. The calibration framework performed well with KGE values ranging from 0.75 to 0.96. This is representative of the entire suite of basins calibrated with this framework.

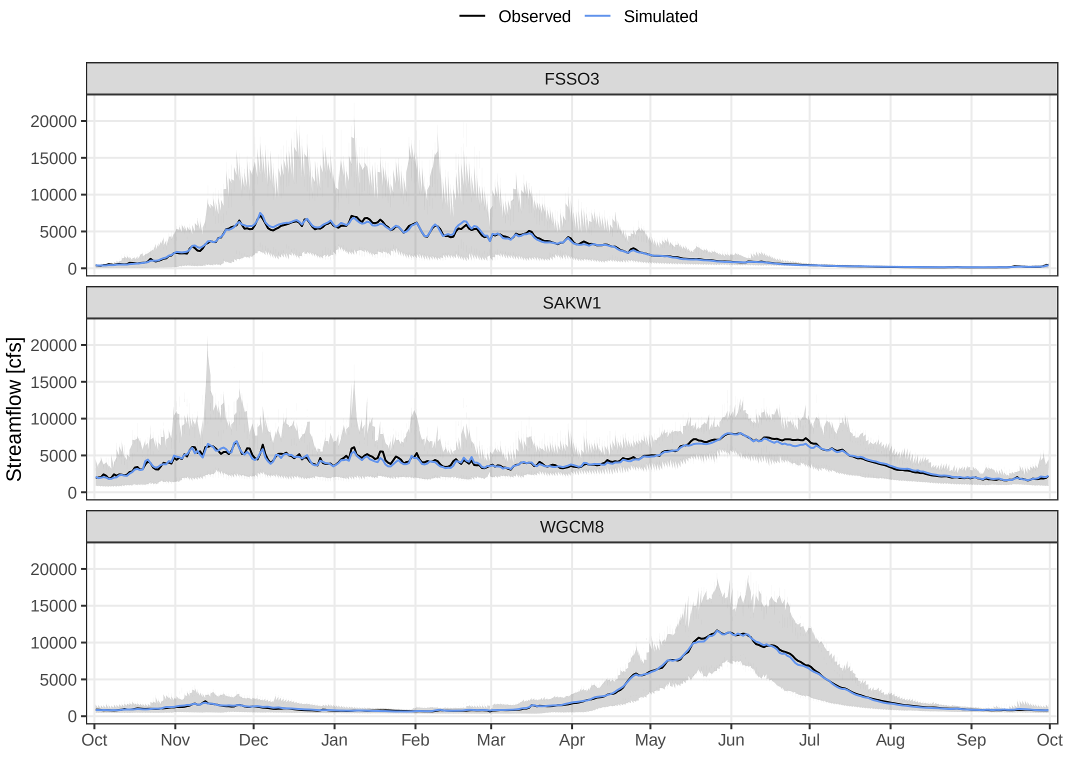

FIGURE 7 Example cyclical plots (average of each day of the year) of calibrated simulations from 1980 to 2022. The black line is observed, the blue line is the average of all the simulation years, and the grey area represents the 10th to 90th percentile of simulation years.

One limitation of this framework is that it cannot represent tidally influenced basins. Such basins require a nonlinear hydraulic model to solve for the tidal influence at the outlet. Another limitation is the lack of reservoir regulation. Regulation is a critical piece of operational hydrologic forecasting. In practice this is done through specialized regulation models or real-time coordination with reservoir operators.

We consider this framework to set a new standard for what is possible with lumped conceptual models. In recent years, the rise of artificial intelligence and machine learning (AIML) models in hydrology has called into question the utility using traditional hydrology modeling approaches. We have demonstrated here that with careful data curation and an objective calibration framework combined with expert local knowledge, lumped conceptual models can produce high quality calibrations that can be used successfully in operational hydrologic forecasting. These results can serve as a benchmark for new and emerging AIML approaches.

10 | CONCLUSION

We have presented a comprehensive objective framework for calibration of hydrologic basins. This framework is being used operationally by the NWRFC to calibrate basins as well as the calibrated models being used to produce operational forecasts for flooding and water supply. We hope that this framework presents a new standard for the quality of calibrations that are possible to produce using lumped conceptual models with careful data curation and an objective calibration framework combined with expert local knowledge (human in the loop). In addition we hope that the wrapper packages we have made available for the entire suite of NSWRFS models (including SAC-SMA and SNOW17) will increase the accessibility of these models and facilitate future research.

In the future we would like to perform calibrations at all CAMEL basins and present the results for benchmarking. An interesting extension of this would would involve detailed comparisons between cutting edge AI/ML models and the calibrations used in our framework.

DATA AND CODE

Data used to generate the figures in this paper are here: https://zenodo.org/records/14057210. The code code used to generate the figures in this paper are here: https://github.com/nwrfc/nwrfc-calibration-paper. The wrapper packages for SAC-SMA, SNOW17 and the remaining NWSRFS models is here: https://github.com/nwrfc/nwrfc-hydro-models. The automatic calibration code is available here: https://github.com/nwrfc/nwrfc-hydro-models.

AUTHOR CONTRIBUTIONS

Geoffrey Walters – Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Project Administration, Software, Validation, Visualization, Writing – Original Draft Preparation, Writing – Review & Editing; Cameron Bracken – Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – Original Draft Preparation, Writing – Review & Editing; Brad Gillies – Conceptualization, Formal Analysis, Investigation, Writing – Review & Editing; Leah Pope – Formal analysis, investigation, Methodology, Writing – Review & Editing; Henry Pai – Conceptualization, Formal Analysis, Investigation, Writing – Review & Editing; Sonali Chokshi – Investigation, Writing – Review & Editing; Victor Stegmiller – Investigation, Writing – Review & Editing; Julie Bracken - Formal Analysis, Writing – Review & Editing; Stephen King – Supervision, Writing – Review & Editing; Taylor Dixon – Project Administration, Supervision, Resources, Writing – Review & Editing; Joe Intermill – Supervision, Writing – Review & Editing.

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CONFLICT OF INTEREST

The authors declare no potential conflict of interests.

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