



Natural Functional Flow Predictions for the Great Salt Lake Basin

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A photograph of a river flowing through a forest with vibrant autumn foliage in shades of yellow, orange, and red. The river is rocky and the water is a brownish color.

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Executive Summary

As Utah pursues an integrated Great Salt Lake (GSL) Basin planning strategy, estimates of environmental water demands are needed not only at gaged sites but across the many ungaged and non-reference stream reaches where flow targets may be set. This report provides this information by estimating reference-condition functional flows throughout the GSL Basin stream network. Functional flows are discrete seasonal components of the annual hydrograph (winter low flow, high flow ascension, peak, and recession, and summer low flow) with documented ecological, geomorphic, and/or biogeochemical importance. Lane et al. (2026) proposed a functional flows framework for GSL Basin's rivers and a 'calculator' for quantifying the annual functional flow metrics at reference-condition streamgages, incorporating input from stakeholders representing a diverse array of federal, state, and local organizations and agencies. This report applies the functional flows conceptual model and calculator to generate natural functional flow predictions across the basin. Collectively, the functional flows framework, calculator, natural functional flow predictions, and associated tools are intended to help maximize the ecosystem benefits of water delivered as part of Great Salt Lake recovery efforts.

In this study, we applied a machine-learning approach to predict the interannual ranges of 18 functional flow metrics across the GSL basin stream network. Random forest models were trained on 2,540 gage-years of streamflows from 180 minimally disturbed reference gages across Utah, the Bear River Basin, and the Middle Rockies ecoregion, using publicly available geospatial and climate predictors. Model performance was evaluated with leave-one-out cross-validation, and a regionalized quantile-mapping correction was applied to address the range-compression bias inherent to ensemble tree models. Seventeen of the 18 flow metrics achieved good or better performance, with the models relying on physically meaningful predictors—groundwater recharge for magnitude metrics, air temperature for timing, and baseflow index for rates of change—lending confidence to the approach. The resulting functional flow metric predictions span ~2,500 stream segments (a 4,561-km network) and are delivered in a publicly accessible geodatabase.

These natural functional flow predictions represent the seasonal and interannual streamflow ranges that would have supported native river ecosystems in the absence of major impairments. The predictions provide the best estimate of natural flows for GSL Basin streams available at this time. They also serve as consistent, broadly applicable environmental flow targets that can help characterize and quantify how much water is needed for water quality and environment—one of many elements being considered as part of the GSL Basin Integrated Plan. However, specific water management decisions remain with local resource managers and should incorporate site-specific refinement of flow targets where data/resources permit. More broadly, the ecological management goals identified by stakeholders through the functional flows framework process can help with setting and modeling water resource system performance measures (WRe and USBR 2024).



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1. Introduction

The Great Salt Lake (GSL) is a terminal lake that reached a record-low lake elevation in 2022 (GSLST 2025). Water development, diversions, and consumptive uses have greatly reduced streamflow and altered streamflow timing, and dry playa now separates the Great Salt Lake wetlands from the wetted body of the lake (Null and Wurtsbaugh 2020). To address human health, economic, and wildlife concerns associated with low lake levels, Utah has been pursuing an integrated planning strategy for the GSL Basin that includes consideration of environmental water needs in upland rivers and wetlands draining to GSL (WRe and USBR 2024).

Environmental flows are widely recognized as critical to maintaining and restoring river ecosystems (Poff et al. 2017), and many methods exist to estimate environmental flow needs (Tharme 2003). A functional flows approach to guide the selection of environmental flow metrics (Lane et al. 2026; Yarnell et al. 2020; Stein et al 2021) considers discrete seasonal and interannual aspects of the flow regimes that have documented or generally recognized relationships with ecological, geomorphic, or biogeochemical processes. In the absence of sufficient data to develop empirical or mechanistic flow – ecology relationships across a region, this approach assumes that managing for these key functional flow components—as quantified by a set of annual flow metrics describing streamflow magnitude, timing, duration, frequency and rate of change—will preserve the necessary processes upon which native species depend.

For GSL Basin streams, key functional flows include winter low flow, high flow ascension, high flow peak, high flow recession, and summer low flow (Lane et al. 2026). In addition to characterizing the specific physical and biological processes associated with these five flows components, Lane et al (2026) developed automated methods to calculate a suite of annual functional flow metrics (FFMs) describing these functional flows and applied them to quantify natural functional flows across a set of 35 reference-conditions stream gages in GSL Basin. However, there remains a need to estimate reference-condition FFM ranges across the many ungaged and non-reference stream reaches in the basin to support various management efforts as part of the integrated planning strategy.

Here, we apply a machine-learning random forest modeling approach to estimate reference-condition interannual functional flow ranges across GSL Basin stream reaches. Our modeling approach leverages and builds on the approach used in Grantham et al. (2022) to predict FFMs across California. We describe data requirements, model development and assessment procedures, and performance metrics. The resulting flow metric predictions provide estimates for identifying flow targets that water managers can use to prioritize instream flow and restoration actions, and to maximize ecological benefits to river and wetland ecosystems when delivering environmental water to GSL.



2. Methods

2.1. MODELING APPROACH OVERVIEW

We calculated annual values of 18 functional flow metrics characterizing 5 functional flows (winter low flow, high flow period ascension flows, high flow period peak flows, high flow period recession flows, and summer low flows) (Figure 1, Table 1) from reference stream gage records in Utah, Bear River Basin, and the Middle Rockies ecoregion. We then compiled a large set of static and time-varying physical and climate variables for the watershed of each reference gage based on publicly available data. We developed a suite of machine learning models to relate the watershed variables to the functional flow metric values (one model for each functional flow metric). Model performance was evaluated using leave-one-out cross-validation and site-specific assessment. Finally, we used the models to predict the interannual range of values of each functional flow metric across the GSL Basin stream network. This section describes these steps in detail.

Rivers

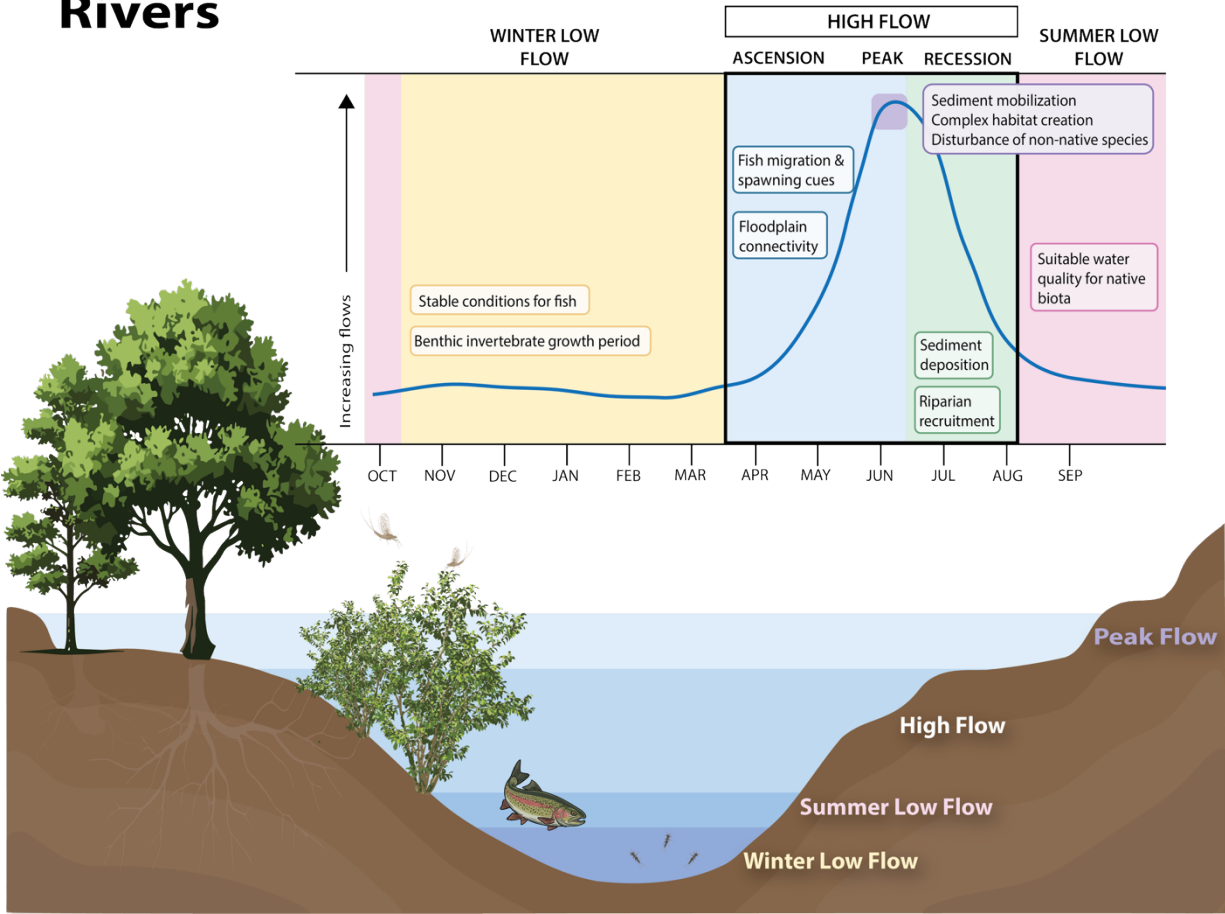


Figure 1. Generalized functional flow components for rivers in Utah's Great Salt Lake Basin, with important ecological functions noted. Used with permission from lane et al. (2026).

Table 1. Functional flow metrics for which predictive models were developed, and their functional flow components and characteristics.

Functional Flow Component	Flow Characteristic	Functional Flow Metric
Winter Low Flow	Magnitude	Winter median flow*
		Winter high baseflow (90 th percentile of daily flows)*
	Duration	Winter duration (# days from Oct 16 [end of irrigation season] to start of high flow period)

Functional Flow Component	Flow Characteristic	Functional Flow Metric
High Flow	Timing	Start of high flow ascension
	Magnitude	High flow period low flow (10 th percentile of daily flows)*
		High flow period median flow*
	Duration	High flow duration (number of days from start of high flow to start of summer low flow)
High Flow Ascension	Rate of Change	Ascension rate (Median daily rate of change during ascension period; calculated only for days with positive/increasing change)*
High Flow Peak	Magnitude	2-year recurrence interval peak flow (50 th percentile exceedance value of annual maximum daily flow over period of record for sites with at least 5 years of data)*
	Duration	Duration of 2-year recurrence interval peak flow (cumulative number of days in which this peak flow magnitude is exceeded in a given water year)*
	Frequency	Number of occurrences of 2-year recurrence interval peak flow within a water year
High Flow Recession	Timing	Start of recession
	Duration	Recession duration (number of days from start of recession to start of summer low flow)
	Rate of Change	Recession rate (median daily rate of change during recession period; calculated only for days with negative/decreasing change)*
Summer Low Flow	Timing	Start of summer low flow
	Magnitude	Summer median flow*
		Summer high baseflow (90 th percentile of daily flows)*
	Duration	Summer duration (number of days from start of summer low flow through Oct 15)

2.2. DATA REQUIREMENTS

Streamflow data and functional flow metric calculations

We used a multi-step screening process detailed in Lane et al. 2026 to identify a set of “minimally disturbed” U.S. Geological Survey (USGS) stream gages in Utah, the Bear River Basin, and the Middle Rockies ecoregion. The Middle Rockies ecoregion, although not in Utah, was included in our analysis because it has steep, high-elevation mountains and intermountain valleys with ecosystems similar to the terrain and ecology of Utah’s Great Salt Lake basin (Taylor, 2012; Wiken et al. 2011). We made every effort to eliminate gages which were highly disturbed, which meant eliminating gages affected by dams or diversions, and engaging local experts to review remaining candidate reference gages for unimpairment. We ultimately identified 180 active and inactive reference gages (Figure 2, Table S1) that provide 2,540 reference gage-years of streamflows from water year 1951 to 2015 (water year starts in October 1 of the prior calendar year). The reference streamflow records range from 1 to 65 years, with an average of 14 years of data. Drainage areas of the streams where these gages are located range from 3.8 to 195,681 square kilometers (km²) with a median area of 61 km². Mean basin elevation values range from 1,640 to 3,494 meters (m) with a median value of 2,493 m. Average annual precipitation varies from 350 to 1,510 millimeters (median 773 mm). The gage locations have yearly average temperatures between -1.9 and 8.8 degrees C, with a median of 2.9 degrees. For each reference gage, we downloaded available daily streamflow records from USGS websites (<https://waterservices.usgs.gov> and <https://waterdata.usgs.gov/nwis>) using the “dataRetrieval” package in R Studio (DeCicco et al., 2022) and used linear interpolation to fill gaps caused by occasional missing days of data.

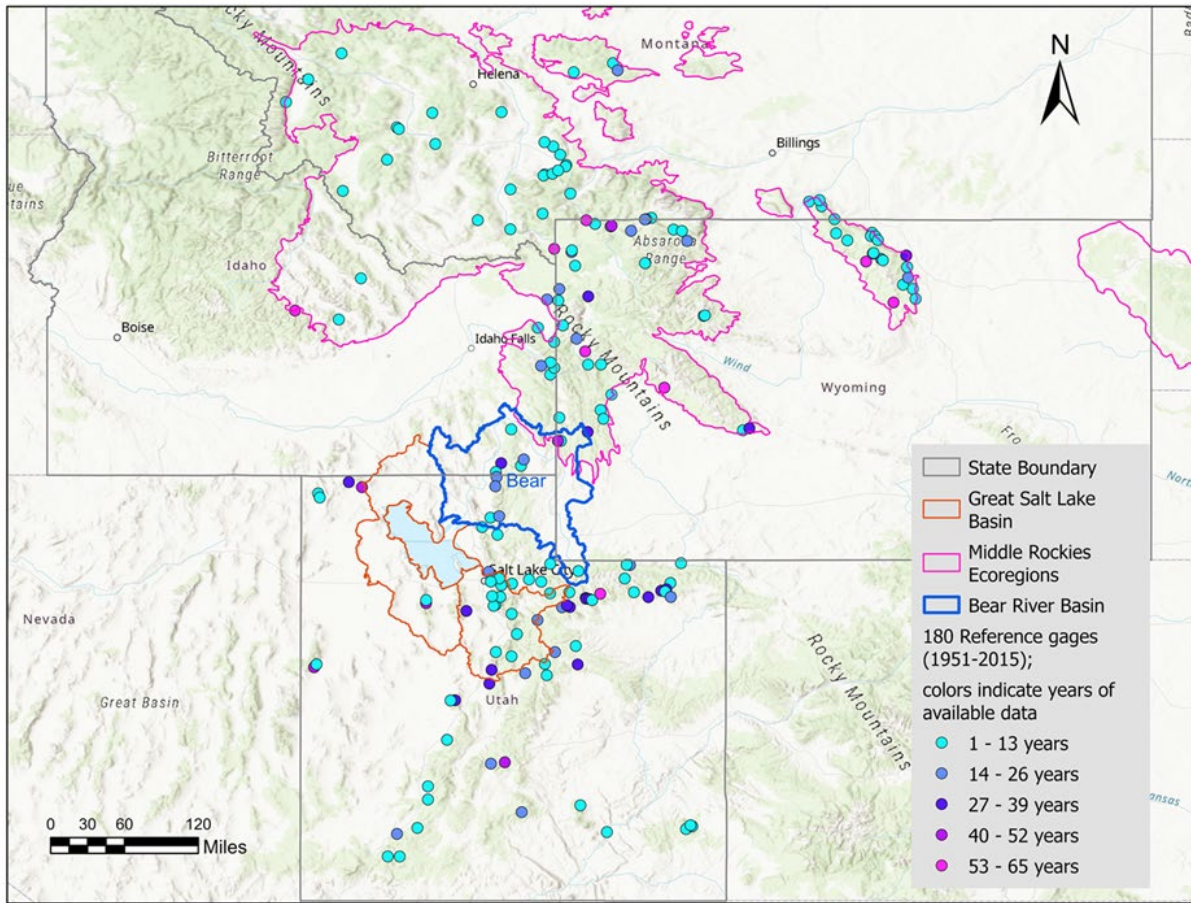


Figure 2. Reference-condition streamflow gages used for training functional flow metric random forest models.

These daily streamflow timeseries were used to calculate 18 annual FFMs (Table 1) using the GSL basin functional flows calculator, as detailed in Lane et al (2026). The functional flows calculator (<https://github.com/USU-WET-Lab/utah-func-flow>) identifies predictable flow patterns in streamflow timeseries to determine the timing of seasonal shifts in each annual hydrograph. A single 2-year recurrence interval peak flow metric was calculated for the whole period of record for gages with 5 or more water years of flow data. The magnitude-based flow metrics were normalized by basin area to account for differences in watershed size prior to being used as model inputs

Geospatial predictor variables

Initially, 353 geospatial predictor variables were compiled for each gage and stream segment from publicly available geospatial datasets. Most information was obtained from the USGS ScienceBase, with additional static climate data information obtained from EPA's StreamCat database. These data included static geographical characteristics (e.g., basin elevation, slope, etc.), geologic /soil characteristics (e.g., proportion of basin composed of clay soils, percent of

basin in carbonate rocks), hydrologic characteristics (e.g., baseflow index, average runoff), and long-term average and time-varying climate information (e.g., 30-yr mean air temperature, mean monthly precipitation, mean precipitation of water year, etc.).

2.3. FUNCTIONAL FLOW METRIC MODEL DEVELOPMENT

Model training

Random forest regression models (Cutler et al. 2012) were developed for each functional flow metric. Random forest models are commonly used to make predictions from non-linear, high-dimensional datasets and identify dominant predictors. The random forest statistical modeling approach used in this study differs from physically based hydrologic models that are commonly used in environmental flow applications. First, rainfall-runoff models are generally trained and calibrated using a small sample of stream gage records to estimate streamflow (e.g., daily time-series) throughout individual watersheds based on intensive field data collection and parameterization. In contrast, the modeling approach used here relies on a large network of gages and can be applied to generate predictions across a broad geographic region. Our approach also calibrates to specific aspects of the flow regime rather than being globally tuned to capture all aspects of the flow regime, which may increase model predictive accuracy of functional flow metrics (Grantham et al. 2022). Model training inputs include reference gage annual FFM values—log-transformed for metrics with strongly right skewed distributions (ten out of 18 flow metrics)—and the associated set of geospatial predictor values.

Specifically, we used the following process to train, evaluate and validate the models. For each functional flow metric, a random forest model was initially trained using the annual reference gage metric values for all years and all 353 predictor variables (352 for magnitude metrics where basin area was used for normalization, not prediction). To limit overfitting and facilitate model interpretability, as a first step we retained just the top 30 predictor variables for each flow metric based on variable importance score. We then reduced the predictor set further by eliminating several geology variables not relevant within the GSL Basin and by eliminating highly correlated predictor variables (Pearson correlation coefficient >0.9). This was done in a step-wise manner, where any lower-ranked variables highly correlated with a higher importance variable were eliminated. A final round of model training using this reduced set of predictor variables (140 total predictors across 18 models) was performed for each flow metric (Table S2).

We evaluated model performance using cross-validation (LOOCV), where each of the 180 training sites was iteratively left out of a model run and calculated flow metrics were compared to model predictions. All modeling was performed using the randomForest package in R (version 4.3.1) with 2000 trees and default parameters. To ensure the computational reproducibility of our parallel simulations, we implemented the L'Ecuyer-CMRG (Combined Multiple-Recursive Generator) random number generator to set modeling seeds, initialized with a fixed seed of 12345 (<https://github.com/farah-nusrat/Predicting-Functional-Flow-Metrics-in-Utah>).

Post-processing

Post-processing was performed on the random forest models to balance model performance and interpretability given several established limitations/challenges. Averaging across an ensemble whose predictors explain only part of the interannual variance shrinks the variance of the predicted time series relative to observations (Belitz and Stackelberg 2021). Additionally, for the ten flow metrics modeled on a natural-log scale, back-transformation introduces a systematic bias to the predictions. Model predictions are formed by averaging trees in log space before back-transformation, and the back-transformed mean of logs is a geometric mean estimate, which by Jensen's inequality lies below the arithmetic mean (Duan 1983). Together, these effects compress each segment's predicted interannual range (lower values are biased high and higher values are biased low), even where the central tendency is relatively unbiased.

We corrected this compression for all 18 flow metrics with percentile-specific form of quantile mapping (cf. quantile delta mapping and CDF matching [Cannon et. al. 2015, Belitz and Stackelberg 2021], an analogous per-percentile correction is used by Booker and Woods 2014). At every reference gage g with at least 10 water years of calculated flow metrics (52-85 gages, varying by metric), we computed the interannual percentiles $q = (10, 25, 50, 75, 90)$ of both the observed values $O_{(g,q)}$ and the corresponding LOOCV central prediction $P_{(g,q)}$, where P is the mean across trees in log space, back transformed to native units. At each percentile level we then estimated a correction factor as the median across gages at each percentile level and applied it to Q_q , the prediction from the model fit to all reference gages, to yield Q_q^* . The correction/mapping family was selected based on each flow metric's measurement scale. Ratio scale metrics (i.e., flow magnitude, rate of change, duration) received a multiplicative ratio correction applied on each metric's native units via Eq. (1); Interval scale metrics (i.e., timing and frequency) were corrected additively via Eq. (2); and 2-year recurrence flood magnitude, which carries no interannual range, was corrected with a single scalar level correction estimate via Eq. (3).

$$c_q = \text{median} \left[\frac{O_{(g,q)}^{(g)}}{P_{(g,q)}^{(g)}} \right], Q_q^* = c_q(Q_q) \quad \text{Equation 1}$$

$$a_q = \text{median} (O_{(g,q)}^{(g)} - P_{(g,q)}^{(g)}), Q_q^* = Q_q + a_q \quad \text{Equation 2}$$

$$c = \text{median} \left[\frac{O_{(g)}^{(g)}}{P_{(g)}^{(g)}} \right], Q^* = c(Q) \quad \text{Equation 3}$$

We applied a monotonicity guard to the high flow period low flow and 2-year flood magnitude metrics as a running maximum over each correction factor that enforces non-decreasing factors to prevent quantile crossing. For performance evaluation, correction factors were re-estimated under a leave-one-gage-out scheme, so that the gage being scored never contributed to the median defining its own factor.

We used several approaches to evaluate changes to the model predictions from this bias correction. Figure 3 shows the distribution across reference gages of the ratio of the predicted to the observed flow metric interannual ranges for both the bias-corrected and the uncorrected predictions, where a value of 1 means the predicted and observed interannual ranges are identical. This shows that the compressed ranges were recovered well for all the metrics, with

most of the metrics' corrected distributions straddling 1 and the 25-75th percentiles within ~25% of 1.

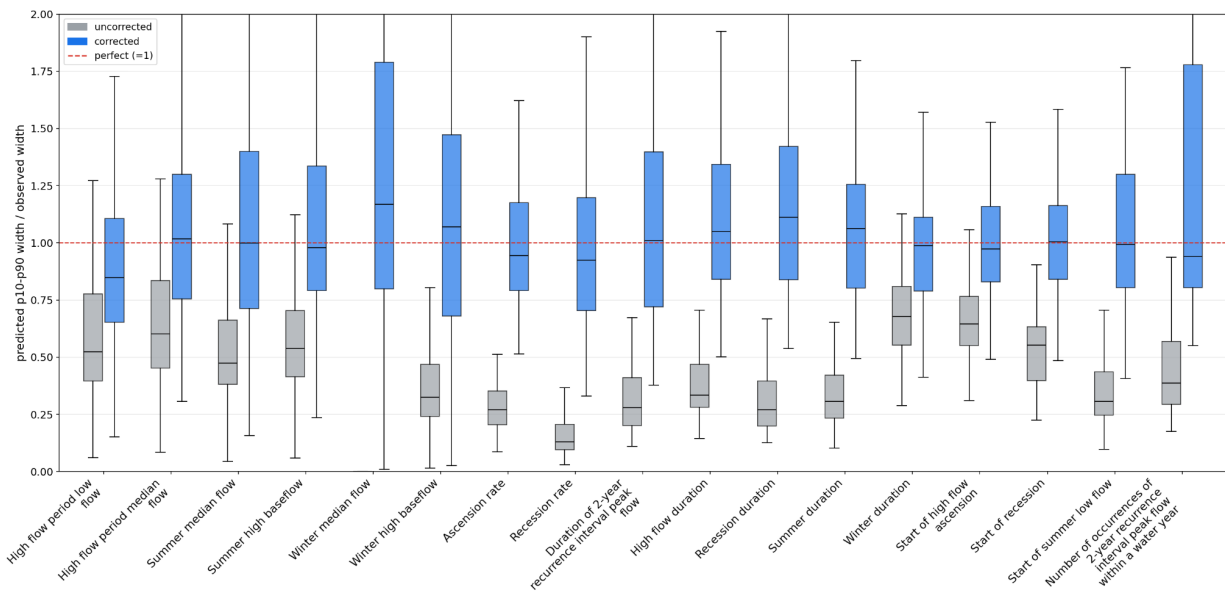


Figure 3. Ratio of predicted to observed value ranges (10th-90th percentile) for each functional flow metric model, before and after bias correction. Boxes summarize the distribution of the ratio across reference gages.

The Winkler interval score metric (Gneiting and Raftery 2007) quantifies the tradeoff in increasing the interannual prediction range between improved coverage of the observations (at training sites) and potential over-prediction beyond the observed interannual range. For both the 50% and 80% prediction ranges, the Winkler score drops substantially after bias-correction for all but a few metrics, indicating that the increased coverage outweighs the potential for oversized prediction ranges. Figure 4 below illustrates the frequency with which the bias-corrected prediction ranges are wider or narrower than the observed ranges. Generally, the occurrence of too wide or too narrow of ranges is balanced, with greater occurrence and larger magnitude of oversized prediction ranges at gages with few years of record (<20 years), at which the observed flow metric ranges likely do not reflect the full range of potential interannual variability.

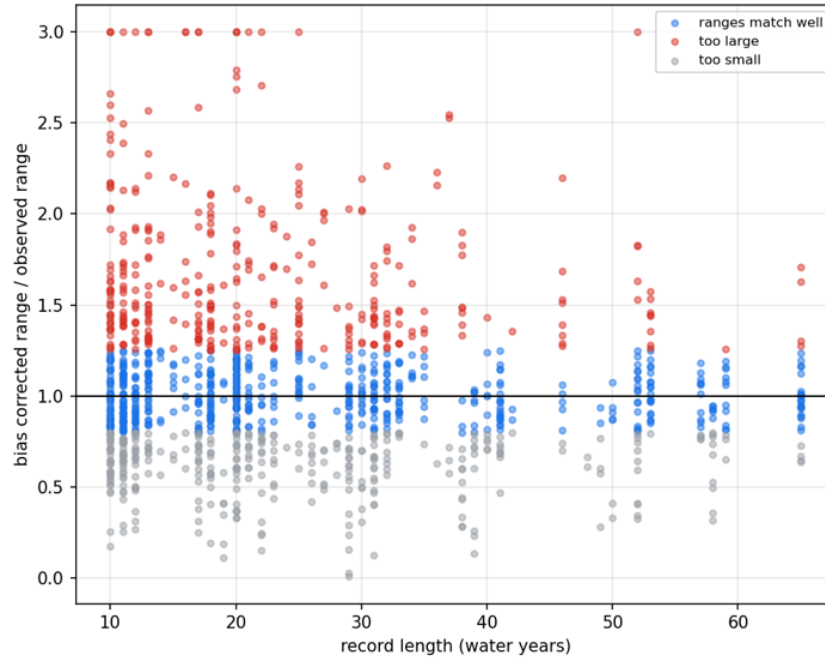


Figure 4. Ratio of bias-corrected predicted range to observed range, plotted against record length (number of water years). Each point is a single metric-gage combination. Point colors represent calibration outcome: blue where the ratio is 0.8–1.25, red where the corrected range is larger than the observed range, and gray where it under-represents the observed range. Ratios are capped at 3 for visualization.

We also tested how bias correction changes hydromodification detection. Applying the hydromodification rules outlined below to reference gages, any “likely altered” classification can be assumed to be a false positive. The bias correction reduced the occurrence of false positives from 58% to 23% of gages (mean across 17 interannual flow metrics). Correctly labeled “likely unaltered” gages increased from 16% to 72% following bias correction, and the “indeterminate” classification occurrence fell from 27% to 5% across reference gages.

Model performance

After bias correcting predicted metric values, we calculated six established performance criteria [Nash–Sutcliffe model efficiency coefficient (NSE), Percent Bias (PBIAS), Coefficient of determination (r^2), Percent_IQR (range between the 25th to 75th percentile values), Percent_I80R (range between the 10th to 90th percentile values), Mean observed-to-expected ratio (O/E)], as well as a composite performance index (CPI) based on the average of the six criteria after rescaling values from 0 to 1, as detailed in Grantham et al. (2022). As our final trained model for high flow peak magnitude did not include time-varying predictors, the Percent_IQR and Percent_I80R performance criteria could not be calculated and the composite performance index used only the remaining four criteria. The summary index categorized overall model performance as excellent, very good, good, satisfactory, or poor following Grantham et al. (2022). Additionally, we identified the top predictor variables for each model and used partial dependence plots of the top predictors to interpret climate and watershed controls on functional flow metrics.

2.4. PREDICTING FUNCTIONAL FLOWS ACROSS THE GSL BASIN

Stream segment selection

To identify the stream segments for random forest model prediction, we used the `nhdplus Tools` script <https://doi-usgs.github.io/nhdplusTools/> (Blodgett and Johnson 2022) to download the NHD medium-resolution stream network for the GSL Basin. We reviewed this dataset overlaid on aerial imagery and removed obvious canals/artificial channel segments and extracted the “StreamRiver” segments identified as Strahler (1957) stream order two and higher (McKay et al. 2012). After further review, 31 first-order stream segments of management interest were also included. Approximately 50 segments were manually removed because they lacked the geospatial attributes used for modeling. Unfortunately, some important first-order streams (e.g. Red Butte Creek in Salt Lake County, Kays Creek and Farmington Creek in Davis County, etc.) were missing from the medium-resolution NHD dataset. To evaluate how well the resulting GSL Basin stream network is represented by the reference gages, we compared the distributions of variables known to influence hydrology (basin area, mean basin elevation, stream length, average precipitation, catchment average annual temperature, and groundwater recharge) by overlaying and visually evaluating their kernel density plots.

Predictive modeling

We used random forest models to predict annual FFMs across the GSL Basin stream network for each water year in the 1951-2015 analysis period. Results from each “tree” in the model for each FFM were averaged to provide one prediction for each water year. For each stream segment, we then summarize annual flow metric values both across the period of analysis and by water year type by calculating the 10th, 25th, 50th, 75th, and 90th percentile values across relevant years. Water years were classified as dry, moderate, or wet (Table S3) based on terciles of the annual runoff summary index time series published by the USGS (2024) for the Great Basin Water Resource Region (region #16). For the peak flow metric, a single value was predicted for the whole analysis period (Grantham et al. 2022).

Refinement of prediction dataset

One limitation of random forest regression models is that they are unlikely to provide reliable predictions when input values are outside of the distribution of the training dataset. Therefore, when preparing our geospatial database of predictions, we opted to remove GSL Basin stream segments that had basin areas or mean elevations <5th percentile or >95th percentile of the predictor value distributions for the 180 reference gages (i.e., the training dataset). Specifically, stream segments with basin areas less than 13.9 km² or greater than 847 km² were removed, and segments with mean basin elevations less than 1,964 m or greater than 3,157 m were removed. Also, during the prediction assessment process, we identified and removed approximately 100 stream segments that had been incorrectly attributed in the NHD database (e.g. canals incorrectly shown as streams, side channels or channel braids attributed w/mainstem-sized attributes, etc.). This process reduced the number of segments in the final prediction dataset from 6,233 to ~2,500. Some errors with NHD segment locations and attributing still remain in the prediction dataset, as correcting the NHD in a comprehensive, systematic manner was beyond the scope of this project.

Also, even after excluding stream segments from the prediction dataset with basin areas or mean elevations <5th or >95th percentile of reference gage distributions, some differences remain evident in the distributions of predictor characteristics (Figure 5). In general, the reference gages trend toward higher elevation, wetter, and cooler segments than the GSL Basin stream segments. This artifact occurs because gages with relatively natural hydrology are more commonly located in headwaters than in valley bottoms. Most lower-elevation, larger streams in the region have long been dammed or diverted for water supply and irrigation, while the smallest headwater streams are not typically gaged (Zimmerman et al. 2018).

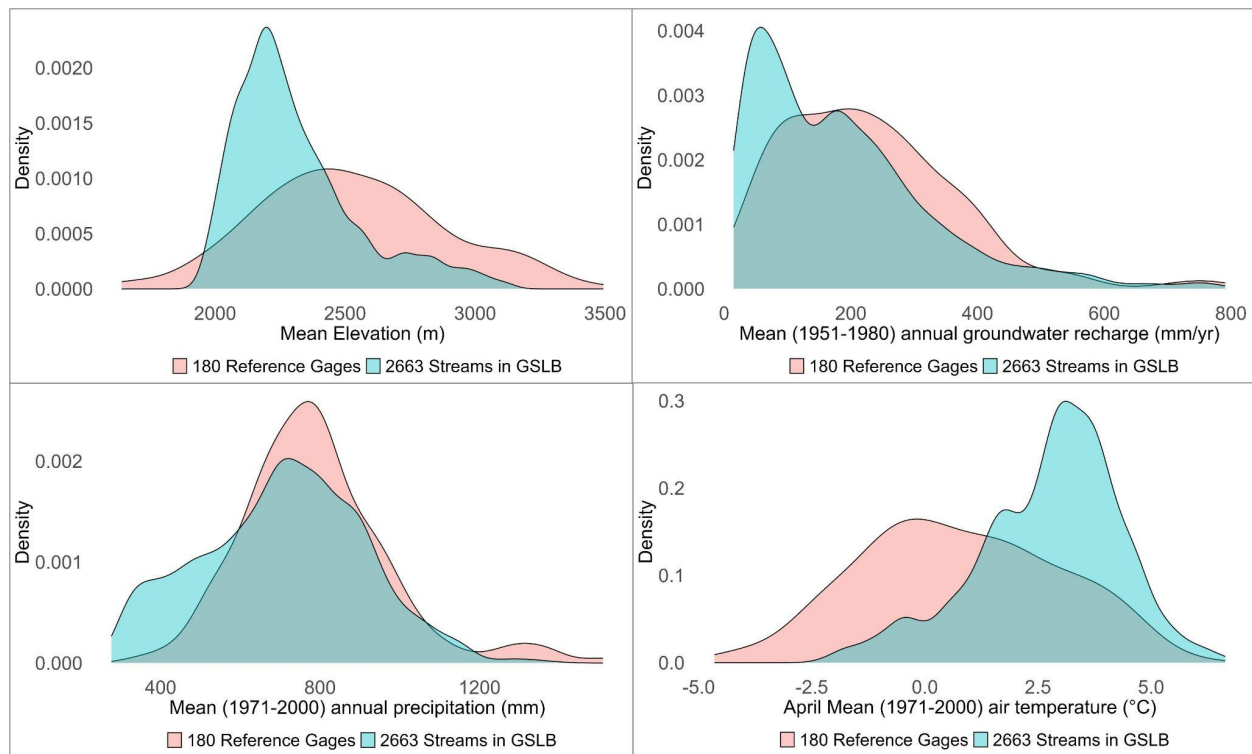


Figure 5. Kernel density plots of reference gage geospatial characteristics compared to the GSL Basin modeled stream segments.

3. Results

3.1. GEOSPATIAL PREDICTOR INFLUENCES ON FUNCTIONAL FLOW METRICS

The random forest models relied on physically relevant variables to generate predictions, including both static and time-varying physiographic and climate attributes. Of the 140 variables used for final model training, 80 were climate attributes (e.g., temperature or precipitation-related variables), 32 were hydrologic (e.g., groundwater or runoff), 19 were geology or soil characteristics, and nine were geographic (e.g., elevation, slope) (Table S2). Specifically, time-varying air temperature variables were top predictors for many timing, duration, and rate of change metrics including winter low flow duration, start of high flow ascension, and start of recession (Table 2, Table S4). Elevation range was the strongest predictor of summer low flow timing and duration (Table 2). The base flow index (BFI; annual average percent of groundwater in streamflow) was the top predictor for ascension and recession rates of change. Additionally, groundwater recharge – calculated by multiplying the base flow index by annual average runoff (Wolock 2003, Gebert et al. 1987) – was the top predictor for all seven magnitude-related flow metrics (Table 2). Time-varying and long-term average runoff variables were among the top five predictors for all three timing metrics and all but one of the magnitude metrics (Table S4). These dominant predictor variables by flow metric largely align with a similar modeling effort performed for California (Grantham et al. 2022).

Table 2. Model performance and most influential predictor variables for each functional flow metric. Only the top predictor is listed except where the next predictor(s) are within 10% of the top predictor. More detailed descriptions of predictor variables are provided in Table S2.

Functional Flow Component	Flow Metric	Strongest Predictor Variable(s) in Model	Composite Performance Index (CPI)
Winter Low Flow	Winter median flow	Estimated mean (1951-1980) annual natural groundwater recharge, mm/yr (GWRECHG)	0.89 [Very Good]
	Winter high baseflow	Estimated mean (1951-1980) annual natural groundwater recharge, mm/yr (GWRECHG)	0.98 [Excellent]
	Winter duration	Sum of seasonal temperature values for spring months for water year, °C (tav_Sprg.wy)	0.84 [Very Good]
High Flow	Start of high flow ascension	Sum of seasonal temperature values for spring months for water year, °C (tav_Sprg.wy)	0.83 [Very Good]

Functional Flow Component	Flow Metric	Strongest Predictor Variable(s) in Model	Composite Performance Index (CPI)
	High flow period low flow	Estimated mean (1951-1980) annual natural groundwater recharge, mm/yr (GWRECHG)	0.92 [Excellent]
	High flow period median flow	Estimated mean (1951-1980) annual natural groundwater recharge, mm/yr (GWRECHG)	0.92 [Excellent]
	High flow duration	Mean (1971-2000) annual minimum air temperature in °C (TMIN); average April temperature for water year, °C (tav_Apr.wy)	0.71 [Good]
High Flow Ascension	Ascension rate	Estimated percent of streamflow that is composed of groundwater (BFI)	0.72 [Good]
High Flow Peak	2-year flood magnitude	Estimated mean (1951-1980) annual natural groundwater recharge, mm/yr (GWRECHG)	0.86 [Very Good]
	2-year flood duration	Mean runoff (1951-2000) in July, mm (WBJUL)	0.65 [Good]
	2-year flood frequency	February precipitation in the previous water year in mm (ppt_Feb.pwy); June precipitation for water year in mm (ppt_Jun.wy); September precipitation in the previous water year, mm (ppt_Sep.pwy)	0.47 [Poor]
High Flow Recession	Start of recession	Sum of seasonal temperature values for spring months for water year, °C (tav_Sprg.wy)	0.84 [Very Good]
	Recession duration	Percentage of lithological potassium oxide content in surface or near surface geology (OLSONK); Percentage of lithological calcium oxide content in surface or near surface geology (OLSONCAO)	0.65 [Good]
	Recession rate	Estimated percent of streamflow that is composed of groundwater (BFI)	0.74 [Good]
Summer Low Flow	Summer median flow	Estimated mean (1951-1980) annual natural groundwater recharge, mm/yr (GWRECHG)	0.95 [Excellent]
	Summer high baseflow	Estimated mean (1951-1980) annual natural groundwater recharge, mm/yr (GWRECHG)	0.93 [Excellent]
	Start of summer low flow	Elevation range, in meters, computed as basin maximum minus minimum elevation (ELEV_RNG)	0.74 [Good]
	Summer duration	Elevation range, in meters, computed as basin maximum minus minimum elevation (ELEV_RNG)	0.75 [Good]

Partial dependence plots (Figure 6, Figure S1) highlight how top predictor variables influence functional flow metrics. For example, higher average spring air temperatures generally result in an earlier start to high flows and high flow recession periods, particularly when the sum of spring temperatures exceeds ~10–15 degrees (Figure 6a). Watersheds with higher BFI values have slower spring snowmelt recession rates, particularly for BFI > 74 (Figure 6b). Summer low flow timing and duration are sensitive to the distribution of elevations across the watershed, with larger elevation ranges (in particular > 1000m)—generally indicating higher order streams—associated with shorter, later starting summer low flow periods (Figure 6c). Winter and summer low flow magnitudes are sensitive to groundwater recharge, with higher magnitude flows associated with higher average annual groundwater recharge (Figure 6d). High flow recession rates and durations are also sensitive to surface lithology, with higher potassium oxide content (OLSONK) associated with faster recessions—reflecting the limited groundwater storage of felsic crystalline rocks—and higher calcium oxide content (OLSONCAO, particularly above 5–10%) associated with slower recessions, consistent with the greater storage of carbonate terrains (Figure 6e-f). Overall, models identified hydrologically relevant variables as top predictors, which lends credibility to the overall functional flow modeling approach.

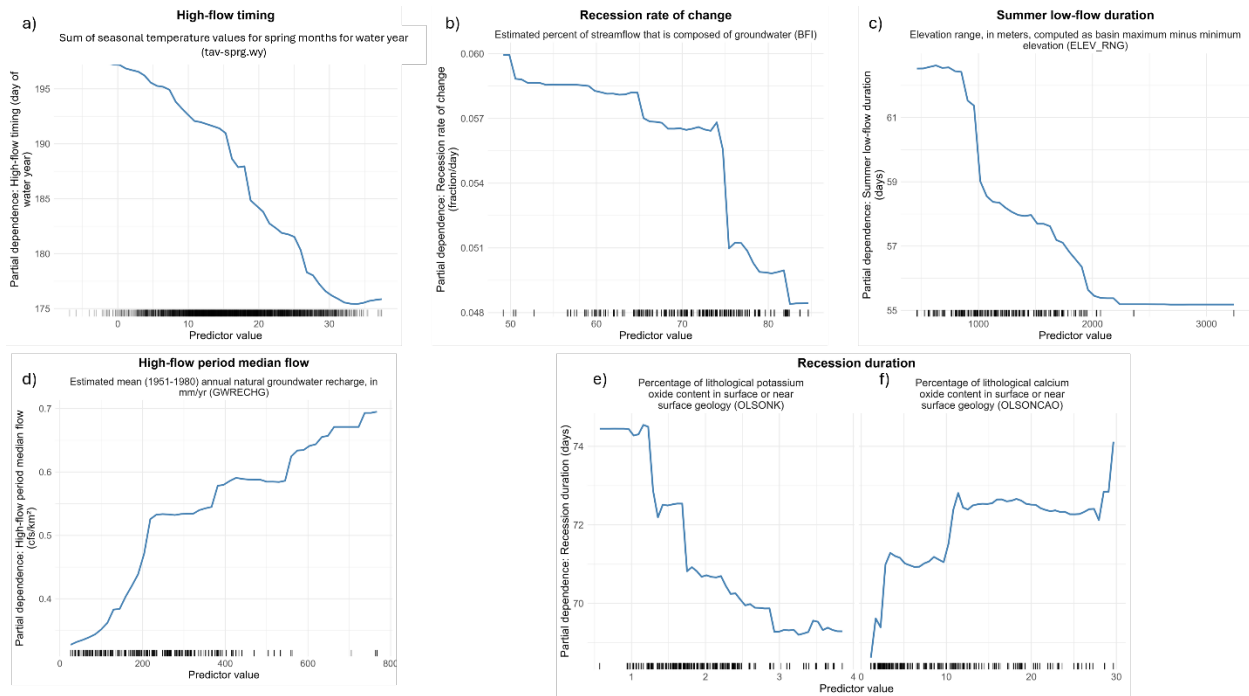


Figure 6. Random Forest partial dependence plots for selected functional flow metrics and predictor variables. (a) Average spring temperature for the start of high flow ascension timing metric. (b) Baseflow index for the high flow recession rate of change metric. (c) Basin elevation range for the summer low flow duration metric. (d) Groundwater recharge for the high-flow period median flow. (e) Potassium oxide content and (f) calcium oxide content for recession duration.

3.2. FUNCTIONAL FLOW METRIC MODEL RESULTS

Performance assessment

For flow metrics, random forest model composite performance index results demonstrate excellent performance ($CPI > 0.9$) for 5 metrics, very good performance ($0.8 < CPI \leq 0.9$) for 5 metrics, and good performance ($0.65 < CPI \leq 0.8$) for 7 metrics. Only 2-year flood frequency had a poor rating ($CPI < 0.5$) (Table 2). All magnitude metric models except 2-year flood magnitude and winter median flow exhibit excellent performance. For those two metrics, their slightly lower CPIs were associated with large PBIAS values (-20.9% for 2-year flood magnitude, indicating that magnitude was underpredicted and 21.3% for winter median flow, indicating median flow was overpredicted, Table S5). Model performance for both rate of change metrics was good, with low NSE and r^2 values reducing the CPI score for those metrics. Those same criteria drove down the overall performance of most duration metrics as well as the summer low flow timing metric. CPI scores for start of high flow ascension, start of recession, and winter duration were all very good, but were pulled down by low IQR or I80R values, indicating that the models for those metrics underestimate the observed range of variation.

The 17 functional flow metrics that exhibited good or better overall model performance (Table 2) were included in a [GSL functional flows geodatabase](#).

Functional Flow Metric Model Results

Example functional flow metric prediction results are provided below, including longitudinal profile plots of predicted ranges for select river reaches and metrics (Figures 7–9) and maps of relative flow metric values across the GSL Basin stream network (Figure 10). The longitudinal profile and mapping plots illustrate expected upstream to downstream patterns, with magnitude metric values generally increasing downstream and showing jumps at confluences. Similarly, the map of the start of high flow ascension timing metric (Figure 10, middle panel) shows later start timing in the highest elevation stream segments (e.g., Uinta Mountains headwater reaches), aligning with later snowmelt start in these locations.

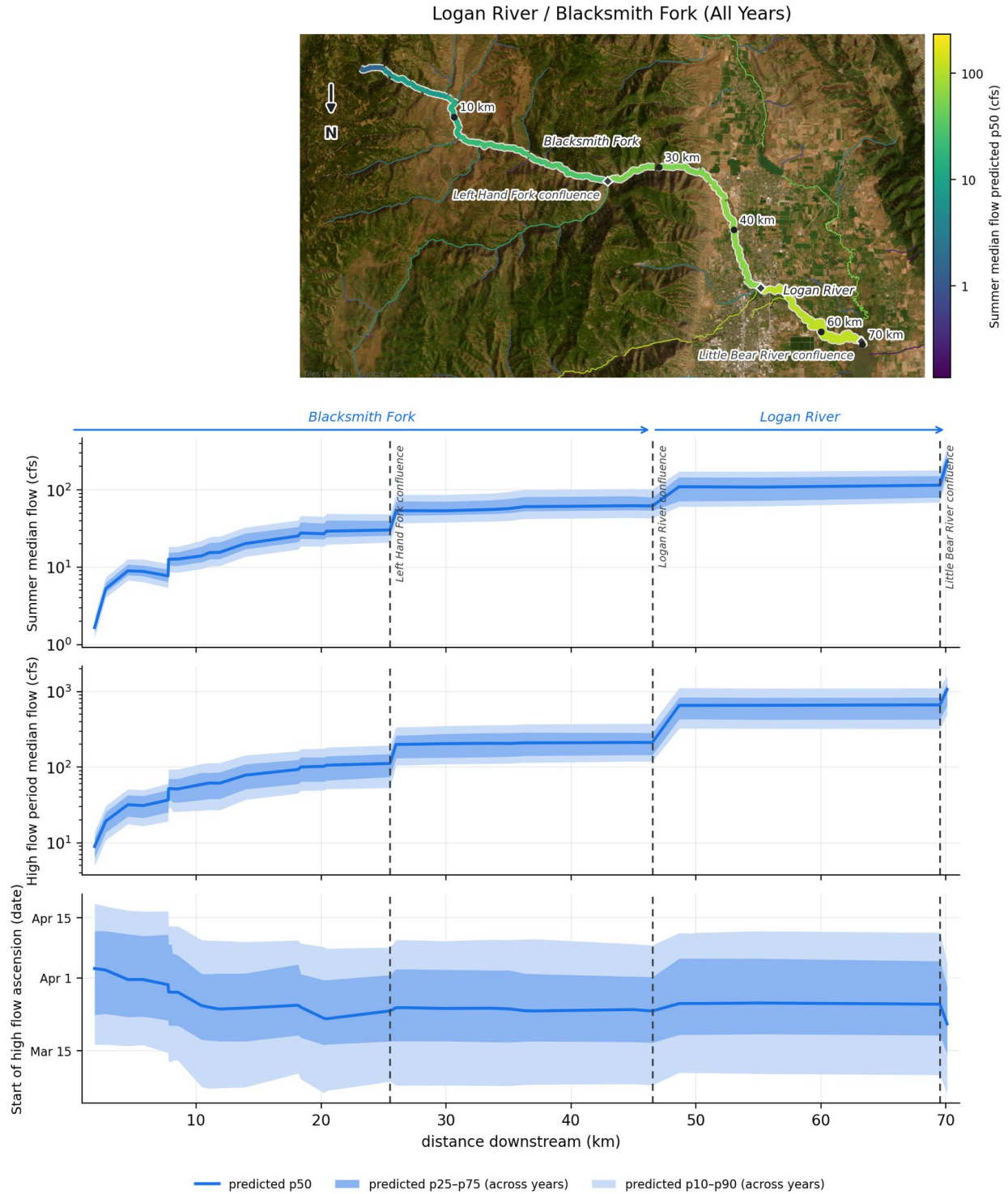


Figure 7. Longitudinal profile plots of three predicted functional flow metrics along reaches of Blacksmith Fork/Logan River. Top panel provides an overview map of the profiled flow path with segments colored by the median (across all years) summer median flow metric predictions. Lower panels provide upstream to downstream profile plots of predicted magnitude and timing metrics.

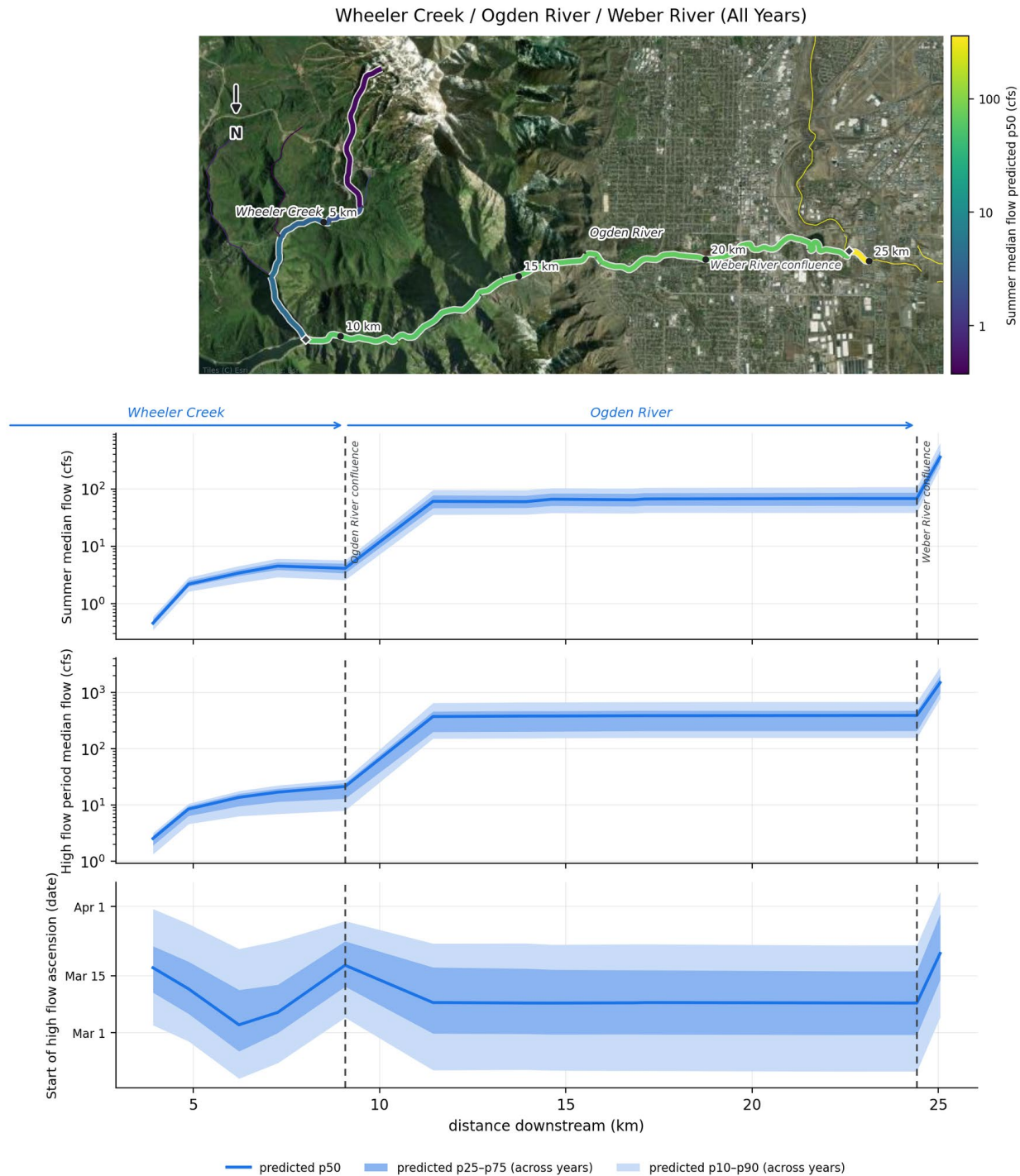


Figure 8. Longitudinal profile plots of three predicted functional flow metrics along reaches of Wheeler Creek/Ogden R/Weber R. Top panel provides an overview map of the profiled flow path with segments colored by the median (across all years) summer median flow metric predictions. Lower panels provide upstream to downstream profile plots of predicted magnitude and timing metrics.

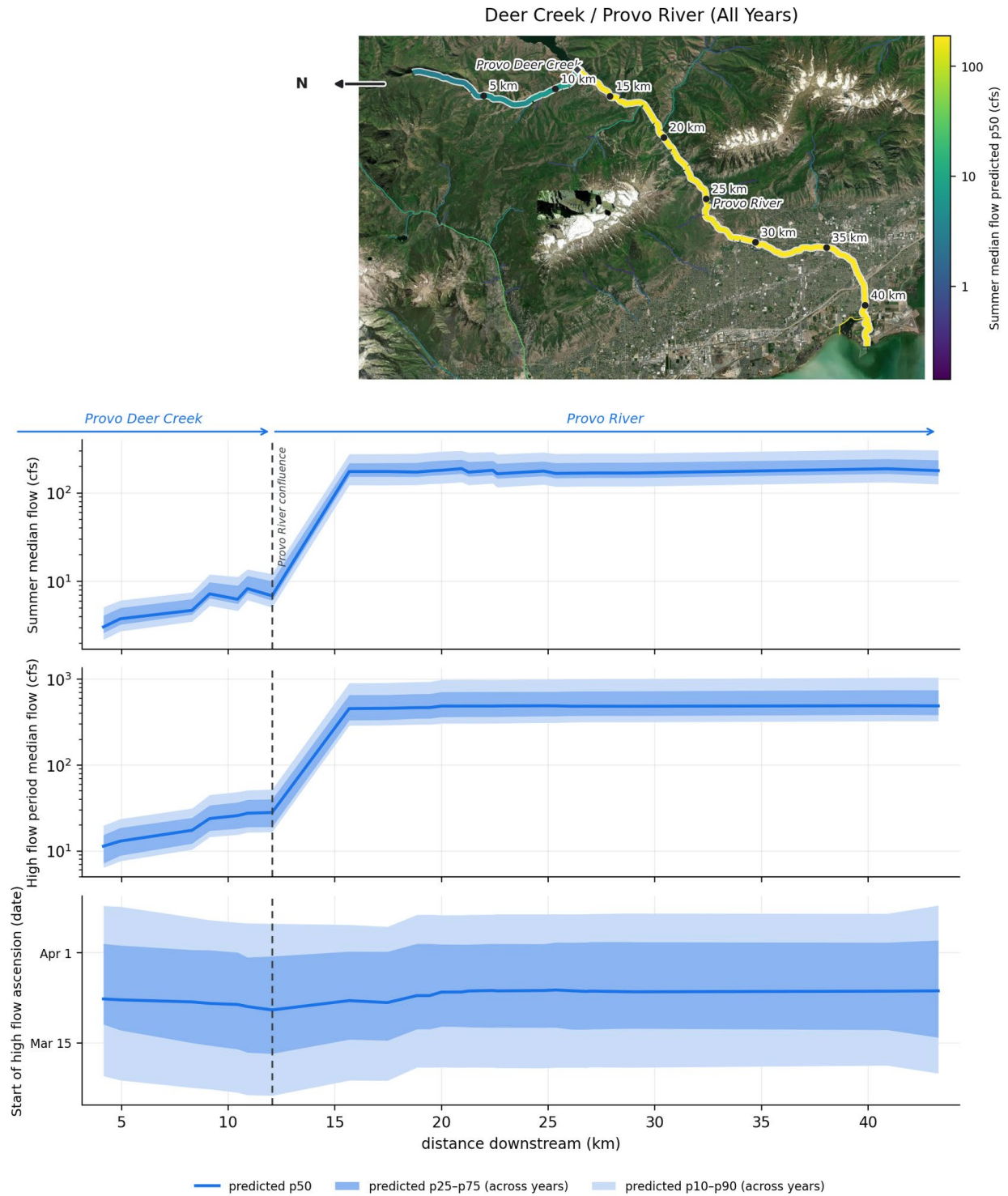
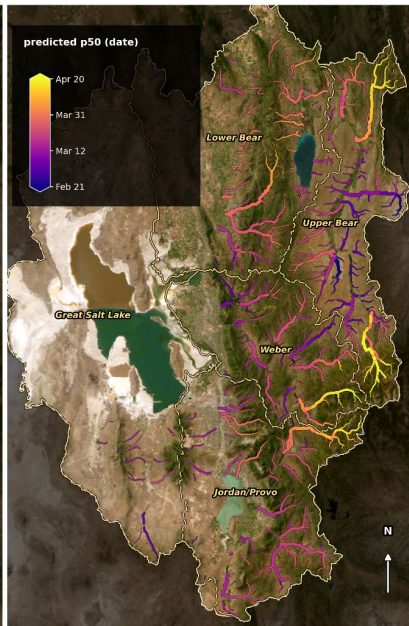


Figure 9. Longitudinal profile plots of three predicted functional flow metrics along reaches of Provo Deer Ck/Provo R. Top panel provides an overview map of the profiled flow path with segments colored by the median (across all years) summer median flow metric predictions. Lower panels provide upstream to downstream profile plots of predicted magnitude and timing metrics.

Summer median flow



Start of high flow ascension



High flow period median flow



Tiles (C) Esri -- Source: Esri, i-cubed, USDA, USGS, AEX, GeoEye, Getmapping, Aerogrid, IGN, IGP, UPR-EGP, and the GIS User Community

Figure 10. Functional flow metric predictions across GSL Basin. Note that many of the larger mainstem river segments are excluded from these maps because they are out of range of the model training dataset.



4. Potential Applications / Next Steps

The GSL Basin functional flows framework (Lane et al., 2026) and functional flows predictions presented here establish a foundation for developing environmental flow estimates that sustain critical ecological functions, and upon which subsequent analyses can be performed. These modeled natural functional flows could be helpful for a range of stakeholders involved in managing or protecting the GSL, its wetlands, or tributary streams - including government agencies, water districts, watershed councils, scientists, landowners, and non-profit organizations. The framework assumes that water management tradeoffs between delivering water for the environment and for people will be evaluated by local resource managers and water users. Our functional flow predictions can help support these evaluations by providing a range of flow criteria intended to sustain key aquatic organisms, ecological functions and water quality; however, this framework does not prescribe any specific water management decisions. More detailed information about potential uses of the functional flows framework and the GSL functional flows geodatabase is presented below.

4.1. SETTING AND REVISING ENVIRONMENTAL FLOW TARGETS

A functional flows approach inherently overcomes resource requirements of site- and species-specific studies by developing consistent, broadly applicable environmental flow targets (Figure 11). The approach assumes that managing for discrete, seasonal aspects of the natural flow regime—as quantified by a set of flow metrics—can preserve the necessary hydrologic patterns upon which native species depend (Yarnell et al., 2020; Lane et al., 2026). These streamflow-based targets are particularly valuable where local data, research, and resources are unavailable. For systems with specific management objectives or where ecosystems have been highly altered, more intensive studies will likely be needed to link changes in flow to specific ecosystem responses and/or to determine if the model-estimated functional flows are appropriate for quantifying ecological flow needs (e.g., Taniguchi-Quan et al., 2022; Stein et al., 2021). Regional or site-specific studies documenting how flows and their alteration relate to important ecological endpoints—such as aquatic macroinvertebrate community health (Utah Department of Environmental Quality 2024) or fish population dynamics (Pennock et al. 2021)—could provide additional evidence of functional flows' effectiveness, where data and resources permit, and help prioritize flow management decisions. For instance, Peek et al. (2022) identified the functional flow metrics and their alteration most strongly associated with stream health across California based on state-surveyed aquatic macroinvertebrate and algal conditions.

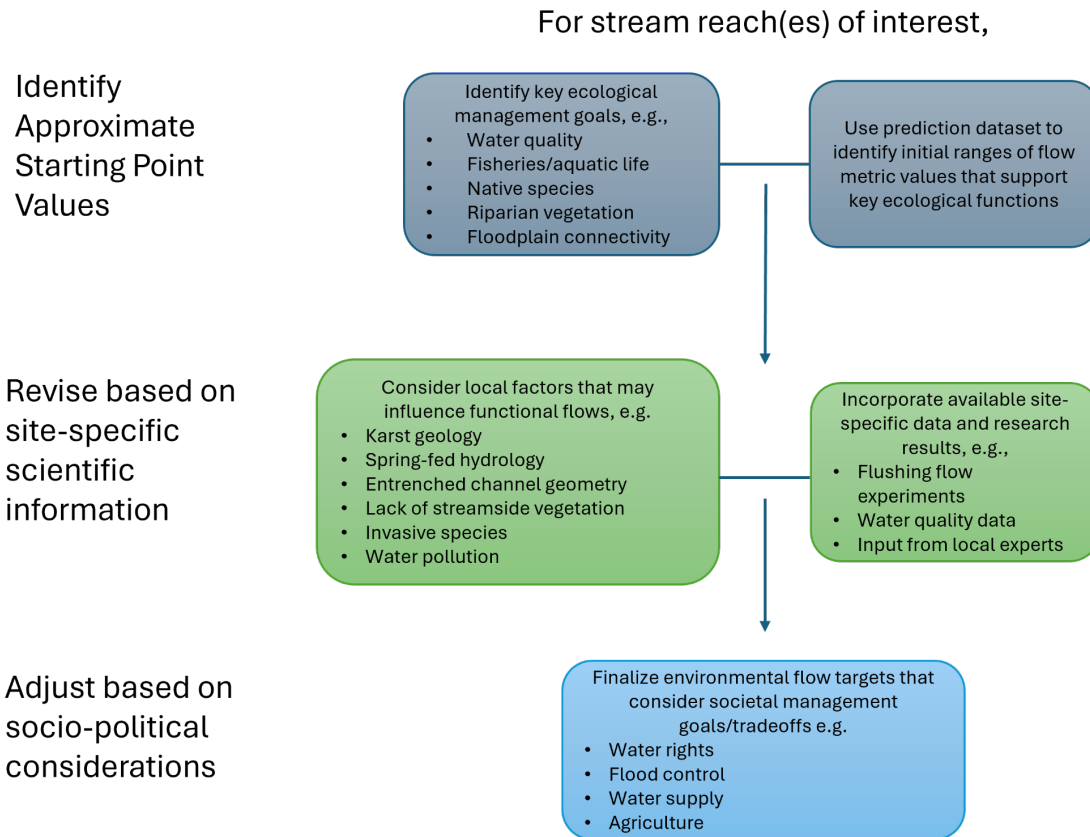


Figure 11. Overview of recommended steps to follow when using GSL Basin FFM predictions to establish environmental flow targets.

Where possible, the predicted natural functional flow ranges should be refined locally where site-specific information suggests that the reference ranges may not achieve the intended ecological functions (Stein et al., 2021). Several local factors and non-flow related alterations (e.g. physical habitat, water quality, biologic conditions, or non-native species) may limit the ability of the natural ranges for flow metrics to support desired ecological functions. For example, Yarnell et al. (2022) found that functional flow metric predictions for California (Grantham et al 2022) tend to underestimate baseflows in groundwater influenced systems. In the Little Shasta River, CA, they added a measured ~10 cfs of year-round spring discharge to the predicted dry-season baseflow (median 9 cfs). In a highly altered Southern California stream, Taniguchi-Quan et al. (2022) used measured habitat-suitability relationships for black willow seed dispersal to raise the spring-recession start magnitude from ~5 to 33 cfs—to achieve the overbank inundation needed for seed dispersal lost to major channel incision. The analysis also exposed the limits of flow-only adjustment: suitable depths for arroyo chub required baseflows far exceeding a plausible range, leading the authors to identify channel restoration rather than a revised flow target as the appropriate action to improve river conditions for native species. Across these cases, flow-ecology relationships were used to adjust specific metrics such that flow targets actually support the functions they are meant to sustain. An initial assessment of these local factors should be completed before using the GSL Basin FFM predictions to set environmental flow recommendations or modify water operations (Figure 11).

4.2. HYDROMODIFICATION ASSESSMENT

The modeled natural functional flow predictions provide a reference condition against which to evaluate current or potential alterations to flow and critical ecosystem functions. Understanding how the hydrology of a particular stream reach is altered relative to reference conditions (i.e., whether and how it is “hydromodified”) can inform conservation, restoration, and water management decisions. To highlight this potential application of the functional flow prediction dataset, we compared the natural FFM predictions to observed values at a selection of active streamflow gages across the GSL Basin to estimate flow alteration status. This effort is not intended to be a comprehensive analysis of flow alteration in the GSL Basin. Rather, it provides a proof-of-concept illustration of how an established approach for assessing hydrologic alteration (CEFWG 2021, Appendix J) could be leveraged in Utah’s GSL Basin to highlight deviations from long-term ranges of reference-condition functional flow metrics. Additional work is needed to systematically evaluate and implement a hydromodification assessment across the basin.

Alteration is evaluated by comparing the predicted functional flow metric range, or distribution, with the current functional flow metric distribution (CEFWG 2021). These values may be derived from available streamgages or from hydrologic models that simulate streamflow alteration. In order to rigorously compare distributions, at least 15-20 years of streamflow data (i.e. annual flow metric values) is recommended, except in cases where flow metrics exhibit limited interannual variability.

Alteration status is then assigned based on the criteria in Figure 12 and CEFWG (2021) as follows: Determine if the current median FFM value falls within the 10th-90th percentile prediction interval and calculate the portion of current values falling within this prediction interval. A FFM is considered (1) ‘likely unaltered’ if the current median value falls within the 10th-90th percentile prediction interval and >50% of current values fall within the same interval, (2) ‘likely altered’ if the current median value falls outside the 10th-90th percentile interval, and (3) ‘indeterminate’ if the current median falls within the 10th-90th percentile prediction interval but <50% of current values fall within the same interval. For likely altered metrics, the current median value relative to these intervals is used to specify direction of alteration. Likely altered flow magnitudes, durations, and rates of change are described as higher or lower than predicted, while timing metrics are described as earlier or later than predicted.

(<https://github.com/farah-nusrat/Predicting-Functional-Flow-Metrics-in-Utah>).

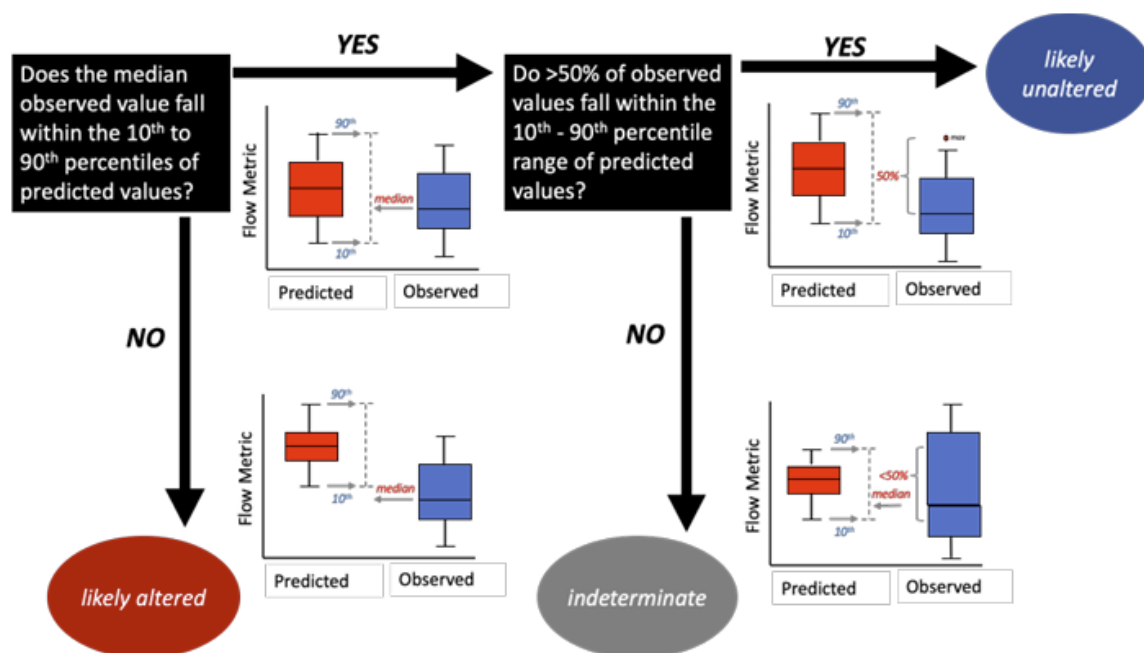


Figure 12. Criteria for assigning functional flow metric alteration status following CEFWG 2021.

To illustrate how this approach could be applied in the GSL Basin, we identified a set of 14 active streamflow gages with more than 15 years of data within the 1951-2024 water years (Table S6). For each gage, continuous daily streamflow timeseries were input into the functional flows calculator (Lane et al. 2026) to generate observed annual FFM series. The corresponding FFM predictions for stream segments associated with each gage location were assembled for comparison, and the hydromodification assessment was performed as described above. We additionally generated site-specific “hydromodigraphs” to illustrate and compare current and predicted functional flow metric ranges over the water year to highlight the type and extent of hydromodification. Complete hydromodification results for a subset of metrics and stream gages are provided in Table S7 and included in the [GSL Basin functional flows geodatabase](#).

Several outcomes from this assessment could directly support environmental flow management and inform water management tradeoffs in the basin. The alteration status of specific functional flow metrics can be mapped at candidate locations (streamgages or hydrologic model nodes) across the basin, as illustrated in Figure 13. The “hydromodigraphs” (Figure 14) provide more detailed, visual explanations of the type, extent, and direction of alteration across functional flow components. These plots simultaneously highlight alterations in long-term flow magnitude and timing, while representing both seasonal and interannual hydrologic variability. Together, these products could help prioritize (1) conservation (highlight which and where FFMs remain relatively unaltered) and (2) flow management / restoration actions (highlight which and where metrics are altered and in what ways). The approach could also be used within a basin tradeoff analysis context to evaluate whether and to what extent alternative water management scenarios may change or mitigate current patterns of functional flow metric alteration (Null et al. 2024).



Figure 13. Summer median flow magnitude alteration status at several active streamflow gages.

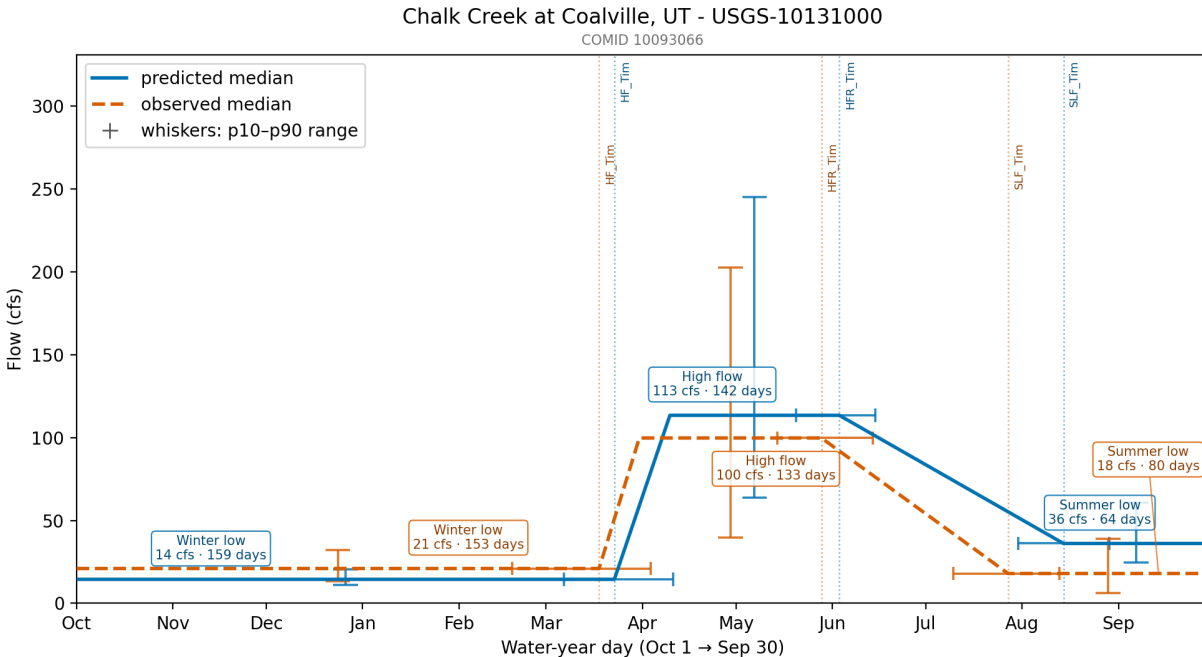


Figure 14. A “hydromodigraph” comparing the interannual distributions of predicted and observed functional flow metrics over all observed/predicted years of data. Thick lines show median magnitude values through time with vertical whiskers indicating the 10th-90th percentile prediction interval; thin vertical lines show median timing for start of high flow ascension (HF_Tim), start of recession (HFR_Tim), and start of summer low flow (SLF_Tim) with horizontal whiskers indicating the 10th-90th percentile interval. This hydromodigraph is for Chalk Creek, a tributary to the Weber River, and provides an example of hydrologic alteration assessment results for a site affected by water diversions for irrigated agriculture. At this location, the observed summer median flow values are well below the predicted range, and the metric is categorized as “likely altered, lower than predicted”. Similarly, summer low flow timing is categorized as “likely altered, earlier than predicted” due to irrigation diversions that truncate the high flow recession period.

Considerations

Several sources of uncertainty may influence the results of functional flows alteration assessments. First, only about 50 of the ~2,500 stream segments for which FFM predictions were generated have active gages on them, fewer with 15+ years of record, highlighting previously identified gaps in GSL Basin streamflow monitoring (Lukens et al. 2024). The hydromodification assessment approach also assumes that the functional flows calculator accurately captures annual FFM values at candidate sites. While the functional flows calculator performs well in highly seasonal perennial streams (Lane et al., 2026), performance can suffer when applying the calculator to highly altered river systems affected by dams or diversions. An alternative “flashy functional flows calculator”, recently developed for California (Carpenter and Yarnell 2025), could be adapted for the GSL Basin to improve FFM alteration estimates for highly altered gages. Errors in the reference-based FFM predictions and/or current condition values could potentially lead to cases of false positives (reference-condition gage assigned as likely altered) or false negatives (hydromodified gages being assigned as likely unaltered) for some FFMs. For example, the functional flow predictions tend to overestimate some magnitude metrics in the karst-dominated Logan River. As a result, the hydromodification assessment at the active streamflow gage near the mouth of Logan Canyon (Table S6, Table S7, gage

#10109000) suggests that observed winter low flows and high flows are depleted relative to reference conditions, which is inaccurate given the minimally altered hydrology at that location. If the FFM predictions were revised for this and other strongly groundwater-influenced systems similarly to Yarnell et al. (2022) (see prior subsection), the hydromodification assessment would likely yield more accurate results.

4.3. INFORMING GSL BASIN INTEGRATED PLANNING EFFORTS

The flow metric predictions provided in the GSL Basin functional flows geodatabase can help characterize and quantify how much water is needed for water quality and environment – one of many elements being considered as part of the GSL Basin Integrated Plan (GSLBIP; Figure 15). More broadly, the ecological management goals identified by stakeholders through the functional flows framework process (Table 2 in Lane et al. 2026) can help with setting and modeling water resource system performance measures (WRe and USBR 2024). Simulated streamflow timeseries developed through GSLBIP Variable Infiltration Capacity (VIC) hydrologic modeling of unimpaired conditions, current conditions, and simulated future scenarios could be input into the functional flows calculator and/or hydromodification assessment to help evaluate alternatives and analyze trade-offs. Ultimately, the functional flows framework, calculator, natural functional flow metric predictions, and associated tools are intended to help maximize the ecosystem benefits of water delivered as part of Great Salt Lake recovery efforts.

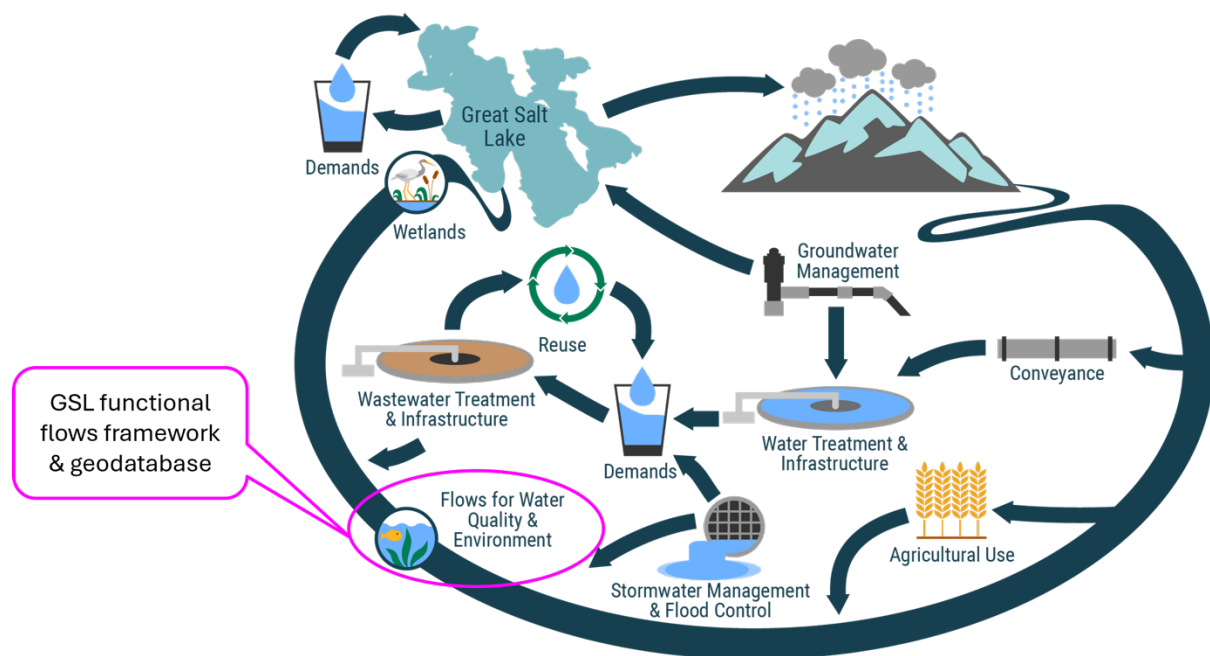


Figure 15. Contextual illustration of how the GSL Basin functional flows framework and predictions geodatabase relate to other GSLBIP elements. Figure adapted and used with permission from Utah Division of Water Resources.

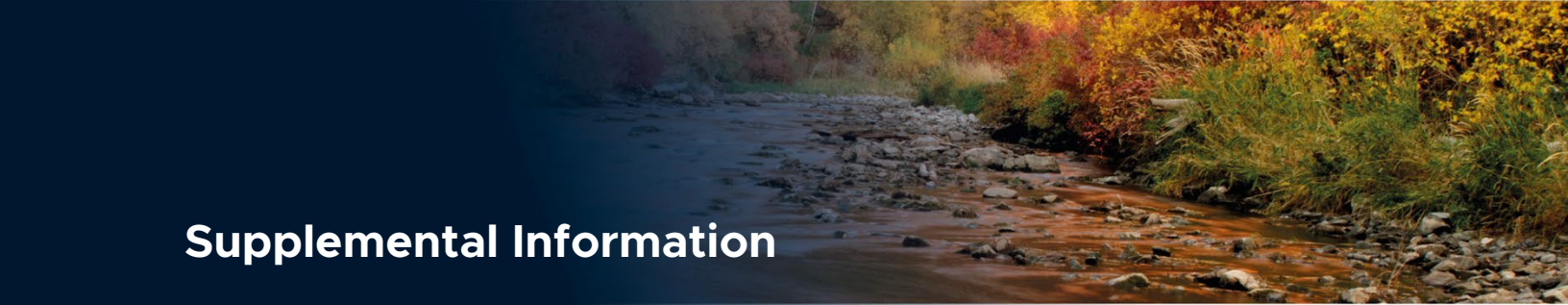


5. Summary and Future Work

This report presents a machine-learning framework for estimating reference-condition functional flows across the Great Salt Lake Basin stream network. Using random forest models trained on 180 minimally disturbed reference gages, we predicted the interannual range of 18 functional flow metrics. Seventeen of the 18 metrics achieved good or better performance and are compiled in a public functional flows geodatabase. Together, these products establish a regional foundation for identifying holistic environmental flow targets, assessing hydrologic alteration, and evaluating water management tradeoffs as part of the GSL Basin Integrated Plan.

The functional flow metric predictions are best understood as a starting point rather than a prescription. They provide holistic, regionally consistent flow ranges that are particularly valuable where local data and resources are limited, but they should be refined locally in light of non-flow constraints (physical habitat, water quality, biological conditions) and revised where site-specific flow–ecology relationships indicate that reference ranges do not achieve the intended ecological functions.

Several priorities would strengthen and extend this work. First, the accuracy and geographic extent of the functional flows models and the hydromodification assessment are constrained by gaps in the reference-condition and the full stream gage networks, respectively; strategically installing gages in more and underrepresented hydrologic settings (e.g., ephemeral streams, strongly groundwater-influenced reaches) would improve prediction accuracy. Second, incorporating additional geospatial predictors not currently available basin-wide (e.g., karst extent and lithology) and correcting persistent errors in the NHD stream network would refine the functional flow predictions. Third, a systematic, basin-wide hydromodification assessment would highlight current patterns of functional flows alteration and help prioritize areas for conservation or flow management activities. Fourth, given long-term natural streamflow simulations from ongoing basin-wide hydrologic modeling, natural functional flows could be calculated at model nodes, improving the geographic scope and accuracy of the functional flow predictions. Fifth, documenting how flows and their alteration relate to ecological endpoints actively monitored by state agencies (e.g., aquatic macroinvertebrate community health (Utah DEQ), fish population dynamics (Utah DNR)) would provide additional evidence of functional flows' effectiveness where data and resources permit, and help prioritize flow management decisions. Sixth, functional flow targets create an opportunity to generate multiple environmental benefits as water moves through rivers, wetlands and Great Salt Lake. A case study conducted in partnership with a water district, irrigation district, or water right holder could implement functional flows and shepherd them through connected river, wetland, and lake systems, demonstrating how a single water lease, purchase, or voluntary agreement can generate multiple compounding environmental benefits across a watershed. Finally, incorporating these initial environmental flow targets within GSL Basin Integrated Plan water resources modeling and tradeoff analysis would allow direct evaluation of how current and alternative management strategies affect functional flows, advancing the shared goal of maximizing the ecological benefits of water delivered to the Great Salt Lake.



Supplemental Information

HydroShare Resource Link:

<https://www.hydroshare.org/resource/a573526e3007489c8abcd1e494c3ea67/>

The “Supplemental” folder is located in the “Content” section of the HydroShare resource.

Contents:

Table S1. Reference gages used for Great Salt Lake Basin functional flows modeling

Table S2. Climate and watershed attributes used as predictor variables in functional flow models

Table S3. Water year types used to categorize calculated reference gage and predicted Great Salt Lake Basin functional flow metrics

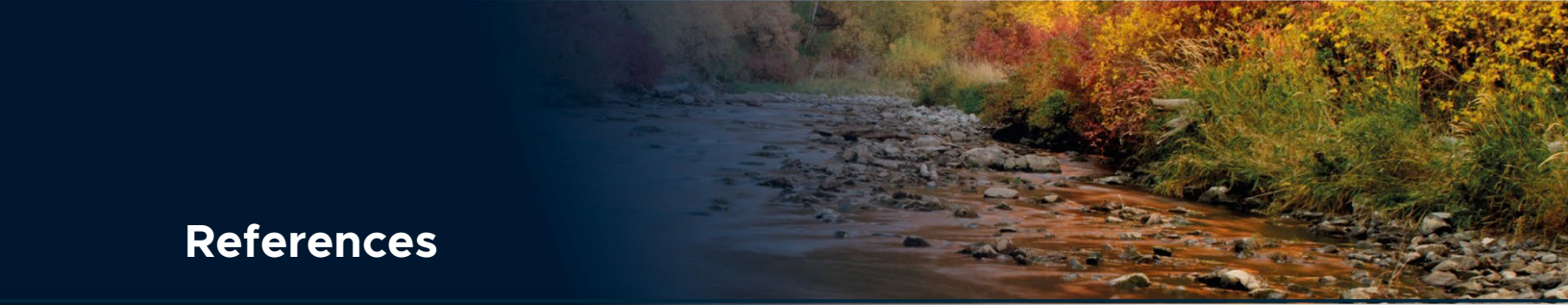
Table S4. Variable importance rankings for functional flow metric models

Table S5. Functional flow metric model performance statistics

Table S6. Active streamflow gages used for proof-of-concept hydromodification assessment

Table S7. Hydromodification results for select gages used for proof-of-concept assessment

Figure S1. Random Forest partial dependence plots for 18 functional flow metrics and their top predictor variables.



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