Benchmarking analog and ensemble-based seasonal forecasting strategies for water management in the Upper Rio Grande basin

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Abstract

In the southwestern US, declining runoff efficiencies driven by a warming climate have undermined the skill of seasonal water supply forecast (WSF) methods used for reservoir management by local to federal agencies. Seasonal water allocations are often based on deterministic inflow sequences, derived by matching historical streamflow traces (analogs) to statistical WSF volumes; yet model-based ensemble streamflow forecasting offers a compelling alternative. We evaluate this alternative through a systematic, hindcast-based benchmarking assessment, applying process-based hydrologic modeling to predict streamflow for US Bureau of Reclamation system inflow points in the Upper Rio Grande (URG). We demonstrate the viability of model-based prediction of disaggregated WSFs for guiding reservoir planning compared to existing analog-based practices, using the Ensemble Streamflow Prediction (ESP) technique to develop a 49-year dataset of April 1st hindcasts. Across thirteen URG forecast points, the bias-corrected ESP mean sequences consistently improved hydrograph shape over analog-based sequences, with a median KGE increase of +0.09. For peak flow characteristics, performance was broadly comparable. These results show that ESP-based predictions of seasonal inflow shape are a compelling option for reservoir management where analog-based methods are still used. This study also presents an early implementation of the SUMMA-mizuRoute framework for regional water modeling and seasonal ESP.

1. Introduction

Water resource management across the snow-fed basins of the western United States (US) critically depends on reliable seasonal water supply forecasts (WSFs) for predicting annual snowmelt-runoff volumes during the spring and summer months. In major systems such as the Upper Rio Grande (URG) basin, these seasonal outlooks provide vital information that helps inform reservoir operations, ensure compliance with interstate agreements such as the Rio Grande Compact, and guide agricultural planning decisions and environmental flow management (Llewellyn and Roach 2013). Recent research has suggested that strong trends in basin hydrology are likely to challenge current operational water supply forecasting techniques, necessitating the consideration of more robust, alternative forecasting techniques in the future (Lehner et al. 2017a; Lehner et al. 2017b; Livneh and Badger 2020).

The URG basin has a semi-arid climate with snow-dominated hydrology and a summer monsoonal influence. The basin's hydroclimate is typically characterized by a distinct early spring snowmelt pulse beginning in late March, often followed by a secondary precipitation peak during mid-to-late summer from the North American Monsoon (NAM). The NAM phenomena begins between late June and late July and manifests as an annually recurring northward flow of subtropical atmospheric moisture which brings warm, moist air from the Gulf of Mexico and the eastern Pacific (Adams and Comrie 1997). This southerly moisture flow results in widespread convective precipitation, which provides a critical late-season supplement to spring snowmelt, particularly during years with below-average snowpack. High variability of both winter snowpack and summer monsoonal precipitation results in large interannual fluctuations in basinwide streamflow (Gutzler 2012).

Like for other snow-fed basins in the western US, operational WSFs for the URG are issued by the US National Water and Climate Center (NWCC), an office of the Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS), using regression-based statistical methods to predict volumetric seasonal (e.g., March-July or April-July) totals from spring snowpack at critical points for water management (Garen 1992; Garen et al. 1999; Pagano et al. 2014; US Department of Agriculture 2008). These forecasts are issued monthly throughout the mid-winter to spring months, though the timing of operational demands means there is a strong emphasis on April 1st forecasts (when key water decisions are made). Notably, WSFs provide only runoff volume predictions, yet deterministic (single-value) daily streamflow forecast sequences ('traces') are required as input to reservoir system operations and management models. Water managers at the US Bureau of Reclamation (hereafter, 'Reclamation') currently convert NRCS seasonal volume forecasts to daily streamflow time series using an analog-based temporal disaggregation method. Historical daily hydrograph sequences from years in which the seasonal total best matches the forecasted volume are selected as daily flow predictions after scaling to the forecasted seasonal volumes. This method, described in general terms by Chen (2016), is also used in other Reclamation projects, including on the upper Klamath River (Reclamation 2019)

Although the analog-based practice has been in use for many years, several factors spur interest in assessing alternative methods. First, despite matching the seasonal inflow volume, the actual sequence blends both the systematic mean runoff timing signal that is characteristic for each basin with unpredictable weather-scale variability (e.g., storm event timing), which varies in each deterministic analog year. The sequences may suggest a need for short term operations timing (such as for a synchronized environmental release) that are not justified by any systematic sequence skill; and monthly updates in each season that adopt different analogs can lack consistency in this weather-scale timing. Second, analog approaches assume stationarity in mean hydrologic response shape and variability. This assumption may be increasingly uncertain in the URG basin (as in the broader western US) as warming alters snowmelt patterns (Musselman et al. 2017; Lukas et al. 2020; Llewellyn and Roach 2013; Lehner et al. 2017), increases evapotranspiration (Walter et al. 2004), and reduces runoff efficiency (Lehner et al. 2017). All of these factors change streamflow characteristics including volumes and to some extent timing, potentially weakening the ability to find strong analogs for current forecast periods. This variability is illustrated in long-term mean streamflow observations over successive, overlapping 3-decade periods for one location in the URG basin, shown in **Figure 1**.

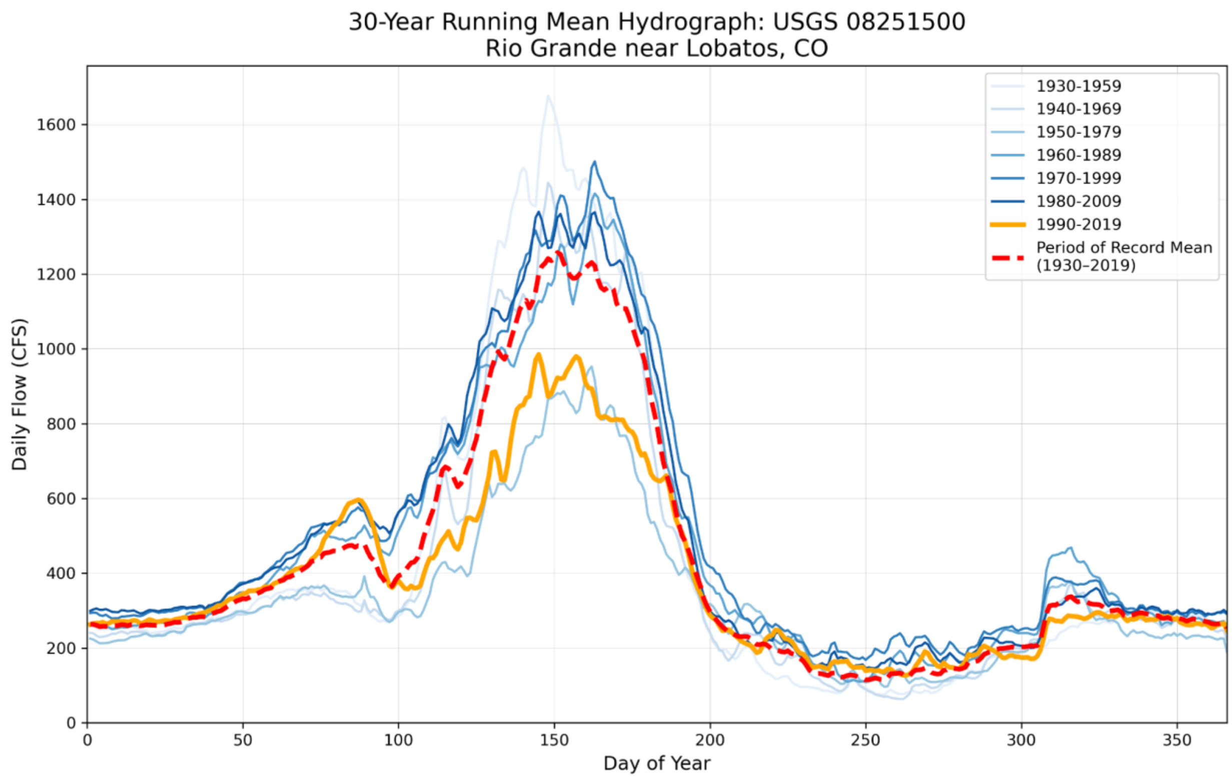

Figure 1: Mean daily hydrograph for the Rio Grande near Lobatos, CO (USGS 08251500) showing 30-year running averages of daily mean flow by day of year, calculated every 10 years from 1930–1959 through 1990–2019. Each line represents the mean hydrograph for its respective 30-year window, with increasingly darker blue colors denoting more recent periods. The most recent 30-year period (1990-2019) is highlighted in orange to show changes relative to the long-term period of record mean (1930-2019, dashed red).

Another core motivation for this work at the time of the study was that the US National Weather Service (NWS) West Gulf River Forecast Center (WGRFC) was developing (and has since operationalized) ensemble streamflow forecasts for key locations across the URG basin (Story 2016). Unlike the NRCS, the NWS RFCs issue seasonal streamflow forecasts with daily timestep flow sequences, or ‘traces’ (as compared to volumetric totals) using a technique called Ensemble Streamflow Prediction (ESP; Day, 1985). The ESP approach uses historical meteorological records combined with short term weather forecasts to produce probabilistic streamflow predictions initialized from current basin conditions simulated by hydrology models. Operationally, the ESP method is implemented using the NWS's conceptual hydrologic (SAC-SMA; Burnash et al., 1973) and snow accumulation and melt (Snow17; Anderson 1973) models, producing ensemble forecasts of daily streamflow across the western US for the upcoming snowmelt season. The addition of this second official agency providing seasonal streamflow forecasts for the URG basin raised the question of whether the ESPs could provide any performance advantages over the analog-based technique for predicting the deterministic sequences of inflow required by the Reclamation reservoir operations models.

Given these motivations and developments, this study evaluates whether process-based ensemble streamflow forecasts (i.e., ESPs) can offer equally (or more) skillful deterministic guidance (inflow shaping) for URG basin water management on seasonal time horizons. Such an evaluation requires analysis over a long period (ideally three decades or more) of hindcasts (also called 'reforecasts', i.e., forecasts initialized on past dates), which enable verification using past observations. RFC-based ESP hindcasts for the URG were not available, necessitating the generation of ESP hindcasts using a different hydrological model. The major methodological effort for the study thus comprises calibrating a land and hydrology model (SUMMA, described below) and building the workflows for hindcasting, followed by hindcast production, extraction of single-value sequences (e.g., the ensemble mean) that mimic the analog forecasts, and analysis. These elements are discussed in Section 2.

2. Approach

The generation of multidecadal ensemble streamflow hindcasts using an ESP method requires implementing and calibrating a land or hydrology model as well as the supporting hindcasting workflows. To this end, we use the Structure for Unifying Multiple Modeling Alternatives (SUMMA; Clark et al. 2015a;b) hydrologic modeling framework, calibrating it for streamflow simulation at the major inflow locations of Reclamation's Upper Rio Grande Water Operations Model (URGWOM; Stockton and Roark, 1999). SUMMA produces watershed runoff, which we route through the channel network to produce streamflow using the mizuRoute model (Mizukami et al. 2016). Although SUMMA represents a different hydrologic formulation, and one that is more process-oriented than the NWS RFC modeling approach, it nonetheless enables evaluation of forecast techniques similar to those now being used operationally by the WGRFC.

We hypothesize that ESP-derived hydrograph shapes can predict seasonal water system inflow shapes with equal or greater accuracy than the current analog-based temporal disaggregation method, which would indicate their viability as an alternative for use in water management. To test this hypothesis, we compare SUMMA-generated ESP hydrographs with Reclamation's Annual Operating Plans (AOPs). These official water management operating plans, issued annually in the spring, provide hydrologic outlooks for the URG basin generated from the NRCS April 1st WSFs using the analog trace selection technique. **Figure 2** outlines a comparison of the steps in the analog method versus the ESP-based sequence generation approach.

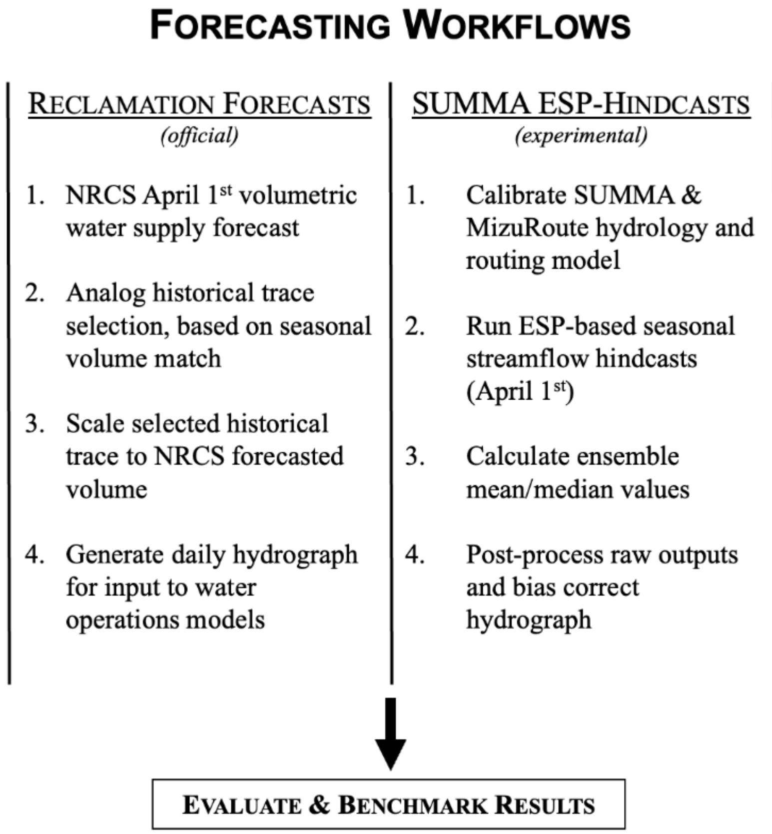

Figure 2. Flowchart outlining the two seasonal streamflow forecasting methods evaluated in this study. **Left**: The Reclamation analog-based approach. **Right**: The experimental SUMMA-ESP process-based workflow. Each method involves a distinct set of steps and is evaluated for its ability to produce a seasonal hydrograph at daily timesteps for input to the Upper Rio Grande Water Operations Model (URGWOM).

The following subsections describe the study setting, the ESP forecasting and hindcasting approach, including the models, model inputs and methods for calibrating and running the model, both retrospectively and using ESP techniques. We also describe methods for post-processing the hindcast traces to improve initialization errors and reduce the model bias. Finally, we provide a brief overview of the Reclamation methodology used to develop the April 1st AOPs (i.e., the analog-based forecasts) for the basin, against which we benchmark our ESP experiments.

2.1 Study setting

For the purposes of this analysis, the URG basin is defined as the region extending from the headwaters of the Rio Grande in the San Juan and Sangre de Cristo mountains of southern Colorado and northern New Mexico down to Otowi Bridge, NM (**Figure 3**). The URG has a semi-arid, snow-dominated hydroclimate, with annual runoff largely controlled by spring snowmelt from high-elevation headwaters and variable mid-summer monsoonal precipitation inputs, resulting in substantial interannual variability in seasonal streamflow volumes (Dettinger et al. 2015; Rango 2006). This headwater runoff supplies much of the water used in the Rio Grande system and supports several major Bureau of Reclamation projects, including the Closed Basin Project in Colorado's San Luis Valley (i.e., the large northeast portion of the study domain), which is a groundwater pumping and transfer project; Platoro Reservoir (ID #5); and the San Juan-Chama Project, an inter-basin transfer project providing water supply from the Colorado River basin to Heron Reservoir on the Rio Chama in New Mexico (ID #13). These projects provide reliable water supplies for the many users along the Rio Grande in New Mexico, including farmers and ranchers, municipalities, and Native American Pueblos. Table 1 summarizes the model calibration points.

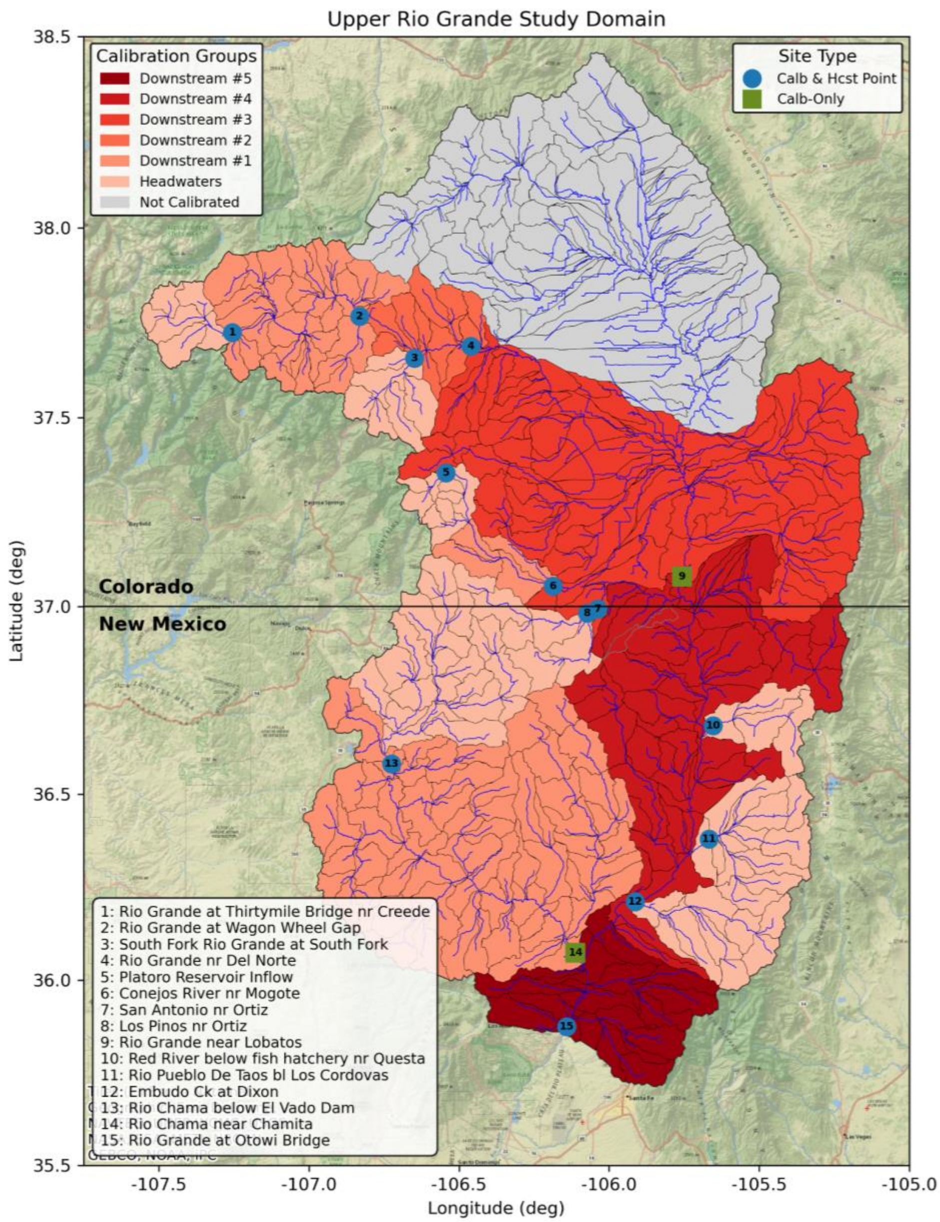

Figure 3: Study domain of the Upper Rio Grande basin, highlighting the SUMMA catchments (USGS Hydrologic Unit Code 12, or HUC12; black outline) and the MizuRoute MERIT-Hydro river network (blue). The red shaded colors show the six calibration groups used in the upstream to downstream nested calibration workflow. Blue circles mark the model calibration points, as named in the inset. The north central portion of the San Luis Valley (grey) is an endorheic/closed basin that was not included in model calibration, but is shown here as it is the source area of a Bureau of Reclamation groundwater pumping project that transfers water to the Rio Grande.

Table 1: Model calibration points with USGS gauge IDs, URGWOM name, and catchment information.

ID #	USGS Name	Gauge ID	BOR URGWOM Name	# HUC12s
1	Rio Grande at Thirtymile Bridge nr Creede	08213500	ThirtyMileBridge.Gage Inflow	6
2	Rio Grande at Wagon Wheel Gap	08217500	WagonWheelGap.Gage Inflow	35
3	South Fork Rio Grande at South Fork	08219500	SouthFork.Gage Inflow	6
4	Rio Grande nr Del Norte	08220000	DelNorte.Gage Inflow	52
5	Platoro Reservoir Inflow	08245000	Platoro.Inflow	9
6	Conejos River nr Mogote	08246500	Mogote.Gage Inflow	13
7	San Antonio nr Ortiz	08247500	RioSanAntonioAtOrtiz.Gage Inflow	2
8	Los Pinos nr Ortiz	08248000	RioLosPinosAtOrtiz.Gage Inflow	4
9	Rio Grande near Lobatos	08251500	Lobatos.Gage Inflow	144
10	Red River below fish hatchery nr Questa	08266820	RedRiverBlwFishHatchery.Gage Inflow	4
11	Rio Pueblo De Taos bl Los Cordovas	08276300	RioPuebloDeTaosAtLosCordovas.Gage Inflow	11
12	Embudo Ck at Dixon	08279000	EmbudoCreekAtDixon.Gage Inflow	9
13	Rio Chama below El Vado Dam	08285500	ElVadoLocalInflow.Local Inflow	20
14	Rio Chama near Chamita	08290000	N/A	83
15	Rio Grande at Otowi Bridge	08313000	Otowi.Gage Inflow	385

2.2 ESP Forecasting with SUMMA and MizuRoute

For hydrological modeling and forecasting, we used the Structure for Unifying Multiple Modeling Alternatives (SUMMA; Clark et al., 2015a,b) to simulate land surface and hydrologic processes across the URG basin. SUMMA is a flexible process-based hydrologic modeling framework designed to accommodate multiple representations (parameterizations) of key hydrologic processes, such as snow accumulation and melt, evapotranspiration, and soil water movement. This flexibility allows SUMMA to represent diverse hydrologic regimes, enabling sensitivity testing of structural model choices within a unified framework, which was the core design motivation. SUMMA solves generalized conservation equations for water and energy, using interchangeable parameterization schemes to represent fluxes at the land surface and within the soil column. SUMMA allows for a hierarchical organization of the spatial scale, in which grouped response units (GRUs) can optionally contain smaller hydrologic response units (HRUs).

We selected model options that reflect the cold-season hydrology and complex terrain of the URG basin, including energy-balance snowmelt, multilayer soil moisture storage, and a baseflow formulation that accounts for groundwater recession. The optimization of model decisions and development of the baseline (uncalibrated) SUMMA model configuration was undertaken in prior watershed modeling studies for water management applications and documented in several project reports (e.g., Broman et al., 2021; Wood et al., 2021; Wood and Mizukami). Building off this baseline, we used a default implementation of SUMMA with GRUs at the spatial scale of (lumped) US Geological Survey HUC12 (USGS Hydrologic Unit Code 12) catchments (average area ~80 km2) for SUMMA flux calculations, solved on 3-hourly timesteps. We used only one HRU per GRU (i.e., the HRU and GRU boundaries were both HUC12). The GRU runoff fluxes are routed to downstream gauged locations using the hydrologic routing model MizuRoute (Mizukami et al. 2016), which was implemented for the MERIT-basin global river network dataset (Yamazaki et al. 2019). The intermediate complexity of the model's temporal and spatial resolutions is a tradeoff that enables representing the predominant topographic variability and hydrologic processes of the basin while maintaining sufficient computational efficiency for effective parameter estimation and multi-decadal, ensemble-based hindcasting experiments.

2.1.1 Model Inputs

The Gridded Meteorological Ensemble Tool (GMET; Newman et al., 2015; Bunn et al., 2022) was used to create the surface meteorological input (forcing) dataset for the SUMMA retrospective simulations and hindcast experiments. GMET applies a locally weighted spatial regression approach to estimate daily gridded precipitation amount, temperature mean and range, and probability of precipitation, as well as the daily, spatially-varying uncertainty in each. This study drew from an implementation of GMET developed previously in support of several Reclamation funded projects (e.g., Broman et al., 2021) for the western United States at 1/16° horizontal resolution. GMET was designed to enable the generation of ensemble forcing datasets (to characterize uncertainty); nevertheless, we used one ensemble member as a deterministic forcing in this study, which is consistent with typical ESP practice. A conservative spatial mapping algorithm was applied to average the gridded GMET fields to the HUC12 spatial resolution to enable a catchment-based modeling configuration. Finally, to provide the additional meteorological variables (e.g., radiation terms, air pressure, and specific humidity) required by SUMMA, as well as a 3-hourly timestep, GMET forcings at the HUC12 scale are temporally disaggregated and augmented using the Meteorology Simulator (MetSim; Bennett et al. 2019), a Python-based wrapper for the MTClim approach (Running et al. 1987). A 3-hourly timesteps has been used in this and other SUMMA studies (e.g., Farahani et al. 2025) to resolve a diurnal cycle of temperature and radiation, which is important to the simulation of snowmelt and evaporative processes. Initial SUMMA parameter values and their default ranges for SUMMA were adopted from an a priori parameter set used in Broman et al. (2021), as were the model vertical configuration, with 3 soil layers (0.1, 0.4, and 1.0 meter depth), a maximum of 5 snow layers, and a bucket aquifer (with exponential baseflow generation algorithm) and a maximum depth of 1.5 meters. These general configurations were also used as a starting point for the SUMMA calibration work of Farahani et al. (2025), which offers additional useful details.

2.1.2 Calibration and Validation Strategy

We optimized model parameters for streamflow simulation using the Dynamically Dimensioned Search (DDS) algorithm within the OSTRICH parameter estimation framework (Matott 2017). Our calibration targeted 13 parameters that collectively control a range of dominant hydrologic processes, such as soil hydraulic properties (controlling soil water transmission), soil storage capacity (via porosities), baseflow dynamics, canopy and vegetation characteristics, frozen precipitation undercatch, and streamflow routing (see Supporting Information, Table S.1). We calibrated these parameters to five-years of daily streamflow observations, grouping catchments by basin units as defined by streamflow gauge locations. Calibration consisted of 1,000 DDS iterations per gage site used to minimize a negative Kling–Gupta Efficiency (KGE; Gupta et al., 2009) objective function to identify the best-performing parameter set across all runs. The SUMMA calibration workflow using Ostrich (with DDS) developed in this and related Reclamation-sponsored studies (e.g., Broman et al., 2021) has also adopted for use in other SUMMA modeling efforts (e.g., Van Beusekom et al. 2022; Tang et al. 2023; Mizukami et al, 2025).

We applied this calibration strategy in a nested, headwater-to-downstream sequence across six calibration groups (Figure 3, with stages identified by colors). By first calibrating all upstream basin units (e.g., Rio Grande at Thirty Mile Bridge, USGS gauge 08213500), we could then generate calibrated retrospective (1970–2019) simulations for inflow boundary conditions for subsequent downstream calibrations. In each case, calibration of downstream groups was only performed after all upstream contributing areas had been calibrated. This incremental approach maintained physical consistency throughout the domain while using the best available streamflow records to optimize streamflow simulations in each sub-basin group.

To assess model performance, we validated simulations against observed and naturalized daily streamflow using the multi-metric statistics KGE and Nash–Sutcliffe Efficiency (NSE; Nash & Sutcliffe, 1970). In basins with multiple candidate parameter sets, we selected the final set based on overall hydrograph fit, with particular attention to streamflow timing and shape. We also evaluated the accuracy of simulated seasonal (April to July, or 'AMJJ') streamflow volumes. These calibration selections informed the full-domain retrospective (1970-2019) simulations and the ESP hindcast experiments described in the following sub-section.

2.1.3 Hindcasting Approach

To evaluate the skill of ESP using a process-based hydrology model, we implemented a hindcasting framework designed to represent operational water supply forecasting on April 1st for the AMJJ period discharge. Starting with the calibrated hydrology model, we first ran a single, deterministic 50-year (1970-2019) simulation across the entire URG study domain, generating SUMMA and MizuRoute state files for each April 1st date in our period of record. These state files provided initial conditions (e.g., snowpack, soil moisture, aquifer storage, and channel storage) for model restarts and allowed us to run hindcast experiments that emulate operational forecasting conditions.

From each April 1st initial model state, we then ran the model forward for one year using the ESP technique, which applies observed meteorological sequences from all other (non-forecast) years to produce an ensemble of streamflow forecasts. For each target forecast year, we withheld that year's meteorology from the ensemble and used it instead to generate a single 'retrospective' simulation for verification. The remaining meteorological years formed the ESP hindcast ensemble, which we aggregated to create probabilistic AMJJ volumetric forecasts and to generate ensemble daily hydrograph shapes for input to URGWOM. Of our 15 model calibration sites, we generated SUMMA-ESP hindcasts for 13 of these locations where official Reclamation AOP April 1st streamflow forecasts were available, as shown in Figure 3.

2.1.4 Post-Processing Techniques

We applied three sequential post-processing steps to the April 1st SUMMA-ESP hindcasts to improve forecast accuracy by reducing model error and bias, as shown in **Figure 4**. These corrections addressed (1) hindcast initialization error, (2) structural model bias, and (3) differences in seasonal (AMJJ) volumes between SUMMA-ESP hindcasts and NRCS WSFs.

First, to correct for forecast initialization error (the difference between observed streamflow and model simulations at the forecast date), we implemented a two-week exponential decay adjustment. This correction sets the first timestep of the SUMMA-ESP hindcast to match the observed flow on April 1st, then gradually decays the correction over 14 days, allowing the hindcasts to transition back to the uncorrected model trajectory. This data assimilation step was independently applied to each trace in the SUMMA-ESP across all April 1st hindcast dates. This type of forecast error correction is common to nearly all operational model-based forecasting systems (see Bellier et al. 2021), including those in the NWS, with methods varying from simple linear initial error correction blends (National Weather Service 2005) to more sophisticated auto-regressive post-processing schemes (National Weather Service 2016).

Second, we addressed systematic biases in the simulated annual cycle of streamflow that can result from errors in meteorological forcings, unaccounted water management (e.g., consumptive use or reservoir operations), or model structure and/or parameterization uncertainties. This type of correction of systematic modeling error has been widely explored as a means of compensating for persistent deficiencies in model structure, forcings, or representation of human influences, and is commonly applied as a post-processing step in forecasting systems (e.g., Hopson et al. 2019; Kavetski et al. 2006). Here, we implemented a cross-validated (leave-one-out), climatological bias correction approach in which multiplicative correction factors were estimated for each day of the year (DOY) using smoothed historical flows on a centered 14-day rolling mean. For each hindcast year, we calculated these smoothed DOY bias correction factors (multiplicative) as the ratio of observed to simulated streamflow using all years except the hindcast target year itself (to avoid using information that would not be known in a real-time forecasting operation). We then applied these correction factors to the ESP hindcast traces, reducing systematic biases in simulated flow timing and magnitude while avoiding data leakage from the hindcasted period.

Finally, we further scaled the SUMMA-ESP ensemble mean seasonal volumes to match the volume of the NRCS April 1st operational forecasts selected by Reclamation in the official AOP forecasts (Section 2.2). This final adjustment allowed for direct comparison of ESP-derived and official analog-based hydrographs on an equal volumetric basis, isolating the contribution of forecast shape from total seasonal flow by removing the discrepancy between SUMMA volume predictions and the official NRCS volume predictions.

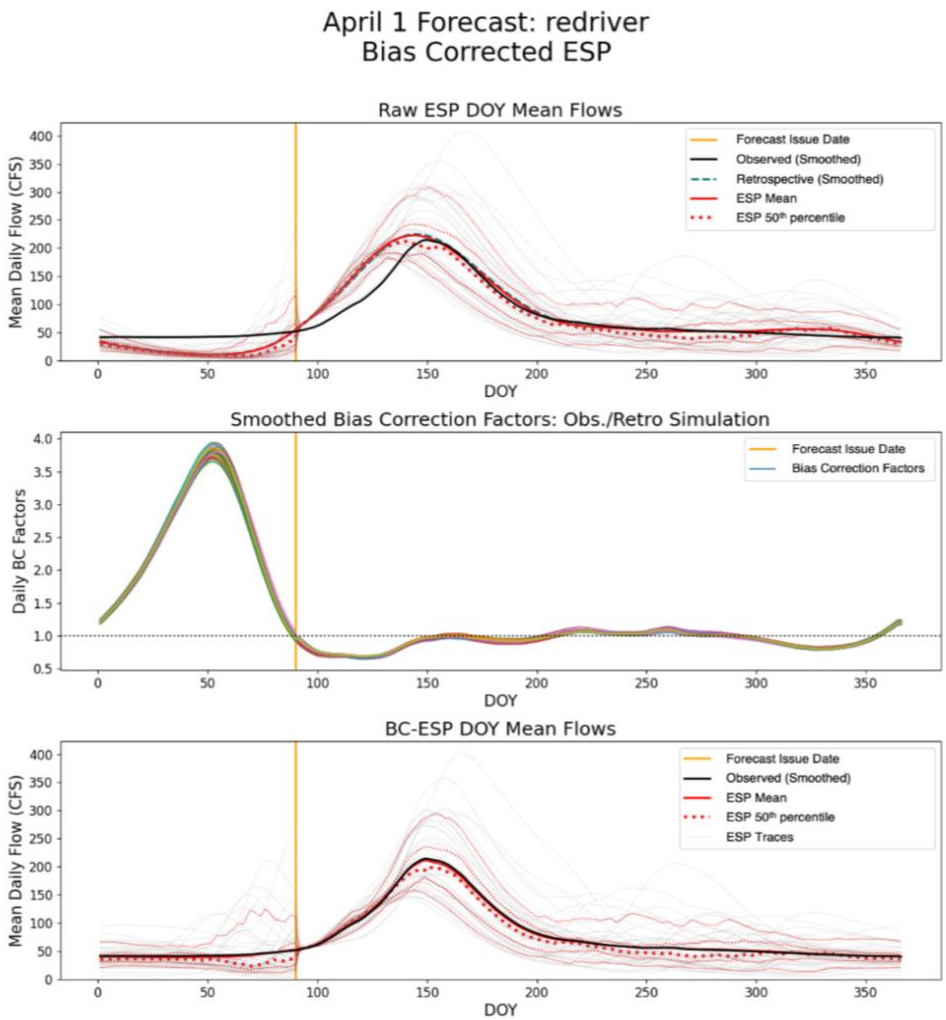

Figure 4: Example of structural error bias correction for Red River, NM (ID #10). **Top:** raw SUMMA-ESP ensemble and observed hydrograph. **Middle:** smoothed daily bias correction factors (ratio of observed to simulated flow). **Bottom:** Bias-corrected ESP ensemble, showing improved agreement with observed daily flows.

2.2 Reclamation Annual Operating Plan (AOP) Forecasts

Every year, the Reclamation Albuquerque Area Office (AAO) produces a series of basin-wide AOPs using the Upper Rio Grande Water Operations Model (URGWOM; Stockton & Roark, 1999), a multi-agency water accounting model for the basin. In this study, we focus on the April 1st AOP and its seasonal streamflow forecasts. While AOPs are developed as early as February, the April AOP water outlook serves as the primary basin forecast for important water management decisions.

For each April 1st AOP streamflow forecast, Reclamation hydrologists and engineers make two key decisions: (1) which historical streamflow trace to use for the daily hydrograph shape, and (2) which probabilistic April 1st NRCS volumetric forecast to use for scaling the analog trace volume.

In general, historical streamflow traces are selected by attempting to find the historical trace with the closest match in AMJJ volume to the forecast AMJJ volumes, although forecaster judgment – considering factors such as observed snowmelt rates and antecedent soil moisture conditions – can also influence the selection. While the official deterministic AOP forecasts typically use the predicted volume from the NRCS median (i.e., 50th percentile) forecast, alternative percentile forecasts may be chosen in some years for a more conservative outlook (e.g., the 70th percentile in 2018). In either case, the same NRCS exceedance probability is used across all sites in the URGWOM domain for a given year. Because the AOP process depends on the April 1st NRCS forecasts, the official forecasts are usually not issued until the first week of April. Any streamflow observations between April 1st and the AOP issue date are typically directly assimilated into the forecast.

To generate daily streamflow forecast sequences required for URGWOM, the selected NRCS seasonal volume forecast is converted to a daily time series using analog-based temporal disaggregation (Chia-Jeng, 2016). This approach scales the selected analog trace to match the selected NRCS forecast volume. The benchmarking results in this study focus on AOP forecasts for the period 2012–2019; however, URG's Colorado forecast points were only incorporated into URGWOM starting in 2016 and are thus not available for the full period.

3. Results

We present the results of our SUMMA modeling and hindcast experiments in the URG basin, beginning with an assessment of model calibration and validation performance across calibration points. We then evaluate the effectiveness of our post-processing corrections, examine the skill and characteristics of the 49-year (1971-2019), 49-member ESP sequence of April 1st hindcasts, and compare these hydrograph shapes with recent (2012-2019) analog-based operational streamflow forecasts from the Reclamation AAO. Comparisons are shown for both a focused case study of all sites during a typical year and in aggregated statistics across all available site-years. The following subsections highlight quantitative performance metrics and representative case studies to illustrate experimental forecast strengths and limitations before discussing implications for water management operations in the basin.

3.1 Model Calibration and Validation

The calibrated URG SUMMA model reproduced daily streamflow timing, magnitude, and seasonality across fifteen gauged locations in the URG basin with acceptable though not perfect accuracy, as shown in **Figure 5**. Across all sites, calibration and validation metrics (KGE, NSE, correlation, and percent bias) indicated skillful model performance (Figure 5a, Table 2). Visual inspections confirmed that key hydrologic processes were well simulated by the model, an example of which is shown in Figure 5b.

KGE scores for the five-year calibration periods (which varied by site, Table 2) ranged from 0.66 to 0.9, with the highest values in unregulated headwater basins such as the South Fork of the Rio Grande (ID #3, KGE 0.88) and in locations calibrated to naturalized streamflow (e.g., Conejos River at Mogote, ID #6, KGE 0.85; Otowi Bridge, ID #15, KGE 0.86). In contrast, sites with significant upstream regulations, such as Rio Grande at Thirty Mile Bridge (ID #1, KGE 0.72) and Conejos River at Platoro Reservoir (ID #5, KGE 0.7), showed lower calibration scores. Scores were also lower in the small headwater tributaries originating in the southern Sangre de Cristo Mountains, such as Rio Pueblo de Taos (ID #11, KGE 0.66). KGE scores across the full simulation period (1970-2019) showed slightly lower performance (KGE 0.54 to 0.88) but good generalizability into the validation period overall (Figure S.1; Table 2). Heavily managed systems such as the Rio Chama and the Conejos River (Figure S.1, e.g., ID #6, #13, #14) showed poorer model generalizability across the full period of record.

In addition to quantitative metrics such as KGE, we also evaluated model performance across various calibration runs using diagnostic assessments of hydrograph shape and seasonal volumes. For each calibration site, we visually compared simulated and observed hydrographs (e.g., Figure 5b, second and third panels) and calculated total flow volumes for both the full water year (WY) and the AMJJ snowmelt runoff season (Figure 5b, bottom scatter plots).

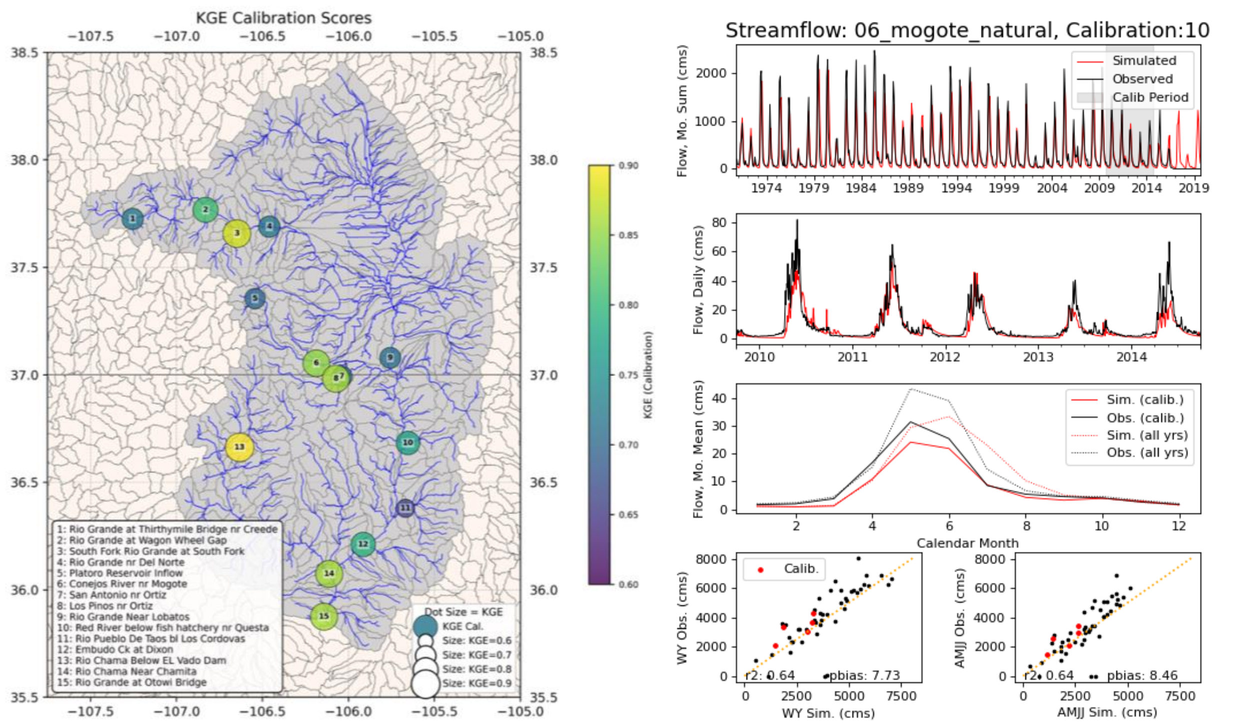

Figure 5: (**a**) Model calibration KGE scores for the respective 5-year calibration periods (variable, Table 2) of each calibration point. (**b**) Example diagnostic assessment of model calibration for the Conejos River at Mogote (ID #6), showing the full deterministic model simulation (1970-2019) at monthly timesteps (top panel), daily streamflow simulations during the calibration period (second panel), monthly average flows grouped by calendar month (third panel), and total flow volumes during the water year (bottom left scatter plot) and the typical water supply forecast period (AMJJ, bottom right scatter plot).

Table 2: Calibration and full domain (1970-2019) metrics and periods for the fifteen calibration points in the study domain.

ID #	USGS Name	Gauge ID	KGE, Full Sim.	KGE, Cal.	Cal. Start	Cal. End
1	Rio Grande at Thirtymile Bridge nr Creede	08213500	0.65	0.72	2008-01-01	2014-09-30
2	Rio Grande at Wagon Wheel Gap	08217500	0.58	0.81	2007-01-01	2013-09-30
3	South Fork Rio Grande at South Fork	08219500	0.87	0.88	2007-01-01	2013-09-30
4	Rio Grande nr Del Norte	08220000	0.67	0.72	2006-01-01	2012-09-30
5	Platoro Reservoir Inflow	08245000	0.61	0.70	2007-01-01	2013-09-30
6	Conejos River nr Mogote	08246500	0.69	0.85	2007-01-01	2013-09-30
7	San Antonio nr Ortiz	08247500	0.64	0.70	2006-01-01	2012-09-30
8	Los Pinos nr Ortiz	08248000	0.84	0.86	2006-01-01	2012-09-30
9	Rio Grande near Lobatos	08251500	0.54	0.71	2008-01-01	2014-09-30
10	Red River below fish hatchery nr Questa	08266820	0.73	0.77	2008-01-01	2014-09-30
11	Rio Pueblo De Taos bl Los Cordovas	08276300	0.60	0.66	2008-01-01	2014-09-30
12	Embudo Ck at Dixon	08279000	0.76	0.79	2007-01-01	2013-09-30
13	Rio Chama Below EL Vado Dam	08285500	0.88	0.90	2007-01-01	2013-09-30
14	Rio Chama Near Chamita	08290000	0.85	0.86	2008-01-01	2014-09-30
15	Rio Grande at Otowi Bridge	08313000	0.69	0.86	2008-01-01	2014-09-30

3.2 SUMMA-ESP Hindcast Evaluation: Volumetric and Hydrograph Skill

At each of the thirteen model forecast points, we applied the calibrated model to generate 49 (1971-2019) April 1st SUMMA-ESP hindcasts at a one year (365 day) lead time. We first present an illustrative example of an ensemble hindcast to highlight characteristic features of the ESP forecasts, including ensemble spread, hydrograph timing, and seasonal volume behavior. We then quantify forecast skill across all basins using AMJJ runoff volumes and daily streamflow metrics, and examine how forecast performance varies by year.

3.2.1 Single-basin case study: Rio Grande at Del Norte, Colorado

To demonstrate the SUMMA-ESP hindcast workflow and post-processing methods, we present a case study for the Rio Grande near Del Norte, Colorado (USGS 08220000; Table 1, ID #4), a key Reclamation WSF location on the mainstem of the URG. This site, located on the western side of the San Luis Valley, drains approximately 3,400 km² from the eastern side of the San Juan Mountains in southern Colorado. The Rio Grande at Del Norte model domain is delineated into 52 HUC12 catchments and includes three upstream calibration groups (shown in Figure 3). Accurate seasonal streamflow prediction at Del Norte, which is a WSF point for both the NWS WGRFC (NWS location ID: DNRC2) and the USDA NRCS, is important for water management and agriculture in the region.

Figure 6 shows the SUMMA-ESP results for this site, including both a single-year example and the full multi-decadal sequence of April 1st hindcasts. The hydrograph shows the raw and bias-corrected ensemble predictions initialized on April 1st, 2017 compared to USGS streamflow observations (USGS Gage 08220000, black line). In this single-year hindcast, we see a substantial initialization error in the raw ESP mean (red dashed line), resulting from an underestimation of the spring freshet onset. Post-processing with hydrologic data assimilation and DOY bias correction (blue line) resolved much of this error, substantially reducing early season model bias and improving AMJJ KGE scores from 0.71 to 0.77 and improving AMJJ volumetric RMSE from 61.6 thousand acre-feet (KAF) to 26.4 KAF.

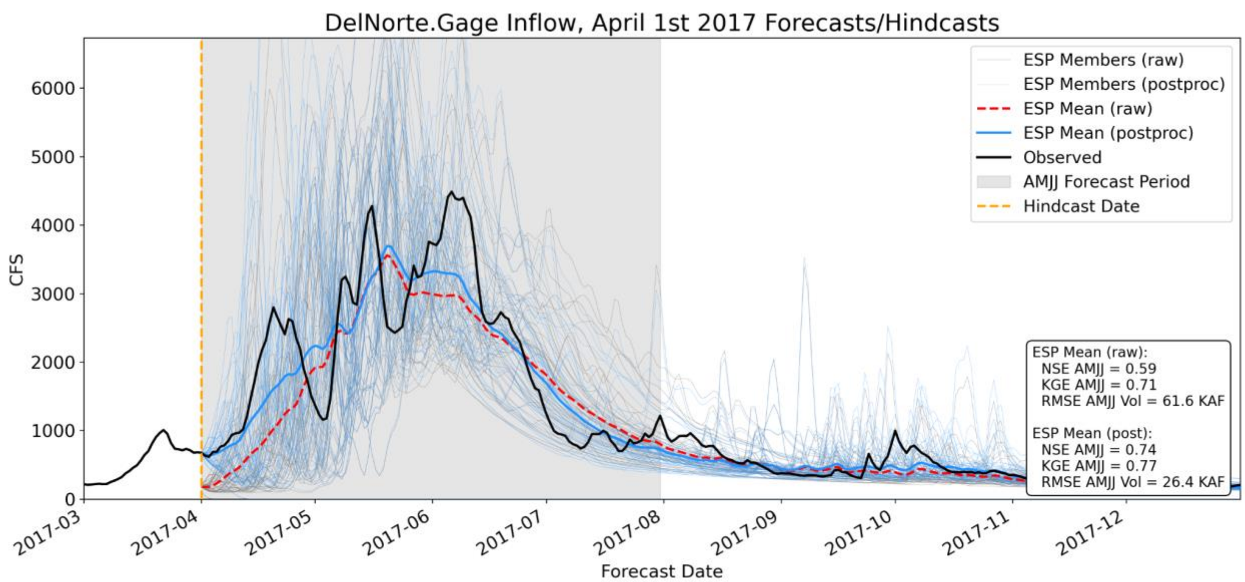

Figure 6: Single-year example of the April 1st, 2017 SUMMA-ESP hindcast for the Rio Grande at Del Norte, Colorado: raw ESP mean (red line), post-processed ESP mean (blue line), and USGS streamflow observations (black line). Individual ESP traces are shown by the fine light grey (raw) and blue (post-processed) lines.

Figure 7 displays the full set of 49 April 1st hindcasts (1971–2019), after post-processing (see Figure S.2 for the corresponding figure for the raw SUMMA-ESP hindcasts). Probabilistic AMJJ streamflow volumes are shown in the bottom scatter plots; the boxes bound the 30/70th percentile predictions, while whiskers mark the 10/90th percentiles (aligning with the typical NRCS WSF exceedance probabilities). Over all years, the ESP mean showed strong skill (KGE = 0.84, NSE =

0.70); post-processed ESP mean timeseries metrics were similar. Seasonal volume errors (RMSE) across all years were higher than in the 2017 example (116 KAF), with minimal change between the raw and post-processed ESPs, but volumetric bias was reduced from 8.1% before post-processing to -1.3% after correction. This case study highlights the impacts of bias correction and initialization error adjustment in improving forecast skill, especially during the AMJJ WSF period (Figure 6a).

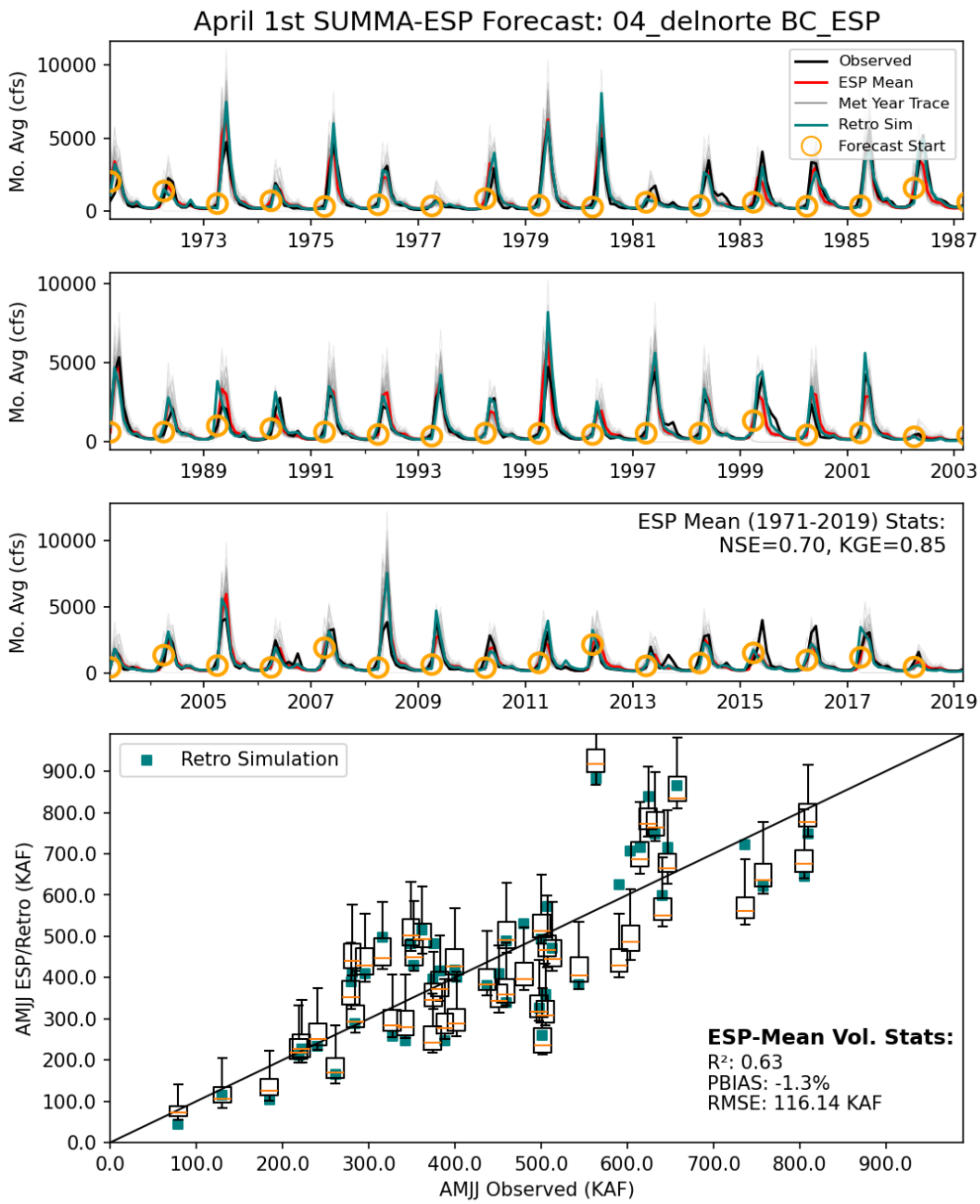

Figure 7: Case study of SUMMA-ESP hindcasts for the Rio Grande at Del Norte, Colorado, showing post-processed ESP hindcasts, using DOY mean bias correction and hydrologic data assimilation. AMJJ volumes are aggregations of USGS observed flows, not adjusted ("naturalized") volumes as reported by the NRCS. See Figure S.2 in the Supporting Information for the corresponding raw SUMMA-ESP hindcasts.

3.2.2 Analysis of SUMMA ESP WSFs at all forecast points

To assess the long-term performance of the SUMMA-ESP hindcasts, we evaluated volumetric ESP mean forecast skill at all thirteen forecast points over the 49-year hindcast period (1971–2019). **Figure 8** summarizes three key metrics for AMJJ seasonal volumes: normalized root mean squared error (nRMSE), coefficient of determination (R^2), and absolute percent bias (abs. PBIAS). The raw ESP mean AMJJ volume showed moderate to high skill at most sites, with median nRMSE of 35.5%, median R^2 of 0.63, and median absolute PBIAS of 10.7%. In the URG headwater region above Lobatos Bridge, AMJJ hindcast skill was higher, with median nRMSE of 28.0% and median absolute PBIAS of 3.6%. These results indicate that the ESP approach is generally able to capture a large fraction of interannual variability across the domain, but persistent systematic errors and biases remain. This is particularly evident in the lower part of the basin, where impacts from consumptive water use, trans-basin diversions, and other water management activities are larger, highlighting the need for post-processing.

Applying the model error correction to the ESPs resulted in consistent improvements in AMJJ hindcast skill at most locations. After bias correction, the median nRMSE across all sites decreased to 28.4%, and the median absolute PBIAS was reduced to just 2.2%, while median R^2 was largely unchanged, decreasing from 0.63 to 0.61. These results demonstrate that bias correction effectively removes most systematic errors in ensemble mean seasonal volumes without removing explained variance (e.g., see the Rio Grande at Del Norte 2017 case study in Figure 6). At a few sites though, bias correction led to small increases in nRMSE or decreases in R^2. This is consistent with cases where the correction factors were inconsistent with year-specific anomalies. Nevertheless, the moderate but widespread reduction in volume errors and bias following post-processing underscores the value of out-of-sample bias correction techniques for improving the operational utility of ESP-based seasonal streamflow forecasts in the URG.

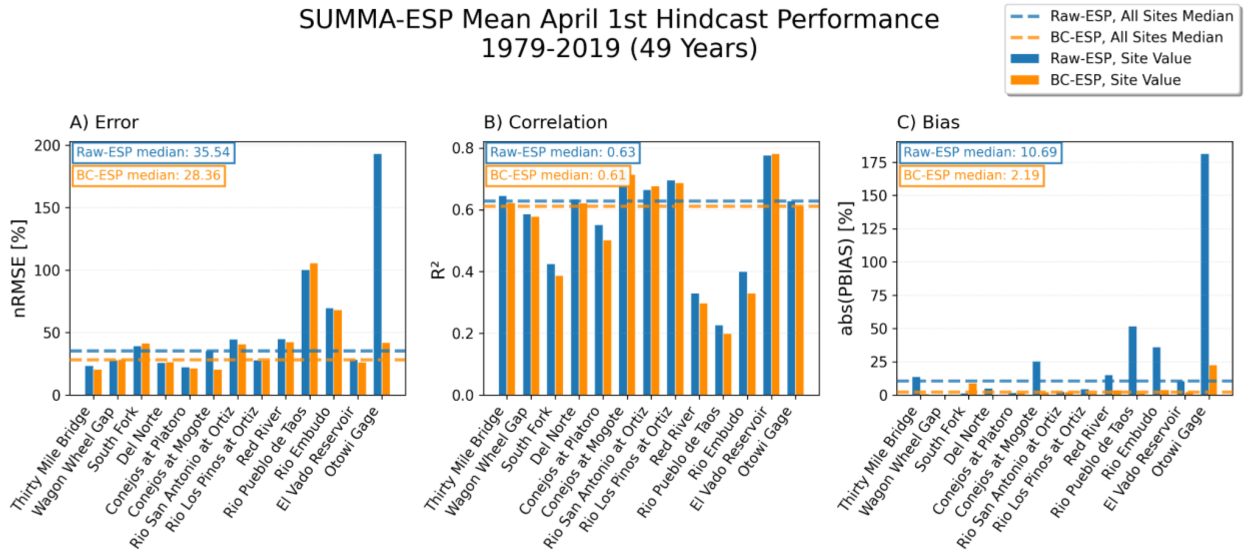

Figure 8: Comparison of April 1st hindcast skill metrics of AMJJ volumes for raw (orange) and bias-corrected (BC; blue) SUMMA ESP WSFs at 13 study sites. Bars show the site-level values for three performance metrics: **(A)** normalized root mean squared error (nRMSE, %), **(B)** coefficient of determination (R^2), and **(C)** absolute percent bias (PBIAS, %), for both the raw ESP and bias-corrected ESP ensemble mean values. Horizontal dashed lines indicate the median value for each ESP method across all basins.

3.3 Comparison of ESP-based WSF daily streamflow sequences with official Reclamation AOP forecast sequences

We assessed the accuracy of the daily streamflow sequences derived from the medians and means of the SUMMA-ESP hindcasts and the official Reclamation water supply outlooks from the Annual Operating Plan (AOPs) using the analog disaggregation method. This section first highlights an assessment from a single recent representative forecast year, then summarizes available forecast points and years with a focus on metrics of hydrograph shape and peak flow magnitude and timing.

3.3.1 Single-year case study: April 1st 2016

To illustrate forecast performance under typical hydroclimatic conditions, we first present results from 2016, a representative year characterized by near-average snowpack and precipitation across the URG. In the headwaters above Lobatos Bridge (Figure 3, ID #9), April 1st 2016 basinwide snowpack as measured at NRCS SNOTEL sites was slightly below normal (88% of the NRCS 1991-2020 median) with average soil moisture conditions (101%). Forecast period (AMJJ) precipitation in the upper basin also tracked close to the median (103%). Below Lobatos Bridge in New Mexico, snowpack was lower (75% of median) but April 1st soil moisture conditions were above average (123%); forecast period precipitation was similarly near normal (93%).

The Reclamation AAO issued 2016 AOP forecasts on April 14th using the NRCS 50th percentile (median) volumetric predictions. For the first two weeks of the forecast period, streamflow observations were directly assimilated into the AOP forecasts. To allow for a direct comparison of hydrograph timing and shape, all post-processed SUMMA-ESP hydrographs in this analysis were rescaled to match the NRCS volumes used in the AOP forecasts (50% exceedance probability). NRCS forecasted volumes on April 1st, 2016 ranged from about 70–80% of average historical conditions in the headwaters to just 56% at Otowi Bridge, NM, reflecting predictions of below- to well-below-average conditions relative to 1981–2020 averages.

Figure 9 shows the official AOP forecasts and experimental ESP hindcasts for April 1st 2016 across all 13 study forecast sites. A visual comparison of the hydrograph shapes shows that the SUMMA-ESP ensemble mean hydrographs (dotted red lines) have a distinctly smoother profile relative to the AOP analog traces (blue lines). This characteristic is a result of the ensemble averaging process, which differs from the analog method applied in the official AOP forecasts. The AOP forecasts held a slight informational advantage, as they incorporated observed flows up to the forecast issue date.

The SUMMA-ESP hindcast shapes were a better statistical fit to observed flows than the AOP forecasts at most locations: median KGE scores were 0.54 for SUMMA-ESP versus 0.26 for the AOP forecasts (Figure 9, histogram, bottom right). Both methods performed similarly in the headwater basins (i.e., to Del Norte), though AOP forecasts developed larger negative biases later in the runoff season compared to ESPs. Neither method captured the late peak flows in the upper basin. In the tributaries originating in the eastern San Juan Mountains (e.g., the Conejos, Rio San Antonio, Rio Los Pinos, and Rio Chama), the SUMMA-ESP mean hindcasts more accurately predicted the timing of peak flows and the recession limb. Further downstream at Otowi Bridge, both methods struggled, with the AOP forecast peaking more than a month early. Overall, the SUMMA-ESP mean provided better or comparable hydrograph shape (KGE) in 12 out of 13 cases for this single-year example, and in all cases when evaluating using NSE, which is more sensitive to high flows (Mizukami et al. 2019).

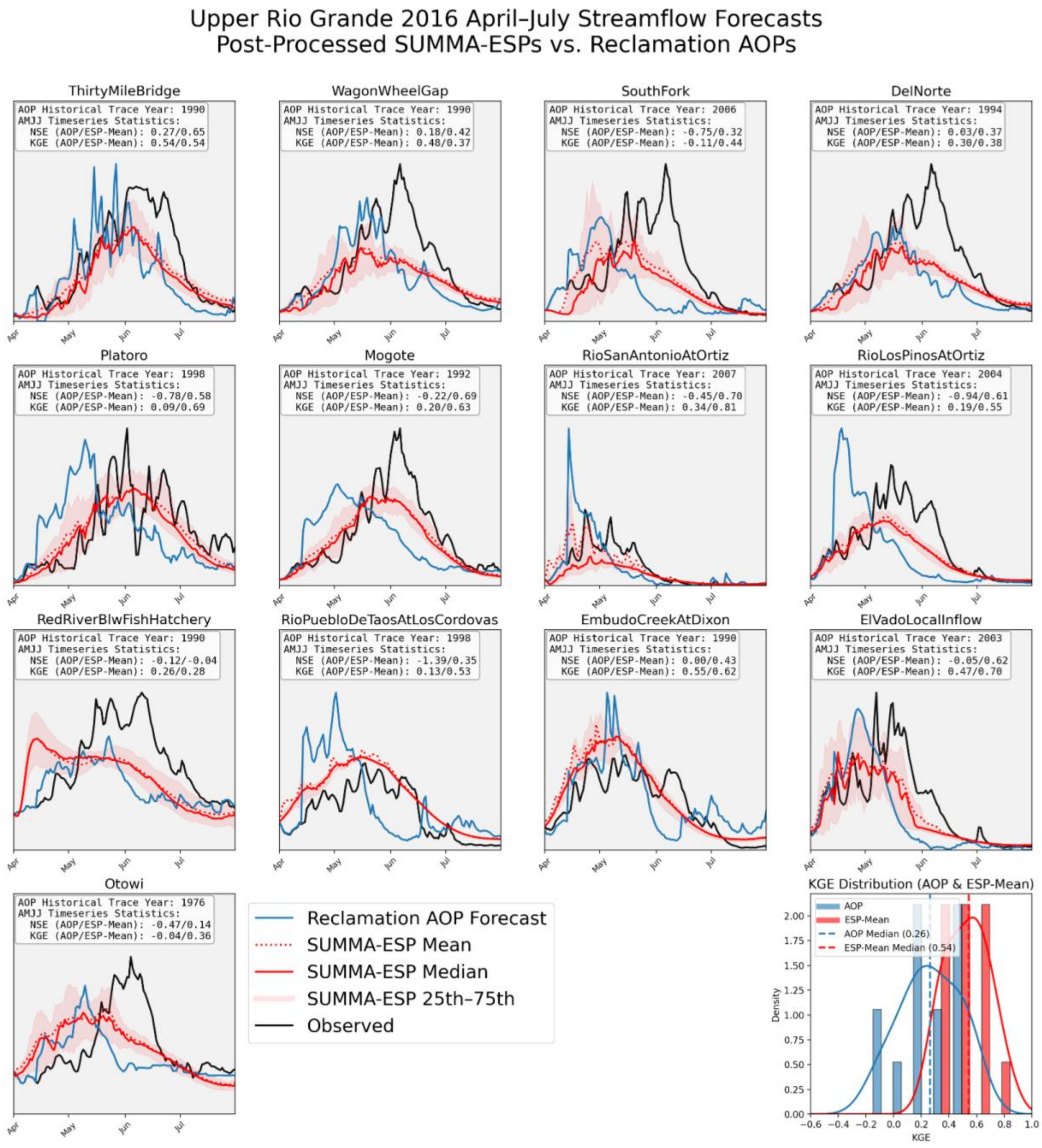

Figure 9: Comparison of post-processed SUMMA-ESP hindcasts and Reclamation AOP forecasts for 13 sites during the 2016 AMJJ water supply forecast season. For each site, hydrographs are shown for the official Reclamation AOP forecast (blue line), SUMMA-ESP ensemble mean (red dashed line), SUMMA-ESP ensemble median (red solid line), SUMMA-ESP 25th–75th percentile range (shaded red band), and observed daily flows (black line). All hydrographs have been rescaled to match the official NRCS volumetric forecast used in the corresponding AOP, isolating differences in hydrograph shape and timing from the volume. Panels include site-specific timeseries statistics for NSE and KGE for both the AOP and SUMMA-ESP mean. The lower-right panel summarizes KGE distributions across all sites. Site thumbnails for additional years (2017-2019) are shown in the Supporting Information.

While the SUMMA-ESP mean is smoother than individual observed events, and the AOP analog method can often imply overconfidence in the timing of weather-scale flow variability, both approaches can replicate important hydrologic features in the basin. One example is the double snowmelt peak in April at the Rio Chama at El Vado (Platoro), which the AAO speculates is a systematic hydrologic signal related to the basin hypsometry. This detail is averaged out in the SUMMA-ESP mean/median, however. Similar analyses for 2017–2019 are provided in Section S.4 of the Supporting Information, and summarized in **Figure 10**. For these other years, results are largely similar, except under the exceptionally dry conditions of 2018, which had April 1st basinwide snowpack that was well below average and only 60% of the average precipitation for the forecast period. AOP forecast hydrograph shape during these drought conditions outperformed the SUMMA-ESP mean in 10 out of the 13 study sites (Figure 10, bottom left; Supporting Information Section S.4).

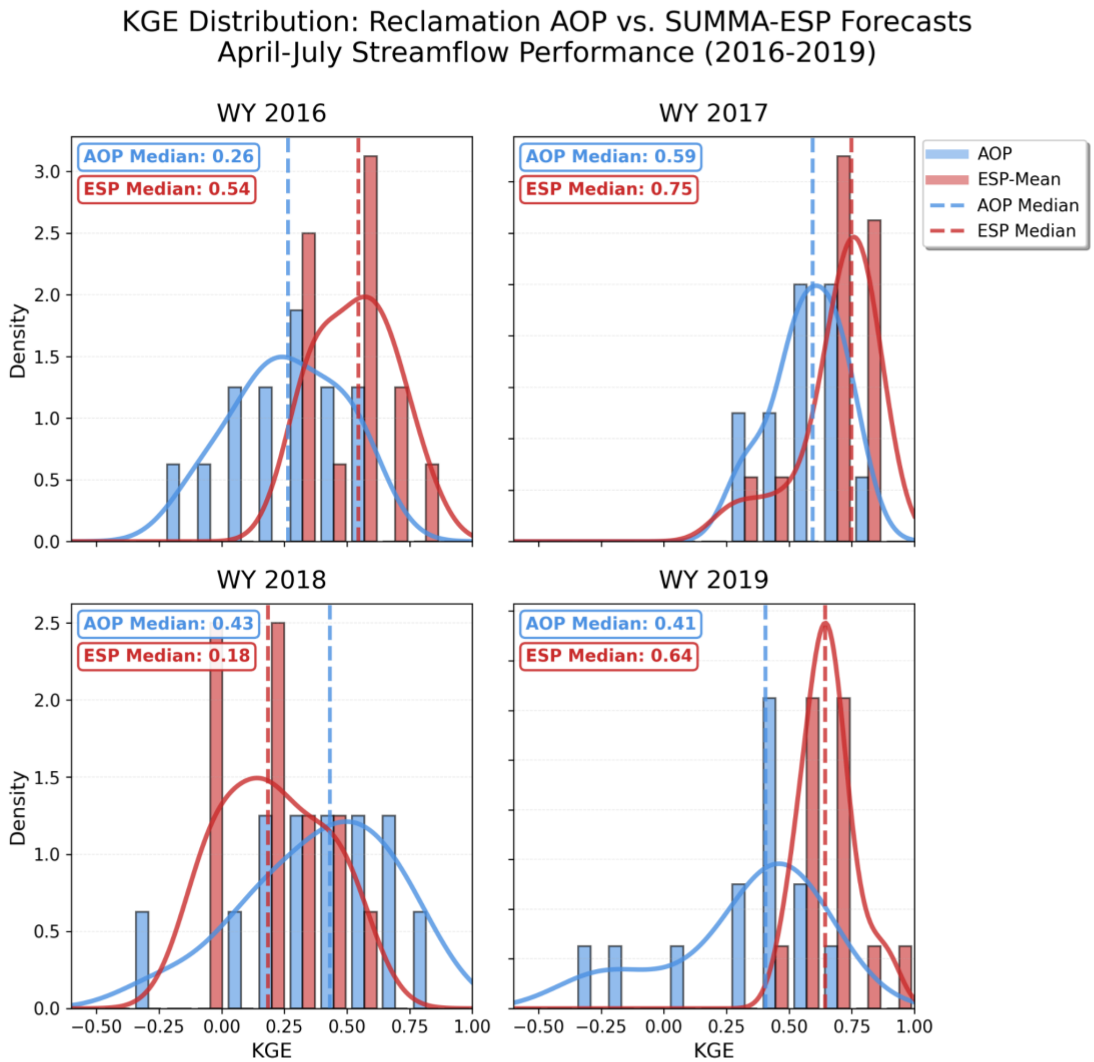

Figure 10: Comparison of post-processed SUMMA-ESP hindcasts (red) and Reclamation AOP forecasts (blue) for 13 sites during the AMJJ water supply forecast season, showing the KGE distributions across all sites during four years (2016-2019).

3.3.2 Assessment across all study forecast points and hindcast years

To systematically compare the performance of the process-based SUMMA-ESP ensemble streamflow hindcasts (scaled to NRCS forecast volumes) with the official Reclamation AOP forecasts across the study region, we evaluated three key hydrograph metrics for all available forecast points and years. **Figure 11** summarizes the differences in (1) AMJJ hydrograph shape, as measured by KGE, (2) the absolute error in spring peak flow magnitude (using a 7-day centered rolling mean, to reduce noise), and (3) the absolute error in spring peak flow timing (also using a 7-day rolling window). In each panel, positive values show improved performance by SUMMA-ESP mean compared to the AOP forecast, while negative values indicate cases where the AOP forecast outperformed SUMMA-ESP for that metric.

The leftmost panel of Figure 11 shows that, across all available sites (n = 13) and years (2012-2019), the SUMMA-ESP mean hindcasts consistently improved the AMJJ hydrograph shape relative to the AOP forecasts (total site-year sample size n = 71). The distribution of KGE differences is skewed positive, with a median improvement of +0.09. On average, this suggests that the SUMMA-ESP mean provided a closer fit to observed flows than the analog-based AOP forecasts. This result shows the potential advantage of an ESP-based modeling approach in forecasting runoff timing and variability from a set of initial hydrologic conditions in the basin.

For peak flow characteristics (center and right panels), SUMMA-ESP mean performed comparably to the AOP forecasts. The median difference in peak flow magnitude error was just -13.4 CFS, indicating that AOP forecasts were closer to the observed peak flows by a small amount. This result is somewhat expected, as ensemble averaging naturally produces smoother hydrographs and underestimates individual event extremes compared to the single-trace AOP method, as illustrated in the 2016 examples shown in Figure 9. In contrast, the median difference in peak timing error was +3.0 days, narrowly favoring the SUMMA-ESP hindcasts, which were generally able to match the timing of observed peak flows as well or better than the AOPs.

In each case, the large spread (positive and negative) in the differences of metrics illustrates that neither method reliably outperformed the other for the prediction of hydrograph shape, peak flow timing, or peak flow magnitude. While the process-based SUMMA-ESP approach was able to replicate – and in some cases improve upon – the official analog-based AOP forecasts for both hydrograph shape and key peak flow characteristics, there were also many cases where the AOP forecasts matched or exceeded the performance of the ESP method.

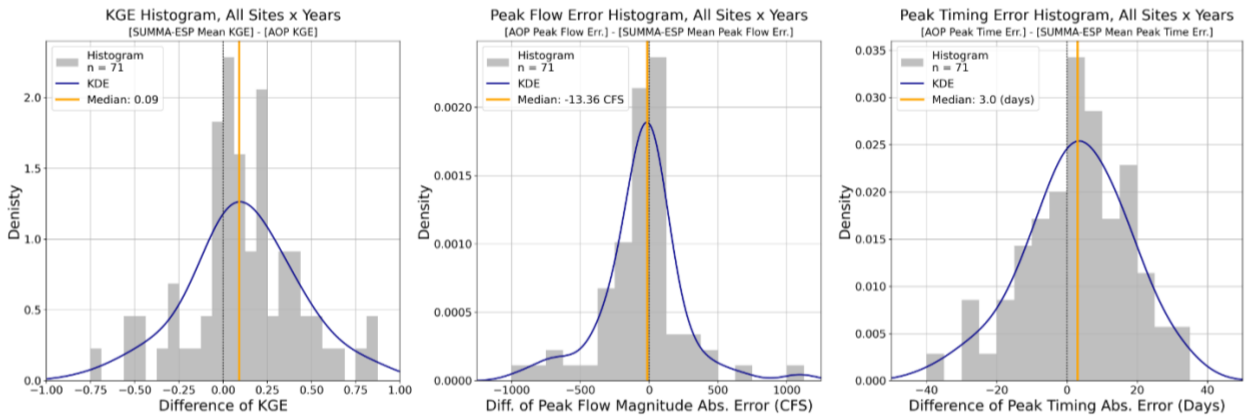

Figure 11: Histograms (gray bars) and kernel density estimates (KDE, blue lines) for three skill metrics comparing April 1st SUMMA-ESP ensemble mean hindcasts to the official Bureau of Reclamation AOP forecasts across all study sites. **Left**: difference in hydrograph shape skill (as measured by KGE) during the AMJJ period. **Center**: difference in absolute error of peak flow magnitude (CFS), based on a 7-day centered rolling average. **Right**: difference in absolute error of peak flow timing (days), also using a 7-day rolling mean. Each panel shows the distribution of metric differences across all years (2012–2019) and sites with available AOP forecasts (n = 71; AOP forecasts were only issued for Colorado sites starting in 2016). Positive values indicate improved performance by SUMMA-ESP mean relative to the AOP forecast, while negative values indicate better AOP performance for the given metric. Vertical orange lines show the median difference across all comparisons.

4. Discussion

This study presents a comparative assessment of two strategies for generating the daily seasonal forecast streamflow sequences required to drive reservoir system operations and management models in the Upper Rio Grande (URG) basin. Sequences based on median flows from ESP-based WSFs were contrasted against the current practice of using historical analog sequences selected and scaled to match WSF volumes. Due to the non-availability of historical ESP WSFs for the URG, the assessment was based on ESP hindcasts generated with an intermediate complexity, process-based watershed model that was calibrated for the URG operational water management models for reservoir operations, management and planning decisions. In general, the results demonstrate the feasibility of deriving the 'shape' of the seasonal runoff from ensemble streamflow forecasts as an alternative to practice of selecting analogs, which bring a random pattern of short-term variability.

The calibrated SUMMA watershed model, coupled to the MizuRoute routing model, accurately reproduced the snowmelt-driven seasonal cycle of streamflow in the URG, resulting in skillful retrospective streamflow simulations, particularly during the spring runoff season and in the less regulated headwater catchments. Multi-metric validation statistics indicated that the simulated streamflows were adequately matched to observed timing, variability, and volume (validation KGE ranging from 0.66 to 0.9) with good generalizability over the full period of record (1970-2021; KGE ranging from 0.54 to 0.88). Further calibration efforts would likely achieve improvements on this performance, but is beyond the scope of this study. As expected, model accuracy was somewhat reduced in areas strongly impacted by water management activities, such as reservoir regulation and inter-basin diversions, which were not explicitly simulated by the models. We also observed sub-optimal model performance in smaller headwater catchments in the Sangre de Cristo mountains, which may be a limitation of the intermediate spatial resolution of our model. However, our bias correction methods significantly improved these systematic errors where strong seasonal signals were present.

A notable limitation of operational streamflow forecasting practices that rely on expert input ("in-the-loop" methods; Pagano et al., 2016) is the inability to easily regenerate forecasts for studying past events or years, both for verification studies and the correction of systematic modeling errors. Here, we applied an automated "over-the-loop" hindcasting approach to re-forecast all April 1st dates from 1971-2019. The generation of nearly five decades of ESP water supply forecasts at the 13 key URG system locations allowed for a comprehensive demonstration and evaluation of an experimental seasonal streamflow forecasting method. It also provided a sufficiently large dataset for calculating cross-validated bias correction factors. Our analysis showed that the SUMMA-ESP method provided robust seasonal forecast skill, particularly in predicting AMJJ hydrograph shape, but also for seasonal volumes.

Compared to the official April 1st NRCS water supply forecasts, SUMMA-ESP hindcasts verified against NRCS-adjusted volumes (Figure S.6) had slightly higher errors (69.9 KAF vs. 52.6 KAF) and greater bias (4.0% vs. -2.7%) across both April–July and April–September forecast periods. The superior performance of the data-driven NRCS approach over the process-based SUMMA model is not surprising, as statistical models trained directly on historical relationships between predictors (e.g., snow, precipitation) and spring water supply often outperform more physically constrained hydrologic models (Rosenberg et al. 2011). This reflects in part an inherent advantage of statistical models in describing substantially linear problems such seasonal runoff prediction, where runoff is a nearly linear function of initial states and boundary conditions (Wood and Schaake 2008; Wood et al. 2016; Arnal et al. 2017), over complex non-linear process-based models that require careful specification of the model parameterizations and parameters. It also reflects the non-operational research study context of the SUMMA model development. Nonetheless, the SUMMA-ESP hindcasts reliably reproduced the hydrograph shapes and interannual variability sufficiently for use in this study. In practice, ESP forecasts are now made by the NWS WGRFC, with expected skill close to that of the NRCS WSFs.

As in any forecasting system, the application of post-processing techniques was essential for generating accurate and reliable predictions. In this study, we demonstrate that simple post-processing steps can substantially improve streamflow forecast skill, though these improvements depend on real-time streamflow observations and access to long-term, multi-decadal streamflow simulations. We implemented two post-processing strategies: a simple correction for initialization error, and a climatological day-of-year bias correction to address systematic model error. These corrections targeted biases resulting from structural model uncertainties, errors in meteorological inputs, or the influence of unmodeled water management activities. Our findings showed that we could reduce absolute biases in SUMMA-ESP mean April 1st hindcasts from 10.7% to 2.2%, while also improving nRMSE by 7.18 percentage points (Figure 8). These results underscored that, regardless of model calibration quality, post-processing is an important component of the operational hydrologic forecasting workflow.

The core objective of this study was to assess the performance of the ESP derived forecasts of seasonal runoff shape relative to existing operational forecast products from the Reclamation Albuquerque Area Office. Across most sites (n = 13) and years (2012-2019), the post-processed

ESP hydrograph shapes provided a better fit to observed streamflow than the analog trace selection techniques, as measured by the multi-metric criteria, KGE: the median improvement in KGE for the April–July period was +0.09 (n = 71 site-years). For peak flow characteristics, the ESP mean performed similarly to the AOP approach: errors in peak flow timing (with a rolling mean) favored ESP forecasts by +3 days, while peak flow magnitude errors slightly favored the AOP method by -13 CFS. This result highlights a key trait of the analog method: because it relies on selecting a single historical year, its performance can hinge on how representative that particular trace is. Sometimes, the analog year aligns well with current basin conditions purely by chance or because it genuinely reflects predictable basin snowmelt dynamics; other times, it reflects anomalous weather conditions from past years that are unrelated to the selection criteria applied in the AOP forecast process. In both cases, the analog approach (like other deterministic methods) implies overconfidence by failing to represent forecast uncertainty. In contrast, an ESP-based shape is a mean of multiple ensemble members (driven by historical weather sequences), and thus assumes only 'average conditions' for the timing of runoff during the WSF period. In practice, operational ESPs incorporate weather forecasts for the early lead times (out to 10 days in some RFCs), which departs from this assumption where it is justified by weather forecast skill.

The improvements in hydrograph shapes from ESPs were not uniformly distributed across the study period, however. Notably, during very dry years, the official AOP forecasts vastly outperformed shapes derived from ESP hindcasts. In these cases, forecaster judgement at Reclamation provided a distinct advantage to AOP forecasts by substantially adjusting forecasted flows toward low values (e.g., see NM sites in 2018, Figure S.4). However, such "in-the-loop" adjustments are not inherently precluded from ESP-based streamflow forecasting methods, and could potentially be incorporated in future implementations.

Beyond demonstrating improved hydrograph shapes compared to analog-based methods, the ESP framework offers several additional advantages. Unlike deterministic analog approaches, ESP ensembles produce a probabilistic range of possible outcomes. While both methods rely on historical information, ESP differs fundamentally by using past meteorological sequences to evolve the basin's current initial hydrologic conditions forward in time. The explicit representation of antecedent conditions allows for ESP forecasts to more accurately forecast under extreme or unusual conditions that deviate from the historical record of past hydrograph shapes. This can be further improved through use of ensemble data assimilation techniques such as the particle filter (e.g., DeChant & Moradkhani, 2011), ensemble Kalman filter for snow water equivalent (e.g., Huang et al. 2017), and variational methods (Mazrooei et al. 2021), including for the use of remotely sensed snow covered area (Fleming et al. 2024). Both ESP and statistical methods also enable the incorporation of future climate information (e.g., Baker et al., 2021; Hamlet and Lettenmaier, 1999; Wood and Lettenmaier, 2006; Lehner et al., 2017) which is particularly valuable at seasonal prediction horizons, but was not a part of this study. In this context, continued development of process-based models remains important even as AI-driven forecasting approaches advance, as they provide physically interpretable predictions and a consistent framework for data assimilation and forecasting under non-stationary conditions.

Another benefit of incorporating ESP forecasts into Reclamation's annual operations planning process is the ability to leverage multiple independent forecast sources. As demonstrated in Figure 11, no single method evaluated in this study consistently outperformed the other across all sites and years. As the NWS WGRFC continues to refine its nascent seasonal water supply forecasting program, a combination of NRCS statistical forecast volumes with ESP volumes may be warranted. Historically, such coordination between the NRCS and RFCs was standard practice in western US water supply forecasting (Pagano et al. 2014). Furthermore, research has demonstrated that multimodal ensembling is an effective way to further improve forecast skill both in hydrologic forecasting (Dion et al. 2021) and numerical weather prediction (Krishnamurti et al. 2016). This study suggests that a blended or collaborative approach that uses both NRCS' volumetric forecasts and WGRFC ESP-based forecasts could improve seasonal streamflow forecast robustness and support more adaptive water management decisions in the future.

5. Conclusions

Overall, this study demonstrates that deriving seasonal runoff shape from ESP forecast medians for input to reservoir modeling systems provides skill that is, on average, comparable to or better than the official analog-based Reclamation AOP forecasts, both in hydrograph shape and in the timing and magnitude of peak flows. An ESP-based technique offers options to address a limitation of the deterministic analog techniques, namely the lack of uncertainty characterization. The study's systematic benchmarking of this experimental method against existing operational capabilities demonstrates the potential for ESP-based hydrologic modeling frameworks to supplement or improve upon traditional analog-based forecasting methods in the Upper Rio Grande basin. If statistical WSFs from NRCS are preferred to WGRFC's ESPs due to skill or other considerations, this study nonetheless demonstrates a strategy for using the runoff shape from ESPs with the statistical WSF volumes, and moving beyond the use of deterministic analogs. These findings, though specific to the URG, support a more widespread uptake of ensemble-based streamflow forecasting techniques in place of historical analog methods and other deterministic modeling approaches.

This work also demonstrated the utility of an intermediate-scale, watershed-based SUMMA-mizuRoute implementation for streamflow simulation and ensemble hindcasting in a regional-scale river basin. While developed for research purposes, this forecasting application documented the integration of multiple components: the configurations of SUMMA and mizuRoute (on the HUC12 and MERIT-Hydro catchment and stream network geometries); multi-decadal 3-hourly model forcings created with the GMET and MetSim approaches; the model calibration approach using Ostrich with the DDS methods and sequential, ordered application; and the use of several post-processing methods to correct for initialization and model error. This effort was largely completed in 2021 and provided the basic SUMMA-mizuRoute modeling and calibration approach for streamflow used in subsequent regional applications (e.g., Mizukami et al, 2025).

Finally, this work highlights the value of close collaboration between researchers and practitioners in the co-development of hydrologic assessment and forecasting strategies for water management. Benchmarking research against operational baselines used in practice is an essential step in this process, and almost always requires an active interaction between personnel from an operational or management center, such as Reclamation AAO in this case, with the research team. Demonstration of hydroclimate prediction research in an operational context may help inform future efforts to adopt more robust ensemble-based systems to support adaptive water management amid increasing hydroclimatic variability, particularly in water scarce regions.

6. Data availability

The SUMMA hydrologic model is available at https://github.com/CH-Earth/summa, and the mizuRoute routing model is available at https://github.com/ESCOMP/mizuRoute. Meteorological forcings were generated using the GMET spatial regression framework, available at https://github.com/NCAR/GMET. Additional meteorological variables needed for SUMMA were simulated using MetSim, which was also used for disaggregating GMET forcings from daily to 3-hourly timesteps (https://github.com/UW-Hydro/MetSim). Observed streamflow data were obtained primarily from the U.S. Geological Survey National Water Information System (NWIS; https://waterdata.usgs.gov/nwis), with supplemental observations for selected headwater sites downloaded from the Colorado Division of Water Resources (https://dwr.state.co.us/tools/stations). NRCS water supply forecasts are available from the National Water and Climate Center (NWCC) Air and Water Database (https://www.wcc.nrcs.usda.gov/snow/).The Bureau of Reclamation Albuquerque Area Office Annual Operating Plans are available at https://www.usbr.gov/uc/DocLibrary/plans.html.

7. Acknowledgements

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8. Supporting Information

This Supporting Information section provides additional methodological details, validation results, and comparative analyses that complement the main text. It includes a summary of calibrated SUMMA model parameters (Table S.1), an assessment of model generalizability across calibration and full simulation periods (Figure S.1), a single-basin illustration of the raw SUMMA-ESP hindcasts (Figure S.2, complementing Figure 7 in the main text), additional comparisons between post-processed SUMMA-ESP and Reclamation Annual Operating Plan forecasts (Figures S.3–S.5, 2017-2019), and a comparison of NRCS and ESP-based volumetric water supply forecasts across Upper Rio Grande forecast sites (Figure S.6).

S.1 SUMMA and MizuRoute Parameter Optimization

Table S.1: Calibrated SUMMA and MizuRoute parameters (n = 13), including the parameter description, and units.

SUMMA Parameters	Description	Units
aquiferBaseflowExp	Exponent in baseflow discharge function	-
aquiferBaseflowRate	Baseflow rate when aquifer is fully saturated	$m\ s^{-1}$
Fcapil	Capillary retention as a fraction of total pore volume	-
frozenPrecipMultip	Multiplier applied to frozen precipitation inputs	-
heightCanopyBottom	Height of bottom of the vegetation canopy	m
k_macropore	Saturated hydraulic conductivity of macropores	$m\ s^{-1}$
k_soil	Saturated hydraulic conductivity of soil matrix	$m\ s^{-1}$
qSurfScale	Scaling factor for surface runoff generation	-
routingGammaScale	Scale parameter of Gamma distribution for routing delay	s
routingGammaShape	Shape parameter of Gamma distribution for routing delay	-
summerLAI	Peak summer leaf area index	$m^2\ m^{-2}$
theta_sat	Soil porosity (volumetric water content at saturation)	-
thickness	Thickness of canopy, added to heightCanopyBottom to estimate heightCanopyTop	m

S.2 Model Validation

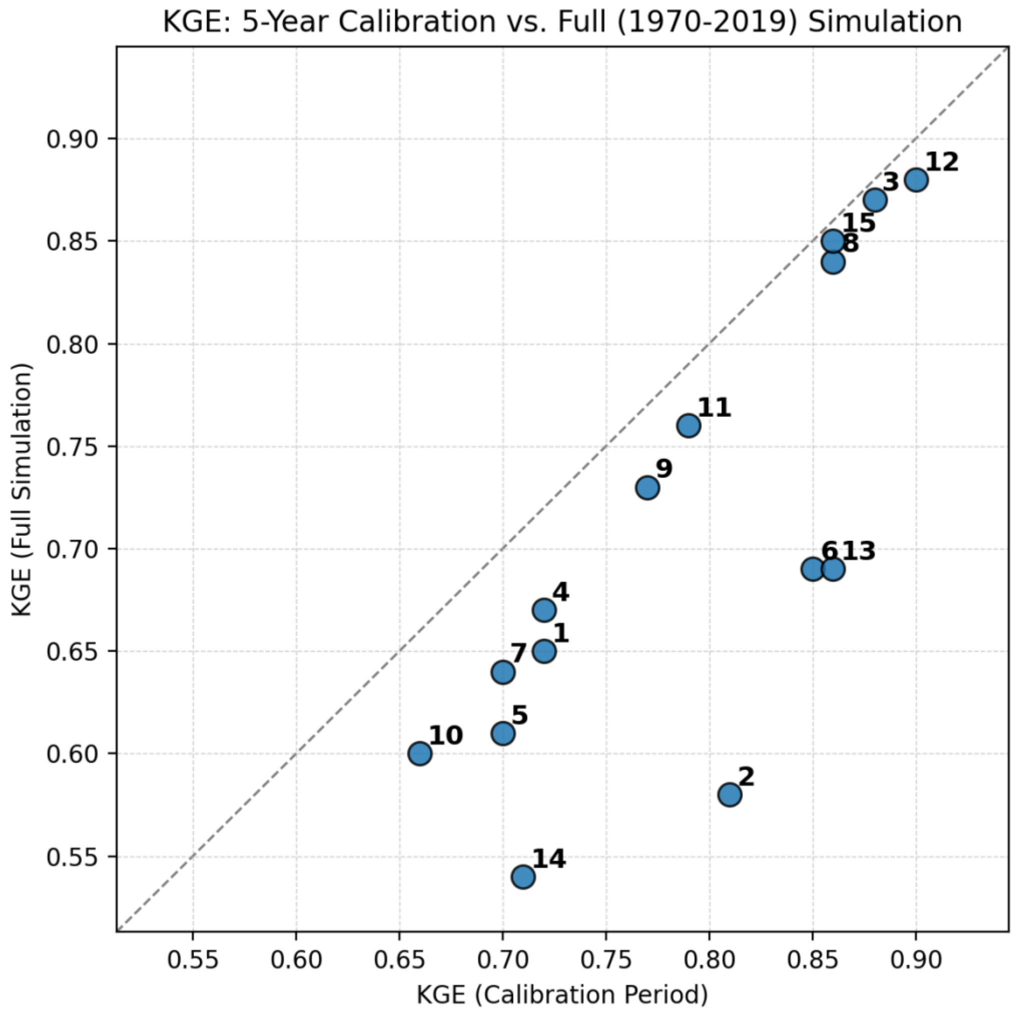

Figure S.1: KGE scores for the model calibration period versus the full simulation period (1970-2019). Scores closer to the 1:1 line show better generalizability across years.

S.3 Single-basin Case Study

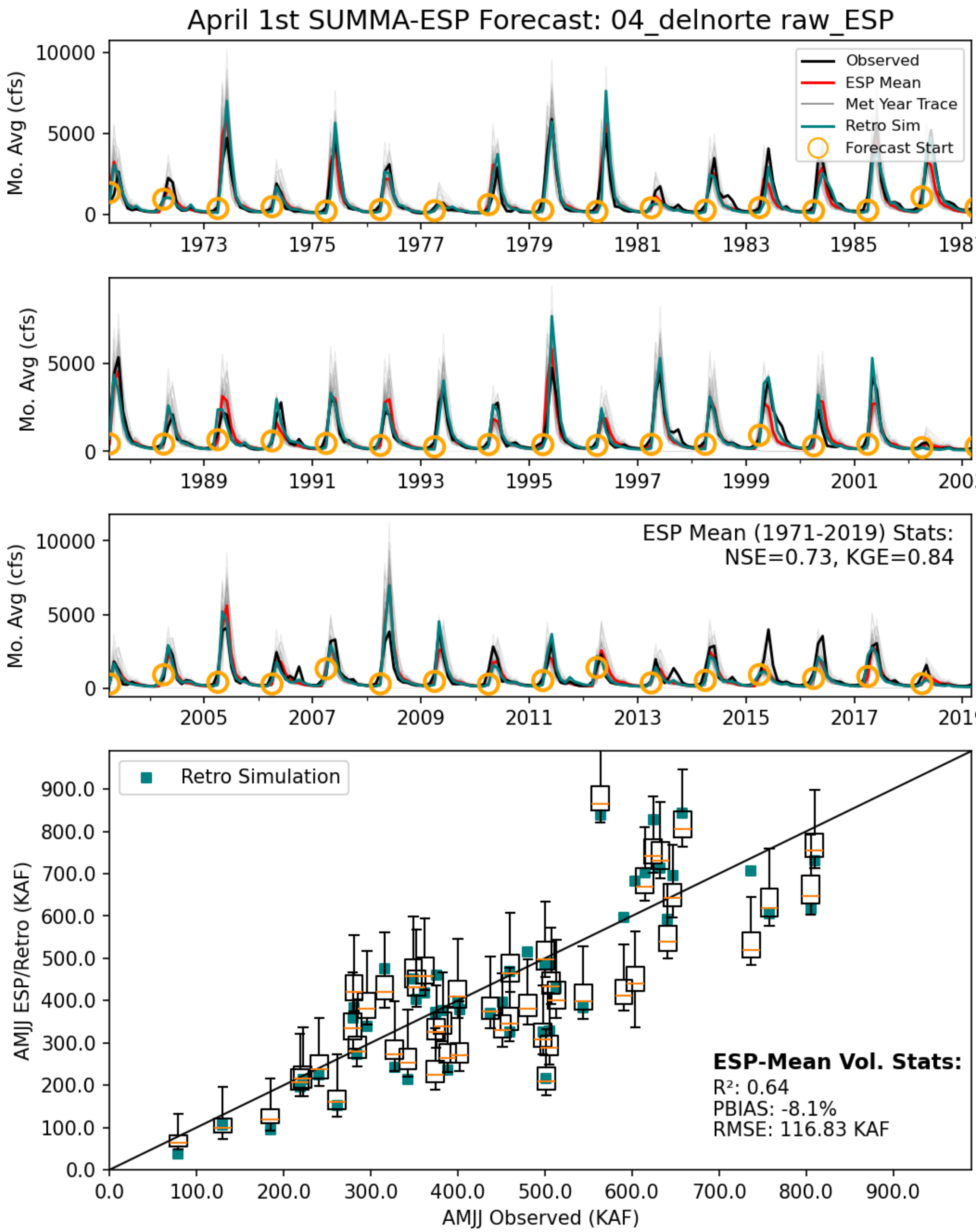

Figure S.2: Case study of SUMMA-ESP hindcasts for the Rio Grande at Del Norte, Colorado. Raw April 1st ESP hindcasts for 1971–2019 (top three timeseries panels) and probabilistic April–July totals (bottom, boxplots show 10th–90th percentiles from ESP). AMJJ volumes are aggregations of USGS observed flows, not adjusted ("naturalized") volumes as reported by the NRCS.

S.4 SUMMA-ESP vs. Reclamation AOP (2017 to 2019)

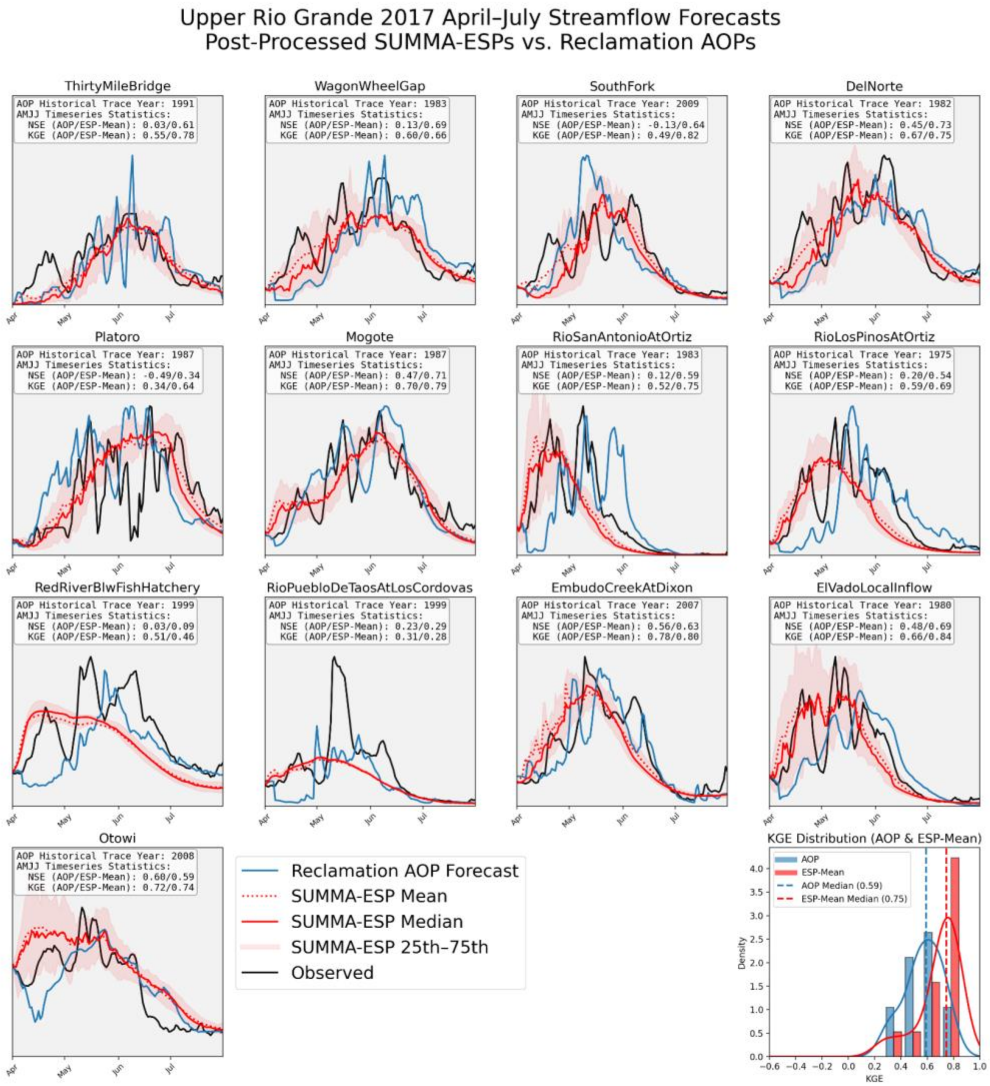

Figure S.3: Comparison of post-processed SUMMA-ESP hindcasts and Reclamation AOP forecasts for 13 sites during the 2017 April–July forecast season.

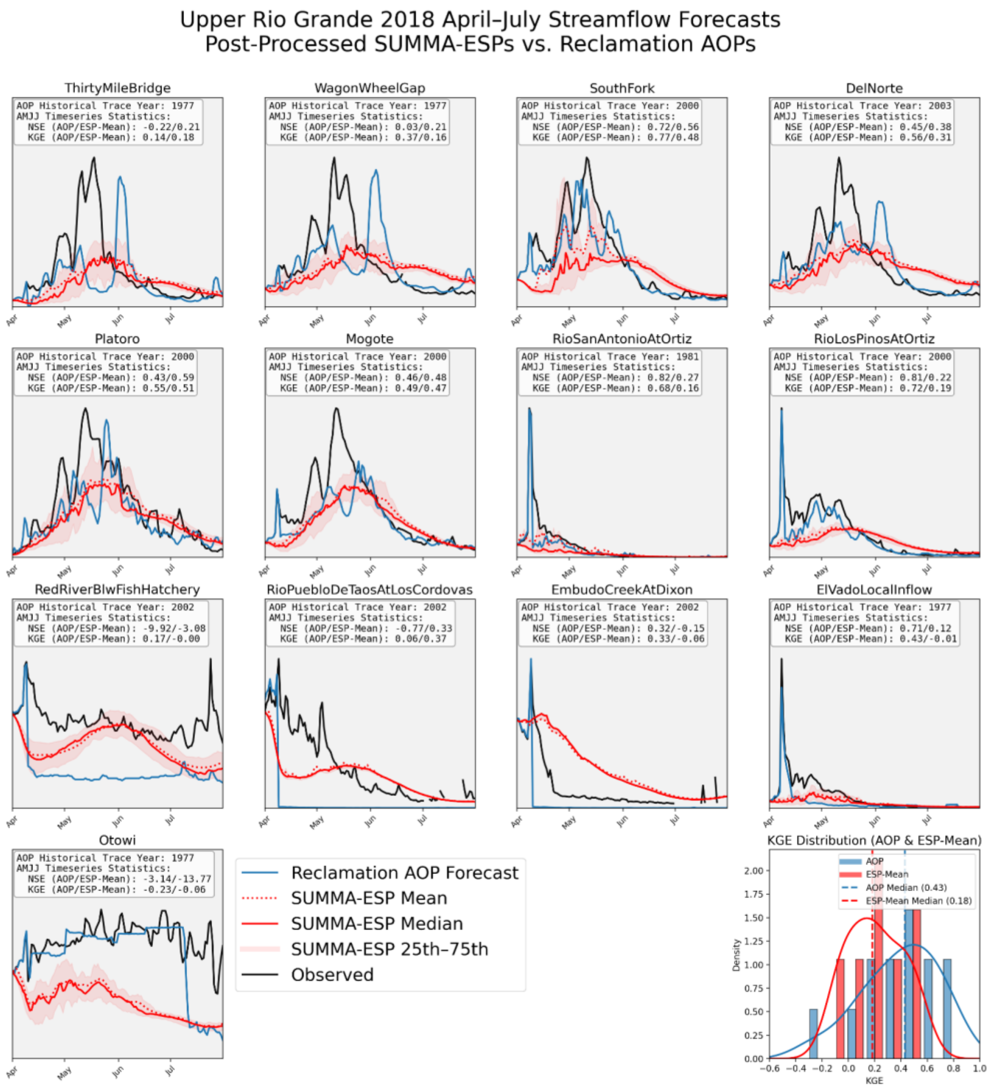

Figure S.4: Comparison of post-processed SUMMA-ESP hindcasts and Reclamation AOP forecasts for 13 sites during the 2018 April–July forecast season.

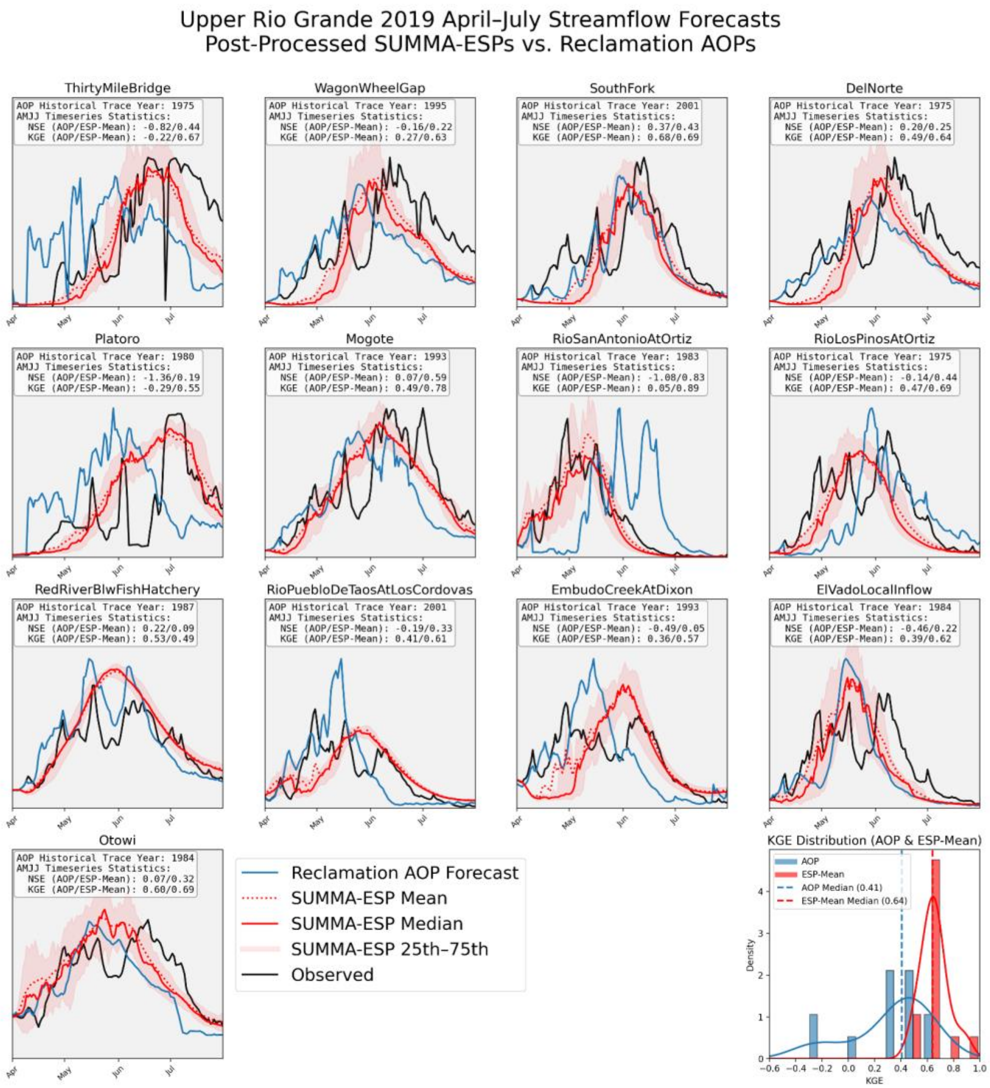

Figure S.5: Comparison of post-processed SUMMA-ESP hindcasts and Reclamation AOP forecasts for 13 sites during the 2019 April–July forecast season.

S.5 NRCS vs. ESP Volumetric Forecast Comparison

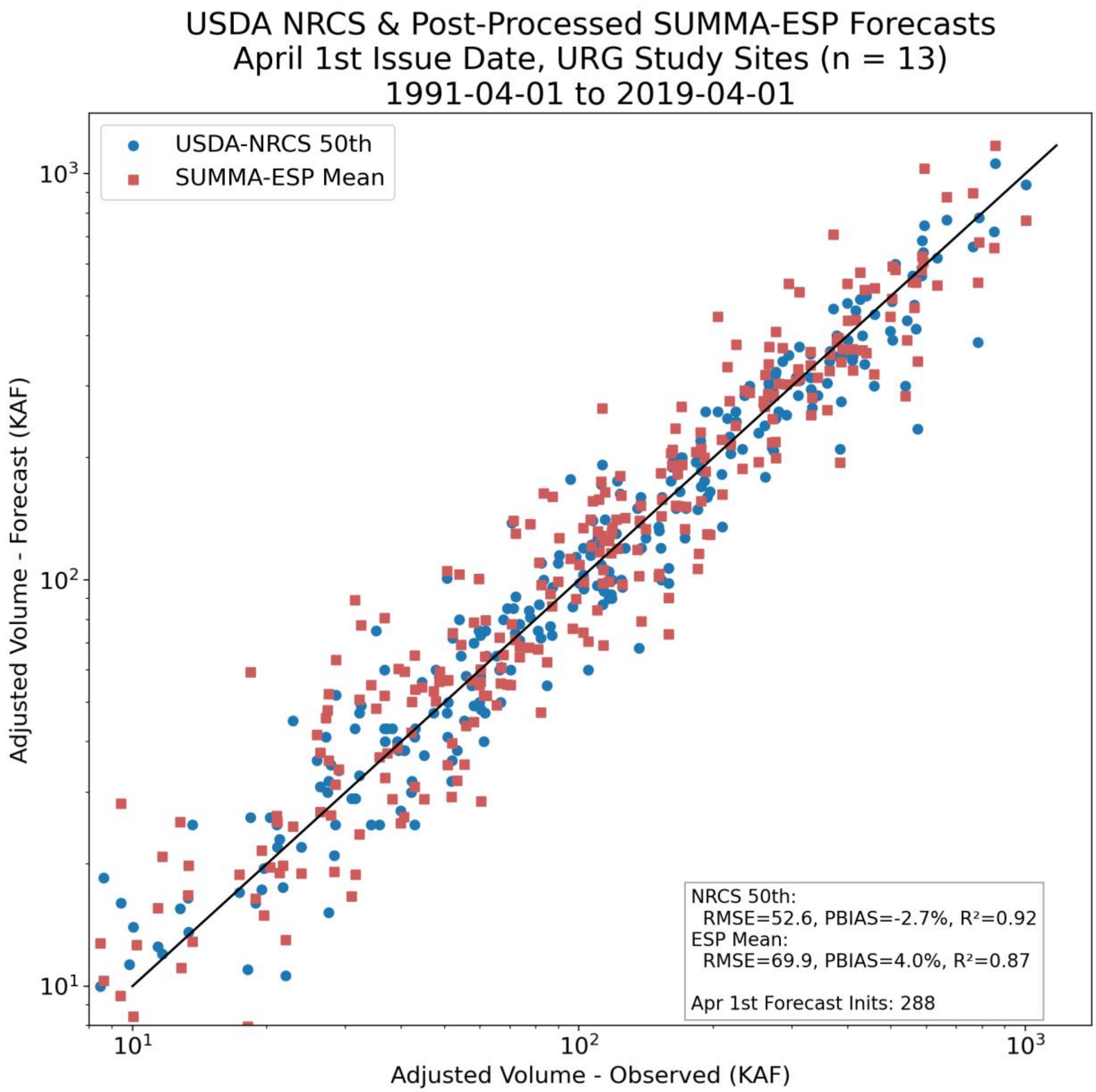

Figure S.6: NRCS and post-processed SUMMA-ESP April 1st water supply forecasts for the 13 URG forecast sites. In 6 of the 13 sites, only April-September forecasts are available from the NRCS, which are shown here. All other sites are for AMJJ forecasted volumes. Observed volumes are NRCS adjusted volumetric flows, which represent naturalized flows. Forecasts are from the period 1991 to 2019.

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