A comprehensive calibration framework for the Northwest River Forecast Center

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Abstract

We present a comprehensive framework developed by the Northwest River Forecast Center for calibrating hydrologically diverse basins. The framework includes models for snow, soil moisture, routing, channel loss, and consumptive use. Data inputs include a wide range of open-access datasets for meteorology, land use, topography, and land cover. The framework uses conceptual hydrologic models to handle basins with various hydrologic regimes including rain-driven and snowmelt-dominated basins. We also develop a flexible automatic calibration system that can handle numerous unobservable model parameters in a computationally efficient manner. A single-basin automatic calibration run can typically be completed on a modern laptop in under 10 minutes. We found that model performance metrics for this new approach match the quality of the NWRFC's previous labor-intensive manual calibrations. The model performance also rivals that of a state-of-the-art deep learning model at a fraction of the computational cost. This framework presents a new standard for the quality of calibrations possible with lumped conceptual hydrologic models, combining careful data curation, an objective calibration framework, and expert local knowledge. In addition, we have made software packages available for the entire suite of National Weather Service River Forecast System models, including SAC-SMA, SNOW-17, and Lag-K. These modern interfaces are intended to increase accessibility and facilitate future research.

1 | Introduction

The Northwest River Forecast Center (NWRFC) is one of thirteen River Forecast Centers (RFC) 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 rivers across the Pacific Northwest in the Columbia River Basin and Coastal Basins in Washington and Oregon, (2) providing seasonal water volume forecasts and guidance for the region, and (3) supporting decision-making while collaborating with NWS core partners. These partners include federal, state, and local government agencies and private companies that oversee water management, environmental stewardship, power generation, and emergency response. The Pacific Northwest region is composed of a wide range of hydrologic conditions including rain-dominated, snowmelt-dominated, glaciated, tidally influenced, and arid basins. Some watersheds 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 hydrologic models developed by the NWS representing snow, soil moisture, routing, channel loss, and consumptive use processes to develop river forecasts for numerous points across the region. The NWS River Forecasting System (NWSRFS) was initially developed in the late 1970s but continues to be utilized today as part of the NWS Community Hydrologic Prediction System (CHPS) (Anderson 2002a and Schaake et al. 2007). Hydrologic forecasts produced by the NWS RFCs remain the official river forecasts of the NWS, providing stage and streamflow forecasts at approximately 3600 discrete locations within watersheds that flow into and through the US and its territories. The NWS Office of Water Prediction (OWP) also provides unofficial river forecasting guidance using the National Water Model (NWM) (Cosgrove et al. 2024), which is an independent modeling system from those used operationally by the RFCs.

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 an effort to modernize its calibration approach by using a new forcing dataset, new zone delineations, better representing hydrologic fluxes, transparently validating models, expanding performance metrics, and applying modern computational capabilities via an automatic calibration system.

To translate precipitation into streamflow, RFCs rely on three models: SNOW-17 for snow accumulation and ablation, the Sacramento Soil Moisture Accounting Model (SAC-SMA) for hillslope routing, and UNIT-HG for inner basin routing. While the NWRFC employs all three models in conjunction, other RFCs operating in regions with minimal snowmelt will omit SNOW-17. Previous studies have successfully used auto-calibration with some or all of these models. Newman et al. (2015 2022) auto-calibrated these models for 671 headwater basins across the contiguous US spanning a range of hydrologic conditions. They calibrated 11 SAC-SMA parameters, 6 SNOW-17 parameters, and 2 parameters for UNIT-HG with a Root Mean Square Error (RMSE) objective function. RMSE-like objective functions more heavily weight high flows due to the square term, which can be a benefit for flood applications but can produce biased or poor quality simulations during low flow periods. Gupta et al. (1998) used 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 setting where a single calibrated model is needed. Hogue et al. (2000) developed a multistep auto-calibration scheme which mimics the best aspects of a manual calibration process but cuts down on the overall time spent calibrating. They calibrated 15 parameters overall in 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 has been shown to work well with smaller parameter sets but struggles with a larger number of parameters.

Recent advances in deep learning, specifically long short-term memory (LSTM) models, have been applied to hydrologic modeling with impressive results (Feng et al. 2022 and Konapala et al. 2020 and Kratzert et al. 2019 and Nearing et al. 2021 and Shen 2018). While these approaches perform well for unimpaired basins, capturing the effects of reservoir regulation and water withdrawals is difficult due to lack of data and nonstationary human water management and use practices. Operational river forecasting must include accurate reservoir operations, water withdrawals, and routing from upstream reaches. In the US, this involves active coordination between multiple federal, state, and local water management agencies, as well as private utilities who oversee releases from their respective reservoirs.

In this paper, we present a comprehensive approach for hydrologic model calibration for use at the NWRFC that is tailored for an operational setting. Our goals were to develop a flexible, reproducible, high-performing auto-calibration methodology that can accommodate most NWRFC basins. The diversity of models calibrated include those with multiple zones, routed upstream flow, channel losses, consumptive use, and up to 90 parameters. Section 2 discusses the existing modeling system at the NWRFC, Section 3 describes the data used for calibration, Section 4 discusses the auto-calibration system developed by the NWRFC for model parameterization, Section 5 describes the software packages which call the NWSRFS models that have been publicly released, Sections 6 and 7 provide calibration results, and Section 8 provides discussion and conclusions.

2 | Existing Modeling System

The NWRFC uses a suite of models available to all RFCs to forecast stage and streamflow at a location. The location of the forecast point normally coincides with longstanding streamflow observation gages like those maintained by the United States Geological Survey (USGS). Typically a streamflow gauge needs an observed record of at least ten years to be a suitable candidate as the basis for model calibration in order to include the forecast point operationally. Figure 1 illustrates the NWRFC domain, including forecast points (black dots) and prominent river reaches (blue lines). To provide geographic context, the Columbia and Snake River mainstems, the two largest river systems in the NWRFC domain, are emphasized with increased line weights. Each forecast point represents a distinct NWSRFS model segment, interconnected via

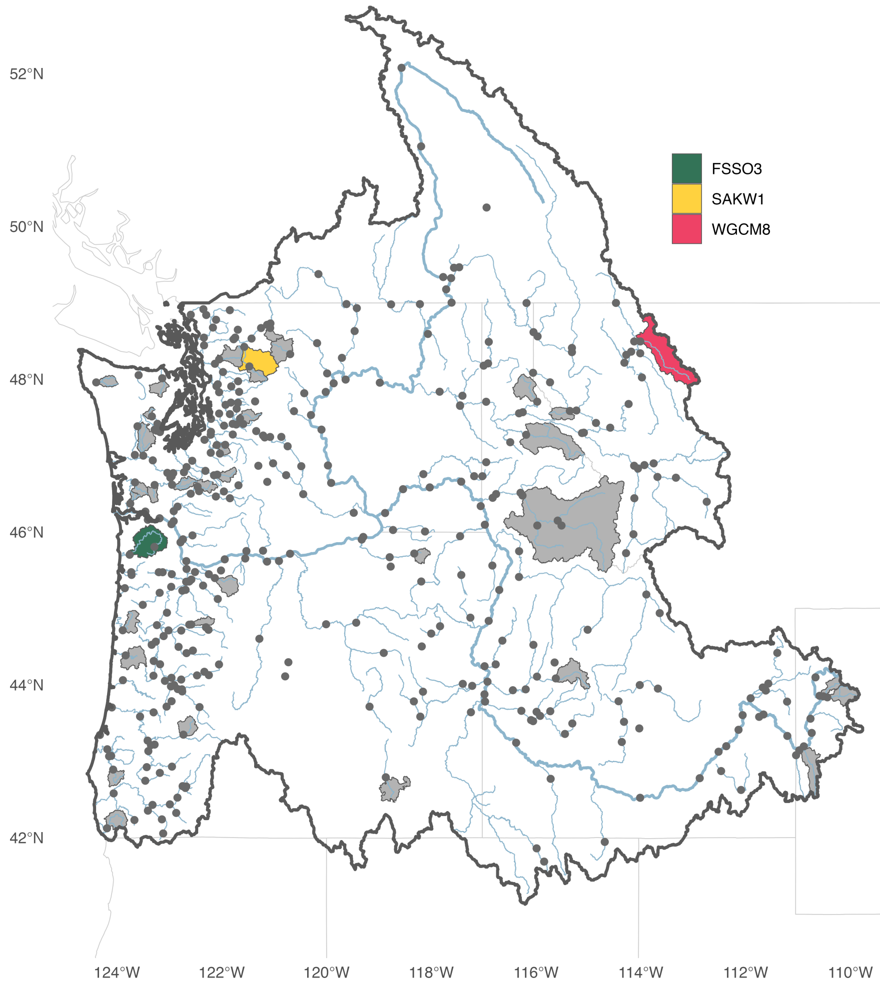

FIGURE 1 | Map of the NWRFC domain (thick black outline), forecast points (black dots), and primary river reaches (blue lines). The mainstems of the Columbia and Snake Rivers are highlighted with increased line weight. CAMELS basins are shaded grey, while the three case-study basins are highlighted in color.

hydrologic routing and requiring rigorous calibration before operational deployment. The grey shaded areas represent unimpaired basins from the Catchment Attributes and Meteorology for Large-sample Studies (CAMELS) dataset (Newman et al. 2015 2022), further detailed in Section 6. Finally, the colored watersheds highlight the three specific basins selected for the case studies presented in Section 7.

The NWRFC model suite is composed of three core models to translate precipitation to streamflow (SNOW-17, SAC-SMA, and UNIT-HG), the Lag-K hydrologic routing model, and three supplemental models used for specific circumstances. The supplemental models are Channel Loss (CHANLOSS) for computing losses and gains along river reaches, the Consumptive Use Operation (CONS_USE) for irrigation water withdrawals, and Streamflow Synthesis and Reservoir Regulation System (SSARRESV). For any given basin, the supplemental models can be deployed in any combination, or omitted entirely, to modify the simulations produced by SNOW-17, SAC-SMA, UNIT-HG, and/or by Lag-K.

The general procedure for linking these models in an operational setting is as follows: SNOW-17 requires meteorological inputs of precipitation accumulation, air temperature, and percent precipitation as snowfall (PTPS) to produce an estimate of rain plus melt runoff (RAIM). SAC-SMA uses RAIM and evapotranspiration demand (ETD) as modeling input and simulates water moving through both the shallow soil column and overland flow to produce total overland and channel flow (i.e. runoff). The runoff is routed to the basin outlet with the UNIT-HG model. The Lag-K model accounts for the lag and attenuation of streamflow routed from upstream forecast points. If the watershed characteristics dictate it, the streamflow simulation can be further modified by any of the three supplemental models to accurately capture gains, losses, or storage. Figure 2 shows the connectivity of these models.

A single instance of the set of models can be used to represent the entire lumped watershed, or alternatively, multiple model sets can be used to represent discrete portions of the basin, often referred to by the RFCs as zones. Each zone

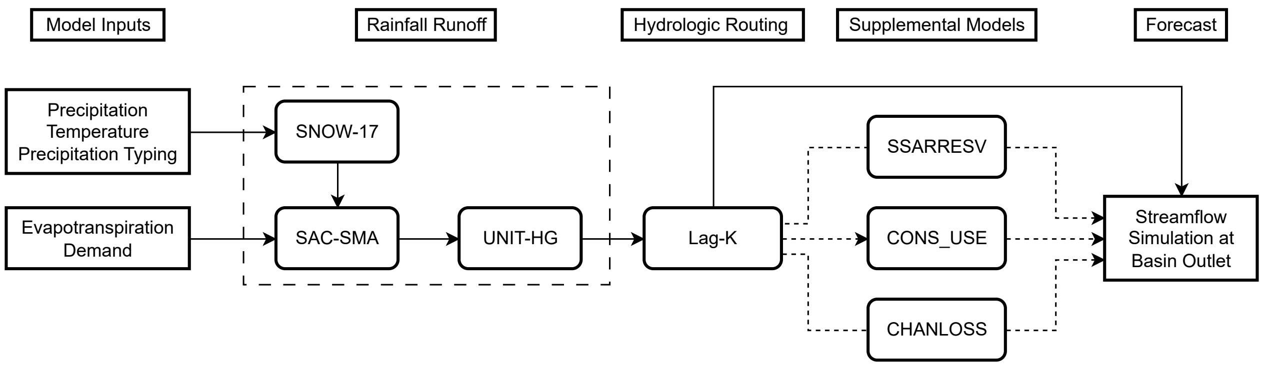

FIGURE 2 | The operational models used by the NWRFC for forecasting. See Section 2 for complete details on each model.

(traditionally delineated based on elevation) has its own unique parameter set corresponding to SNOW-17, SAC-SMA, and UNIT-HG. The simulated streamflows from each zone are combined to produce the total basin contributing flow at the outlet before Lag-K and the supplemental models are applied as needed. The following sections provide an overview of the models used by the NWRFC for operational forecasting; for complete technical specifications, please refer to the relevant manuals.

2.1 | SNOW-17 - Snow Accumulation and Ablation

The SNOW-17 model is a lumped temperature-indexed snow accumulation and ablation model (Anderson 2006). The time series inputs to SNOW-17 are precipitation accumulation, air temperature, and PTPS. The physical processes of accumulation and ablation of snow cover are captured by the model but in a simplified form. The model uses precipitation and PTPS to inform the accumulation of snowmelt. The model captures air temperature sensitivity and its impact on the melt rate through the use of a seasonally varying melt factor (Figure 3, left). The energy and mass balance are captured in an accounting component within the model that tracks the snowpack heat deficit, liquid water ratio, and snow-covered area. The heat deficit needs to rise to 0°C and the melted water stored in the snowpack has to rise above the 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). The primary output of the SNOW-17 model is a time series of simulated RAIM for the modeled basin or zone which is used as an input to SAC-SMA. SNOW-17 also outputs several state variables such as snow water equivalent (SWE) depth and areal extent of snow cover (AESC) which are useful operationally to validate and tweak model performance.

2.1.1 | Glacial Zones in SNOW-17

Eleven basins within the NWRFC domain contain permanently glaciated areas; these are delineated into distinct zones to accommodate their specialized model configurations (Anderson 2002a). The SNOW-17 model for glacial zones must account for effectively unlimited available melt. The approach for modeling glacial zones with SNOW-17 differs in three key ways. First, the initial snow water equivalent depth is set very high so that it never melts off completely. Second, the liquid water ratio accounting is turned off. Finally, the snow is always assumed to cover the entire area. Other components of the SNOW-17 model, such as seasonally varying melt factor and the heat deficit, are modeled similarly to non-glaciated zones.

2.2 | SAC-SMA - Hillslope Runoff

SAC-SMA is a conceptual soil moisture and hillslope runoff model (Burnash et al. 1973 and Anderson 2002b). SAC-SMA inputs are RAIM from the SNOW-17 model and a time series of ETD. The model contains several interconnected parameterized buckets which fill and drain according to the model parameters. These buckets simulate discrete aspects of the rainfall-runoff process such as impervious runoff, surface runoff, interflow, and baseflow (Figure 3, right). SAC-SMA also accounts for losses from evapotranspiration, riparian vegetation, and deep ground water recharge. 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 more detailed overview of the SAC-SMA model is provided in the manual (Anderson 2002b).

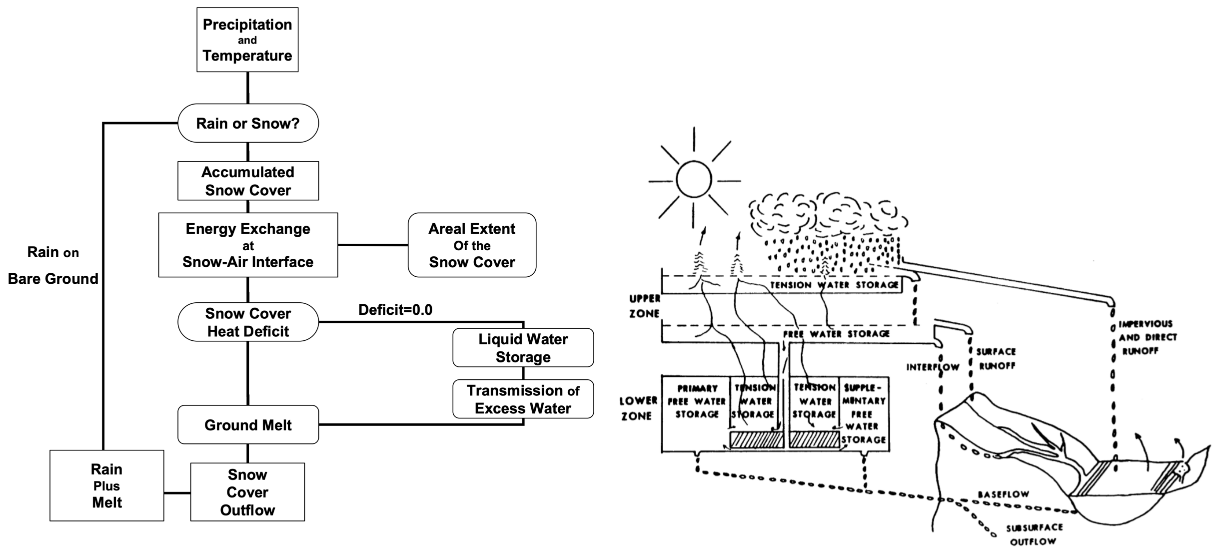

FIGURE 3 | SNOW-17 diagram (left) from Anderson (2006) and SAC-SMA diagram (right) from Anderson (2002b).

2.2.1 | Glacial Zones in SAC-SMA

For glacial zones, only certain components of SAC-SMA are used, primarily those that control the attenuation of water through the soil column due to the frozen ground conditions. The following components are disabled: tension water storage, impervious runoff, evapotranspiration, and losses from riparian vegetation (Anderson 2002a).

2.3 | UNIT-HG - Inner Basin Routing

The primary output of SAC-SMA is a time series of combined overland and channel flow which represents the available water in a basin that needs to be routed to the outlet. A unit hydrograph is an empirical hydrologic method for representing a basin's outlet hydrograph from a known quantity of runoff uniformly available within a basin or zone for each modeled time step. This approach is available in the UNIT-HG model which computes 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 UNIT-HG model does not consider the excess water until it either becomes overland flow or enters the channel system (Anderson 2002a). This routing method differs 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 UNIT-HG model and the zone hydrographs are added together to form the outlet hydrograph for the basin. We note that Unit Hydrographs and their parameters are not typically measurable, though in some cases they can be estimated from data in specific circumstances. See Section 4.8.2 for more details on how these parameters were estimated during calibration.

2.4 | Lag-K - Hydrologic Routing

Typically, the RFCs route a streamflow simulation downstream to the next forecast point using a hydrologic routing approach to capture lag and attenuation in the hydrograph. In lower river reaches where local inflow entering the stream channel between two forecast points is negligible, a hydrologic routing model is used exclusively. Conversely, when local inflow is significant, Lag-K is supplemented using additional SNOW-17, SAC-SMA, and UNIT-HG models. There are multiple hydrologic routing models used by RFCs, but for this approach Lag-K was exclusively used. 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 (Linsley et al. 1982). It is a flexible method of routing since both the lag and k elements can be either constant or a function of streamflow magnitude (National Weather Service 2002). For this study, a lookup table was used for both the lag and k parameters based on upstream flow.

2.5 | Additional Models

There are three supplemental models utilized at the NWRFC. The use of these models for a particular basin depends on specific local conditions.

The 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 (National Weather Service 2003a). The magnitude of these fluxes is calculated either as a percentage of the simulated streamflow or as a constant fixed value. Additionally, the model allows for temporal flexibility, enabling unique values to be defined for each month.

The CONS_USE model accounts for surface water diverted for irrigation based on crop ETD and irrigation efficiency (National Weather Service 2003b). It also includes a parameterized lagged return flow component, modeled similarly to SAC-SMA, using a single conceptual bucket. Other water demands, such as municipal and industrial use, can be captured using the CHANLOSS model.

Between the thirteen NWS RFCs, there are several different reservoir regulation models used: Single Reservoir Regulation Operations (RES-SNGL), Joint Reservoir Operations (RES-J), U.S. Army Corps of Engineers Hydrologic Engineering Center Reservoir System Simulation (HEC-ResSim), and SSARRESV. Generally, all these reservoir regulation models are used to model the effects of reservoir storage and releases on streamflows. NWRFC exclusively uses the SSARRESV model (National Weather Service 2004). The NWRFC coordinates with local water managers to input accurate regulations into these models operationally. Although used operationally, SSARRESV is not used in the model calibration process (see Section 3.2 for details).

3 | Calibration Data

3.1 | Meteorology Inputs

The NWS's Analysis of Record for Calibration (AORC) is a multi-decadal, high-resolution dataset containing all weather information necessary as forcings for land-surface and hydrologic models. It includes the period 1979-Present, hourly data on a 30" (0.008333°) latitude/longitude grid. 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 US (Fall et al. 2023).

The AORC variables used for this study are 2-meter above ground air temperature, specific humidity, terrain-level pressure, and precipitation accumulation. Variables other than precipitation are instantaneous at the start of the hour; precipitation accumulation ends at the given hour. We used specific humidity and terrain-level pressure grids to derive PTPS (Section 3.1.2). For each time step, basin or zone average air temperature, precipitation accumulation, and PTPS values were calculated and used as forcing input for the SNOW-17 model. The zone average air temperature was also used to calculate PET (Section 3.1.1).

3.1.1 | Dynamic Evapotranspiration

ETD is used as input to SAC-SMA and removes water from the model's soil tension water components. Monthly crop coefficient parameters PEadj are used to convert the potential evaporation (PET) to ETD. Previous NWRFC operational SAC-SMA models used a static daily ETD regardless of basin conditions. For the new calibration approach, the Hargreaves-Samani equation was used to calculate daily PET (Hargreaves and Samani 1982). This equation is a temperature-indexed evaporation approach, but also incorporates extraterrestrial radiation (calculated based on latitude and day of year) given by

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

where T_a, T_x and T_n are daily average, max, and min temperatures, respectively, R_e is extraterrestrial radiation, λ is the latent heat of vaporization, and C_1 and C_2 are fitting coefficients. Twelve unique calibrated C_1 coefficients were used, corresponding 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. Air temperature inputs were basin or zone averaged.

The PEadj parameters were derived using the remote sensing-based methodology established by Kamble et al. (2013). The underlying remotely sensed dataset used was the Vegetation Index and Phenology Vegetation Indices due to its high temporal overlap with the calibration period, gap-filled nature, and acceptable spatial resolution (5.6 km) (Didan et al. 2015 and Didan and Barreto 2016). From the continuous data, basin or zone averaged monthly PEadj factors were calculated for the 15th of each calendar month. Similarly to the C_1 coefficients, for days between the 15th of each month, the factors were linearly interpolated using the adjacent months.

3.1.2 | Precipitation Typing

PTPS is one of the three inputs to the SNOW-17 model, and is used to partition the precipitation between rain or snow within the model to aid in calculating RAIM and update internal model states (Figure 3, left). Historically, to derive PTPS the NWRFC relied on a representative air 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 was precise for individual storms.

For this recalibration effort, we used specific humidity and terrain-level pressure from the AORC gridded dataset to derive surface wet-bulb temperatures. NWS Western Region guidance uses a standardized approach in which a wet-bulb temperature of 0.5 °C is equivalent to the rain-snow level (Cleave et al. 2019). Based on this guidance, a terrain-level precipitation typing grid was generated for each time step using a wet-bulb temperature threshold of 0.5 °C, where values below the threshold are assigned a 1 (snow) and values above are assigned a 0 (rain). The binary grid values were converted into basin or zone averaged time series of PTPS, which was used as input for the SNOW-17 model.

3.2 | Streamflow Data

Hydrologic models developed for operational forecasting by an RFC are typically set at locations that are also occupied by an established measurement station that collects streamflow observations. Prior to beginning a calibration, we collected all subdaily instantaneous and daily average streamflow observations at calibration sites for the same temporal period for which AORC data were available (1979-present). When daily average streamflow was unavailable (e.g., the station was not established until after the start of AORC availability), we imputed the daily average data.

Statistical estimation of missing streamflow records, also known as imputation, is a common practice for supplementing hydrologic records with gaps in the observations. Traditional imputation methods include regression and resampling techniques (Hirsch 1982 and Hamzah et al. 2021). Recently, machine learning approaches have been shown to be effective for imputing hydrologic data (Wangwongchai et al. 2023). For this study, we imputed missing daily average streamflow data using the MissForest algorithm (Stekhoven and Bühlmann 2011), a random forest-based algorithm implemented in the missRanger R package (Mayer 2024). To assess the quality of the imputed data, we cross-validated the analysis using available streamflow records by randomly dropping 50% of the data at a time and imputing the rest. We compared the imputed values to observations and assessed performance using coefficient of determination (R^2), Nash-Sutcliffe Efficiency (NSE), and percent bias (PBIAS). We repeated this analysis five times and averaged the results to assess overall imputation performance. Additionally, we performed imputation using a linear regression model to provide a performance baseline. Performance of the MissForest algorithm is generally very favorable with imputed values showing high R^2 and NSE and low bias. On average the MissForest imputation algorithm performed 43% better than the linear regression model (average NSE of 0.90 vs. 0.58).

3.2.1 | Streamflow Data for Routing

Instantaneous and daily observed streamflow data were collected at upstream locations to serve as input for the Lag-K routing model. Where data gaps existed in the daily record, values were imputed using the methodology discussed in Section 3.2.

To produce a continuous subdaily time series, the CHPS AdjustQ methodology (Deltares 2021) was applied to merge instantaneous and daily observations. AdjustQ uses instantaneous data to ”shape” the daily streamflow; for periods where instantaneous data are unavailable, simulated streamflow from the upstream model is used as a substitute.

The SSARRESV model was not recalibrated as part of this framework. Instead, when an upstream forecast point represented reservoir inflow, observed reservoir releases were used as the routing source. Similar to other locations, AdjustQ merged the instantaneous and daily release observations. However, for reservoir releases, no upstream simulation data were used to fill gaps in the instantaneous record; the merge relied strictly on the available observed datasets.

3.2.2 | Naturalized Streamflow Data

The NWRFC has an internally developed naturalized streamflow record at each of its forecast points with a period of record (POR) of 1980 to 2020. The dataset is used to establish climatological normals associated with its seasonal volume

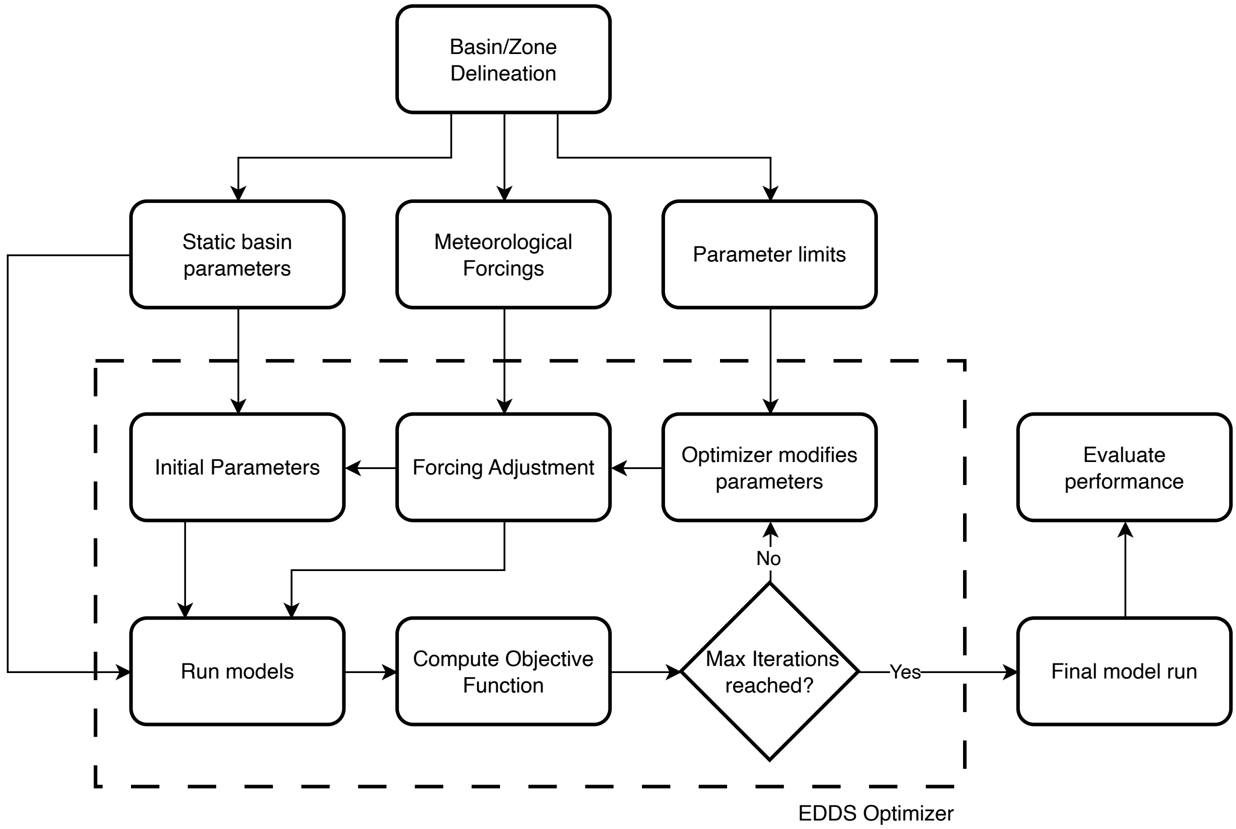

FIGURE 4 | Flowchart of the NWRFC auto-calibration processes for utilization of the EDDS optimizer.

forecasts published by the NWRFC. For the dataset development, the effects of any upstream model use of CHANLOSS, CONS_USE, or SSARRESV to account for anthropogenic impacts are removed from the historical record. This dataset was used in this study to aid with the statistical clustering of modeled basins to establish parameter limits (See Table B2 in Appendix B) but not used directly for calibration.

4 | Automatic calibration

Auto-calibration of models attempts to estimate unknown parameters by comparing model output to observations and formulating an optimization problem to solve for the unknown parameters. The procedure involves selecting a calibration algorithm, identifying an appropriate objective function, choosing which parameters to optimize, and establishing their constraints (typically upper and lower limits). For each iteration, the optimizer selects a specific parameter set used to run the model, which is then compared against observations to compute the performance metric (objective function). The optimizer uses a specific algorithm to maximize the objective function value by modifying the unknown parameters within given limits. After a predetermined stopping criterion is reached (typically a pre-specified maximum number of iterations or a change tolerance between iterations), the optimizer stops and the final parameter set is further evaluated. This section describes the methodology for auto-calibration used by the NWRFC for a single basin. The algorithm has interconnected processes, some of which continuously exchange information, in an effort to select NWRFC model parameters that best suit the selected objective function (Figure 4). Design decisions and special considerations associated with the processes, illustrated in Figure 4, are discussed in detail.

4.1 | Optimization Algorithm

A variant of the dynamically dimensioned search (DDS) algorithm (Tolson and Shoemaker 2007) was developed for optimization of model parameters. DDS has been recognized as a robust tool to perform hydrologic model optimizations

(Arsenault et al. 2014). The DDS algorithm is not designed to find global optimal parameter values but instead to find reasonable parameter values within a given computational budget (i.e. iteration limit). Initial NWRFC testing found that a 10,000-iteration DDS run on a single CPU core yielded run times and performance comparable to other statistical optimizers. This was true even when compared to algorithms like particle swarm optimization (PSO), which typically utilizes multiple cores and significantly more iterations. The computational efficiency gained opened up the possibility that each CPU core could run an independent auto-calibration of the DDS optimizer in parallel, with the best result from all of the parallel runs used as the final solution. Running the DDS optimizer independently on multiple CPU cores simultaneously is referred to as an embarrassing parallel approach (EP-DDS). Another parallel DDS implementation approach was explored by B.A. Tolson (2014) where, in contrast to the EP-DDS approach, there are frequent routine check-ins to exchange information between the optimization runs on each CPU core (P-DDS). Their study found that there is no clear winner between EP-DDS and P-DDS, but each has a distinct advantage depending on how close an optimization run on each CPU core is to its iteration limit. B.A. Tolson (2014) 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 B.A. Tolson (2014) to utilize the strengths of both EP-DDS and P-DDS, we developed a technique where the frequency of information exchange between independent parallel optimization processes increases as iterations progress. For example with a 10,000 iteration budget, initially the parallel processes only exchange information every 1,000 iterations, to closely resemble a EP-DDS 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). An auto-calibration run can be completed on a modern laptop in about 10 minutes.

4.2 | Objective Function

The NWRFC auto-calibration approach allows for the use of various objective functions. One simple choice for objective function is to use one of the desired model performance metrics such as RMSE, NSE, Kling-Gupta Efficiency (KGE), and R^2. The objective function value can be calculated on either average daily flow data or instantaneous data at the model time step. In practice, a single objective function often used with univariate optimization algorithms and multiple objectives are used with specialized multi-objective optimization algorithms (Gupta et al. 1998). Alternatively, two or more objective functions can be combined as a weighted sum and used as a univariate objective function values (Madsen 2000). This type of combined objective function is a practical alternative to multiobjective optimization. While multiobjective approaches provide detailed information about tradeoffs, they can be difficult to interpret in an operational setting where a single model solution is often preferable.

The choice of objective function is an important step in any calibration workflow and can significantly impact the calibrated parameters and model performance. We explored different combinations of metrics and time steps to derive a suitable operational model for site-specific needs. In general, we found that calibrations at the NWRFC are most successful when metrics are combined to emphasize both location-specific high and low flows.

4.3 | Optimized Parameters

Calibrators configure the auto-calibration run by selecting models appropriate for the basin's characteristics (e.g., local runoff, routing, losses); however, the set of parameters optimized for those models is fixed. Generally, we did not optimize parameters if we could observe or derive a measurable physical value for a specific basin. Examples of this would be basin area, mean elevation, effective forest cover, travel time to the outlet, and latitude. Other parameters were not optimized when they represented the limits of an assumed physical process. These were exclusively SNOW-17 parameters and they included: maximum negative melt factor, antecedent snow temperature, base temperature for non-rain melt, maximum percent of liquid water held in the snowpack, and daily melt at the snow-soil interface. In both instances, these parameters which are either measurable or represent physical limits are referred to as static parameters. However, the majority of parameters associated with NWRFC models cannot be directly linked to measurable basin attributes, and were optimized during the calibration process (Table 1).

For glacial zones, the SAC-SMA parameters uztwm, lztwm, adimp, pctim, pfree, and riva, as well as the SNOW-17 areal depletion curve (ADC) and si, are not optimized. The SNOW-17 parameter mbase is only calibrated for glacial zones.

SNOW-17	SAC-SMA	Unit Hydrograph	Lag-K	CONS_USE	CHANLOSS
adc	adimp	shape	var_lag	accum_rate	adj_factor
mfmax	lzfpm	scale	var_K	decay_rate	
mfmin	lzfsm			irr_eff	
scf	lzpk				
si	lzsk				
uadj	lztwm				
mbase	pctim				
	pfree				
	rexp				
	riva				
	uzfwm				
	uzk				
	uztwm				
	zperc				

TABLE 1 | Model parameters that are optimized as part of the auto-calibration procedure.

4.4 | Initial Conditions

Prior to executing any model run in the optimizer, reasonable initial model states must be established, which are commonly referred to as cold states. These states represent the pre-existing volume of water in the soil column, channel, or held frozen in the snowpack when the model is initialized. The start date of a model run is always set to October 1, so it can be assumed that there is no preexisting snowpack (with the exception of glacial zones). This assumption has been validated multiple times over the years by examining the SNOW-17 model states operationally and using regional snow observations. For glacial zones, the SNOW-17 snow depth is set to be large enough that it never fully melts, which represents year-round snow/ice cover. We also assume that for Lag-K states the upstream river reaches start the model run in baseflow conditions, which has been confirmed using streamflow observations.

Both SAC-SMA and CONS_USE models have components which represent the movement of water through the soil column using a series of linked conceptual buckets of known maximum capacity (uztwm, uzfwm, lztwm, lzfsm, and lzfpm in SAC-SMA and rfstor in CONS_USE). We use a spin-up technique to initialize the water content states at the onset of the auto-calibration run, following an approach similar to the North American Land Data Assimilation System (NLDAS) (Cosgrove et al. 2003). Using the parameters selected by the optimizer, the model is run iteratively for the first water year. At the end of each iteration (September 30), the final states are used to re-initialize the model at the start of the same water year (October 1), in the following iteration. This process repeats until the water content of each bucket at the beginning and end of the first water year converge (within a 1% tolerance) or a predefined iteration limit is reached. Once all the buckets have converged, those bucket volumes are adopted as the initial states. Although this is an empirical approach and not guaranteed to converge, it usually does, and tends to provide acceptable initial states for basins in the NWRFC domain under a wide range of hydrologic conditions. The first year of the simulation used for spin up is discarded when computing the objective function to account for any remaining transience in the initial states.

4.5 | Zone Delineation

Part of the NWRFC calibration process involves exploring if it is advantageous to split a basin into multiple discrete modeling zones. Breaking a basin into zones can be helpful for representing complex terrain, multiple land use types, or distinct dominant hydrologic processes which would not be well captured by a single lumped model. For each zone, meteorological forcings and static parameters are calculated prior to an auto-calibration run.

In the Western US, when snow is prevalent in a basin, two zones have often been 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 threshold was used to delineate the basin into upper and lower zones. For certain complex basins it is sometimes necessary to model the basin with more than two zones.

As part of the new calibration approach, we developed a method for zone delineation that incorporates several recent sources of hydrologic and land surface data (Table 2). The datasets were re-gridded to a common 1-km resolution and k-means clustering was used to classify basin grid cells into a pre-defined number of zones. Due to the role that orographic effects play in many of the hydrologic characteristics utilized, the k-means clustering often followed elevation contours but with additional variability due to changes in forest cover, soil type, or basin aspect (Figure 5). A calibrator will extensively test and compare the appropriate number of zones for each model using performance metric associated with auto-calibration runs. We have found that two zones perform better at most locations with the exception of low elevation basins. Glacial regions, which are typically modeled as their own zone (see Section 2.1.1), were omitted from the k-means clustering.

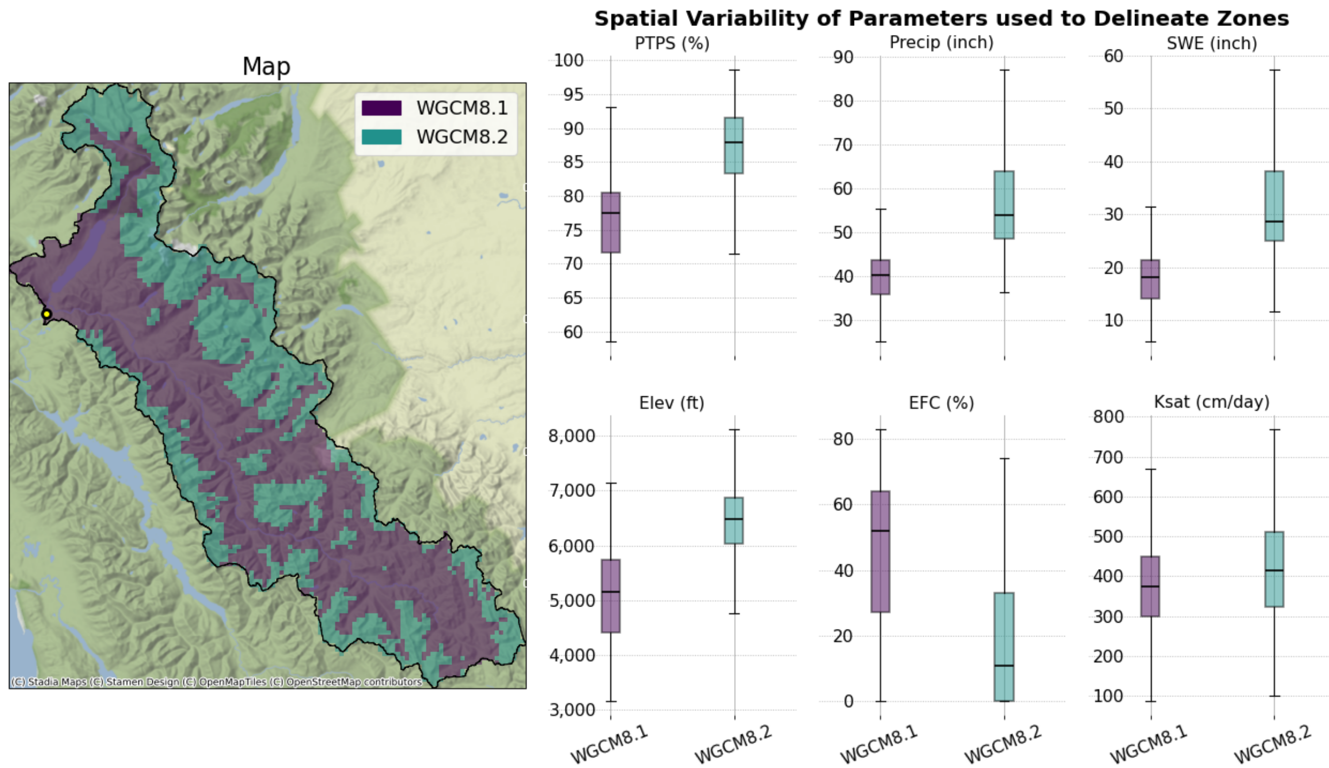

FIGURE 5 | Example basin delineation using k-means clustering for the Middle Fork of the Flathead River near West Glacier, Montana. WGCM8.1 and WGCM8.2 indicate the two zones where zone 1 typically corresponds to lower elevations with the shortest travel time to the outlet. The yellow dot indicates the basin outlet.

Dataset	Data Source	Reference
Average PTPS from Nov-Mar	AORC	Fall et al. (2023)
Average Annual Precipitation Accumulation	AORC	Fall et al. (2023)
Topographical Elevation	USGS	USGS (2023)
Effective Forest Cover	NLCD, Canada	Beaudoin et al. (2014)
Saturated Hydraulic Soil Conductivity	Global Soil Hydraulic Properties	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 2 | Hydrologic characteristics used for clustering and references for each dataset.

4.6 | Basin Parameter Limits

To define appropriate parameter limits for the optimizer, hierarchical clustering was performed to create groups from approximately 325 basins modeled by the NWRFC, ensuring that physically similar basins shared common constraints. Clustering was done using basin averaged hydrologic properties (Table 2) and average daily hydrograph shapes for each modeled basin. Initially, we clustered based on hydrologic properties alone, but the resulting groups were too hydroclimatically diverse. To address this diversity, we imposed a secondary constraint to ensure that groups also shared similar average naturalized hydrographs (Section 3.2.2). This was achieved by modifying the weights to the clustering features in an optimization algorithm which uses the correlation of the natural flow hydrographs of basins in a cluster to compute the objective function:

$$\max \sum_{k=1}^{K} q_{50}(C_k) \quad (2)$$

where K is the number of basin groups (clusters), $q_{50}(C_k)$ is a function that computes the median of all the elements of a matrix C_k, which is the correlation matrix of all the average natural flow hydrographs in a group of basins k.

This approach created groupings of basins which tended to be part of similar hydroclimatic regions (i.e. coastal, arid, etc.), which was adequate for the purposes of creating shared parameter limits. The number of clusters is somewhat arbitrary but should be determined based on the total number of basins to be modeled, the geographic diversity of the basins, and the desired number of groups. We used 25 clusters where each cluster had between 5 and 15 basins. See the supplemental material for details on each cluster of basins.

For each group of modeled NWRFC basins determined by the clustering algorithm, the optimizer parameter limits were collectively shared. This sharing of constraints is conceptually similar to the idea of hydrologic landscape regions (Leibowitz et al. 2016 and Patil et al. 2013). Parameter limits were informed by literature review, prior NWRFC calibration efforts for each basin in a group, NWSRFS calibration literature Anderson (2002a), and trial and error. A final manual review of the limits in each cluster was conducted to ensure reasonable ranges were captured. See Appendix B for a list of typical parameter limits used in this study. We found that appropriate physically realistic parameter ranges are critical for mitigating equifinality (multiple parameter sets with similar objective function values) when using the NWSRFS suite of conceptual hydrologic models (Her et al. 2019).

In the absence of prior calibrations to help set parameter limits, we recommend using a combination of available literature and trial and error. One effective approach is to initially optimize a small subset of parameters while holding the others constant, then iteratively narrow the allowable ranges for that subset. This process can be repeated for other groups of parameters until distinct limits are established for the full set. Once reasonable bounds are determined, all parameters may be optimized simultaneously. Setting large ranges of all parameters simultaneously will likely lead to equifinality or optimizer convergence issues.

4.7 | Climatological Forcing Adjustments

Gridded meteorological observations datasets have some accepted level of spatial and temporal error at any particular grid cell because the data must be interpolated or estimated to derive a complete dataset (Lundquist et al. 2019). The AORC forcing dataset used for this study is no exception (Fall et al. 2023). Errors in gridded meteorological input data can lead to cumulative discrepancies in the model's water balance relative to observations, particularly during calibrations spanning multiple water years.

For the auto-calibration approach adopted by the NWRFC, we assumed that the errors in the AORC dataset relative to climatology could be multiplicative (scaling factors) or additive (bias) on a monthly scale. Adjustments were applied per basin and were allowed to vary independently for each forcing type (e.g. precipitation, air temperature, PTPS, and PET). The optimizer selected a single adjustment factor for each month, anchored to the 15th day of the month (Figure 6). This same value is applied to that month in every simulated year. To avoid abrupt steps between months, daily factors are linearly interpolated between these adjacent mid-month values. We converted the adjusted PET to ETD forcings for SAC-SMA using PEadj (Section 3.1.1).

The adjustment factors were subject to two key constraints. First, the resulting climatology for each forcing type in the calibration POR was required to stay within specific bounds defined by an external gridded dataset (Table 3). Second, to maintain temporal consistency, we imposed constraints using four parameters (Table 4) that preserve the relative ranking of monthly magnitudes, preventing unrealistic shifts in the seasonal cycle. Adjusting forcing data during hydrologic calibration is not standard practice. However, this approach is viable when the forcing data has known, complex biases relative to observations and a high-quality calibration is required. This adjustment technique is akin to an on-demand bias correction which is typically performed as a preprocessing step before calibration.

4.8 | Model Tables and Parameterized Curves

This section describes noteworthy design considerations for parameters that required more complex definition than simply selecting a single value within a range. These parameters represent tables or parameterized curves that require optimization while maintaining both physical realism and temporal consistency. The following subsections detail how these constraints were enforced by optimizing a small number of coefficients that parameterize the tables, rather than optimizing the entire table or curve. We also discuss how limits were imposed on these coefficients to maintain physically realistic processes.

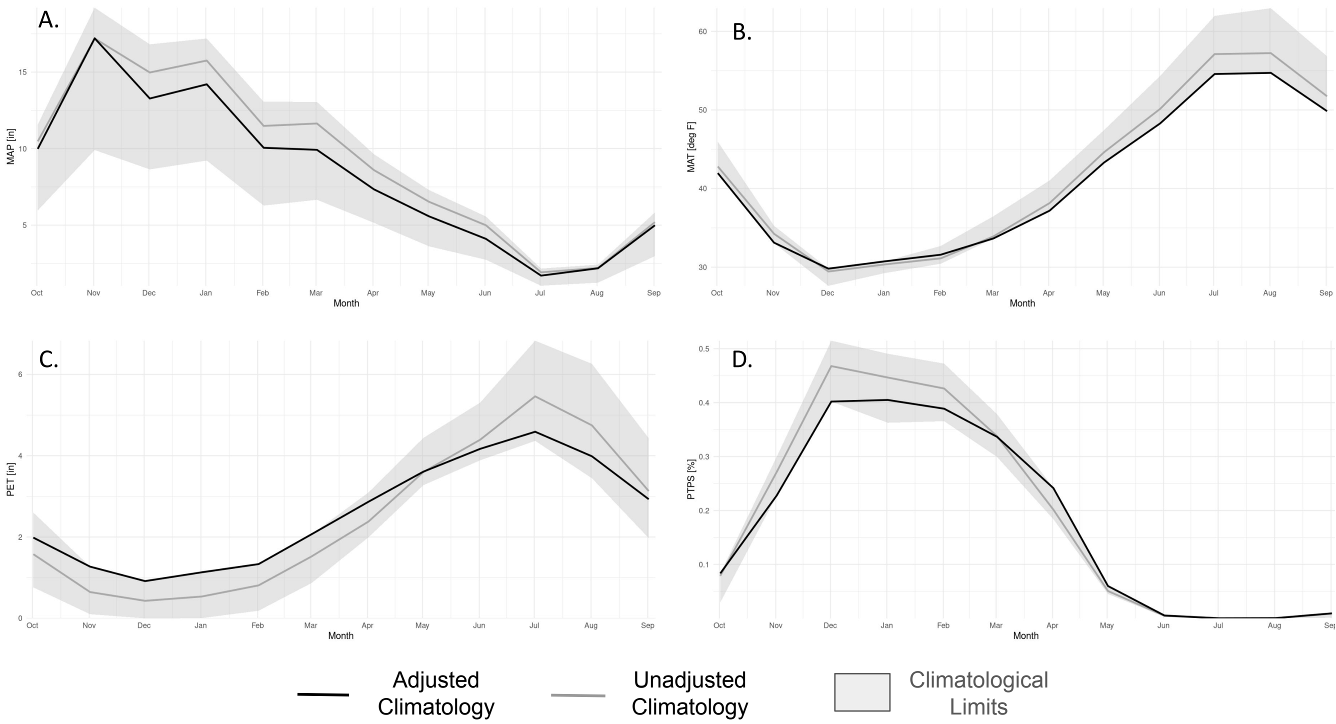

FIGURE 6 | Examples of climatological monthly forcings before (grey line) and after adjustments (black line) applied through optimization during the auto-calibration routine. Imposed climatological limits used during optimization are also displayed (shaded area). A. precipitation (MAP), B. air temperature (MAT), C. evapotranspiration (PET), and D. precipitation typing (PTPS)

Precipitation Datasets	Reference
CHIRPS	(Funk et al. 2015)
ERA	Muñoz-Sabater et al. (2021)
NCAR	Newman et al. (2015)
PRISM	Daly et al. (2008)
Air 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)
Precipitation Typing Datasets	Reference
ERA	Muñoz-Sabater et al. (2021)

TABLE 3 | External gridded datasets for climatological forcing adjustment limits.

4.8.1 | SNOW-17 - Derivation of Areal Depletion Curve

In order to apply SNOW-17 to an area, the model uses an ADC. The ADC is a relationship between the AESC and the basin's SWE Index. The SWE index is defined as the fraction of the current SWE relative to the season's maximum modeled SWE, which we refer to as the areal index (A_i). By design, both the AESC and the SWE index are normalized variables ranging from 0 to 1 and their relationship is expected to be physically reasonable and continuous. To ensure these two requirements are met, the following equation was used within the optimizer:

$$\frac{S}{A_i} = a \cdot A^b + (1 - a) \cdot A^c \tag{3}$$

where S is the SWE, A represents the AESC, and a, b, and c are parameters that were optimized with limits that ensured a physically reasonable result (see Appendix B). In practice, the ADC is typically discretized into 10 evenly spaced points.

Parameter	Description
f_mult	Multiplication factor to apply directly to the forcing.
p_redist	The percentage of the climatological forcing to redistribute.
std	Controls the weighting factor on how the p_redist is partitioned out to each climatological month based on ranking.
shift	Shift the climatological values by x numbers of days in the positive or negative direction.

TABLE 4 | Climatological forcing adjustment parameters

As recommended by the Anderson calibration manual (Anderson 2002a), the ADC was treated as a latent parameterization and no observed data was used to calibrate it directly. The three parameter curve shown in Equation 3 was developed to capture the full range of shapes of previous NWRFC ADCs. Including the ADC as a latent process contributes to the equifinality of the final parameter sets, but this allowed us to avoid the arbitrary manual process used in the past.

4.8.2 | UNIT-HG - Optimization of Unit Hydrograph

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

To constrain the shape of the unit hydrograph, we estimated the maximum travel time for overland flow and channel runoff using the method proposed by Maidment et al. (1996). First, we derived an overland flow velocity grid from USGS National Hydrologic Dataset (NHD) slope and flow accumulation data (U.S. Geological Survey 2023), limiting velocities to a range of 0.02 to 2 m/s. By combining this velocity field with NHD flow direction grid, we calculated the maximum travel time to the basin outlet. This value served as a physical constraint during optimization, limiting the shape and scale parameters to those that produce a unit hydrograph duration (i.e., time base) within 25% of the calculated maximum travel time.

For prior NWRFC calibrations, duplicate unit hydrographs were used for each zone. With the inclusion of auto-calibration, each zone had its own optimized unit hydrograph using the calculated maximum travel time to the basin outlet. In practice, this flexibility improves calibrations by allowing the model to better capture the nuances of both rapid runoff and baseflow. However, in some cases, this added freedom exacerbates the equifinality of the solution space and causes something akin to label switching in hidden Markov models (Bracken et al. 2014 2016). For example, we observed instances where the hydrologic roles of the zones switched between successive optimization runs due to stochasticity in the optimizer. For example, a zone acting as the baseflow component in one run might switch to become the flashy component in a subsequent run. This issue was generally avoided by careful use of parameter limits or a reconsideration by the calibrator of the number of zones used to model the basin.

4.8.3 | Lag-K - Derivation of Variable Lag and K Tables

The Lag-K model characterizes upstream tributaries using two lookup tables for the lag and k parameters. As with the SNOW-17 ADC, these curves are constrained to be physically realistic and smooth. The specific values were determined using:

$$\text{lag or k table entry } i = d(Q_i - g)^2 + eQ_i + f \tag{4}$$

where d, e, f, and g were optimized and Q_i represents streamflow for the ith.

Upper and lower limits for the lag and K tables were established using historical streamflow observations at the upstream point and estimated travel times derived from an assumed velocity range of 1.6 to 11 km/h. Furthermore, restrictions were applied to the lag curve's parameter limits to guarantee a monotonic decrease in travel time as streamflow increases.

4.9 | 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. The overall objective of this process is to assess the quality of the parameterized model produced by the auto-calibration tool and to ensure it does not represent a degradation in performance compared to the current hydrologic model utilized operationally.

In this step an expert human forecaster reviews all the automatically calibrated parameters and examines the model output for inconsistencies or errors. Manual edits can be made to any of the optimized parameters by the calibrator to further improve performance. This step incorporates expert local knowledge and helps to mitigate the equifinality for which conceptual hydrologic models are especially prone (Her et al. 2019). If any issues are identified, they tend to indicate data issues or parameter limits that need to be refined before a new run of the auto-calibration is done.

5 | Accompanying software packages

As part of this calibration effort we sought to improve access to the original NWSRFS Fortran code and provide modern interfaces to the full suite of models used by the RFCs for operational forecasting (see Section 2). To this end, we created packages in R (rfchydromodels) and Python (py-rfchydromodels) that call the original NWSRFS Fortran 77 source code (via Fortran 90 wrappers). The original code has undergone minimal updates to allow it to compile and run on modern systems and the code has been verified to be functionally equivalent to the Java-based implementation used in CHPS. The packages and documentation are available here: https://github.com/NOAA-NWRFC/nwsrfs-hydro-models. Community contributions are welcome.

6 | Calibration Results - CAMELS basins

The CAMELS dataset is a widely used benchmark dataset for calibration and comparative modeling studies (Newman et al. 2015 2022). There are 38 CAMELS basins that share an outlet with an NWRFC forecast point. In this section we provide results for our calibrated models at these points.

Calibration studies often use a single objective function such as 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, which put more weight on high flows. This unequal weighting can misrepresent low flows, which can be just as important as high flows to water managers in the Pacific Northwest due to their impacts to hydropower, fish management, navigation, and recreation. For these reasons we selected a combined objective function which balances low and high flows

$$\max \sum_i \mathrm{NSE}(s_i - o_i) + \mathrm{NSE}(\log(s_i) - \log(o_i)) \tag{5}$$

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

Figure 7 shows cumulative distribution functions (CDFs) of four commonly used metrics: NSE, PBIAS, R^2, and KGE. All metrics besides R^2 have been normalized (nNSE, nKGE, nPBIAS; See Appendix A) to facilitate comparison on a common axis. The figure provides CDFs for calibrations of 27 basins in the NWRFC domain using three modeling approaches: (1) calibrations of the NWSRFS models using auto-calibrated framework described in this paper (black line), (2) calibrations of the NWSRFS models using the legacy NWRFC manual approach (orange line), and (3) a trained LSTM deep learning model from Kratzert et al. (2024). Note that the LSTM was trained on 531 basins across contiguous US and we compute the ensemble mean from the 27 available CAMELS basins that are also NWRFC basins.

In overall quality the auto-calibrations and the legacy manual calibrations exhibit similar performance overall which is notable due to the large difference in the calibration times between the two methods (hours vs days). These auto-calibration metrics are shown prior to any human-in-the-loop adjustments which may improve the results further. The LSTM model tends to outperform calibrated conceptual models in terms of nNSE, which favors mean behavior and weights higher flows more strongly. However, nKGE performance is similar; the LSTM's larger bias offsets its higher R^2 values. These results indicate that for the NWRFC domain an auto-calibrated conceptual model can rival the quality of both expert manual calibrations and state-of-the-art deep learning models at a fraction of the human time and overall computational cost, respectively. We note that basins in the Pacific Northwest tend to perform relatively well in large sample hydrologic modeling studies and this level of quality may not be achievable in other regions (Newman et al. 2015 2022) .

The second set of results is shown in Figure 8, a Budyko diagram (Chen and Sivapalan 2020) for each of the 38 CAMELS basins that share a NWRFC forecast point. A Budyko diagram displays the limits (energy or water) of a basin based on long term averages of ET and precipitation which play a strong role in its overall hydrologic behavior. Basins in the NWRFC domain are typically energy limited due to ample precipitation but some basins particularly on the east side of the Cascade Range can be water limited. We used the KGE metric to evaluate the calibrations (Gupta et al. 1999). Any value above -0.41 indicates a calibration better than the mean, and values closer to 1 indicate better alignment with

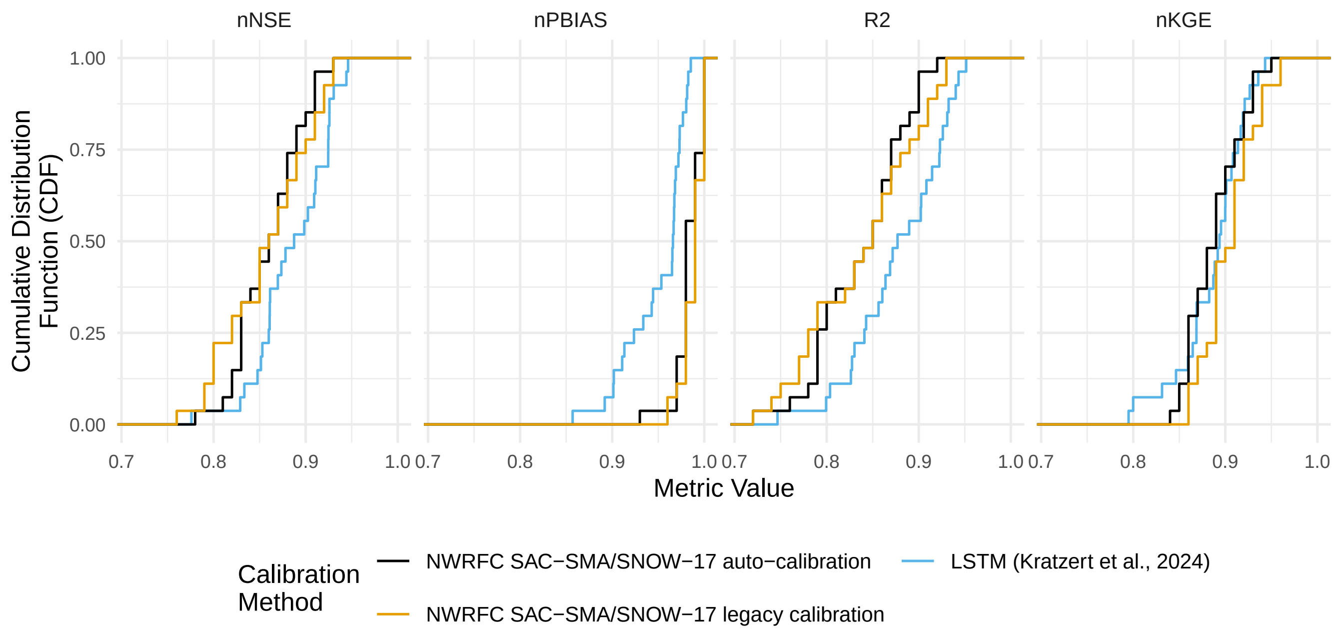

FIGURE 7 | CDF of metrics scores from 27 basins in the NWRFC domain comparing NWRFC calibrations and metrics from a trained LSTM model from Kratzert et al. (2024). All basins are part of the CAMELS dataset. See Appendix A for definitions of the normalized metrics as well as tables of metrics for each basin.

observations (Knoben et al. 2019). The high performance scores (KGE 0.75–0.98) observed across the domain illustrate that the calibration framework effectively captures the wide range of hydrologic conditions across the Budyko space.

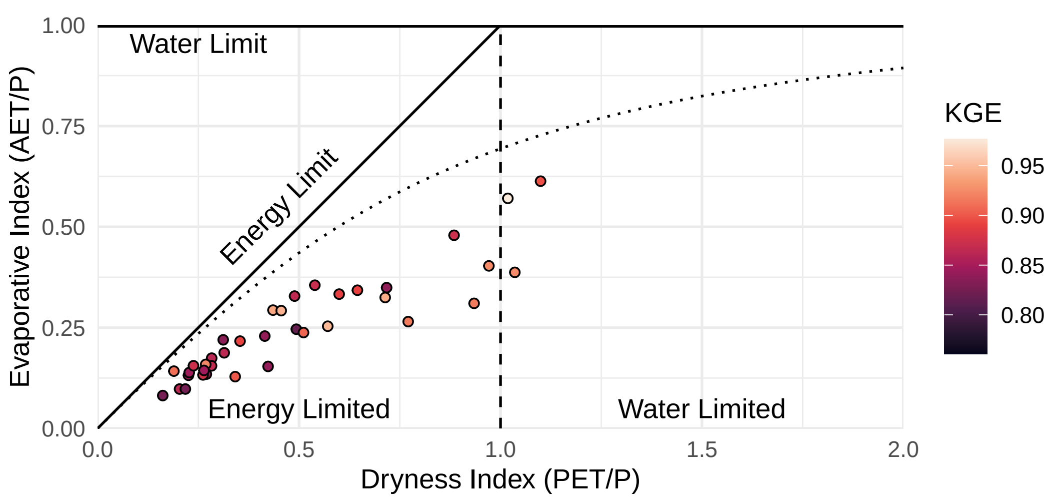

FIGURE 8 | Budyko diagram showing long term behavior of the calibrated simulations for each zone of the three test basins. AET = Actual Evapotranspiration, P=Precipitation, PET=Potential Evapotranspiration, where all values represent long term annual averages, typically 10 years or more.

7 | Calibration Results - Case Studies

In this section we provide a detailed look at the calibration results of three representative CAMELS basins in the NWRFC domain (Figure 1). The first is the Nehalem R near Foss, Oregon (USGS #14301000, NWS ID FSSO3), which is a rain dominated basin with a winter peak and limited snowmelt. The second is the Middle Fork of the Flathead River near West Glacier, Montana (USGS #12358500, NWS ID WGCM8), which is a snow melt dominated basin with a summer peak and limited winter rainfall. The third is the Sauk River Near Sauk, WA (USGS #12189500, NWS ID SAKW1), which is a basin with Lag-K routed upstream inflow and both winter rain and summer snowmelt.

To demonstrate the framework's flexibility in modeling diverse hydrologic conditions, Figure 9 compares continuous simulations with observed streamflow for the three CAMELS basins. These plots highlight the 2019–2022 period, a representative subset of the full POR calibration record (1980–2022). The POR parameters represent the calibration that is used operationally by the NWRFC. The modeled time series (orange) shows good agreement with observations (black), though divergences occur during peak flows and along some falling limbs. This divergence is likely due to the combined objective function which equally weights low and high flows at a daily time step. Figure 10 shows cyclical plots which combine the entire POR continuous simulation. Each year of simulation (1980-2022) is overlaid 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 observed 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 for each of these basins.

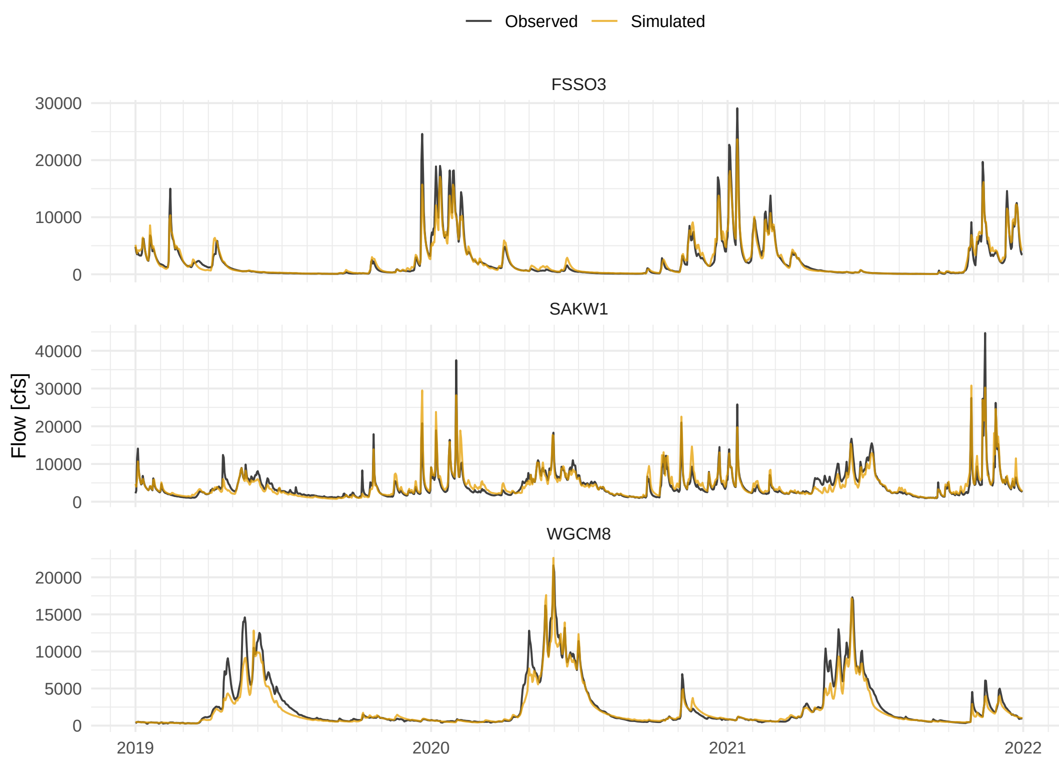

FIGURE 9 | Calibrated continuous simulations (2019–2022) for three diverse CAMELS basins within the NWRFC domain. The black line represents the observed streamflow, while the blue line represents the simulated streamflow.

It is common modeling practice to split the available data record into an independent calibration and a validation period to ensure the calibrated parameters are robust and reliable when the model is used in periods outside of the training data. Models which have notable differences in performance between the calibration and validation periods may suffer from overfitting. Overfitting is a situation in which a model fits well to observed data used for calibration but performs poorly when used on unobserved conditions. While it is typically not a large concern in physically based modeling, it is a concern here due to the flexibility of the conceptual NWSRFS models and the numerous latent parameters optimized by the auto-calibration approach. To ensure the auto-calibration results are robust and reliable (i.e. not overfit), we used two validation techniques to test for this issue: cross-validation (CV) and stationary bootstrapping (SB). We used 4 CV periods, also known as "folds" denoted CV1 through CV4, using 3/4 of the total data as a calibration period and the remaining period (approximately 10 years) as an independent validation period for each fold. There was no temporal

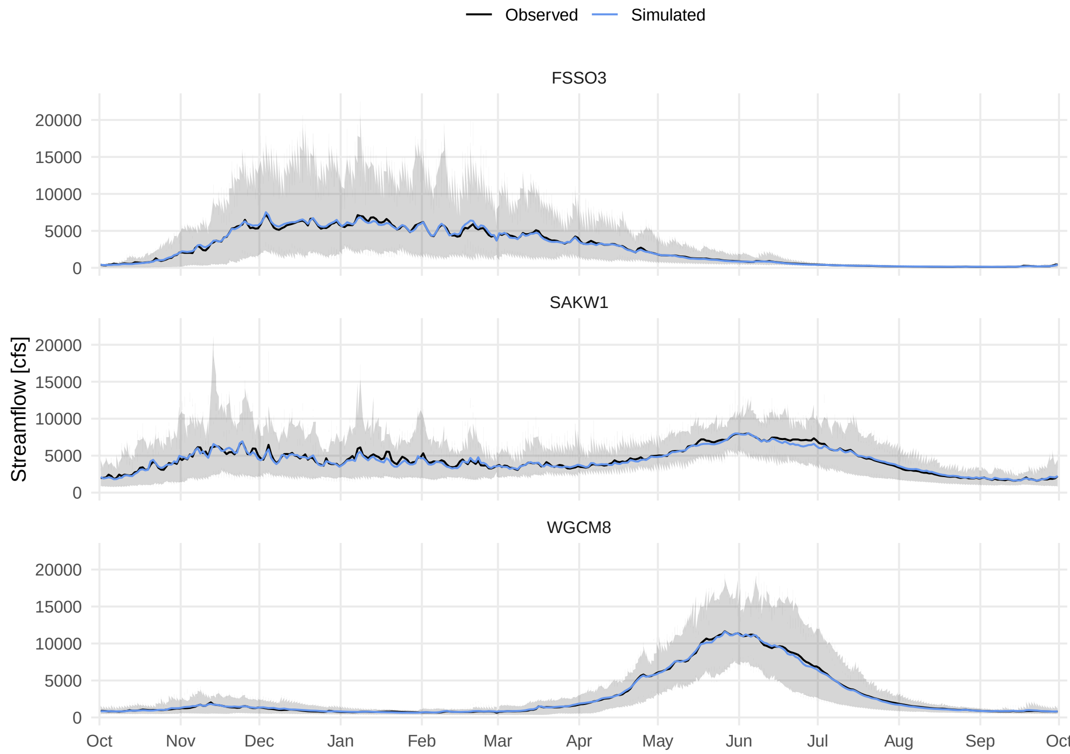

FIGURE 10 | Cyclical streamflow plots showing the daily hydrologic regime from 1980 to 2022. The black line represents the median observed streamflow, while the blue line represents the median simulated streamflow. The grey shaded area indicates the 10th to 90th percentile range of the simulations.

overlap between the 1/4 of the data used for validation from each fold. SB is a resampling technique to aid in identifying optimization parameter overfitting (Politis and Romano 1994 and Politis and White 2004 and Patton et al. 2009). The approach works by randomly sampling complete water years from the POR simulation and stitching them together until it has an equivalent length to the CV fold's validation period. For each randomly sampled record, model performance metrics were computed. In total 24,000 SB records, of approximately 10 years, were sampled for each of the three basins. For a model that is not overfit, the CV metrics should fall within the distribution of the resampled SB metrics. Figure 11 shows the nNSE, nPBIAS, R^2, and nKGE metric scores for each CV fold validation period and compares them to the distributions generated by the SB method, which is presented as a violin plot. The stability of metric scores across the CV folds and their alignment with the SB runs in Figure 11 indicates that the auto-calibration found similarly optimal solutions and that the resulting parameter sets are not overfit to the calibration data.

The NWRFC utilized a climatological forcing adjustment technique (Section 4.7) to allow for corrections of forcing inputs during optimization. To demonstrate both the value added by the technique and that the additional model flexibility does not suffer from overfitting, Figure 11 compares results with climatological forcing adjustments and those without. For all three basins the addition of the climatological forcing adjustments does not result in overfitting, as the CV fold scores in comparison to the SB results are similar whether the method is or is not used. At SAKW1 and WGCM8, the forcing adjustment run provides minor improvement across all metrics, but at FSSO3 the forcing adjustments dramatically improve the validation results, indicating a potential issue with the raw AORC forcings in this basin. These results also indicate that including forcing corrections may not benefit every basin but they do not degrade the performance when used.

8 | Discussion and conclusions

In this paper, we present a comprehensive framework developed by the NWRFC for calibration of hydrologic basins in the Pacific Northwest US. The framework includes snow, soil moisture, routing, channel loss, and consumptive use models. Data inputs include a wide range of open-access sources for meteorological inputs, observed streamflow, land use, topography, and land cover. The framework can account for basins with diverse hydrologic conditions, from rain-dominated

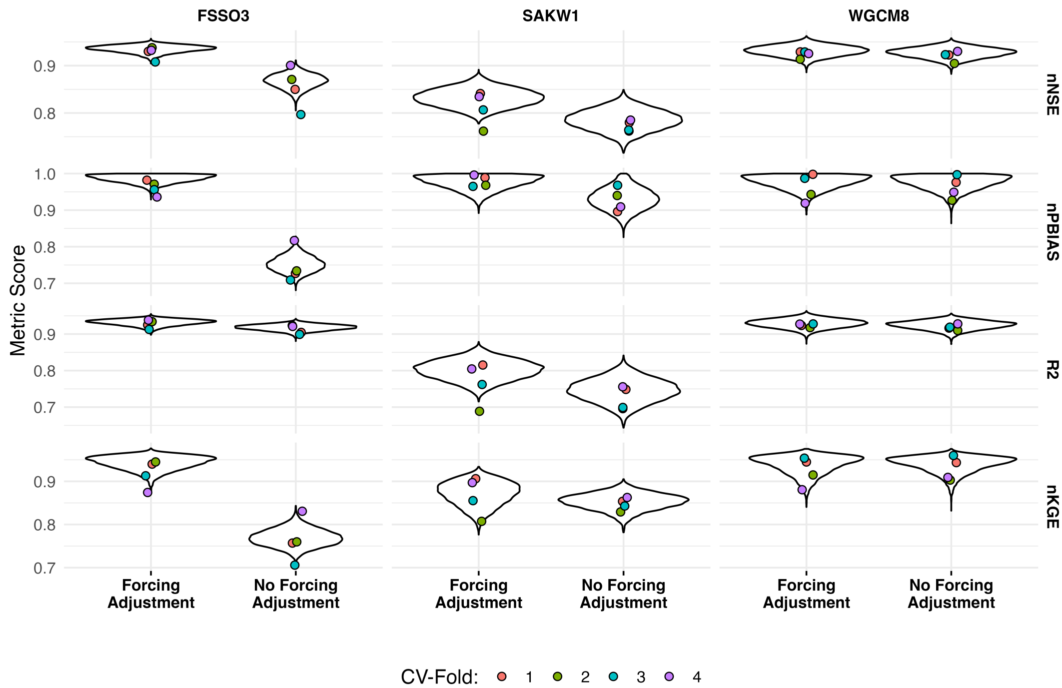

FIGURE 11 | Cross validation (points) and POR bootstrapping (violin plots) metric scores with and without using climatological forcing adjustments

to snowmelt-driven. We have also developed a flexible, objective auto-calibration system that can handle numerous unmeasurable or latent model parameters in a computationally efficient manner. A full auto-calibration run can typically be completed on a modern laptop in under 10 minutes. In addition, we have made accompanying R and Python packages available for the entire suite of NWSRFS models, including SAC-SMA, SNOW-17, and Lag-K. These modern interfaces are intended to increase the accessibility of these models and facilitate future research.

We presented results where we applied this calibration approach at CAMELS basins that are also NWRFC forecast locations, which are representative of the broader set of basins calibrated by the NWRFC. The calibration framework performed well overall, with KGE values ranging from 0.75 to 0.96. From this broader set, we presented detailed results for three specific basins selected for their distinct runoff characteristics (rain, snowmelt, and mixed rain/snowmelt). We provided simulation results from the POR run in comparison to the observed streamflow by presenting a sample of the result from Water 2019 through 2022 and cyclical plot from the full POR calibration record (Figures 9 and 10). In both plots, the simulation is capturing the streamflow response from both winter rainfall and spring snowmelt. The CV results combined with SB have been shared for the three CAMELS basins which provide evidence that the auto-calibration is successfully avoiding the pitfall of model overfitting (Figure 11). The CV and SB results compare performance with and without the climatological forcing adjustment. The findings demonstrate that the approach mitigates aleatory uncertainty in meteorological inputs without inducing overfitting or degrading model performance.

In Figure 7, we present results for 27 CAMELS basins which illustrate that the parameterizations produced by the auto-calibration framework are on par with the performance of legacy NWRFC manually calibrated NWSRFS models. It is not surprising that manual calibrations conducted by expert hydrologists perform better in some basins, however the auto-calibration results shared were produced at a fraction of the human cost and time. In the past, manual calibrations took up to a week of dedicated time from an expert calibrator for each basin whereas now multiple basins can be calibrated in the same amount of time.

In recent years, the rising use of artificial intelligence and machine learning (AIML) models in hydrology has called into question whether traditional hydrologic modeling approaches still have utility (Nearing et al. 2021). We have demonstrated that in the Pacific Northwest US, calibrated lumped conceptual models can rival the performance of a state of the art LSTM deep learning model (Figure 7) at a fraction of the computational cost. The results presented in this paper can serve as a benchmark for new and emerging AIML approaches. In the future we would like to perform calibrations at all CAMELS basins and present the results for benchmarking. An interesting extension of this would involve additional detailed comparisons between new AIML models and the calibrations used in our framework in an attempt to identify where both might be combined or further improved.

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. These hydraulic models are significantly more computationally expensive to run than the conceptual model and was therefore prohibitive to auto-calibrate. Another limitation is that the auto-calibration process does not include 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 and the calibrations it produces to set a new standard for what is possible with lumped conceptual models. This approach reduces the overall resources required when compared to both manual calibrations (labor hours) and AIML model training (computational cost), and enables rapid re-calibrations as new data becomes available. We have demonstrated here that with careful data curation of an objective calibration framework, combined with expert local knowledge, can produce high quality lumped conceptual hydrologic model calibrations that can be used successfully in operational hydrologic forecasting. The NWRFC currently uses this approach to calibrate basins which in turn are being used to produce operational flood warnings and seasonal water volume forecasts.

DATA AND CODE

The Python package nwsrfspy is available on PyPI: https://pypi.org/project/nwsrfspy/

The R package nswrfsr is available on CRAN: https://cran.r-project.org/web/packages/nwsrfsr/

Data used in this paper for analysis and figure generation can be found in (Walters and Bracken 2026b), the code and files for the figures can be found in (Walters and Bracken 2026a), the auto-calibration code can be found in (Walters and Bracken 2026c) and the models can be found in (Walters and Bracken 2026d).

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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APPENDIX

A | Normalized Model performance metrics

Definitions of Nash-Sutcliffe Efficiency (NSE) Nash and Sutcliffe (1970), Kling-Gupta Efficiency (KGE) (Gupta et al. 1998), and percent bias (PBIAS) are widely reproduced in the literature so we will not include them here, but the normalized versions of these metrics are not as widely known. Normalization primarily helps with visualization because the metrics fall in a fixed range of [0, 1]. The interpretation of these metrics is slightly different but analogous to the non-normalized versions. Table A1 provides the normalization formulas, viable ranges, and reference values for each metric.

Metric	**Normalization Formula**	**Original Range**	**Normalized Range**	**Model Mean Reference**	**Perfect Score**
nNSE	$\frac{1}{2-\text{NSE}}$	$(-\infty, 1]$	$[0, 1]$	0.5	1
nPBIAS	$1-\frac{\lvert\text{PBIAS}\rvert}{100}$	$(-\infty, \infty)$	$(-\infty, 1]$	varies	1
R^2	None	$[0, 1]$	—	0	1
nKGE	$\frac{1}{2-\text{KGE}}$	$(-\infty, 1]$	$[0, 1]$	0.415	1

TABLE A1 | Performance metrics and their normalized versions. For NSE, a value of 0 indicates model performance equal to using the observed mean as the prediction (nNSE = 0.5). For KGE, a value of -0.41 indicates performance equal to the mean (nKGE = 0.415). PBIAS measures bias as a percentage, where 0 indicates no bias. The coefficient of determination (R^2) is already bounded between 0 and 1, where 0 represents no correlation (equivalent to predicting the mean).

B | Average parameter limits for the optimizer for all CAMELS basins in the NWRFC domain

	param name	lower	upper	mean
1	adc_a	0.00	0.25	0.25
2	adc_b	0.05	50.00	49.95
3	adc_c	0.50	50.00	49.50
4	adimp	0.00	0.20	0.20
5	lzfpm	146.99	546.62	399.63
6	lzfsm	45.38	156.71	111.34
7	lzpk	0.00	0.01	0.01
8	lzsk	0.06	0.19	0.14
9	lztwm	69.47	235.40	165.93
10	mfmax	0.62	1.17	0.55
11	mfmin	0.13	0.38	0.25
12	pctim	0.00	0.05	0.05
13	pfree	0.14	0.53	0.38
14	rexp	1.30	3.42	2.12
15	riva	0.00	0.20	0.20
16	scf	0.70	1.50	0.80
17	si	1.00	5000.00	4999.00
18	uadj	0.06	0.17	0.11
19	unit_shape	1.01	3.30	2.29
20	unit_toc_adj	0.75	1.25	0.50
21	uzfwm	28.67	87.64	58.97
22	uzk	0.20	0.47	0.27
23	uztwm	41.70	112.19	70.49
24	zperc	24.00	156.66	132.66

TABLE B2 | Average lower and upper parameter limits as well as the average actual optimized value for all 38 CAMELS basins in the NWRFC region.